Generalization of ANN Model in Classifying Stance and Swing Phases of Gait using EMG Signals

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***Abstract*—Exposure to physical therapy in rehabilitation shows a major interest in recent years. Even though the detection of gait events based on Electromyography (EMG) signals help the development of various assistive devices, the main issue arises on how to utilize EMG signals especially for two phases, stance and swing. Previous works had proposed various classification model of EMG signals for five and seven phases. However, the performance of the classification model for any individual has not been explored. Thus, this study investigate the generalization of classification model for two gait phases, stance and swing based on EMG signals. The model was developed by extracting five time domain (TD) features and fed into a classifier, artificial neural network (ANN). Eight participants were divided into two groups that is learned data and unlearned data. The ANN model was designed based on learned data with levenberg maquardt (LM) training algorithm. Then, the model will be further evaluated with EMG signals of both unlearned data and learned data to observe the generalization of ANN model. The ANN model gained 87.4% of classification accuracy in discriminatiing stance phase and swing phase. This study found the generalization of the ANN model were acceptable with 87.5% for learned data and 77% for unlearned data. Future works could enhance the classification accuracy with different TD features and number of hidden neurons for ANN.**

***Keywords*—EMG signals, time domain features, ANN, gait phases**

I. Introduction

Gait events detection is an important topic in recent research since it provides an effective method for medical treatment especially in rehabilitation. The analysis of gait events facilitate the assessment of parkinson's disease [1] and children with cerebral palsy [2]. Furthermore, detection of gait events is a continuing concern within the development for assistive devices in rehabilitation such as hip knee (HK) exoskeletons, ankle foot (AF) orthoses, and knee ankle foot (KAF) orthoses as been reviewed by Yan et al. [3]. They also highlighted gait events, stance phase and swing phase are the main locus in the development of KAF, HK, active and passive AF orthoses. The stance phase begins as heel strike (HS) with the ground, while swing phase begin as the toe off (TO) from the ground. These phases have a positive effect when using AF orthoses based on ankle kinematics as proven by Nikamp et al. [4]. Thus, the stance phase and swing phase are enough to control the active motors in assistive devices for functional electrical stimulation.

Electromyography (EMG) signals were reported to be useful not only for diagnosing patients with neuromuscular diseases [2], but also for gait phase detection [5]–[9]. According to Nardo et al. [10], the variability between the subjects were low especially during walking on the ground. The EMG signals is known as the electrical manifestations activation of neuromuscular originated in the muscles during relaxation and/or contractions. In intent recognition and onset gait initiation for transfemoral amputees, it has been revealed that the combination of mechanical or kinematic sensors with EMG signals seemed to have a promising potential [11], [12]. With this approach, users are able to operate electric-powered wheelchair [13] and robot arm [14] using their own muscles. In addition, the ankle positioning and EMG signals had been used as an inputs to control the passive AF orthoses [15]. Since the EMG signals are difficult to analyze, the pattern was categorized into stance and swing phases through visual observation. To overcome this problem, an interpretation of EMG signals during stance and swing phases could improve the development of AF orthoses of previous study. The overview of current research with previous study [15] was illustrated in Fig 1. Note that this study focuses on signal processing.

The detection of gait events based on EMG signals has been thoroughly examined. According to Nazmi et al., machine learning approach widely applied for a periodic pattern such as EMG signals [16]. The adaptive neuro fuzzy inference system (ANFIS) was sucessfully predicting the seven phases of gait in the child with cerebral palsy less than 30 ms [5]. Nonetheless, this study could benefit in development of HK orthoses as they recorded the EMG signals from the right and left vastus lateralis muscles. Besides that, the classification accuracy of eight gait phases were obtained between 80% to 90% with time domain (TD) features and LDA as a classifier [17]. However, this may be applicable for HKAF orthoses, as the EMG signals are collected from quadriceps, hamstring, gastrocnemius and tibialis anterior muscles.

