Estimation of Gait Parameters using EMG Signal with Extreme Learning Machine

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***Abstract*—In this paper, an algorithm to estimate the gait parameters based upon EMG signal is proposed. The algorithm is developed using extreme learning machine (ELM). Experiments were conducted to acquire the gait parameters from 18 healthy human subjects. EMG signals from Tibialis Anterior (TA) and Gastrocnemius Lateral (GL) muscles were obtained during the gait cycle. The target temporal gait parameters are gait speed and stance/swing phase which were measured using inertia sensor and camera system. The ELM algorithm was developed using a single hidden layer feedforward network architecture where the weights from the input layer to the hidden layer are randomized and not updated during the run. Results obtained from ELM were compared with artificial neural network (ANN) model with the same architecture as the ELM algorithm. In ELM, the mean estimation errors of gait speed, stance percentage, and swing percentage were 11.86%, 7.62%, and 6.07% respectively. This was compared to the errors of 12.92%, 11.75% and 9.56% using ANN. Besides that, ELM achieved shorter training and testing time. The robustness of ELM algorithm demonstrated the capability of real-time computation due to superior computing performance compared to conventional ANN models.**

***Index Terms*—Artificial Neural Network; Extreme Learning Machine; Gait Analysis.**

I. INTRODUCTION

Human gaits describe patterns in which human walk. They are dependent on various factors such as walking speed, forces and other personal factors (e.g., age, joint impairment, etc.). Observation and analysis of these gaits provide a vital aspect on the diagnosis of gait impairment so as to devise a proper treatment plan for the patient (e.g., gait rehabilitation after stroke). Gait profile and parameters such as gait velocity, cycle time, stride length etc., could be acquired via camera or inertia sensor systems. Meanwhile, electromyography (EMG) signals record electrical activities of the muscle as active muscles produce electrical current and this can be correlated to the level of muscle strength.

In recent years, doctors conduct objective assessment utilizing machine learning technologies, and this has been applied to gait analysis [1]. Artificial neural network (ANN) could distinguish normal and impaired gait due to its strong nonlinear learning ability [2]. However, one of the problems ANN faces is that it could either reach a global minimum or get stuck at a local minimum. The accuracy of the ANN classifier could also decrease through the over-trained of training samples. In addition, to apply the techniques of ANN techniques on real-time gait analysis is undesirable as it requires a huge gait database and the process of getting a huge database would be time-consuming. As a result, the system would become more complex with the greater computational burden and longer training time.

The emergence of machine learning techniques such as extreme learning machine (ELM) has become a popular area of research over the past years. It is a learning algorithm for single-hidden layer feed-forward neural networks (SLFNs) where the weights connecting inputs to hidden nodes are randomly chosen whereas the output weights of SLFNs are determined through iterations [3]. ELM has been found to overcome some of the bottlenecks faced by the classical neural network and ever since then; it has been applied in several unique problem-solving applications areas, including engineering, biomedical and forensic science [4-10], often with promising results.

This paper aims to develop an algorithm to estimate the temporal gait parameters from EMG signals alone. The results obtained from ELM are compared with the feedforward ANN so as to investigate the robustness of ELM model to predict the gait parameters in real-time. Section II describes the ELM and ANN theory required in this work. Section III outlines the experimental methodology where EMG signals acquired from commercial EMG sensor is used as input data while gait parameters measured from inertia sensor and camera system serve as the target data. The gait parameters investigated in this study are gait speed, % swing phase, and % stance phase. Section IV discusses the results, and Section V concludes the paper. Results indicated that ELM could perform function approximation in a faster and more efficient way than conventional ANN. In this study, ELM yielded lower root mean squared error (RMSE), shorter training time and lower mean estimation error compared to conventional ANN.

