Recent Trends in Civil Engineering and Built Environment Vol. 2 No. 1 (2021) 372-380

RTCEBE

Homepage: http://publisher.uthm.edu.my/periodicals/index.php/rtcebe
e-ISSN :2773-5184

Detection of Human Fall Using Floor Vibration and Artificial Neural Network

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DOI: https://doi.org/10.30880/rtcebe.2021.02.01.040
Received 30 January 2021; Accepted 28 April 2021; Available online 30 June 2021

Abstract: High rates of wellbeing and improved life expectancy have resulted in the rapid growth of the world's older population. Older individuals are more likely to suffer from falling with adverse side effects, including chronic illnesses threatening health and life. Hence, many systems are used to detect a falling event on the floor. Being empowered to generate accurate fall detection will minimize the effects of the fall experienced by older people would ultimately boost health outcomes and decrease healthcare expenses after falling. A new approach used in this study was proposed to accomplish the goal by utilizing an artificial neural network from acceleration signal measurement through floor vibration to detect human fall. Experiments from four types of events such as dummy falling, free jumping, sitting, and walking was conducted at Jamilus Research Centre laboratory, UTHM. The feature vector of variance, peak value, and mean value was selected as input parameters extracted using the average of all the eight sensors to train and test the dataset performance using the neural network algorithm in MATLAB software. The results showed that the data set testing could accurately identify the actual human fall from other human activities with an accuracy of 96.6%, a 96.5% specificity, and a sensitivity of 97.1%. Therefore, the proposed Artificial Neural Network has verified high accuracy and confidence in the predicting model.

Keywords: Elderly, Falling Detection, Floor Vibration, Neural Network

1. Introduction

Owing to a rise in age, older individuals are more susceptible to be in danger of falling with significant side effects and chronic conditions [1-2]. In the face of the particular situation within the elderly, the Medicare system is struggling in Malaysia, where older consumers are more inclined to hunt for medical treatment than young people [3] . Falling may be a situation during which an individual falls accidentally to the ground or a lower stage [4] . Falls may often occur to someone due to personal negligence or health considerations. Nonetheless, there is a greater probability of collapsing for older individuals residing alone instead of being in nursing homes [2,5,6].

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Populations among older people much need a fall detection system that relies on quick response and rescue. Different technologies are used to develop human fall detection systems, including vision-based devices, wearable-based devices, and non- wearable sensors [7]. Vision-based devices are very accurate in determining the occurrence of falls and may produce fewer false signals. However, it is expensive and requires a complicated setup. Wearable devices like a watch, clip, or belts are for detecting rapid changes in users' network to report emergency falls by interacting through the device being used. However, this method may generate a high false signal because it cannot identify falls when an accident occurs. The non-wearable sensor method is a fall detection system using an infrared camera to regulate user behavior and detect falls through computer vision techniques. The utilization of the camera is often related to invading the privacy of users who feel uncomfortable being watched by the camera. Conversely, the floor vibration method may be a new approach used to detect falling events without using a camera by installing a sensor accelerometer on the floor structure that can be detecting the movement of human behavior [8].

A floor vibration method is a new approach used to detect falls events without cameras by installing accelerometer sensors on the floor structure to capture any human behavior movement that produces different acceleration signals. Thus, the Artificial Neural Network algorithm is proposed to analyze and classify the acceleration response between human fall and other human activities through a measurement accelerometer sensor from floor vibrations. Therefore, this study aims to achieve the objectives where to determine the fall testing using floor vibration method. Also, to analysis and differentiate the accelerations response between human fall and other human activities using artificial neural network (ANN). The scope of this study is the testing used eight (8) accelerometers sensor to measure the acceleration signals movement generated by daily movement patterns performed on the ground floor of Jamilus Research Centre (JRC) laboratory in Universiti Tun Hussein Onn Malaysia. The dimensions are 4.5 meters in length and 3.0 meters in width. A randy rescue resembling a real human model is used in falling human samples to gain the same fall momentum. Accordingly, four types of the situation were carried out such as dummy falling, free jumping, sitting and walking. Then, the data collected would be analyzed by using the Neural Network Toolbox in MATLAB software.

2. Materials and Methods

This part is represent the methodology that explain the implementation that has been carried out to achieve the objectives of the study. Details of the procedure and technique also were provided to obtain and analysis the data.