For AF orthoses, EMG signals recorded on the lower limb muscles such as tibialis anterior (TA) and medial gastrocnemius (mGas) are preferred to represent the stance and

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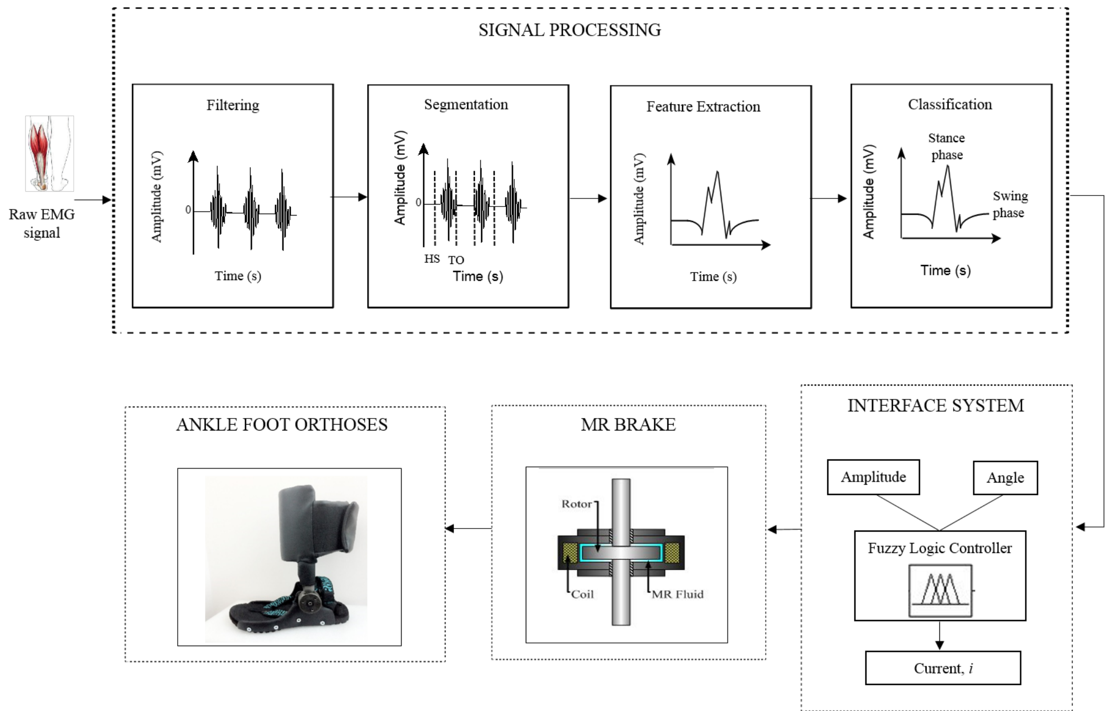

Fig. 1. An overview in developing EMG control systems

swing phases [18]. By using both muscles, an artificial neural networks (ANN) model proposed by Nazmi et al. [8] successfully discriminated the EMG signals during stance and swing phases. In particular, ANN are useful for complex classification tasks. In addition, ANN are not only can represent both linear and nonlinear relationship, but also able to establish the relationship directly from the modelled [7]. This statement has been proven with 96.7% and 88.4% of accuracy in classifying neuromuscular diseases [19] and upper limb movement [20], respectively. Even so, the generalization of ANN model for lower limb has not been investigated. Therefore, this study evaluates the generalization of ANN model by extracting TD features of EMG signals collected on lower leg muscles, TA and mGas.

II. Methodology

Eight healthy male subjects aged between 23 and 26 years (age=23.6±1.9 years, height=169.8±6.9cm; mean±sd) participated in this study with range body mass index (BMI) between 21.5 and 23. The participants were recruited from the Shibaura Institute of Technology's student population. Their details are shown in Table I.

The inclusion criteria of this study included no history of nerve or physiological injuries that could affect the gait pattern during walking. The experimental protocol for this study was approved by the ethical committee of College of Systems Engineering and Science at Shibaura Institute of Technology, Japan. As the investigation of this study was focused on the lower leg, the participants were required to do some movements such as dorsiflexion and plantar flexion to obesrve the activation of TA and mGas muscles. The timing of stance and swing phases was based on the timing of HS and TO from the footswitch data. The footswitch data were recorded by placing two force sensing resistors at the hallux and heel under the sole of foot [21], [22], after cleaning with wet tissues.

