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Walking gait event detection based on electromyography signals using artificial neural network

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A B S T R A C T

In many gait applications, the focal events are the stance and swing phases. Although detecting gait events using electromyography signals will help the development of assistive devices such as exoskeleton, orthoses, and prostheses, stance and swing phases have yet to be observed using electromyography signals. The core of this study is to propose a classification system for both stance and swing phases based on electromyography signals. This is to be done by extracting the patterns of electromyography signals from time domain features and feeding them into an artificial neural network classifier. In addition, a different number of input features and two prominent training algorithm of artificial neural network have been employed in this study. Eight subjects that participated in this study were divided into two categories namely, learned (first seven subjects) and unlearned data (the remaining one subject). It was observed that Levenberg-Marquardt algorithm with five time domain features performed better than other features with an average percentage of classification accuracy of 87.4%. This system was further tested with electromyography signals of learned and unlearned data to identify the stance and swing phases in order to detect the timing of heel strike and toe off. The mean absolute different values between artificial neural network and footswitch data for learned data were 16 ± 18 ms and 21 ± 18 ms for heel strike and toe off, respectively. For this case, no significant differences ($p < 0.05$) were observed in mean absolute different for heel strike and toe off detections. Besides, the mean absolute different values of unlearned data were shown to be acceptable, 35 ± 25 ms for heel strike and 49 ± 15 ms for toe off. By the end of this experiment, basing the examination of gait events with electromyography signals using artificial neural network is possible.

1. Introduction

The recent increase on gait event detection can be attributed to it being and effective method in medical rehabilitation treatment. Other than facilitating the examination of Parkinson's disease [1], the analysis and monitoring of gait events also help in treatments for children with cerebral palsy [2] and muscle injuries [3,4]. Furthermore, gait event detection can also aid the development of assistive devices for human body such as ankle foot (AF), hip knee (HK) and knee ankle foot (KAF) orthoses and exoskeletons, as discussed by Yan et al. [5].

Stance and swing phases of gait are generally the locus of HK, KAF, passive and active AF orthoses development [6–9]. These events were also proven to have a positive, albeit short-term effect on AF orthoses of ankle kinematics [10], in addition to potentially enhancing ones walking capacity [11]. Therefore, the gait granularity of the two phases are enough to synchronize the active motors in wearable sensors in functional electrical simulation [12].

In the development of assistive devices, wearable sensors such as accelerometer and gyroscope were used to control the actuator. Such wearable sensors will require gravity compensation, correct placement of sensors, specific calibration procedures, chances of drift error if the angle needed to be computed and may produce

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errors with negative percentages [12,15]. Recent developments of assistive devices have heightened the concept of using electromyography (EMG) signals as the input for the control of powered human-machine interactions [19]. For instance, the combination of EMG signals with mechanical/kinematic sensors in transfemoral amputees seemed to have promising potential in intent recognition [20] and onset gait initiation [21]. Such approach will enable users to operate protheses device using their own muscles. Similarly for electric-powered wheelchair [22], robot arm [23] and exoskeleton robots [24]. In 2016, the development of passive AF orthoses is drawn from EMG signals and ankle positioning as its main sources [25]. However, EMG signals during stance and swing phases had not been addressed [12,27].

A periodic pattern such as EMG signals is usually classified using machine learning approach [28]. Such approach are able to establish relationships between data directly from the model data and can represent both nonlinear and linear relationship [19]. Hence, machine learning approach, such as artificial neural networks (ANN), is useful in analyzing and classifying complex patterns. The ability of ANN in studying and establishing relationship between data of EMG signals has been proven for upper limb movement [29] and neuromuscular diseases [30]. Meanwhile, this statement has not been explored for lower limb movement especially stance and swing phases.

Apart from practicality, accuracy is also important in any calculation system. It is crucial to have the right and effective features to ensure higher accuracy. Therefore, features of time domain (TD) have been widely adopted in discriminate upper limb movements, as calculation of features will then be based on raw EMG time series, eliminating the need for transformation [29,31,32,55]. It should be noted that single and multiple feature sets will produce different accuracies [32,33].

At the point this paper was written, this is the first attempt on using EMG signals to quantify stance and swing phases among young, healthy subjects during normal gait events. It is hoped that the end data will help in creating a system with acceptable, if not high, accuracy in detecting stance and swing phases. Also, the proposed system will adopt some features of TD to represent EMG signals for tibialis anterior (TA) and gastrocnemius medialis (mGas) muscles. The features will also be computed into an ANN classifier. Then, the performances of a single and combination of TD features will be compared. The designed ANN with higher accuracy will be further evaluated with learned and unlearned data to test its suitability with EMG classification. Based on the stance and swing phases characterised by the system, the timing of stance and swing phases was identified and compared with footswitch data as a validation.