2.1 Test arrangement and instrument

Eight (8) accelerometers (Model: KS48C; Sensitivity: 1000 mV/g; Frequency Range: 0.1 to 4000 Hz) were used to record the floor accelerations signals where four (4) accelerometers were placed near the wall, and the rest has been put toward a target located at excitation position A and B as shown in Figure 1. The dimensions of the testing area were 4.5 meters in length and 3.0 meters in width. The measuring instrument used in this study was an accelerometer sensor as a floor vibration detector and Imc CRONOS flex (model: KS48C) with eight analog input channels (16-bit/24-bit resolution) was used as a data logger. Hance, laptops were also used as a device to produce outputs that have been manipulated by data loggers using IMC studio software.

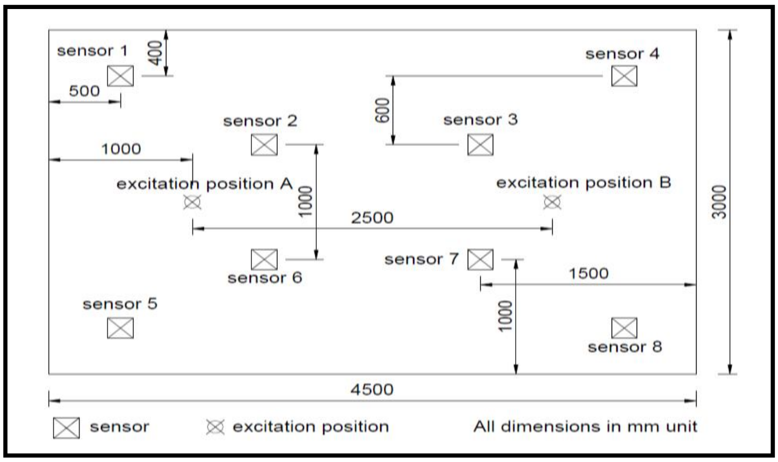

Figure 1: Accelerometer position arrangement in laboratory experiment

2.2 Falls test

The fall testing procedures were adopted from [8]. Four types of sample events were testing from dummy falling, free jumping, sitting, and walking as shows in Table 1. This experiment start by dropping the dummy forward or backward with an estimated time of 10 seconds as shown in Figure 2(a) and it was performed 55 times repetitions at each excitation position A and B. Next, free jumping and sitting was conducted by using the same step with a weight of 80kg jumped and sitting freely for 10 seconds as shown in Figure 2(b) and 2(c) by repeated 55 times at point A and B with a total of 110 samples respectively. The rest was walking test with walking at a normal pace and continue to walk back to the test area for 10 seconds with 55 repetitions as shown in Figure 2(d).

Table 1: Types of events according to their specifications

Type of event	Event detail
Dummy falling	Dummy with weight 26kg falling backward/forward at point A and B
Free jumping	Volunteers with weight 80kg jumping at point A and B
Sitting	Volunteers with weight 80kg sitting at point A and B
Walking	Volunteers with weight 80kg walking freely

(a) **(b)** **(c)** **(d)**

Figure 2. Type of event (a) Dummy Fall (b) Jumping (c) Sitting (d) walking

2.3 Data analysis using neural network in MATLAB software

A total of 385 samples obtained from these experiments with four different types of events was converted into a MATLAB file. Then, graph of acceleration versus time were plotted to see acceleration response between each sample events. The time was calculated based on a rate value of 200Hz were setup in IMC studio where it generated 2000 data in 10 seconds. The time was calculated based on a rate value of 200Hz were set in IMC studio.

Next, analysed data using the Neural Network Toolbox in MATLAB. The feature vector of variance, peak value and mean value was extracted using the data from average of all the eight sensors and it called as a input data. Pattern recognition applications were used to predict the model by select the data input and target where target data is the data that needs to be processed in vector form to allow the system to read as predicted.

The data set consists of the Training (70%), Validation (15%), and Testing (15%) of 385 samples with the number of hidden layers was set to 20. A training set data used to train the model during each epoch, which is repeatedly trained on comparable data within the training set. It continues to find out about this feature vector data that can deploy the model and accurately predict new data that it's never seen before. After setting all the parameters, the data set has been trained and stopped when getting a good performance and provided the output.