TABLE I
Demographic data of the subjects

Subjects	Age (years)	Height (cm)	Weight (kg)	Body Mass Index (BMI)
S1	23	178	68	21.5
S2	25	166	60	21.7
S3	23	167	63	22.5
S4	23	163	62	23.3
S5	23	168	65	23.0
S6	26	183	74	22.1
S7	23	168	58	20.6
S8	23	165	60	22.0

The surface EMG signals were collected from TA and mGas muscles with a reference electrode located at the patella. The placement of electrodes are following the recommendations by Surface Electromyography for the Non-Invasive Assessment. Then, a two-channelled EMG device (Nihon Kohden, Japan) will processed the surface EMG signals with range (± 2.5V). A multichannel amplifier (Nihon Kohden, Japan) amplified the surface EMG signals with bandwidth filtering from 15 to 1000 Hz.

Both EMG and footswitch devices were connected to 64

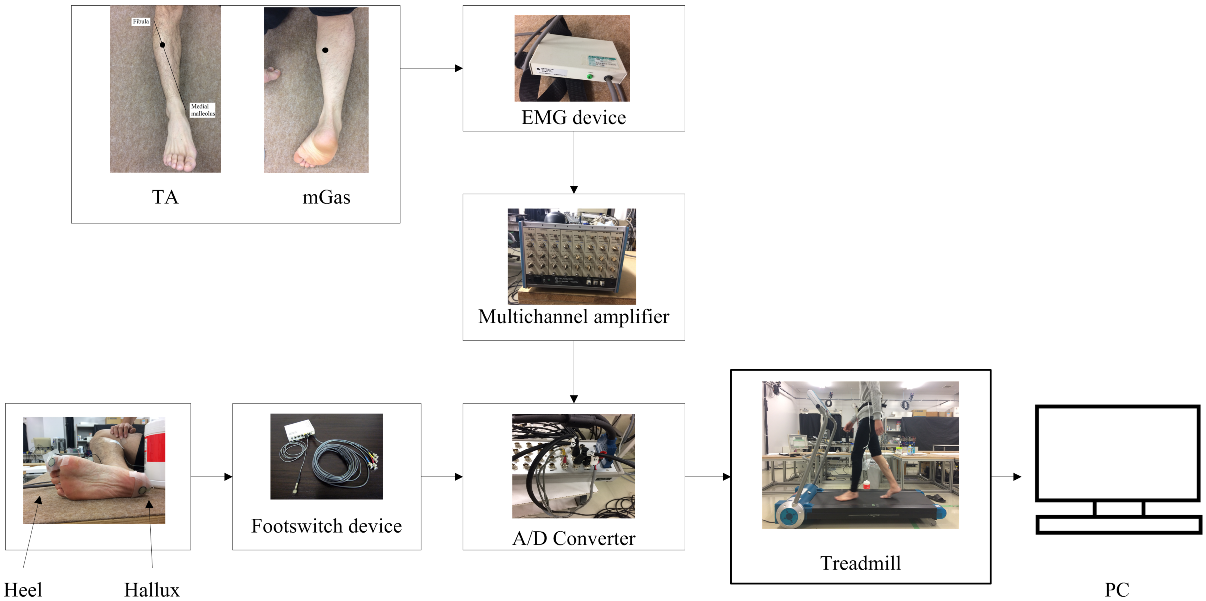

Fig. 2. The experimental setup

Ch analog-to-digital converters (Model ZO-928, NAC, Japan) as shown in Fig. 2. Using Cortex software, the sampling frequency of surface EMG signals and footswitch data were set to 1000 Hz. For initial warm up, each subject were instructed to walk on the treadmill for 30 seconds at a constant speed of 3 km/h at a self-selected comfortable pace. Then, the subjects underwent the tasks by walking on the treadmill using similar speed but for 60 seconds.

