

# Optimal Accelerometer Placement for Fall Detection of Rehabilitation Patients

Nor Surayahani Suriani, Fadilla 'Atyka Nor Rashid and Nur Yuzailin Yunos  
*Department of Computer Engineering, Faculty of Electrical and Electronics Engineering  
Universiti Tun Hussein Onn Malaysia, Batu Pahat 86400, Johor, Malaysia  
nsuraya@uthm.edu.my*

**Abstract**—The development of health monitoring system using wearable sensor has lots of potential in the field of rehabilitation and gained lots of attention in the scientific community and industry. The aim and motivation in this field are to focus on the application of wearable technology to monitor elderly or rehab patients in home-based settings to reduce resources and development cost. The wearable sensor such as accelerometer used to emphasise the clinical applications of fall detection during rehabilitation treatment. This paper is intended to determine the optimal sensor placement especially for lower limb activity during rehabilitation exercise. Accelerometer data were collected from three different body locations (hip, thigh, and foot). The lower limb activities involve normal movements such as walking, lifting, sit-to-stand, and stairs. Other unexpected activity such as falls might occur during normal lower limb exercise movement. Then, acceleration data for various lower limbs activities was classified using k-NN and SVM classifier. The result found that the hip was the best location to record data for lower limb activities including when fall occurs.

**Index Terms**—Activity Recognition; Home-Based Rehabilitation; Fall Detection; Wearable Sensors.

## I. INTRODUCTION

Wearable sensors technologies have been widely used in human behavioural recognition to identify activities of daily living (ADL). These technologies provide a low-cost, practical, effective and privacy-aware solution for activity recognition. The most generally used inertial sensor is accelerometer which provides quantitative measures of acceleration depending on the mass movement and displacement.

Nowadays, wearable technology extends its range into the development of healthcare monitoring, diagnostic and wellness purposes. Extensive research has been carried out to prove the feasibility of inertial sensor in health monitoring development system [1-2]. In rehabilitation application, wearable sensors are used to gather movement data for home-based patient's monitoring. Sensors are deployed at the appropriate parts of the human body during the treatment process. Online patient's treatment activities will be monitored by a medical expert or therapist. Then, clinical information provided by the sensors will be used to assess performance, and the medical expert will send feedback on the treatment process via online. The feasibility of inertial measurement unit (IMU) especially accelerometers has been reviewed by many researchers as motion sensing devices for ambulatory monitoring (e.g. elderly falls) [3].

Sudden event detection for human activity recognition is intended to provide safety and comfort to the society

especially for the elderly who live independently at home [4]. Therefore, this paper is built to investigate the optimal sensor placement for lower limb activity to detect falls during rehabilitation exercise. Plus, this paper also determines the effectiveness of assistive device development for a home user or rehabilitation patients. An accelerometer is being used as the assistive device as well as the sensor for this research.

A gait can be measured by an accelerometer. These measurements help to identify sudden gait changes during an emergency situation (e.g. human falls). When the accelerometer detects any falls, an alarm system will notify the caregiver to provide immediate assistance to patients. Accelerometer also used in gathering skill assessment information to monitor the progress of physical rehabilitation and for coaching sports activities.

## II. RELATED WORKS

The research in biomechatronics sensing help in treatment and assessment of rehabilitation process such as for stroke patients, patients after surgery, and also the use of mobility assisting devices for elderly. Online healthcare system used by the doctors to monitor the treatment performances and patients' assessment. Zhang et al. used sensing devices such as accelerometer sensor, gyroscope and magnetic sensor used to develop motion tracking system and model 3D animation for rehab patients with chronic pulmonary disease and stroke [5]. Mazilu et al. used accelerometers to analyse the gait for Parkinson disease [6]. Bartalesi et al. suggest kinesthetic wearable sensor in an upper limb gesture recognition system for stroke patients[7]. Pan et al. focused on upper part rehabilitation treatment for home-based monitoring online system [8]. Dobkin et al. classified activity pattern and speeds for healthy and hemiplegic patients by placing an accelerometer over the tibia which is just above the ankle [9]. Human activity classification through wearable sensor can accurately measure the quality of movement, especially in a rehabilitation progress monitoring system.