2. Materials and methods

2.1. Data acquisition and processing

Eight healthy male subjects with age range from 23 to 26 years old and height from 163 cm to 183 cm participated in this study. The subjects had no history of physiological or nerve injury that may have affected gait.

As force sensing resistors (FSR) system showed significantly lower errors than the accelerometer system [34], the footswitch based reference was widely adopted in the identification of gait events on other wearable sensors such as accelerometers [35,36], gyroscopes [2,37–39], and IMU [4]. Similarly, with the analysis of EMG signals, footswitch data determined the starting and ending of stride as conducted in [18,40]. Thus, this study used footswitch data as a reference.

Two FSR were placed under the sole of their foot, beneath the hallux and heel [41]. The footswitch data was recorded using Load Switch System (DKH, Japan) with activation force 0.3 N. Also, the subjects were asked to perform dorsiflexion (upward movement of foot at the ankle) and plantar flexion (bending the foot toward plantar surface) to verify the precision of the on/off activation of footswitches. This was to calibrate and ensure the accuracy of the footswitches' outputs, as these outputs will become the reference signals. The stance phase began with the initial foot contact. It was the Heel Strike (HS), as the pressure at the heel increases. Meanwhile, foot contact, or toe off (TO), ended when swing phase began. In this study, HS was when the heel touched the ground, while TO was when there was a termination of hallux from the ground.

The detection of EMG signals on the surface were done by placing double-sided adhesive skin interfaces electrodes of EMG sensor on TA and mGas muscles. This was derived from the Surface Electromyography for Non-Invasive Assessment, with a reference to electrode at the patella. It is worth noting that the electrodes contact point, or in other words, the skin, was shaved and then cleansed with alcohol. It was to reduce impedance on the skin surface. Apart from that, the online processing of surface EMG signals were done using a two-channeled EMG device (Nihon Kohden, Japan) with 30 mm electrode diameter, 10 mm inter-electrode distance, input impedance $>10^{15}\,\Omega$ and input referred noise 1.2 μV. The device was amplified using a multichannel amplifier with bandwidth filtering ranging from 15 to 1000 Hz. The raw EMG signals were then high-passed and low-passed filtered with the second order Butterworth at 20 Hz and 500 Hz respectively to minimize interference and unwanted line frequencies (50/60 Hz) [28].

Afterwards, a 64Ch analog-to-digital converters (Model ZO-928, NAC, Japan) was connected to EMG signals and footswitch data. This is shown in Fig. 1.

On top of that, the EMG signals and footswitch data were sampled using Cortex software at a rate of 1000 Hz. Fig. 2 represents an example of EMG signals recorded from TA and mGas muscles for one subject. The subjects were then asked to walk bare-footed at their self-selected pace on a treadmill that has been set to a speed of 3 km/h for 60 s.

Next, MATLAB software was used to design an algorithm to recognize the timings of HO, TS, and EMG signals on TA and mGas muscles. With reference to footswitch data, HS and TO timings were recorded as 1, while anything other than those two were recorded as 0. The values formed the base for the segmentation of EMG signals on TA and mGas muscles. The whole data of EMG signals were then divided into overlapping segments. They are 200 data value long with a one point delay to the next segment. Such length contained enough information to estimate EMG signals' pattern.

On a related note, feature extraction is an effective and important method in extracting meaningful information from EMG signals. As mentioned before, features in TD are widely used to solve pattern recognition problems.

MAV not only one of the most popular features used in EMG signals analysis [42], but also recommended Phinyomark et al. suggested MAV features based on energy information method [31]. This result had supported the combination of MAV and WL proposed by Oskoei et al. [32] using four channel of EMG signals in isometric contractions.

The TD features that were incorporated into this study were root mean square (RMS), standard deviation (SD), mean absolute value (MAV), integrated EMG (IEMG), and waveform length (WL) [29,32]. The RMS, SD, MAV, IEMG, and WL of TA muscles were assigned with p_1, p_2, p_3, p_4, and p_5 respectively. Meanwhile, p_6, p_7, p_8, p_9, and p_{10} represent RMS, SD, MAV, IEMG, and WL of mGas muscles. Those features were selected based on the study conducted by Nadzri et al. for EMG signals in isomteric contractions [43]. This study extends the research for isotonic contractions and the variance features of