Chapter

A Review of EMG Techniques for Detection of Gait Disorders

Rajat Emanuel Singh, Kamran Iqbal, Gannon White and Jennifer K. Holtz

Abstract

Electromyography (EMG) is a commonly used technique to record myoelectric signals, i.e., motor neuron signals that originate from the central nervous system (CNS) and synergistically activate groups of muscles resulting in movement. EMG patterns underlying movement, recorded using surface or needle electrodes, can be used to detect movement and gait abnormalities. In this review article, we examine EMG signal processing techniques that have been applied for diagnosing gait disorders. These techniques span from traditional statistical tests to complex machine learning algorithms. We particularly emphasize those techniques are promising for clinical applications. This study is pertinent to both medical and engineering research communities and is potentially helpful in advancing diagnostics and designing rehabilitation devices.

Keywords: electromyography, feature extraction, classification, gait disorders, machine learning, time-frequency analysis

1. Introduction

EMG is an electrodiagnostic technique used to record the electrical activity in skeletal muscles. EMG signals are complex and exhibit intricate patterns that are dependent on the anatomical properties of the muscle [1–3]. The signal manifests the neuromuscular activation underlying muscle contraction [1, 3]. Therefore, an abnormality in the contraction of a muscle due to an injury, nerve damage, or muscular or neurological disorder that causes motor dysfunction can be identified through EMG signal diagnosis. The motor neuron signal carries information from the CNS aimed for limb displacement by flexing and extending the joints [4, 5]. The dynamic electrical activity of these motor units is called motor unit action potentials (MUAPs). These are super-positioned and recorded by the EMG device [6]. EMG can be recorded using surface electrodes, fine wire electrodes as well as anal and vaginal probes for pelvic floor muscles [2]. A simple model of an EMG signal is given by Eq. (1), where, $y(n)$ is the sampled EMG signal, $a(r)$ is the MUAP, $x(n)$ is point processed firing impulse, w_n is the white Gaussian noise and N is the number of motor unit firing at a particular time.

$$y(n) = \sum_{i=1}^{N-1} a_i(r)\, x_i(n - r) + w_n \tag{1}$$

Our aim in this article is to review EMG signal processing techniques that facilitate detection of gait and movement disorders. We discuss techniques from simple enveloping to complex computational machine learning algorithms that may help detect alterations in EMG patterns while performing daily life activities. We may note that there are number of highly cited review articles such as Raez et al. [7], and Chowdhury et al. [8], that review EMG processing and classification techniques. The novelty in our review is that in addition to discussing innovative processing techniques we have emphasized their applications, particularly focusing on lower limb disorders. In Section 2, we review the basic techniques such as EMG enveloping, followed by EMG onset/offset detection in Section 3. In Section 4, we review current literature on the decomposition of EMG signals into MUAPs and muscle synergies. In Section 5, we discuss the analysis of the EMG signal in the frequency and time-frequency domain to understand changes due to motor impairment. When working with a larger sample size, a machine learning system can be used to classify subjects with altered muscle activation and abnormal gait patterns [9, 10]. In Section 6, we discuss algorithms that employ supervised and unsupervised learning to detect patterns of gait disorders, followed by a discussion of future trends and conclusion in Section 7.

2. EMG envelopes

Visual inspection of the raw EMG plot or its envelope requires high dexterity and clinical experience to detect motor impairment. The methodology to obtain the EMG envelope includes preprocessing, signal filtering, rectification, smoothing, standardization, statistical testing, and intricate computational algorithms. Scientific recommendations by SENIAM project and International society of electromyography and Kinesiology (ISEK) suggest use of bandpass filters (10–500 Hz) to reduce aliasing effects when using a sampling frequency of 1 kHz. Intramuscular and needle recordings should be made with the low-pass cut-off set at 1500 Hz. Avoiding notch filter is recommended as it destroys the signal information [2]. De Luca et al. recommended root mean square (RMS) value to compute the signal amplitude of the EMG during voluntary contraction [3]. Methods to form EMG envelopes include moving average, root mean square, spline interpolation over local maxima, integrated EMG etc. EMG envelope can also be obtained from low pass Butterworth 6 Hz filter. Hilbert finite impulse response (FIR) filter computes magnitude of the analytic EMG signal.