II. ELM AND ANN ARCHITECTURE

Extreme learning machine (ELM) has been proposed as a learning algorithm for single-hidden layer feed-forward neural networks (SLFNs). In ELM, the hidden nodes are randomly initiated and never updated. The only parameters to be updated are the weights between the hidden layer and the output layer. Compare to the conventional feed-forward neural network (FFNN), ELMs are known to shorten the learning time, better generalization performance, and ease of implementation. In general, the learning rate of FFNN is relatively long and this has become the bottleneck in their applications. According to [3], the reasons of FFNN having longer learning rate are firstly because it uses slow gradient based learning algorithms to train the network. Secondly, the parameters must be iteratively tuned. The recently proposed ELM for SLFN by [3, 11, 12] was meant to overcome these problems as it is a simple tuning-free algorithm to achieve fast learning speed and provide the best generalization performance [12]. Therefore, ELM has great potential for developing the efficient and accurate model as a real-time predictor for applications which require better generalization ability.

Nonetheless, ELM learning algorithm is different from the classical gradient-based learning algorithms as it tends to reach the minimum training error while considering the magnitude of weights [5] and that it can be used to train SLFN with non-differentiable activation functions [11].

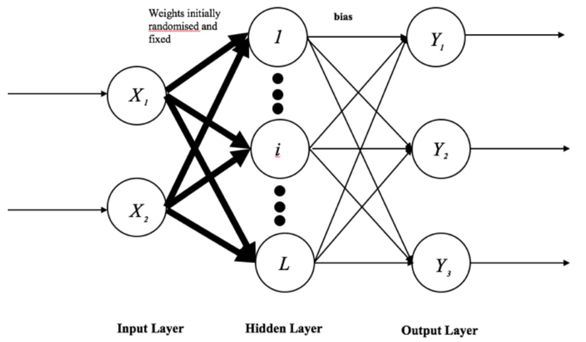

Figure 1: ELM architecture (X_1 and X_2 are the inputs, 1…i…L are the activation functions, Y_1, Y_2 and Y_3 are the output neurons)

Figure 1 shows the ELM architecture used in this study. The input layer consists of two neurons which are EMG signals from two muscles, i.e. Tibialis Anterior (TA) muscle and Gastrocnemius Lateral (GL) muscle. As for the hidden layer, the number of hidden neurons are set to 250, 300, 350 and 400 as this is the parameter to be tuned for performance comparison. A sigmoid activation function, L, is used to compute the inputs and bias. The output layer consists of 3 output neurons since we have three parameters (gait speed, %stance, and %swing) to output as targets. The layers are all interconnected with the previous and next layer of that specific layer. The connections (weights) from the input layer to the hidden layer are initiated, randomised and never updated during the iterative tuning; it is only the weights from the hidden to the output layers that are iteratively tuned.

Artificial neural networks are models that were developed from studying how biological systems work, in particular, the human brain. ANNs consist of an interconnected group of artificial neurons. The ANN's knowledge comes from the experience they encounter which means that they have a learning process and to learn; they adapt their weights so that can be used for training and prediction. A multi-layered neural network consists of several layers of a large number of neurons. Each layer is interconnected with the layer immediately before and after it. The input layer is the first layer that receives the external inputs while the last layer is the output layer which provides the classification solution and in between them are an arbitrary amount of hidden layers. In this study, the ANN architecture has the same input, the same amount of hidden neurons configuration and the same target as the ELM model. The difference in ANN is that *tanlin* (L) and *purelin* (Y_n) are used as the transfer function for hidden and output layer respectively. A three-layered network can accurately classify any non-linear function [13].

III. METHODOLOGY

The experiment was conducted to acquire gait profile from 15 healthy human subjects. Ethical approval was obtained from the institution's Research Ethics Committee. The inclusive criteria of the subjects are (i) no other known neurological disorder disease, (ii) understand and follow basic instruction. Participants were provided with written consent for this research. The data acquisition and preprocessing are divided into two parts: i) Gait parameters and ii) EMG signals. The data would then feed into the ANN/ELM model for training and testing.