The evaluation of accuracy, sensitivity, and specificity from the prediction results is determined using the following question 1, 2, and 3 respectively [7].

$$\text{Accuracy} \quad = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$\text{Sensitivity} \quad = \frac{TP}{TP + FN} \tag{2}$$

$$\text{Specification} \quad = \frac{TN}{TN + FP} \tag{3}$$

3. Results and Discussion

This part presents the results of experiments conducted on sample events through the floor vibration method induced by human behavior. The data analysis results using the Neural Network algorithm are also shown to prove the objectives of the study achieved.

3.1 Fall Acceleration Response

The graph acceleration against time as shows in Figure 3 has different color represent the different sample events at each accelerometer sensor. Based on these graph, the acceleration signal from the dummy fall at excitation position A and B produces high vibration due to the dummy fall's impact on the floor. It proved the acceleration signal has dominated by dummy fall compared to the other sample events. However, the vibration signal generated by the sitting test has a lower acceleration. Sitting has a lower value because of the lower impact on the floor with the minimum movement. Then, the other sample events have a similar value produced signal by the accelerometer sensor. To be more clearly, Figure 4 shows the graph of peak acceleration against time for each sample events at each accelerometer sensor.

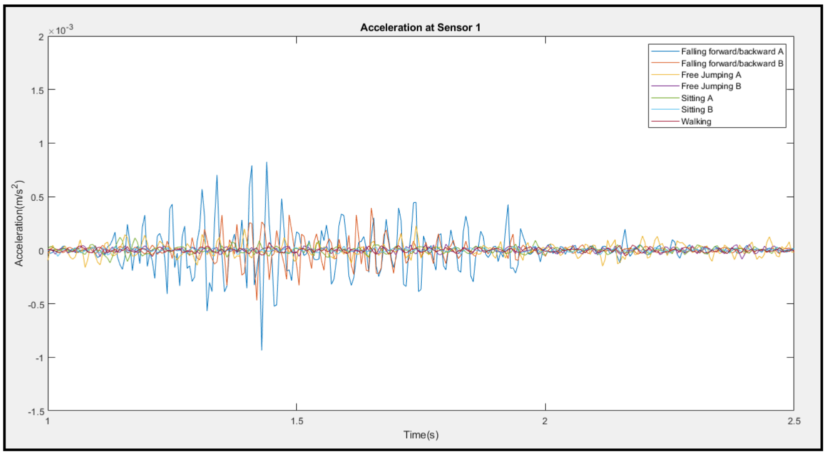

Figure 3: Acceleration signal from each activities at accelerometer sensor 1

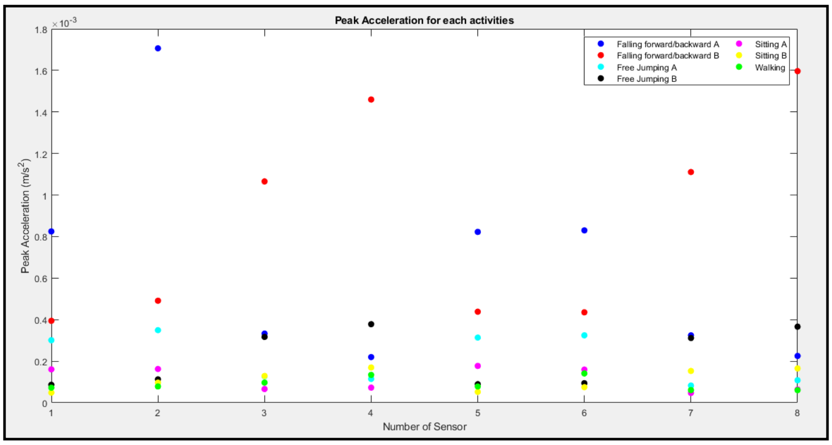

Figure 4: Peak acceleration signal from each activities

3.2 Artificial neural network analysis

Based on the data analysis using neural network algorithm from the pattern recognition, the validation to determine the accuracy assessment as indicated in Figure 5 until Figure 7. The best validation performance with the value of cross-Entropy is 0.06776 at epoch 11 as shows in Figure 5. The total epoch provided the number of the same process has been repeated to get the best performance, and the number of epoch should be increased to reduce the performance error. Cross-validation dataset is required to check the neural network model does not overfitting the train data set during training. The cross-entropy decreased on both the training and validation data set after the train set would continue to go down while the validation set would be increase where it called the overfitting. Therefore, the training process has stopped at 17 epoch. The best validation has been chosen at 11 epoch to avoid the underfitting and overfitting occurs where the model does not have enough variables to solve the training data set.