In fact, the acceleration data collected from any rigid part of the human body can be measured to identify the pose and types of human activities. Researchers reported many related works in estimating the spatiotemporal human gait or estimation of head motion by using accelerometers. Motion patterns derived by accelerometer also help to detect eating behaviour for many health applications [10]. Furthermore, the combination of accelerometers is also sufficient to detect sudden changes of posture imbalance which may help to predict and detect sudden fall events [11]. Edward et al. designed a shoe-based device which provides sensor data to classify physical activities and detect fall through postures

positions for stroke patients using support vector machine (SVM) [12]. Khan et al. proposed a hierarchical approach to recognise statistical signal features carried out from accelerometers using artificial neural nets (ANNs) for walking, lying, sitting, and running physical activities [13].

For detection of real-time monitoring using wearable sensors, various classifiers can be used such as k-Nearest Neighbor (k-NN), least squares, hidden Markov Model, Artificial Neural Network (ANN), Gaussian Mixture Model (GMM) and Support Vector Machines (SVM). Modelling of single sensor single classifier (SSSC) and multi sensor multi classifier (MSMC) [14] used to enhance detection of action transitions between defined actions in real time. The unique features of action transitions such as sit to stand or lie to stand are the most likely causes of a sudden fall event in a home environment.

Although inertial sensor system provides useful clinical information for assessment, there is still a number of challenges in technical issues raised up [15]. The challenges identified that variations sequence of activities from different individuals and culture might produce invalid results. Furthermore, the reliability and accuracy of sensors depend on placement or positions of sensors during motion. Besides, users move in control manner because they worried if the device will be damaged. Then, device placement remains a complex decision that needs further investigation related to issues of different orientation and measurement.

Therefore, this paper aims to determine the optimal place for accelerometer for detecting lower limb rehabilitation activities. Apart from that, this paper also highlights the optimal place for accelerometers to detect when sudden fall occurs during the rehabilitation exercise. Although, placing multiple sensors on various parts of the body will generate collectable data but users will be uncomfortable and data collected will have large interference.

The lower limb activities focus on walking, sit to stand, and leg lifting training for rehab patients. The sit to stand movement is a useful indicator of rehabilitation. The rise from a chair and to sit down exercise in a controlled manner is important to assess individual functional ability. This sit to stand training does not require much space and the usage of accelerometers sensors have great potential in a low-cost home-based rehabilitation environment.

### III. SYSTEM OVERVIEW

This section describes the data collection from tri-axial accelerometer sensor and feature extraction for classification of lower limb rehabilitation activities. The lower limb exercise involves typical activity for a normal human being such as walking, sitting, walking up, and down the stairs. Meanwhile, this system can detect an abnormal event (e.g. patient fall) occur during the exercise activity.

#### A. Data Collection

As shown in Figure 1, the sensor used in the experimental setup was a 4mm long and 4mm wide sensor composed of a triaxial accelerometer ADXL335 with a minimum full-scale range of  $\pm 3g$  and connected to Raspberry Pi. Acceleration data were collected from five male and five female subjects within a range of age from 12 to 40 years old. The average height of all subjects is 153.67cm. Subjects wore three accelerometer sensor attached to their lower body parts. These locations are the typical placement for lower body parts

assessment. The raw data acquired by accelerometer with 50 Hz were transmitted via Bluetooth to a notebook computer for further analysis. MATLAB software has the GUI for data storage and running the analysis.