A. Gait Parameters

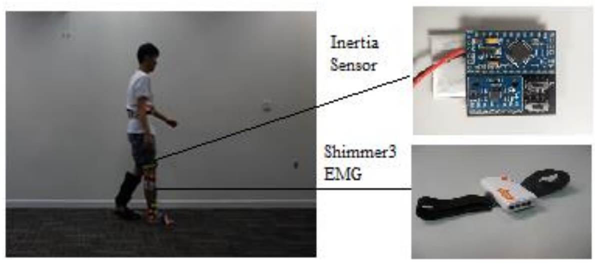

Figure 2: A subject completing the gait cycle

All participants (mean ± std, Age: 23 ± 1.6 years old, Height: 173.3 ± 6 cm, Weight: 63.7 ± 10.3 kg) were asked to wear the inertia sensor system (Figure 2) along with EMG sensor device (Shimmer Sensing – Shimmer3 EMG) and perform a series of walking tasks, namely slow speed walking, normal speed walking and fast speed walking - for 2 minutes respectively on a 5-meter walkway. The inertia sensor system consists of a programmed Arduino Mini Pro and a MPU-6050 module (InvenSense – MPU6050) (Figure 3). A phone camera operating at 60 frames per second was setup to capture walking activities concurrently. Red LED lights were placed on the areas of interest which include knee joints and heel and toe part of outsole as shown in Figure 2. The videos are then transferred to the computer where MATLAB will be used to analyse the videos. An algorithm was coded to track the red LED lights in the video which outputs the co-ordinates of the LED lights against time. The outputs were later used to obtain the heel-strike and toe-off time. The purpose of camera system is mainly used to validate and double confirm the measurement from the inertia sensor system. The temporal gait parameters are derived from the inertia sensor system using the method described in [14] while gait speed is determined manually using video tracking process acquired from a camera system where the x-coordinates between toe-off points are converted into metres and divided by its gait cycle time. The gait cycle time, percentage of swing phase and stance phase could be calculated based on the heel-strike and toe-off time obtained as follows:

$$GC_i = T_{i+1} - T_i \tag{1}$$

$$ST_i\ \% = \frac{T_{i+1} - H_i}{GC_i}\ x\ 100 \tag{2}$$

$$SW_i\ \% = \frac{H_i - T_i}{GC_i}\ x\ 100 \tag{3}$$

where: GC_i = Gait cycle time for the i-th gait cycle
H = Heel-strike moment (initial contact ground of heel)
T = Toe-off moment (terminal of toe leaving from ground)
$ST\%$ = Stance phase percentage
$SW\%$ = Swing phase percentage

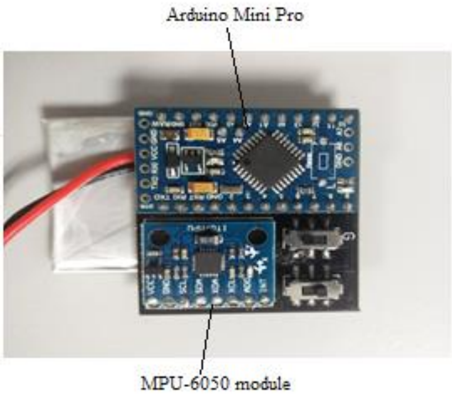

Figure 3: Inertia sensor used for the experiment

B. EMG Signal

Figure 4: Shimmer3 EMG unit (ShimmerSensing)

To acquire EMG signals, 2 Shimmer3 EMG (Shimmer Sensing – Shimmer3 EMG, Figure 4) units were used. The units were configured to have a sampling rate of 512 Hz to ensure high-quality reproducibility of the actual summation of the muscle's activity. Each EMG unit is connected to five electrodes, namely, a positive and a negative electrode for each for two channels and a neutral reference electrode. The 2 Shimmer3 EMG units were placed on the shins whereas the reference electrodes were placed on the knee and the other electrodes were placed on the two muscles, namely Tibialis Anterior (TA) muscle and Gastrocnemius Lateral (GL) muscle. The reason for using three electrodes in this way is that the EMG signals, typically, exhibit low signal-to-noise ratio. Noise interferences are usually from power lines and nearby electrical sources. The signal recorded up by each individual electrode consists of noise from the environment along with the local electrical signal from the muscles at the position of skin contact. The noise from the environment is common to all electrodes, whilst the local electrical signal depends on the electrode's position. Thus, if one signal is subtracted from another, the common component (the undesired noise) will be cancelled by the subtraction, whilst the local signals (the desired EMG component) will remain after subtraction and can be amplified to make it easier to process. This process is called Common Mode Rejection (CMR) and is used in the Shimmer3 EMG unit.