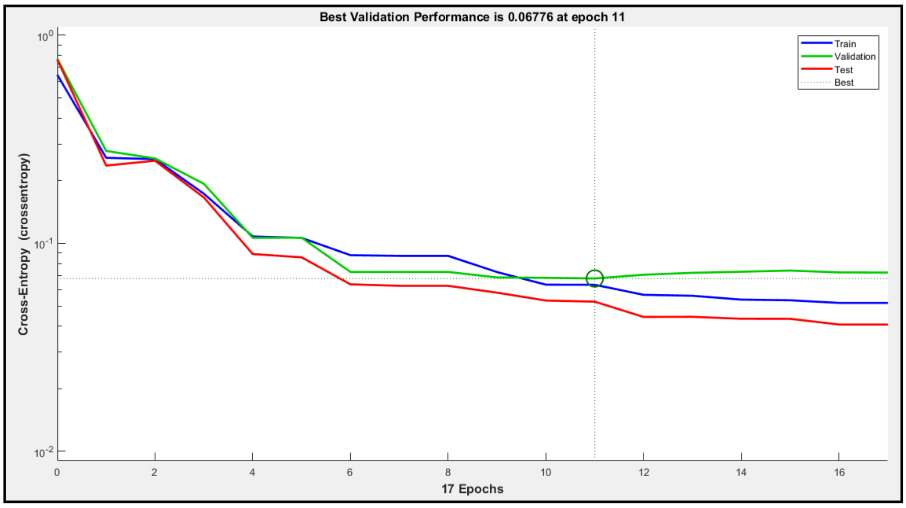

Figure 5: Validation performance of dataset model

The Receiver Operating Characteristic (ROC) graph was provided in Figure 6. The operating characteristics of the receiver are the metrics used to check the quality of the classification. ROC applies the threshold value at interval [0, 1] for each classification class in output. For each threshold, two values are calculated, namely True Positive Ratio (TPR) and False Positive Ratio (FPR). Class 1 represented the human fall from dummy fall with the weight of 26kg at point A and B while class 2 represented the non-human fall from jumping, sitting and walking with the same weight of 80kg. The graph of true positive rate versus false-positive rate shows how the model was performed regardless of where the threshold was set. So, the grey line is a random prediction to see how close class 1 and class 2. When the class 1 and class 2 below the grey line, the model even worse than random prediction. Instead, when class 1 and 2 are upper the grey line, it can accurately predict the model.

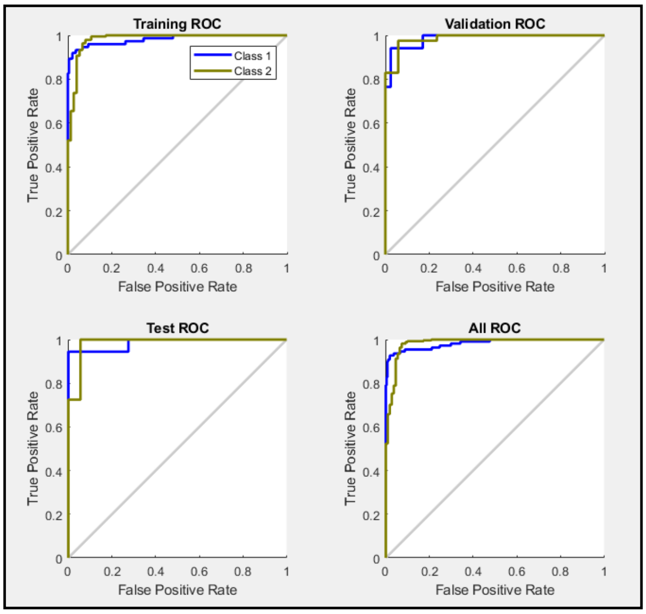

Figure 6: ROC graph of dataset model

The confusion matrix in Figure 7 shows the sample events from human fall (class 1) and human activities (class 2), which were classified correctly in the green squares. It also shows how many data sets were improperly classified in red square. The total percentage of correct and incorrect classification is shown in the grey square. The percentage of the prediction was provided in a white square column, and actual data percentage were shown in a white square row.