A decrease in EMG amplitude was visually observable for chronic spinal cord injury (SCI) patients while walking for 3 min [11]. Biceps femoris (BF) and gastrocnemius medial (GM) revealed consistent activity, but that was not the case for tibialis anterior (TA) and rectus femoris (RF). The RMS magnitude of the signal from BF and GM muscles decreased with longer activity duration (10 min) followed by an EMG burst resulting from muscle spasm. Identification of chronic SCI was done by simple visual inspection of the raw EMG [11]. The inter-neuronal degradation was the cause of decreased locomotor performance [11]. The RMS amplitude of the EMG signal using a paired t-test showed a higher duration of muscle activity for BF and TA among cervical spondylotic myelopathic patients (CSM) [12]. The amplitude of the muscle burst activity was not statistically different between the healthy group and CSM [12]. The muscle stretch analyzed from kinematic data did not relate with spasticity, but the ratio of EMG RMS amplitude to the mechanomyogram data showed statistically significant results for healthy and myotonic control groups [12, 13].

The stochastic and nonstationary nature of EMG signals makes it harder to study the innate patterns of the electrical activity of the muscles. Statistical tests such as Pearson's, Pearson's r, the Kolmogorov-Smirnov T-test, ANOVA F ratio and t-test, and Wilcoxon Signed Rank Test can demonstrate significant changes in the EMG profiles associated with different behavior [14, 15]. Domingo et al. performed an ANOVA on the normalized EMG amplitude of spinal cord injured patients, which led to the conclusion that with increased speed and no manual assistance the EMG pattern exhibited statistical significance when compared to the control group. The shape and timing of EMG patterns were less similar to controls [16]. Among stroke patients, the EMG activity displayed heterogeneity in comparison with healthy individuals [17]. Nieuwboer et al. [18] demonstrated that raw EMG and its linear envelopes of Parkinson's patients during freezing episodes displayed abnormal activity of TA and GM. Nonparametric tests on the RMS EMG envelope of the hemiplegic patient showed statistical significance during push off and early stance phase [14]. EMG data acquired from Parkinson patients' shoulder muscles revealed higher activation than those of healthy control subjects [19]. Average and maximum EMG amplitude were calculated for comparison [19].

Traditional statistical testing of the EMG uses ANOVA techniques that may not identify visually differentiable waveform features. McKay et al. [20] developed a more reliable statistical method to find the underlying patterns with the wavelet-based functional test (wfANOVA). Its performance to detect the changes in the magnitude and shape of EMG was more precise than the time domain ANOVA test. Wilcoxon signed rank tests were also used in studies with non-parametric data [12]. EMG envelope extraction using time domain features from multichannel sensors and their statistical tests can assist in the detection of altered myoelectric activity. Specific features such as EMG onset/offset, MUAP etc. can be analyzed from the envelopes for the diagnosis of gait disorders. **Figure 1** shows signal envelope extracted from the EMG signal with RMS. MATLAB functions were used to extract envelope and perform a statistical hypothesis test for a healthy individual and other disorders.