Understanding of anatomy of each muscle is required for proper EMG electrode placement. Hence, TA and GL muscles are selected as TA contributes to dorsiflexion and inversion of the foot while GL is responsible for plantarflexion of foot at the ankle joint and the flexing of the leg at the knee joint. Another reason why GL is chosen is that GL is primarily involved in fast movements of the leg which provides a contrast to slow, normal and fast speed. Quality of EMG signal depends on muscle's shape, fibre directionality, motor points, tendon positions and insertion points. In this study, the placement of EMG electrodes follows the recommendation from SENIAM [15].

The raw EMG signals were processed in MATLAB. To remove signal interference from mains electricity, notch filtering was used where a band-stop filter was adjusted to remove the local mains frequency of 50 Hz and noises at 100 Hz and 200 Hz (noisy peaks were observed at these frequencies in the Fast Fourier Transform frequency spectrum). Next, to observe the overall level of activity in a particular muscle, the linear envelope of the EMG signals were extracted by first applying full wave rectification to the signal and subsequently pass it through a low pass filter of 6 Hz.

Normalisation is used to eliminate variability across subjects, electrode placement and day to day differences in measures of the same muscle site. In this study, the EMG signals were normalised against the maximum voluntary contraction of every subject.

Finally, the EMG signals were segmented to each gait cycle. There was a total of 1471 gait cycle EMG extracted from 18 subjects and these data were then fed into the ANN and ELM networks.

C. ANN and ELM Model Training

The ANN model has been developed using built-in MATLAB functions while the ELM model was based upon the open source algorithm from [16]. All data were divided into 75% training, 10% testing and 15% validation. For effective comparisons, the training and testing accuracy was calculated using root mean square error (RMSE) and mean estimation error (in percentage), which are the measure of differences between estimated gait parameters and the actual measurement.

The conventional ANN consists of a single hidden layer and it is a feed-forward neural network. As EMG signals were segmented to each gait cycle, each set of EMG signal would have different data length (due to the differences in gait cycle time). Each set of EMG signal was then resized to 2000 elements and they are trained based on scaled conjugate gradient algorithm with hyperbolic tangent sigmoid as the hidden layer transfer function and *purelin* as the output layer transfer function. Parameters such as learning epoch, goal error and learning rate are set to 1000, 0.001 and 0.01 respectively. In the case of ELM, sigmoid activation function was chosen. The hidden neurons for both models were set to 250, 300, 350 and 400. To strengthen the network and reduce over-fitting, a 10-fold cross validation was performed 30 times for each set of hidden neurons and the average results were used.

IV. Results and Discussion

Experimental results are presented from Tables 1 to 4 and they represent the performance and duration for both ANN and ELM model. Both models output 3 parameters, namely Gait Speed, % Stance Phase and % Swing Phase. From Tables 1 to 4, it can be observed that, overall, ELM performed better than ANN for all the three parameters; not just in terms of lesser error, but also shorter training duration.