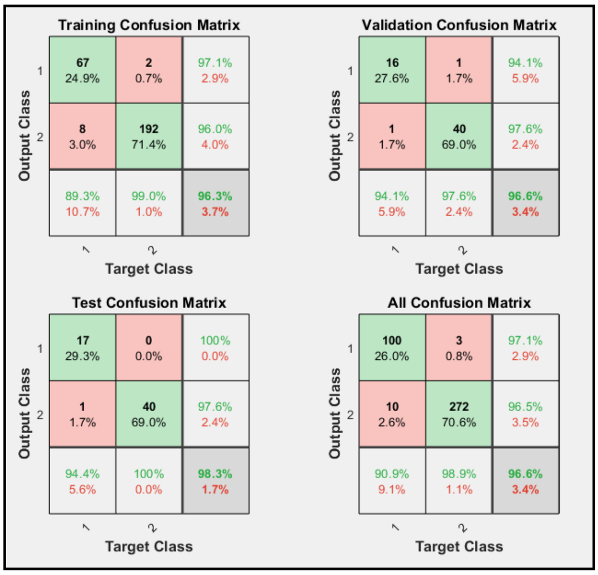

Figure 7 : Confusion matrix of output dataset

The results of the confusion matrix also can be illustrated in the Table 2. It consist of the overall number of trained conducted with the prediction value for each sample events.

Table 2: Overall sample events with actual and prediction values

		Predicted							Total Predicted	
		Dummy Fall A	Dummy Fall B	Jumping A	Jumping B	Sitting A	Sitting B	Walking	Falls	Non-Falls
Human fall	Dummy Fall A	48	0	0	1	0	0	0	**True Positive (TP)** 100	**False Negative (FN)** 3
	Dummy Fall B	0	52	0	0	2	0	0		
Non-Human fall	Jumping A	7	0	55	0	0	0	0	**False Positive (FP)** 10	**True Negative (TN)** 272
	Jumping B	0	3	0	54	0	0	0		
	Sitting A	0	0	0	0	53	0	0		
	Sitting B	0	0	0	0	0	55	0		
	Walking	0	0	0	0	0	0	55		

Using equation (1) to question (3) on the total prediction between human fall and non-human fall from Table 2, the model has obtained an accuracy value of 96.6% with specificity of 96.5% and sensitivity of 97.1%. The percentage of sensitivity is not achieve 100% in classify a human fall because there were 10 data samples from jumping activity making the model confusing. Besides, three sample data from dummy fall misinterpreted with classify into non-human falls. Among human behavior with some activities like jumping and sitting are very similar to human fall. These similarities can lead to difficulties in distinguishing such brutal movements. However, the model shows good performance with average accuracy, which correct classification from the overall number of data predictions.

4. Conclusion

The main objective of this research is proposed to detect human fall using neural network analysis from the accelerometer sensor signal through floor vibration measurement. The proposed algorithm's performance has been confirmed by testing sample events, including human falling using dummy randy rescue, free jumping, sitting and walking. The results showed that the algorithm used on the model from the data set testing could accurately identify the actual human fall from other human activities with the accuracy of 96.6%. The data misinterpreted in classification the model reported on an average of 3.4%. Human activities from free jumping and sitting recognized as the most confusing in identifying the falls due to the similar characteristics from momentum impact on the floor as falling. The percentage of specificity was 96.5% and sensitivity of 97.1% proven that the algorithm can classify the model properly and there were misreporting also generated from human fall and other human activities classification which the percentage of 3.5% and 2.9% respectively. As a compendium, the pattern recognition from neural network algorithm verified the performance of the dataset model that was great potential in identifying the human fall even with just 385 samples collected data and small training dataset. Therefore, the objective of this research can be achieved successfully based on the analysis results were obtained. Simultaneously, the new approach of using a floor vibration technique produced by the accelerometer sensor mounted on the floor that can be applied to detect the human fall among the elder.

Acknowledgement

The authors would also like to thank the Faculty of Civil Engineering and Built Environment, Universiti Tun Hussein Onn Malaysia for providing lab instrument and its support.

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