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IJIE

Journal homepage: http://penerbit.uthm.edu.my/ojs/index.php/ijie
ISSN : 2229-838X e-ISSN : 2600-7916

The International Journal of Integrated Engineering

Neural Network Algorithm-based Fall Detection Modelling

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DOI: https://doi.org/10.30880/ijie.2020.12.03.018
Received 25 April 2019; Accepted 30 November 2019; Available online 27 February 2020

Abstract: Fall is a major threat among elderly people which may lead to injuries or even death. High recognition of developed fall detection model is very significance for the elderly to detect the falls. Related algorithm for the fall detection has been discussed in depth by researcher from the previous research. However, the improvement of model accuracy is still needed. This article presents results of modelling for fall detection system by using nonlinear autoregression neural network NARnet algorithm. The algorithm is trained by network training function; LM, SCG and RP by collocation with threshold-based setting value. Two participants involved in obtaining the acceleration and angular velocity. The type of input source is divided into 4 different types for training. The selection of the model was based on the comparison of optimization epochs, magnitude of validate error or mean square error (MSE), magnitude of correlation performance, the convergence graph in term of MSE performance, accuracy of regression and non-zero value of autocorrelation graph. The simulated result shows that the training model of Type 2 is the best model with a training result of 6.1551mse, 40 epochs, time 0.06s, and 0.92742 accuracy. The result indicates that LM function produce the better solution when compared to another optimization function. In fact, the model accuracy demonstrated that the proposed method was reliable and efficient.

Keywords: Fall detection system, NARnet, mean square error (MSE), scenarios, Levenberg-Marquardt (LM), Scaled Conjugate Gradient (SCG), Resilient Propagation (RP)

1. Introduction

Fall are a major cause lead to fatal and non-fatal injuries among the older people. This is due to as the age of people growing, their physical condition become weaker [1]. People who age above 65 years old are the most frequent age group that suffered with the falling issue [2]. This is because, at the old age, they become prone to different accident as they lose their self-efficacy. Hence, they may suffer a fall incident when doing their daily routine. The fall from doing daily activity like running, climbing can cause to fatal or non-fatal injuries[3]. The effect of fall may lead to fatal when the patient did not get an assistant immediately. Effective way to predict the fall has become serious issues that many researchers are studying in recent years. Model development of fall detection system is necessary to detect the falls effectively. Classification of the falling scenarios between normal activity is always a tough task to be distinguish [4]. There is a previous research that has been try lot of motion as experimental scenario for analysis purpose [5].

There are three basic approaches to analyze the fall scenarios in the detection system [6] which were camera device based, ambient device and wearable device. Harrou et.al, [7] adopted camera on behaviors for vision-based detection in detecting fall events. This method is limited because it only caters for certain angle at that place only. Another type of detection device was ambient device where it measures the condition of a subject under protection. Common ambient-based technology was infrared, sound and vibration sensing. The existence of persons was detected by the sensor and the falls is detected consequently if the person remains in the same position for a long time where this proposed system is called infrared ceiling network system [8]. To cover the whole area, this system needs to be installed in several rooms. The wearable device implements sensors in one device to be embedded in daily activity that allowing free body movement. An accelerometer is proposed by [9] as a sensor to detect fall events and obtained high detection rate. It was

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a device which measures acceleration indirectly through inertial force[10]. However, there still need an improvement in modelling because the sensor can generate false warning due to the sensitivity of body movement.

The wearable fall detection device is usually used or wear at the waist, wrist, chest and ankle [11]. Waist always is the accurate location as the center of body is located at this body part [12-13]. It is often using tri-axial accelerometer to measure the acceleration at three axis; x-axis, y-axis and z-axis [14]. The accelerometer was a sensitive electrical motion sensing device for measuring the acceleration due to the gravity of earth [15]. A gyroscope is applied as an optimum sensing method for increasing the accuracy of results [16]. Scenarios will be predicted as fall when the data exceeded the threshold value [17]. Chen et.al [18], Guo et.al [19]set high acceleration threshold value, low acceleration threshold [20] and angular threshold for detecting the fall event.

Methods such as Support Vector Machine, K-Nearest Neighbor, threshold method and other are applied for the detection system [21–22]. Threshold of the angle and time method proposed by [23] results in low recognition rate and low consistency in detecting fall events. Machine learning technique can enhance the detection system performance. There is some training algorithm to be applied in the neural network when model is being trained. For instance, Levenberg-Marquardt, Quasi-Newton and others. Nukala et al. [24] had developed a wireless gait analysis sensor in artificial neural network for constructing the model. Validation step is a critical part to determine the model architecture and the model accuracy [25].

After analyzing all those methods, this article proposed a method to enhance model accuracy by using wearable device method. Therefore, the objective of this work is to develop a model for fall detection system from the data acquired by interfaced mobile device and Matlab software. Two participants will conduct 13 set of testing motion by 5 times to obtain the acceleration and angular velocity. The data were trained by using nonlinear autoregression neural network NARnet algorithm. The algorithm is trained by network training function; LM, SCG and RP by collocation with threshold-based setting value. The selection of the model is compared in terms of optimization epochs, magnitude of mean square error or MSE, magnitude of correlation performance, the progress of convergence graph in term of MSE performance, accuracy of regression and non-zero value in autocorrelation graph.

2. Methodology

2.1 Fall Detector Architecture

The fall detection architecture in collecting data is using a mobile device Apple Iphone 6 with IOS system and interfaced with Matlab software. This device is built in with an Invensense MPU-6700 sensor type. Invensense MPU-6700 is a sensor which consist of 6-axis sensor. This is the combination of 3-axis accelerometer and 3-axis gyroscope in a single chip. Accelerometer is used for detecting the acceleration in this 3-axis with range of +-16g whereas gyroscope is used for detecting the radian at each axis. Acceleration is the main feature of falling event, thus it is more practical to use where this module requires low power and low cost. It consists of 16 bits analog to digital conversion hardware for each channel. Since this sensor can obtained acceleration and angular velocity, so it will be used for distinguishing the scenarios. Then the data generated in Matlab is trained to get the accurate model based on the training results. Fig.1 describes the overall process of this falling study.