Table 1
Experimental Results of Basic ANN and ELM for the Parameter – Gait Speed

Gait Speed (m/s)					
ANN					
Hidden Neurons	Testing RMSE (m/s)	Testing Time(s)	Training RMSE (m/s)	Training Time(s)	Mean Test Estimation Error (%)
250	0.1419	0.0354	0.0166	15.7352	12.9271
300	0.1650	0.0511	0.0173	20.7394	13.5948
350	0.1543	0.0580	0.0192	20.3116	13.2240
400	0.1722	0.0614	0.0217	22.4238	14.0108
ELM					
Hidden Neurons	Testing RMSE (m/s)	Testing Time(s)	Training RMSE (m/s)	Training Time(s)	Mean Test Estimation Error (%)
250	0.1236	0.0170	0.1020	0.1434	11.8646
300	0.1357	0.0152	0.1003	0.2091	12.6031
350	0.1428	0.0114	0.0987	0.2552	12.6902
400	0.1483	0.0213	0.0935	0.2813	12.9716

Table 2
Experimental Results of Basic ANN and ELM for the Parameter – % Stance Phase

% Stance Phase					
ANN					
Hidden Neurons	Testing RMSE	Testing Time(s)	Training RMSE	Training Time(s)	Mean Test Estimation Error (%)
250	5.1087	0.0220	1.4372	15.4622	11.7519
300	6.1807	0.0411	1.6775	17.1960	13.1505
350	7.2955	0.0489	1.8534	20.2427	15.1321
400	7.9291	0.0538	1.8587	22.0761	16.4648
ELM					
Hidden Neurons	Testing RMSE	Testing Time(s)	Training RMSE	Training Time(s)	Mean Test Estimation Error (%)
250	3.2709	0.0149	3.0043	0.0420	7.6201
300	3.2412	0.0155	3.1441	0.0989	7.3545
350	3.3217	0.0157	2.5674	0.0953	8.0131
400	3.4432	0.0163	2.4719	0.1028	8.5426

Table 3
Experimental Results of Basic ANN and ELM for the Parameter – % Swing Phase

% Swing Phase					
ANN					
Hidden Neurons	Testing RMSE	Testing Time(s)	Training RMSE	Training Time(s)	Mean Test Estimation Error (%)
250	5.0545	0.06972	0.92185	19.26792	9.55680
300	6.16469	0.06217	1.27358	22.92138	12.20432
350	5.81581	0.06334	1.48631	23.21076	11.86815
400	7.39040	0.07205	1.62517	28.17323	13.40730
ELM					
Hidden Neurons	Testing RMSE	Testing Time(s)	Training RMSE	Training Time(s)	Mean Test Estimation Error (%)
250	3.4462	0.02170	2.01872	0.24800	6.06871
300	3.6835	0.02274	1.97239	0.23296	6.51340
350	3.8749	0.01876	1.68943	0.25170	6.73352
400	3.9461	0.02164	1.37365	0.21653	6.91475

Table 4
Validation Results for Gait Speed, Stance % and Swing %

	Validation RMSE for 250 hidden neurons		
	Gait Speed(m/s)	% Stance	% Swing
ANN	0.0925	12.5184	9.2920
ELM	0.2939	1.6134	1.7952

Another important trend shown by ELM is that as the amount to hidden neurons increases, the training RMSE decreases while the testing RMSE increases. This trend could not be observed from the ANN which makes ELM a more predictable and stable model. It also can be seen that though for ELM, the training RMSE is higher than that of the ANN for gait speed, but generally, ELM yielded better testing results. For 250 hidden neurons, ELM yielded 11.86%, 7.62% and 6.07% mean test estimation error for gait speed, % Stance and % Swing respectively. These were compared to 12.92%, 11.75% and 9.56% generated by ANN. Hence, it can be deduced that ELM is less prone to over-fitting and can generalize function better than the ANN. The reason is because when the training RMSE is small, the function produced is almost exactly dedicated to the training set. So, if there is an unseen data being tested on the model, it will most likely not show appropriate result if the data is not similar to the data trained. This can be seen in Table 4 where the neural network is being validated with unknown data (data from 3 out of 18 subjects were used in validation without training). The results further strengthen the view of ELM being a better generalizer with the validation RMSE of % Stance and % Swing being closer to the testing RMSE. The ELM performed relatively poorer for gait speed recognition during validation. Furthermore, it is more difficult to do a parameter search for ANN as the training duration is much longer than ELM. In addition to that, there are more parameters to be tuned (e.g. learning rate) for the ANN which can either be an advantage or a disadvantage. The advantage is that the function fits properly with the dataset while the disadvantage is that complexity brings inefficiency which leads back to a longer training duration and a lower performance on unseen data. Though, ANN triumphs in having a better training performance but in the end, the testing performance is the major consideration as better testing performance will depict a more robust model.