The surface EMG signals and footswitch data were further processed offline to investigate the walking pattern in respect to the muscle activation for each subject as reported in previous studies [10], [23]. In this study, the segmented surface EMG signals are highpass and lowpass filtered at 20 Hz and 500 Hz cut-off frequency with second order Butterworth [24], respectively. The entire data set of surface EMG signals was then divided into windowing segments, adjacent overlapping.

Meaningful information for both TA and mGas muscles will be interpreted using five TD features. The surface EMG signals and footswitch data are grouped into two categories that is learned data and unlearned data. Learned data were collected from the EMG signal of the first seven subjects while unlearned data were EMG signals of the remaining one subject. The learned data will be used to develop the model and unlearned data to determine the generalization of the ANN model.

Root mean square (RMS) is widely used in represneting the surface EMG signals [25]. For RMS feature, the mathematical definition can be expressed as (1).

$$RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2} \tag{1}$$

where n is the number of observations.

Standard deviation (SD) for data set is the positive square root of the variance whereas it shows how much variation or dispersion exits from the mean. Also, variance measures the variability existing in a set of data by finding the difference between each data point and the mean by squaring the value. The SD is large if the data are widely spread around the mean and will be smaller for a data set more clustered around the mean. The standard deviation is defined as (2).

$$SD = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \mu)^2} \tag{2}$$

where n is the number of observations and μ is the mean.

Mean absolute value (MAV) is mostly popular features applied in extracting the surface EMG signals [26]. MAV feature is defined as an mean of absolute value of the surface EMG signals amplitude within a segment, that can be expressed as (3).

$$MAV = \frac{1}{n}\sum_{i=1}^{n} |x_i| \tag{3}$$

where n is the number of observations.

The complexity of the surface EMG signals can be measured using waveform length (WL) feature. WL feature is a summation length of surface EMG signals within the time segment. It can be calculated by using (4).

$$WL = \sum_{i=1}^{n-1} |x_{i+1} - x_i| \tag{4}$$

where n is the number of observations.

The sequence firing point of surface EMG signals is related with Integrated EMG (IEMG) feature. Definition of IEMG feature is a cumulative absolute values of surface EMG signals, which can be calculated as (5).

$$IEMG = \sum_{i=1}^{n} |x_i| \tag{5}$$

where n denotes length of the EMG signals, x_i represents the surface EMG signals within a segment i. The TD features of each muscles during stance and swing phases in 30 cycles for each subject will be extracted and fed into the ANN classifier. In total, 245673 datasets with input and target vectors of stance and swing phases of learned data were computed into the ANN.

In this study, multilayer perceptron (MLP) of ANN model with its basic architecture network was applied. The model consists of three layers of the feed forward included input layer, hidden layer and output layer. Generally, the input vector M with N rows can be expressed as $m_1, m_2, ..., m_N$. Each input was weighted by corresponding element $w_{1,1}, w_{2,1}..., w_{S_1,N}$ of the weight matrix, W1 and S1 represent the number of neurons. For hidden neurons, 10 tan-sigmoid neurons are considered as it performed better compared with 20 and 30 hidden neurons [20]. In our case, the RMS, SD, MAV, WL and IEMG feature of TA muscles were assigned as m_1, m_2, m_3, m_4, and m_5 respectively. Meanwhile, m_6, m_7, m_8, m_9, and m_{10} represent RMS, SD, MAV, WL and IEMG feature of mGas muscles. The data for training input were divided randomly with 70% for training, 15% for validation and 15% for testing.

Moving on, a suitable training algorithm was required to adjust the synaptic biases and weights at different layers after designing the ANN model. ANN consists two types of training algorithm that is levenberg maquardt (LM) and scaled conjugate gradient (SCG). According to Ibrahimy et al. [20], LM training algorithm more powerful and was faster than SCG training algorithm as it train moderately-sized, fed-forward neural networks for hand movements based on the numerical optimization. It is an agreement in identification of the driver's steering behaviour [27]. Thus, LM training algorithm were evaluated to test it capability and performance in ANN.