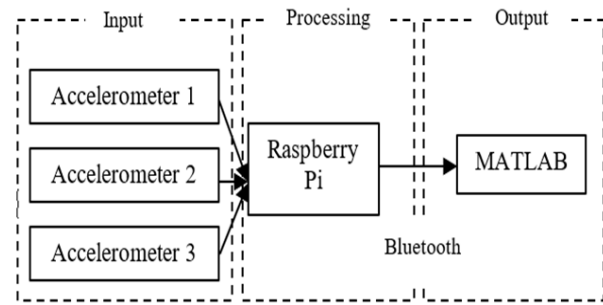


Figure 1: The overview of the overall system

The raw accelerometer data were sampled into dynamic sampling window and filtered to suppress the noise. Normally, the average window size for all activities is in the range of 2s to 5s. The window size of more than 5s was assuming too long enough to segment some transitional activity signals. Although smaller window size could ease the signal split process, suboptimal information during the transitional activity might occur. Therefore, dynamic sampling window will overcome the problems in sampling short period activity (e.g. walking) and long period activity (e.g. sit-to-stand or stand-to-sit).

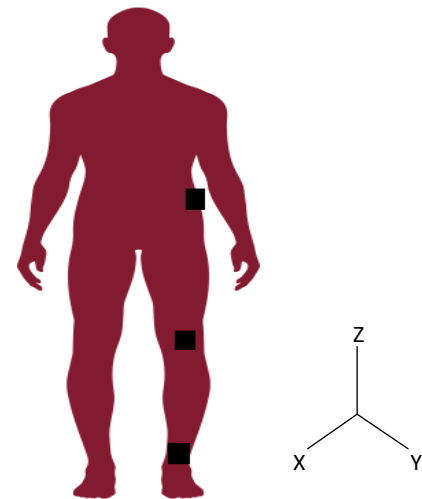


Figure 2: Selected placement for the accelerometer (hip, back of thigh and foot)

Figure 2 shows the tri-axial accelerometer sensor placed at the hip, back of thigh and foot. Triaxial sensors are used because that this device has high sensitivity and can detect light movement like slow walking. A sensor located at the thigh and foot is obviously can detect vertical up and down movement. However, the signal used to be corrupted by noise easily.

Meanwhile, another sensor located at the hip will impact on major fall detection which measured by the given large displacement. The lower limb activities are classified into a list of normal activities for rehabilitation patient, which for some reasons that fall might occur during the rehabilitation exercise. The normal lower limb activities are walking, leg lifting, sit-to-stand, going up and down stairs. The abnormal

event includes fall during normal exercises. The subjects had to remain on the floor for about 10-25 seconds after the fall in order to ensure that the person is really in fall condition.

### B. Feature Extraction

For machine learning algorithm, pattern recognition does not measure from raw sensor data. Normally, classification is carried on after data representation is built in the form of feature sets. The feature extraction normally involved standard metrics such as mean, average mean, average standard deviation, skewness, and kurtosis. For optimal computation, this work attempt to analyse six features as presented in Table 1. A total of 12 attributes were extracted from the raw acceleration data for different types of lower limb exercise such as walking, leg lifting, sit to stand, and stair walking. Features 1-4 are simple and standard statistical metrics used in many human action, activities and postures recognition.

Table 1  
Features Extracted from Raw Accelerometer Data

No.	Features
1	Mean of x, y and z-axis
2	Average mean of 3 axes
3	The standard deviation of x, y and z-axis
4	Average standard deviation of 3 axes
5	Correlation over (x_y axis), (x_z axis) and (y_z axis)
6	Acceleration, g

Meanwhile, correlation axes features (No. 5) used to improve the detection of multiple body parts movements for different activities. It is helpful to describe the strength of the relationship between two axes and translation of one-dimensional movement. Refer Equation (1) for correlation between two axes is calculated as the ratio of the covariance and the product of standard deviations. Correlation is useful to differentiate activities that involve one dimension of translation. For example, walking activity only involve one dimension compared to stair climbing which has a translation in more than one dimension.

$$corr_{(x,y)} = \frac{cov(x,y)}{\sigma_x \sigma_y} \quad (1)$$

Acceleration feature,  $g$  (No. 6) is the total sum vector of acceleration components,  $SV_{Total}$ . The raw acceleration vector projections  $ax$ ,  $ay$  and  $az$  must be converted into Volt by referring to the sensor specification.

$$SV_{Total}(t) = \sqrt{x^2(t) + y^2(t) + z^2(t)} \quad (2)$$

where  $x(t)$ ,  $y(t)$  and  $z(t)$  is the acceleration in x, y and z-axes at time  $t$ , respectively. The total sum vector is also sufficient to determine the threshold value for activity monitoring system when sudden fall occur.