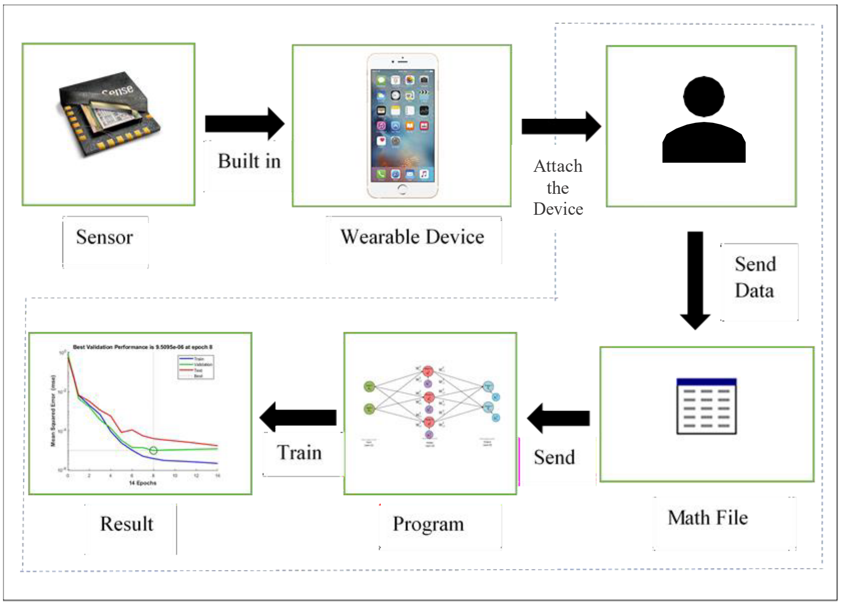


Fig. 1 - Process of modelling fall detector

2.2 Motion Characteristic

The scenarios are basically divided into two parts, which the first part is the non-fall activity part while the other part is fall activity. Fall activity consist of 7 types of motion, while non-fall activity consist of 6 types of activity daily living. Table 1 and Table 2 describes the details about the characteristic of motions.

Table 1 - Classification of activity daily living

Activity daily living	Motion description	Accessories
Lying	Sit and lying on platform	Platform
Jogging	Jogging for certain distance	-
Sitting and standing	Sitting and getting up from chair	Chair
Hopping	Jumping	-
Walking	Walking strength for certain distance	-
Bending	Body squatting	-

Table 2 - Classification of falling scenarios

Falling scenario	Motion description	Accessories
Forward fall	Straight and no step is performing	Platform
Backward fall	Sitting down on empty	Platform
Lateral fall	Step down from platform	Platform
Faint	Suddenly fall when standing	Platform
Slip	Step on slip thing	Platform
Trip	Trip between ankle when walking	Platform
Loss of balance	Fall when sitting	Chair and platform

2.3 Framework Algorithm

The framework of algorithm is about the training, validation and testing process. After the training input dataset is prepared, the input is imported to the model and the training function is chosen. As the model is training, the train, validate and test performance is observed. A model is validated by observed on the performance measure after the training, if the model is not validated, then the model will be trained again. The weight and bias obtained after the model is decided to be the reference of fall detection system. The overall process of this framework is shown in Fig.2. which is implemented in Matlab software.

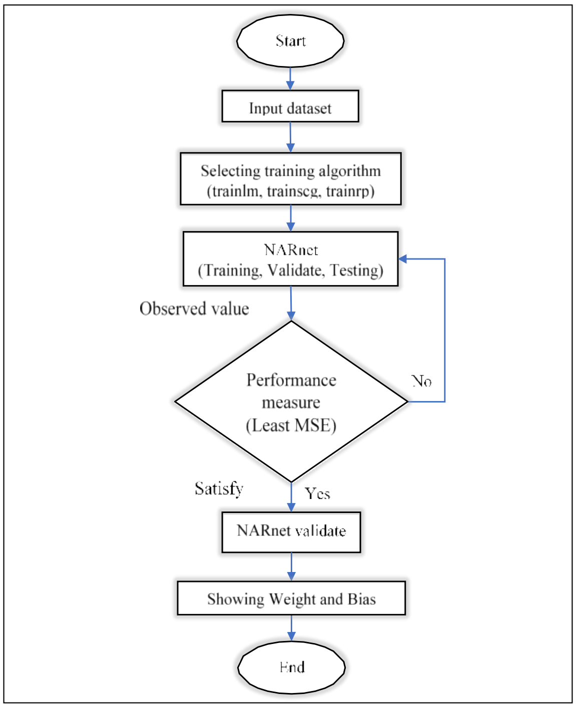


Fig. 2 - Flow chart of training process

2.4 Data Collection

Two volunteers which age 24 years old were participated in the experiment. One with 56kg and while the other was 120kg. Each participant is requested repeat 5 times for these 13 set of motions by wearing the system located at the waist. Approximately 150-300 datasets for each motion are recorded. The data is then acquisition at frequency of 50 Hz when doing the experiment. After that, the data collected are extracted by applying the equation of signal vector magnitude and angular velocity in (1) and (2).

$$\text{Signal Vector Magnitude, } SV = \sqrt{{A_X}^2 + {A_Y}^2 + {A_Z}^2} \quad (1)$$

$$\text{Angular Velocity, } G_{to} = \sqrt{{G_X}^2 + {G_Y}^2 + {G_Z}^2} \quad (2)$$

2.5 Threshold Setting

Threshold value for this fall detection device had set for different condition. The first condition is set at $68ms^{-2}$ which is the upper limit of acceleration data. The second condition is set at the 8 rad which is the upper limit of angular velocity data. If the input data is exceeding the first condition, then it continues to the second condition for the second recognition of the activity motion whether it is fall or non-fall motion. However, if the input data is not exceeding the first condition, then the activity will be classified as non-fall motion.