Without computing the Hessian matrix, LM training algorithm was designed to approach the second-order training speed. The Hessian matrix can be approximated as Equation 6 and the gradient can be calculated as (7).

$$H = JJ^T J \tag{6}$$

$$g = J^T e \tag{7}$$

where J is the Jacobian matrix. The J matrix much less complex than computing the Hessian matrix as it can be calculated through a standard back-propagation technique. By using this approximation, the LM training algorithm was applied to the Hessian matrix with the following Newton-like update as defined in (8).

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e \tag{8}$$

The step-size of gradient descent becomes small if the value μ is large. An overall process of this study were illustrated in Fig. 3.

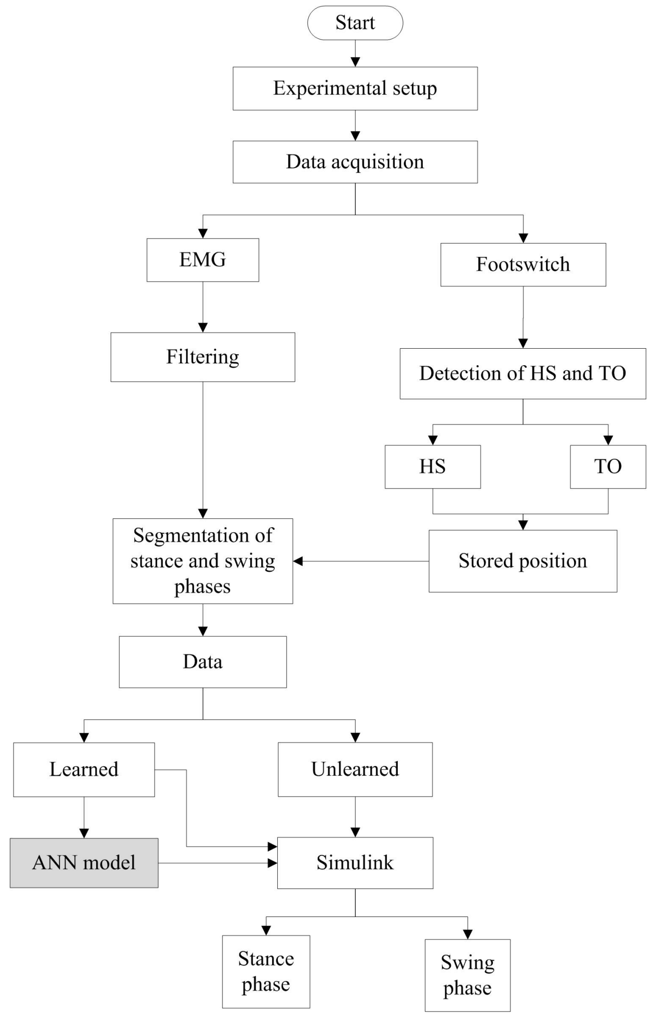

Fig. 3. Research flow of this study

III. Result and Discussions

An example of footswitch data and surface EMG signals during stance phase and swing phase within five seconds were shown in Fig. 4. It can be seen TA muscle activates more during swing phase than stance phase. Meanwhile, mGas muscle activates during stance phase.

The performance and network responses for five TD features of learned in terms of stop epochs, time elapsed and regression (R) value data for each training sessions is shown in Table II. In the table, classification rate were divided into three; training (TR), validation (V) and test (Te). The time taken to build the ANN model were between 24.33 to 39.48 seconds. Nonetheless, the time elapsed does not effect the classification rate of the ANN model. Meanwhile, the R value equals to one