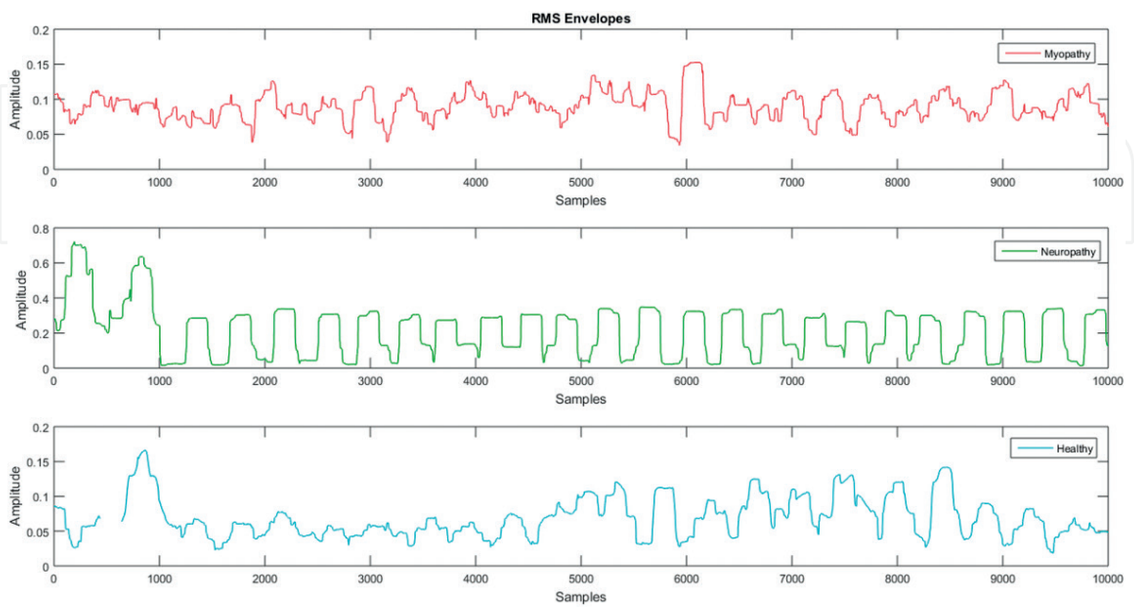

Figure 1.
RMS envelope from a healthy, a myopathic, and a neuropathic patient. A non-overlapping window of 200 samples was used and a paired student t-test revealed statistical significance ($p < 0.05$) between healthy and neuropathic, and healthy and myopathic conditions. The data was obtained from physionet [21].

3. EMG onset detection

EMG onset parameters define the duration for the muscles to stay active [2]. Onset estimation is useful to diagnose abnormality in muscle coordination. To detect the EMG onset, visual inspection or measurement of nerve conduction velocity may be used [22]. The basic thresholding method for onset detection is sensitive to the type of trials, EMG amplifiers and noise level in the signal. The thresholding based on SD baseline noise can be improved with local peak value. In a study [23], integrated EMG provided more information about early activation. During preconditioning, Teager-Kaiser Energy Operator (TKEO) also improved the onset detection accuracy by constricting the energy of the baseline noise [24, 25]. Staude et al. compared onset detection methods based on the statistical optimal decision threshold [26]. The simple threshold algorithm of Hodges and Bui [26] identifies the onset at a point where the mean of the samples within a fixed time window surpasses the baseline level by a defined multiple of standard deviation [27].

The basic framework of the threshold detection algorithm includes signal conditioning (rectification, filtering, whitening etc.), detection (Test Function and Decision rule), and postprocessing [26]. A block diagram is shown in **Figure 2**.

Double threshold methods are considered better in comparison to single threshold methods [7]. The Bonato algorithm [28] includes pre-whitening filter and data sample squaring in the conditioning unit. The test function is computed between two successive samples from the conditioned EMG signal. The onset point identification is based on the following rules: (1) x out of y samples must exceed the threshold and (2) activation state of the muscle after surpassing the threshold should last for a certain number of samples or duration of time [26].

In Lidierth [29] method, the signal conditioning unit performs full wave rectification. The test function and decision rule are based on Hodges [26]. Additional post-processing rules increase the efficiency of the algorithm. The test function unit detects the onset if the sEMG signal exceeds the threshold. Any decline in the activity below threshold within a defined duration, should not be longer than the defined range of samples [29]. The power spectral correlation coefficient method performs better than TKEO and utilizes the moving average method of Hodges and Bui [30]. The statistical estimation algorithm includes an optimal estimator and approximated generalized likelihood-ratio detector. The statistically optimized algorithms are more robust in terms of signal parameters [26]. Tenan et al. [25] reviewed three classes of standard EMG (linear envelope, entropy, TKEO) and

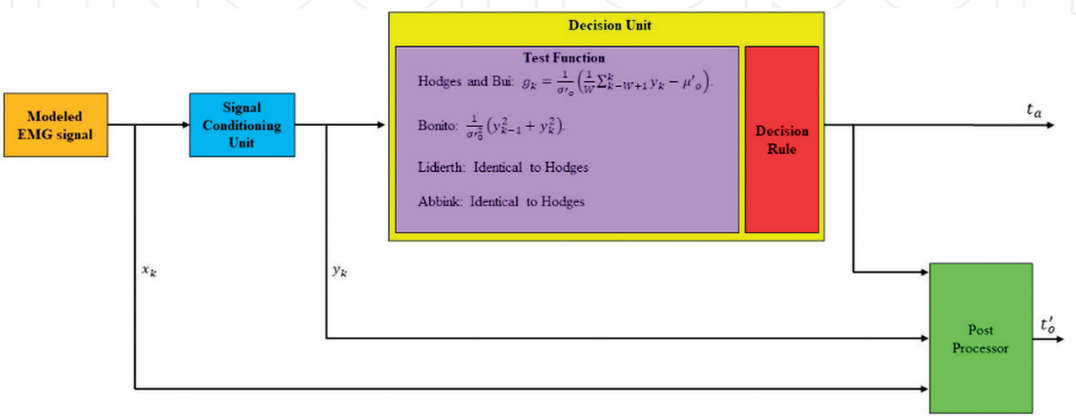

Figure 2.
EMG onset estimation framework; x_k is Gaussian noise signal, y_k is the processed signal, σ'_o and μ'_o are standard deviation and mean of samples, respectively, $g_k \geq Th$ (Threshold) is the value to trigger an alarm t_a, and t'_o is the change time estimation.

six classes of statistical EMG onset detection (general time series/mean–variance, sequential change point detection with parametric and non-parametric methods, batch change point detection, and Bayesian change point analysis). The Bayesian Change Point analysis algorithm showed higher reliability and accuracy for the singular EMG onset detection.