2.6 Learning Method

Neural network is the supervised learning algorithm applied for this fall detection device. The back propagation neural network of time series nonlinear autoregressive neural network (NAR) function for predicting the result and train for the Mean Square Error (MSE) is applied. This network consists of 1 input layer, 1 hidden with 1:5 delays and 1 output layer. The neurons number for input layer is 2 neurons which is the accelerometer and gyroscope value. The neurons number for hidden layer is set to be 10 for counting the behavior of the input value by using the sigmoid function while the output will be 2 neurons. The data is assigned as 75% of training datasets, 15% of validate and test datasets respectively.

There are 3 type of training optimization function implemented in constructing the model which were trainlm (Levenberg-Marquardt), trainscg (Scaled Conjugate Gradient) and trainrp (Resilient Propagation). These 3 algorithms are changed alternately as one training process is completed.

2.7 Variation of Input Source

The training process had been divided and assigned by arranged the raw data into 4 different types. See Table 3.

Table 3 - Input dataset

Input type	**Extracted data (ms^{-2} and radian)**	
Type 1	P1	P2
Type 2	P1 + P2	
Type 3	Normalize of P1 + P2	
Type 4	Normalize of fall data P1 + fall data P2	

3. Results and Analysis

The algorithm performance is tested by collecting the simulated falling and activity daily living data. The acceleration and angular velocity were successfully generated from the Invensense sensor by interfaced between mobile device and Matlab software. The user interface for data acquisition of the sensor can be referred from Fig.3.

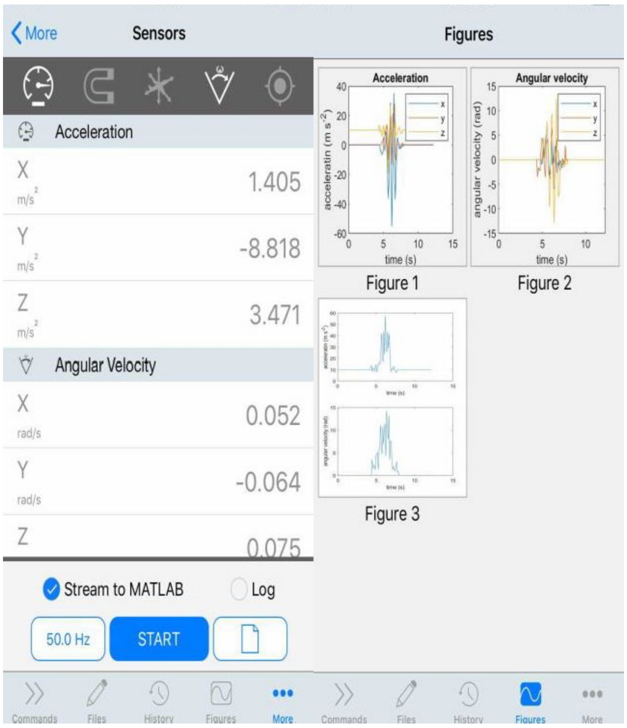
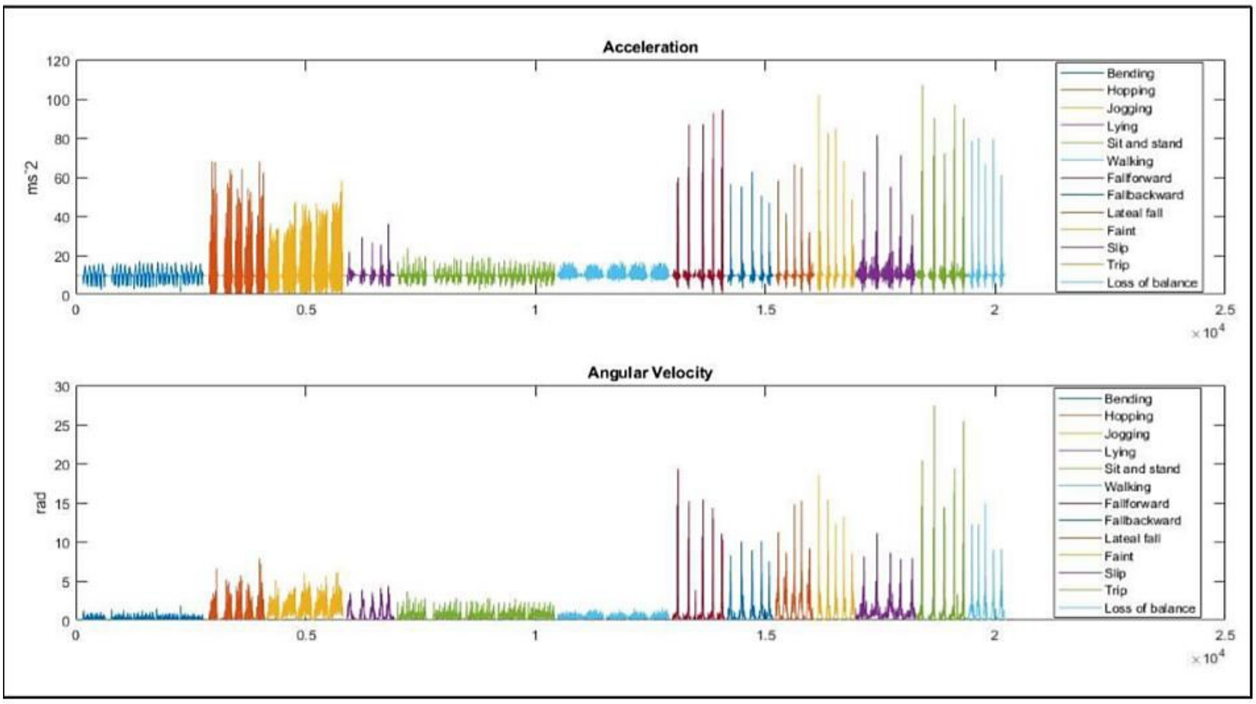
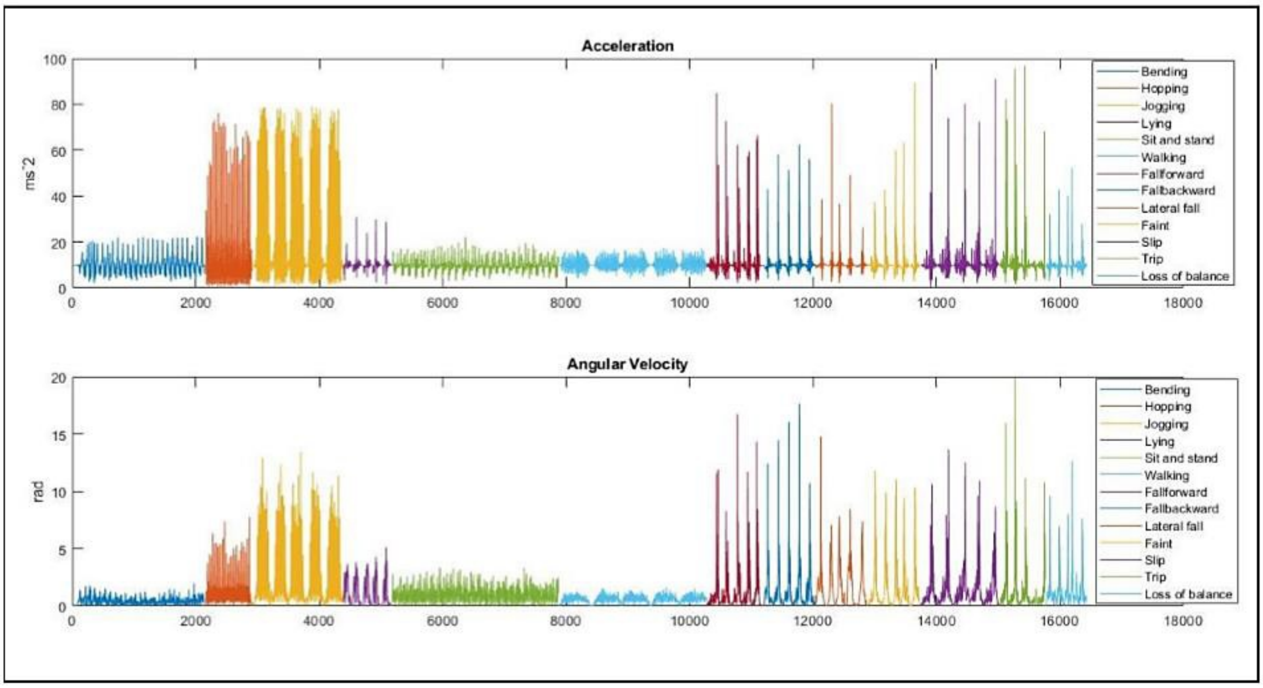