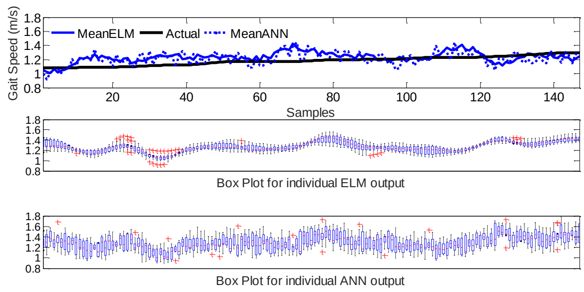

Figure 5: Comparison between the actual target, and ELM and ANN max, min predicted values for 250 hidden neurons (gait speed). Box plots for individual ELM and ANN output are shown in the bottom two plots

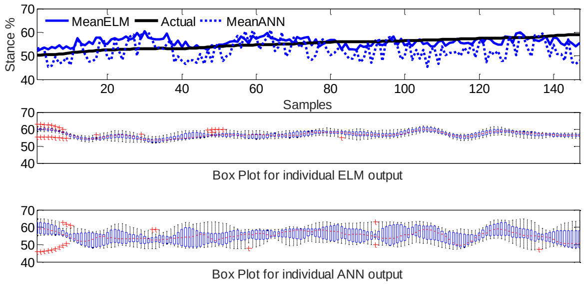

Figure 6: Comparison between the actual target, and ELM and ANN max, min predicted values for 250 hidden neurons (%Stance). Box plots for individual ELM and ANN output are shown in the bottom two plots

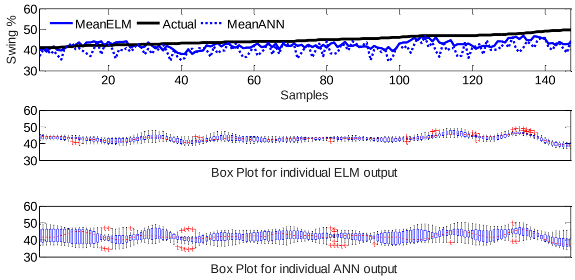

Figure 7: Comparison between the actual target, and ELM and ANN max, min predicted values for 250 hidden neurons (%Swing). Box plots for individual ELM and ANN output are shown in the bottom two plots

Figure 5 to 7 shows the comparison between the actual target and the maximum, minimum predicted values by ELM and ANN for 250 hidden neurons. Box plots for individual ELM and ANN output (total 10 outputs for each sample/target data) are also included in the figures. Red marker represents the outlier of the 10 data and the blue color box represents the data in the interquartile range (between the first and third quartile). The reason for choosing 250 hidden neurons is because it shows the lowest RMSE or means estimation error when compared with another amount of neurons used. Results showed that the ELM outputs have less variation in value (i.e. the smaller interquartile range in the box plot) whereas the variation range is large for ANN outputs. ELM mean estimated gait parameters were also closer to the actual target.

Overall, the estimation errors of both ELM and ANN models are still large. This might be due to using EMG signal as the only input data. Further improvement could be made by extracting useful features from EMG signals as other inputs to ELM and ANN models.

V. Conclusion

In this paper, ANN and ELM models are compared when trained and tested on a gait dataset where the EMG signal served as the input while the parameters – gait speed, % Stance and % Swing phase – serves as the target. Overall, ELM performs better in terms of predicting the values and it takes a shorter duration to train than the ANN. ELM also shows a more balanced value approximation as there is less difference between the training RMSE and the testing RMSE which gives rise to a robust model when compared with ANN. Future work would focus on further development of ELM model to achieve a more accurate estimation of temporal gait parameters.

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