## IV. RESULTS AND ANALYSIS

The recognition rate to determine the optimal placement of accelerometer was tested using  $k$ -nearest neighbour ( $k$ -NN) and Support Vector Machine (SVM) classifier. Both  $k$ -NN and SVM are discriminative models which known as a successful classifier in numerous applications. The classifier

parameters for each classification method were configured by partitioned the sample into  $k$  subsamples. In the testing stage, a single subsample is retained as the true test data, and the remaining  $k-1$  subsamples are used as the training data. The larger values of  $k$  will reduce the effect of noise on the classification, but obscure the boundaries between the classes. The  $k$  results from the folds will be averaged to produce a single estimation.

Table 2 shows that the classifiers produced the best result when  $k$  equals to 3. The result shows that data from all sensor locations were best classified from normal or fall activity using SVM classifier. The SVM classifier is able to detect a fall while doing lower limb rehabilitation exercise with 88.7% accuracy.

Table 2  
Recognition Rate of Different Sensor Location for Lower Limb Exercise

Sensor Location	k-NN		SVM	
	k=3	k=5	k=3	k=5
Hip	85.9%	82.3%	92.3%	89.1%
Thigh	82.4%	81.8%	87.5%	83.6%
Foot	81.7%	79.5%	86.4%	82.7%
<b>Average</b>	<b>83.3%</b>	<b>81.2%</b>	<b>88.7%</b>	<b>85.1%</b>

Further analysis is needed to verify the best sensor location on human body parts and help to improve the accuracy of healthcare monitoring system. The analysis was carried out using  $F_{measure}$  parameter [16] to select the optimal sensor location.  $F_{measure}$  in Equation (3) is a score adjustment between precision and recall parameter to evaluate ability performance index for SVM classifier in classifying different types of lower limb activities including fall event.

$$F_{measure} = 2 \times \frac{precision \times recall}{precision + recall} \quad (3)$$

Precision is the percentage of classifier ability to detect a relevant number of fall events among the total number of falls during lower limb rehabilitation activities, while recall or sensitivity is the percentage of the classifier to detect the relevant number of fall events among the entire set data (falls and non-falls) classified as falls event. Table 3 presents calculated  $F_{measure}$  for all lower limb activities at three different location using cross-validation SVM classifier.

Table 3  
 $F_{measure}$  values for different sensor location using SVM classifier

Activity	Hip	Thigh	Foot
Walk	0.90	0.90	0.85
Leg lifting	0.82	0.90	0.90
Sit-to-stand	0.90	0.82	0.81
Walking upstairs	0.88	0.81	0.91
Walking downstairs	0.85	0.81	0.90
Walk-Fall	0.90	0.85	0.82
Unbalanced leg lifting	0.90	0.90	0.86
Fall on stairs	0.90	0.86	0.82
<b>Average</b>	<b>0.882</b>	<b>0.859</b>	<b>0.861</b>

Results show that the lower limb activity using hip data give highest  $F_{measure}$  value with an average 0.882 while placing accelerometer at the thigh give the lowest  $F_{measure}$  average value of 0.859. Therefore, this paper concludes that the hip was the best single location to record data for lower limb rehabilitation activities. In addition, the  $F_{measure}$  for simulated fall activity through walk-fall, unbalanced leg

lifting and fall on stairs during the rehabilitation exercise are shown in Table 3. The fall incidents have been accurately detected with the highest  $F_{measure}$  result (0.9) for simulated falls activity when placing the accelerometer at the hip. However, the most important attributes which are very significant to sudden changes in fall detection in Table 1 is not analysed. Further analysis will be carried out using another classification algorithm to identify the significant attributes for sudden fall event detection.