Fig. 3 - Data acquisition from the sensor

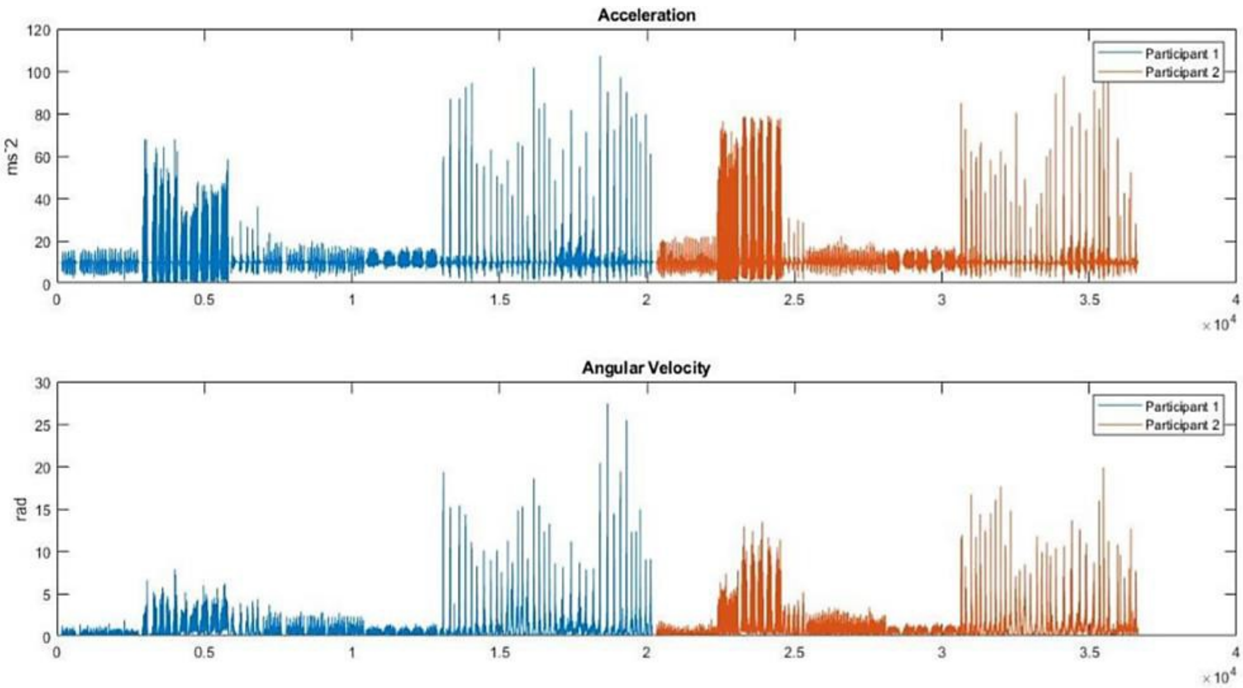
The data obtained from two participants were different which might due to the difference in height and weight. The magnitude of acceleration usually higher than angular velocity is due to the acceleration is included the gravitational force while the angular velocity is the orientation of the body. From Fig.4 (a) and (b), it is noticed that the trip fall scenario produced the highest magnitude among all the scenarios. While the hopping and jogging produced the highest magnitude among all the normal daily living activity. The acceleration and angular velocity data are assigned into 4 types which represented by Fig.4.