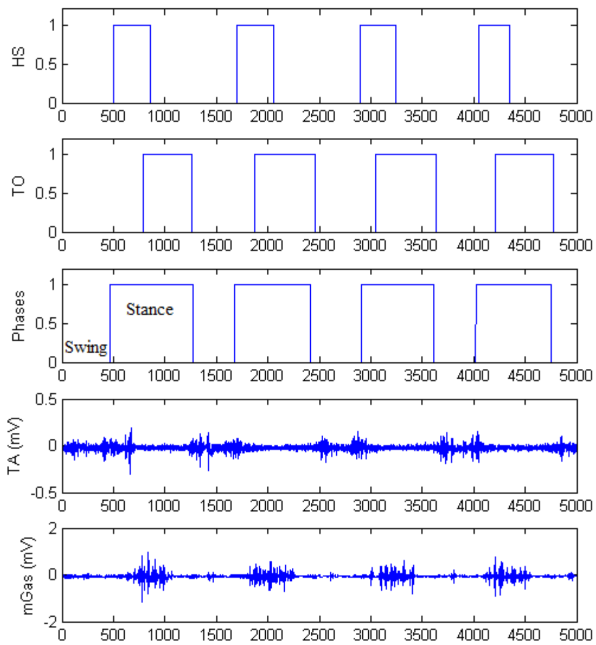

Fig. 4. The EMG signals recorded on TA and mGas muscles with HS and TO detection

suggests the relationship between the targets and outputs of the model are closed.

TABLE II
COMPARISON OF CLASSIFICATION PERFORMANCE USING LM TRAINING ALGORITHM OF ANN

Number of train	Stop epochs	Time elapsed	R	Classification rate (%)		
				Tr	V	Te
1	133	24.33	0.79517	87.2	87.2	87.1
2	225	24.17	0.79558	87.8	87.3	87.5
3	338	39.48	0.79544	87.5	87.3	87.5

An overall accuracy of classification rate of ANN model were 87.2%, 87.7% and 87.4% for train 1, 2 and 3, respectively as shown in Fig. 5. The average classification accuracy for ANN model was 87.4%. As aforementioned, the study will further evaluated the ANN model with learned data and unlearned data for generalization.

Table III presents the result of classification accuracy for both learned data and unlearned data. Comparing with the footswitch data, the ANN model successfully classified the stance and swing phases approximately 92% and 81%, respectively for learned data. The small difference in percentage of classification accuracy indicate that LM training algorithm performed well in ANN model. This finding is consistent with that of Ibrahim et al. [20].

On the other hand, the percentage difference between footswitch data and ANN model for unlearned in detecting stance phase and swing phase data was approximately 29%

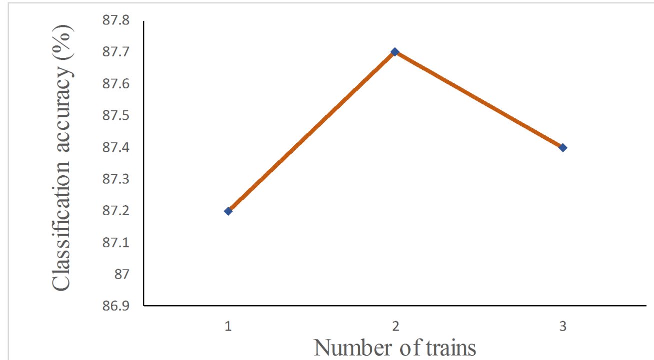

Fig. 5. Overall classification rate for each train of ANN model

and 10%, respectively. A possible explaination for this might be that the ANN model dependent on the training datasets. The large percentage difference in stance phase effect the overall accuracy of classification.

All in all, the generalization of ANN model were reliable as overall classification percentage for learned data and unlearned data were 87.5% and 77%, respectively. Although learned data had shown a better performance than unlearned data, it can be concluded the detection of stance phase and swing phase of classification model, ANN may applicable for any individual. However, future works could enhance the performance of ANN model by using other TD features, number of hidden neurons and training algorithm.

TABLE III
CLASSIFICATION PERFORMANCE OF ANN WITH RESPECT TO REFERENCE DATA FOR EACH DATA

Data	Footswitch (%)		ANN (%)		
	Stance phase	Swing phase	Stance phase	Swing phase	Overall
Learned	61	39	55.8	31.7	87.5
Unlearned	67	33	47.3	29.7	77.0

IV. CONCLUSION

This work evaluate the generalization of ANN model in discriminating the stance phase and swing phase of gait. An ANN model with LM training algorithm using five TD features gained 87.4% of accuracy in classifying stance phase and swing phase. This study revealed the ANN model was applicable for any individual based on the generalization result for both learned data and unlearned data. One interesting finding, the ANN model performed better with learned data compared with unlearned data. The classification accuracy might be improve by redesigned the ANN model near future.

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