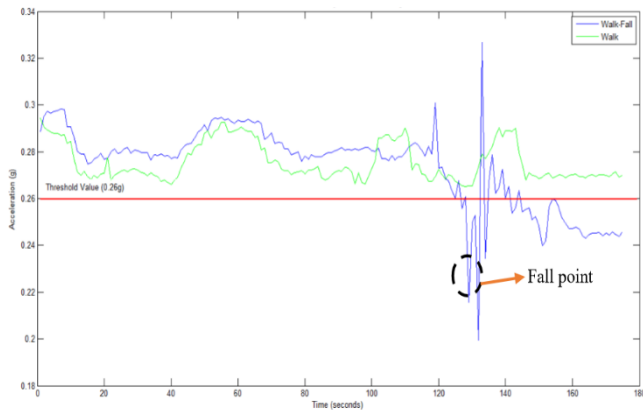


Figure 3: Sample for walk and fall activity

The threshold value calculated from accelerometer sensor data and determined by the average start of point detected for all sample data. Figure 3 shows sample for walk and fall activity signal where fall is detected when the signal drop below the threshold value (0.26g). Meanwhile, the time required to detect a fall can be categories into several fall stages. As shown in Figure 4, the time taken for each stage was compared between the accelerometer data with the ground truth video. The average of time required to detect a fall at various stages is calculated and presented in Table 4. Based on the timing respond to the fall event, unstable and unconscious stages takes the longest time to verify the subject conditions. While fall and sudden impact of fall detected below than 0.5 seconds.

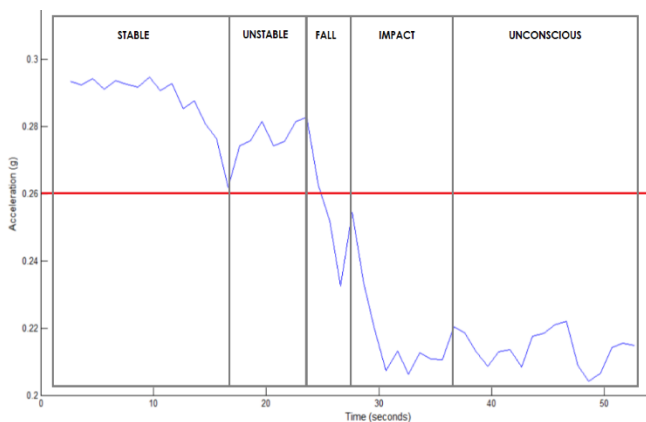


Figure 4: Various detected fall stages

Table 4  
Time Required to Detect a Fall

Stage	Time(s)
Start of fall	0.2
Unstable	0.6
Falling	0.3
Largest impact	0.2
Aftermath/unconscious	0.8

So far, this system observed that the used of accelerometer sensor data is applicable for monitoring rehabilitative patients and is extendable to a larger class of movements and postures. Furthermore, the adaptive threshold might be helpful to improve the system performance for high sensitivity and excellent specificity.

## V. CONCLUSIONS

This paper investigated the optimal sensor placement specifically for lower limb activity. The simulation data was carried out for normal exercise for rehabilitation patient and also detecting falls during the rehabilitation exercise. This research was in line with previous work which has validated the effectiveness of accelerometer sensor for daily human monitoring. However, the previous study does not attempt to investigate the optimal sensor placement especially when involving human fall detection monitoring in their system. The results and analysis found that for lower limb activities, accelerometers attached at the hip gave optimal performance rather than sensors attached to the thigh and foot. These results may reduce the number of sensors that users need to wear. In future, this work will extend towards focusing on the quality of rehabilitation exercise through extensive computational statistical approach.

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