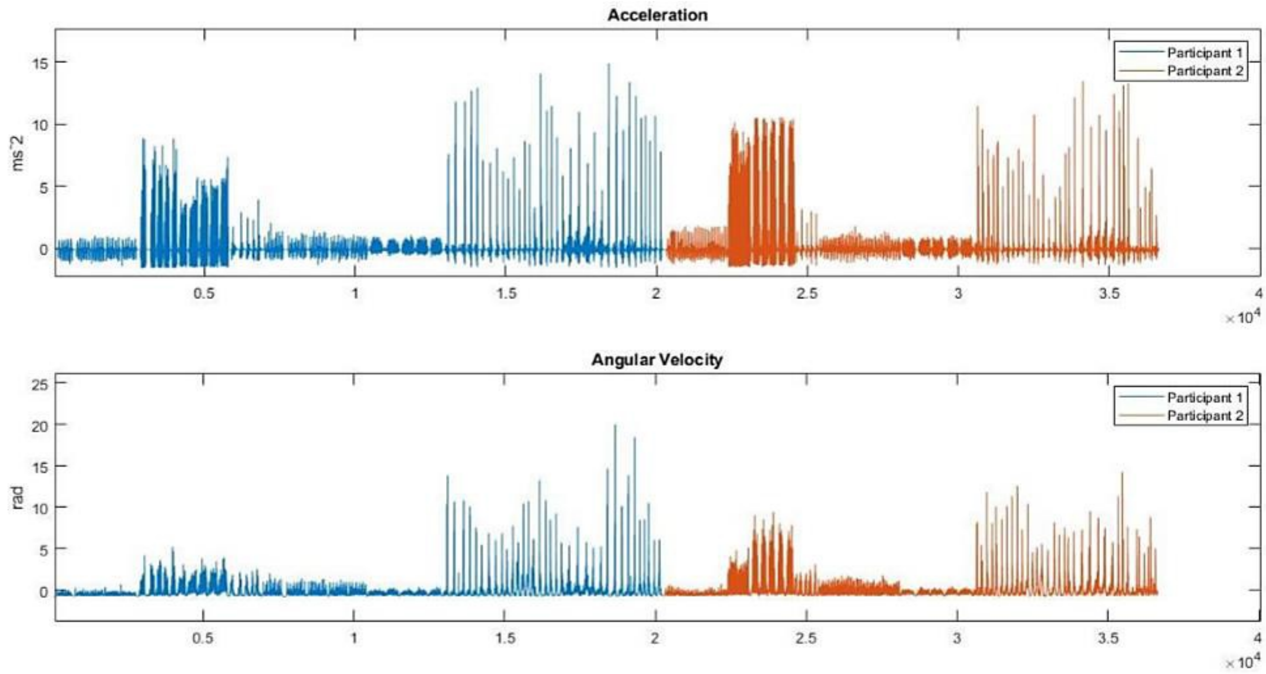
(a)


Acceleration
ms^2
Bending
Hopping
Jogging
Lying
Sit and stand
Walking
Fallforward
Fallbackward
Lateral fall
Faint
Slip
Trip
Loss of balance
Angular Velocity
rad

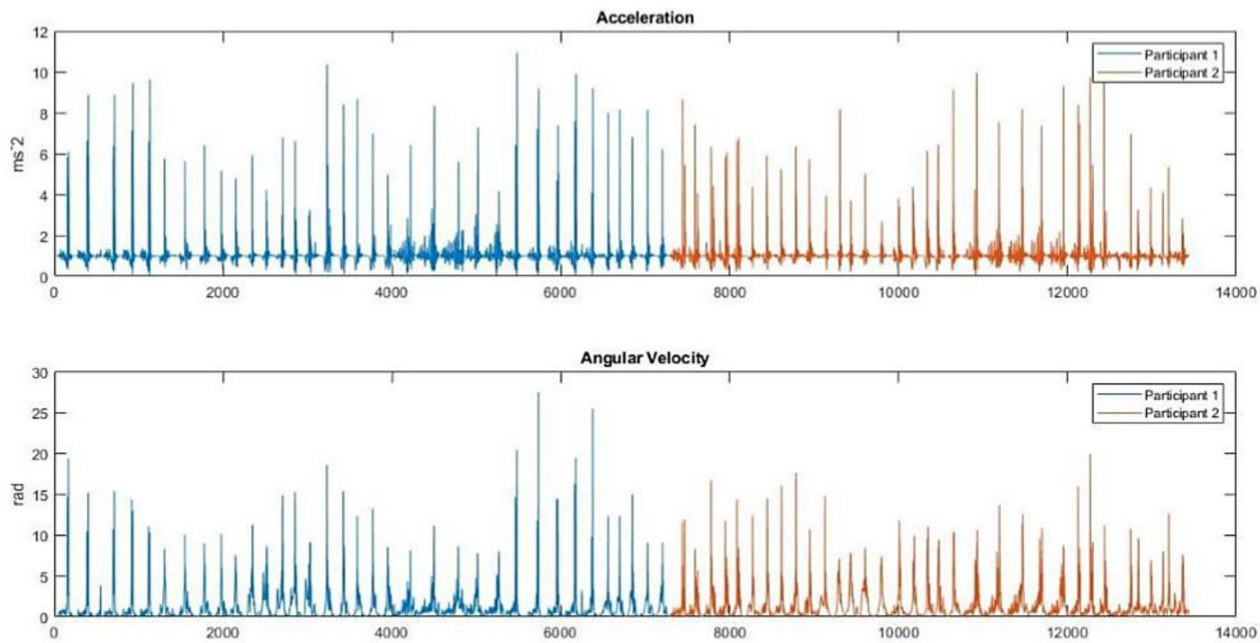
(b)


Acceleration
ms^2
Participant 1
Participant 2
Angular Velocity
rad
$\times 10^4$

(c)



(d)



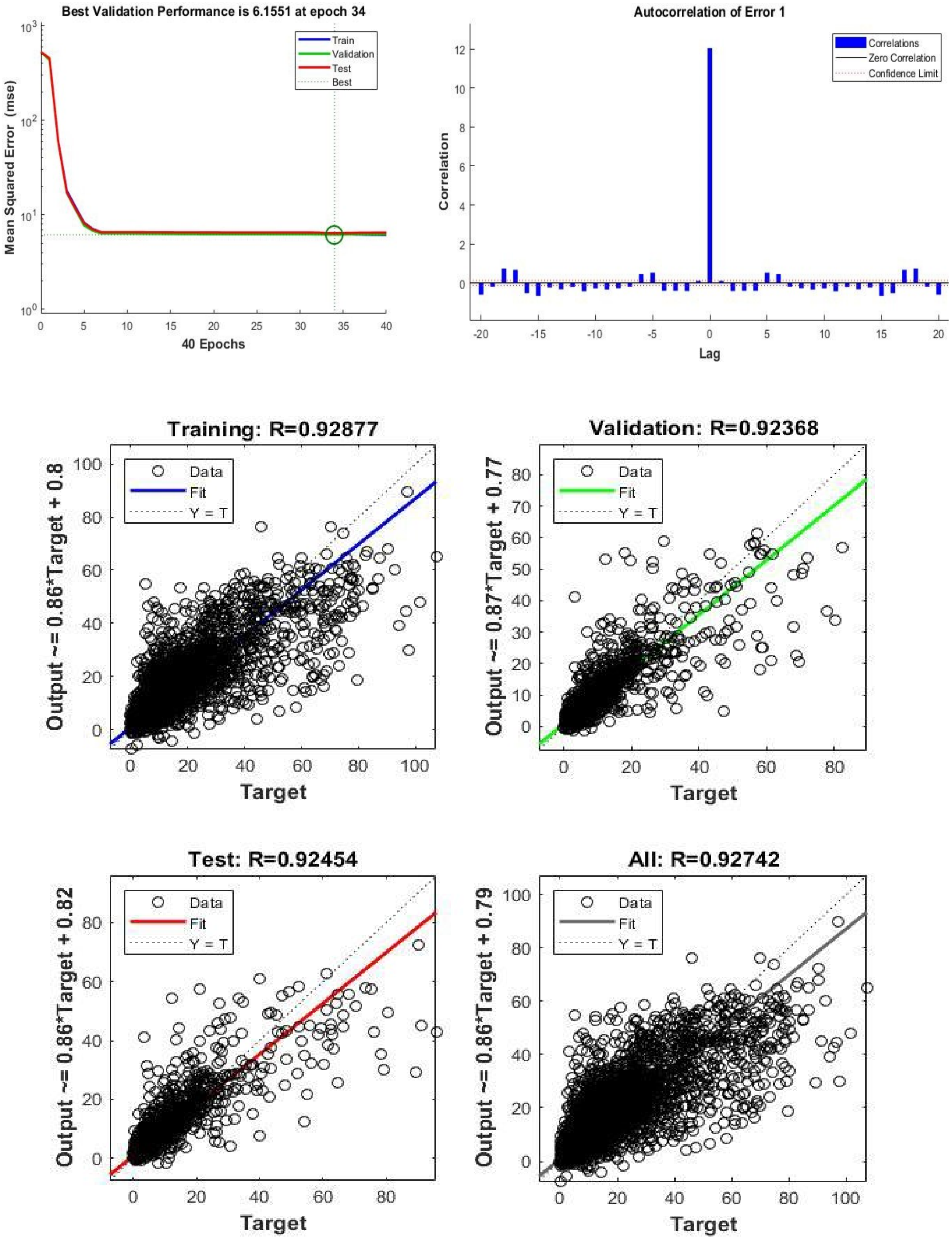
(e)

Fig. 4 - (a) Type 1 P1; (b) Type 1 P2; (c) Type 2; (d) Type 3, and (e) Type 4

3.1 Evaluation of The Training Result

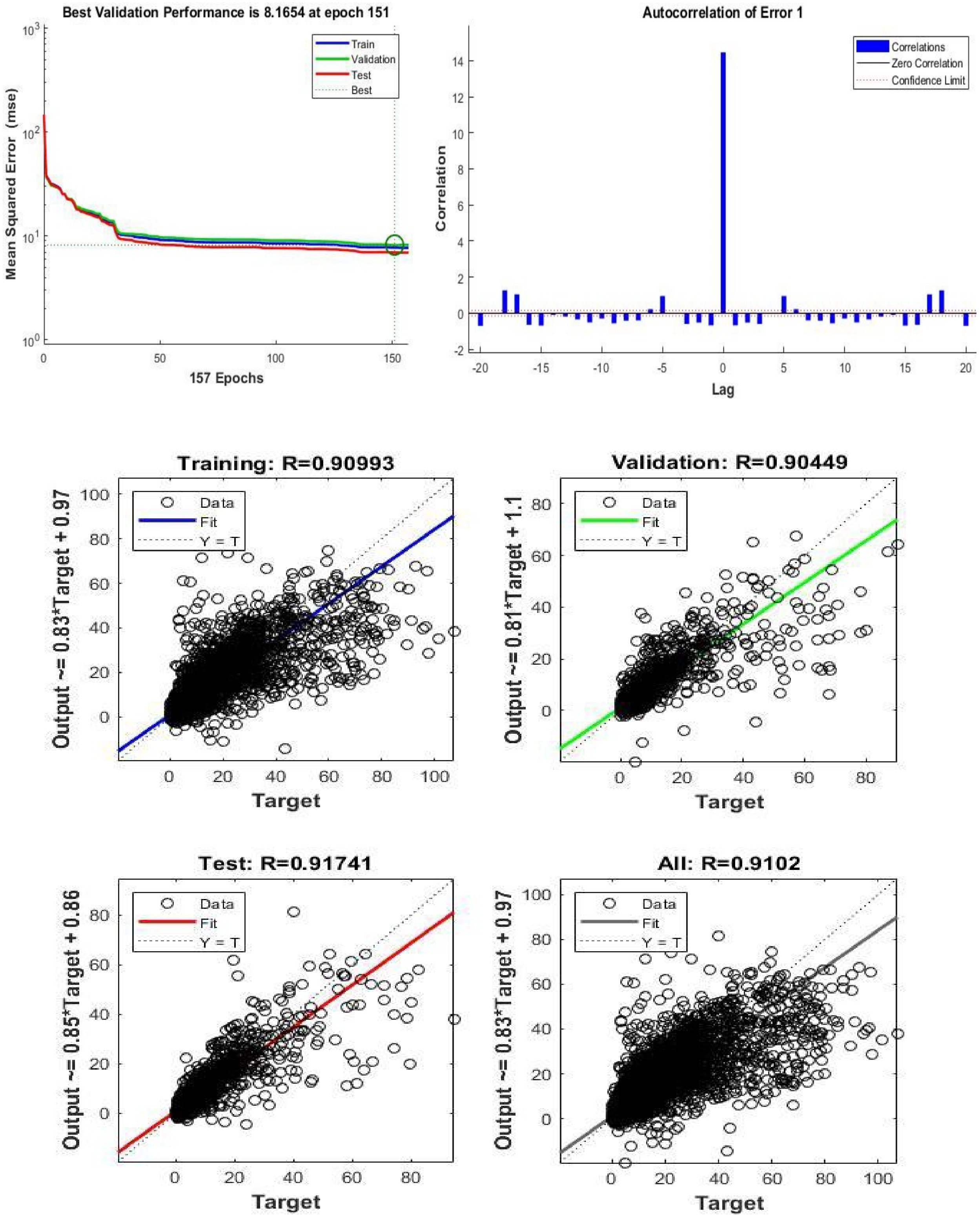
The performance of the artificial neural network model can be evaluated by the value of the mean square error, MSE, and correlation coefficient, R. The best performance of a model is selected from the epoch with the lowest validation error during the training process. For the correlation function is shown in the regression diagram which included the train, validate and test regression. The autocorrelation is used00 to validate the network performance in term of confidence limit and error lag. Thereby, selection of the model can be referred from the progress plot of the MSE performance, regression diagram of correlation coefficient and autocorrelation of error diagram. The random selected training performance diagrams by applied each training optimization function that obtained by variation of input source is shown in Fig.5.

Type 2: LM


Best Validation Performance is 6.1551 at epoch 34
Train
Validation
Test
Best
Mean Squared Error (mse)
40 Epochs
Autocorrelation of Error 1
Correlations
Zero Correlation
Confidence Limit
Correlation
Lag
Training: R=0.92877
Output ~= 0.86*Target + 0.8
Validation: R=0.92368
Output ~= 0.87*Target + 0.77
Test: R=0.92454
Output ~= 0.86*Target + 0.82
All: R=0.92742
Output ~= 0.86*Target + 0.79
Data
Fit
Y = T
Target

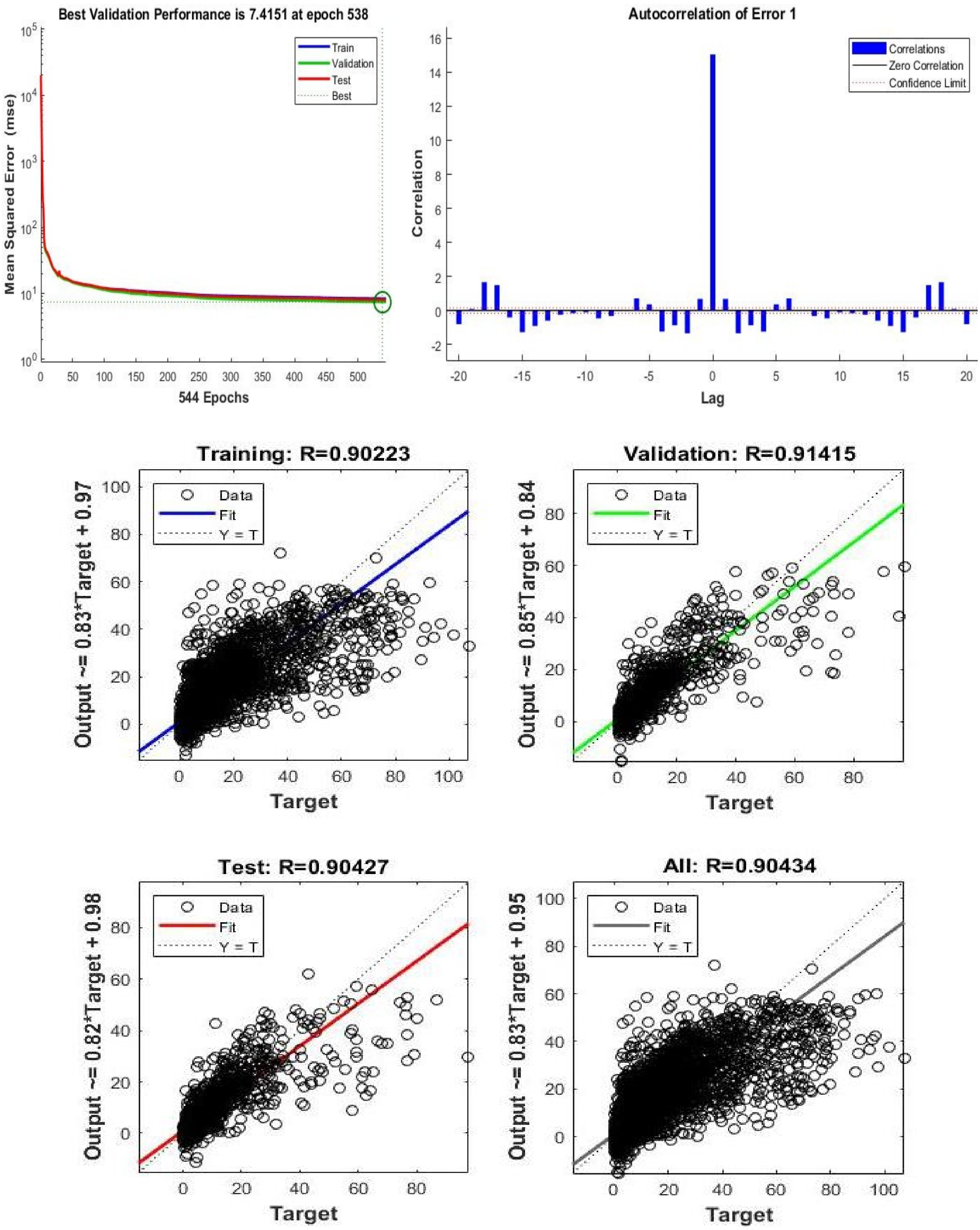
(a)

Type 2: SCG


Best Validation Performance is 8.1654 at epoch 151
Train
Validation
Test
Best
Mean Squared Error (mse)
157 Epochs
Autocorrelation of Error 1
Correlations
Zero Correlation
Confidence Limit
Correlation
Lag
Training: R=0.90993
Output ~= 0.83*Target + 0.97
Validation: R=0.90449
Output ~= 0.81*Target + 1.1
Test: R=0.91741
Output ~= 0.85*Target + 0.86
All: R=0.9102
Output ~= 0.83*Target + 0.97
Data
Fit
Y = T
Target

(b)

Type 2: RP



(c)

Fig. 5 - (a); (b); (c) Selected training result diagram (Type 2)

In Fig.5, the MSE performance similar convergence trend and significant overfitting problems does not occurred. However, the epoch trend for SCG are slightly rough while epochs of SCG and RP is longer than LM. The regression performance for the LM, SCG and RP are quite accurate in the range of 0.9-0.99 which the output and target were the same although some data did not plot near the line of 45 degree. The autocorrelation for LM, SCG and RP displayed that non-zero error value is located at the zero lags but result of RP shows a lot of correlations transcend the confidence limit. To evaluate the training model, the overall regression performance is not enough to justify whether a model is performed well or not. So, the number of epochs and the validate performance (MSE) must also considered as a part of the significant analysis. Data Type 1 until Type 4 had been trained respectively and all the training results are tabulated in Table 4 until Table 7.

Table 4 - Training result of Type 1

Participant	**Participant 1**			**Participant 2**		
Data Division	**Training (70%) Validation (15%) Testing (15%)**					
Training Function	**LM**	**SCG**	**RP**	**LM**	**SCG**	**RP**
Number of Epochs	26	151	317	33	212	271
Training Time (s)	0.01	0.02	0.02	0.01	0.02	0.01
Mean square error (MSE)	4.028	7.0735	7.3451	4.5345	6.7566	7.9834
Regression	0.93863	0.90736	0.9106	0.94294	0.91509	0.91257

Table 5 - Training result of Type 2

Data Division	**Training (70%) Validation (15%) Testing (15%)**		
Training Function	**LM**	**SCG**	**RP**
Number of Epochs	40	157	544
Training Time (s)	0.06	0.03	0.07
Mean square error (MSE)	6.1551	8.1654	7.4151
Regression	0.92742	0.9102	0.90434

Table 6 - Training result of Type 3

Data Division	**Training (70%) Validation (15%) Testing (15%)**		
Training Function	**LM**	**SCG**	**RP**
Number of Epochs	49	338	472
Training Time (s)	0.06	0.08	0.06
Mean square error (MSE)	0.2914	0.3269	0.3495
Regression	0.2914	0.3269	0.3495

Table 7 - Training result of Type 4

Data Division	**Training (70%) Validation (15%) Testing (15%)**		
Training Function	**LM**	**SCG**	**RP**
Number of Epochs	25	110	270
Training Time (s)	0.01	0.01	0.01
Mean square error (MSE)	0.3635	0.5723	0.4873
Regression	0.87962	0.85255	0.83789

In Table 4, the training function of LM for P1 and P2 shows the fastest response which is only 26 and 33 epochs when compared to other training function. The validate value of LM produced by P1 is the least among other function which is 4.028. The regression performance obtained of LM for P1 and P2 are 0.93863 and 0.94294. Thus, a hypothesis can be concluded that the LM model by P1 is more accurate as compared to LM model by P2 because the validate error of P1 is smaller than P2, at the same time, P1 model can be performance in a fastest response with a high accuracy of prediction. Table 5 show that the epoch of RP is the longest compared to other train model which is about 544. Thus, it required a longer time to complete the training process. The validate performance of training function LM is the smallest and the overall R performance is the highest which are 6.1551 and 0.92742 respectively. From Table 6, the validate performance for the LM function is 0.2914. However, the overall regression performance is only 0.86001 which did not lie in the accuracy range. The data had been normalized by using z-scores which the default function in Matlab to improve the input data become more smother. The data is totally different as compared to the original data, so the training result was also different with the original training results. In Table 7, the train function LM takes the fastest time during training process, which is 25 as compared to 110 in SCG and 270 in RP. The validate performance and regression performance are 0.3635 and 0.87962. The result is not the same might because the effect of normalized data.

As comparison among these three training functions, LM performed a better and fastest solution as compared to SCG and RP. This might due to LM is basically a speed up training function meanwhile the SCG is involved the choose and search of step size which required more memory and the RP involved in eliminating the undesired effect by changing in weight and bias. A 1:5 of feedback delays is chosen as it is enough for the training model to be trained in fastest time which in term to produced high accurate of predicted result. The number of epochs for LM in Type 2 and Type 3 were longer than Type 1 and Type 4. This might due to the input data source are too large which required more optimization time to process. But the Type 2 result is considered as well because it is applied all the input data. Although the number of epochs and training time for Type 4 LM model is the shortest and fastest, but the regression performance did not achieve the accuracy range which mean the relationship of output result and target result are not perfect. Hence, the training model of Type 2 is selected as the best model with a training result of high validate performance 6.1551, faster responses with 40 epochs, short training time 0.06s with high accuracy of 0.92742.

4. Conclusion

In this work, it had presented modelling of fall detection system by using neural network algorithm and acquired data by experiment the 13 set scenarios (activity daily living and falling) testing. The algorithm is trained by network training function; LM, SCG and RP. The comparison of optimization epochs, magnitude of validate error or mean square error (MSE), magnitude of correlation performance, the progress of convergence graph in term of MSE performance, accuracy of regression and non-zero value in autocorrelation graph were used to validate the model. Type 2 with LM optimization function which using the data source of P1 and P2 is chosen as the most accurate model. It provided a faster response with high accuracy and least error when compared to SCG and RP optimization function. Thereby, the weight and bias of Type 2 with LM optimization function model had been recorded and it can be used for further testing. It can be concluded that the best model has been developed throughout the proposed method.

Acknowledgement

The authors would like to thank for the financial support from research allocation by Universiti Tun Hussein Onn Malaysia (UTHM).

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