Maximum voluntary contraction (MVC) is a common scaling technique for EMG onset detection. MVC is the largest RMS amplitude a muscle generates in maximum contraction [31]. MVC has a curvilinear relationship with the muscle force production, where less force production amount to muscle weakness. EMG onset on a normalized time series with MVC can help diagnose gait disorders associated with atrophy [2]. Muscle spasticity/co-contraction during tremors among patients with neurological gait disorder exhibited abnormality in EMG onset compared to healthy individuals [12, 32]. EMG envelope indicated alterations in EMG onset for patients with Parkinson's during freezing episodes [20]. A premature activation of TA and GM muscles before a freezing episode was observed. In gait impairment, due to cervical spondylotic myelopathy, delayed onset and prolonged activation were present [12]. In cerebral palsy earlier onset suppression of EMG within cutaneous muscular reflex is associated with motor dysfunction, which results in inhibitory postsynaptic potentials [33].

4. EMG decomposition into MUAP

Raw EMG signal consists of superpositioned motor unit activation potentials (MUAP) and noise components. Muscle crosstalk is a major issue during recording of the biological signals. The crosstalk is dependent on factors such as anatomical site for the placement of electrodes, type of movement, and skin thickness. Since it is harder for sEMG to detect the origin of muscle electrical activity, the chances of muscle crosstalk are higher in sEMG than needle EMG [13]. Besides, low spatial resolution, high movement artifact, and narrow frequency range makes needle EMG more promising as a diagnostic tool in nerve conduction studies for assessing neurological disorders [13]. Changes in the shape of MUAPs, large dynamic range of action potential among motor units and superposition of motor units pose major challenges to decomposing the sEMG.

Fang et al. [34] decomposed EMG into MUAP by wavelet transform. The technique utilized spectrum matching in wavelet domain as opposed to waveform matching. De Luca et al. [35] proposed a method to decompose the sEMG into MUAP during cyclic dynamic contractions. The algorithm solved two main problems, the first associated with the displacement of the electrode on the surface of the skin leading to alteration in the shape of MUAPs, and second regarding lengthening and shortening of the muscle fibers while undergoing those contractions. The algorithm was an extension of the algorithm by Nawab et al. The process was followed as an extracting time-varying time template parameter, performing time-varying filter analysis, clustering on MUAP trains, shape refinement, test, and decomposition. If the test failed, the iterations were done again for shape refinement of MUAPs. Precision Decomposition I (PD I), which was earlier used to decompose needle EMG data was updated to decompose sEMG and referred as PD (III). An updated approach of PD III reported by Nawab et al. has PD-IPUS (Integrated Processing and Understanding) and PD-IGAT (Iterative Generate and Test) [36, 37]. Another method to decompose sEMG into MUAP trains included a hybrid approach of K-means clustering and convolution kernel compensation method. K-means clustering was performed to estimate the pulse trains, which were later updated iteratively by convolution kernel compensation method [38].

MUAP abnormality	Anatomical relation to changes
Increased amplitude	Increment in connective tissues, loss of muscle fibers
Decreased amplitude	Muscle fibers grouping
Decreased duration	Loss of muscle fibers
Increased duration	Increased muscle fibers
Increased spike duration	Variation in muscle diameter and increased endplate thickness
Increase in number of turns and phases	Slow conduction of terminal axons/increased diameter of muscle fiber and end plate
Increase in firing rate	Loss of motor units
Increase in the jiggle	Atypical neuromuscular transmission

Table 1.
MUAP abnormalities and indicated anatomical changes.

The question arises, what changes may a neurological disorder or injury bring to MUAPs? The features of a MUAP (rise time, duration, amplitude, phases/turns, recruitment and, stability) are vital to diagnosing the cause of abnormality in muscle coordination leading to gait or other movement disorders. A normal motor unit and a motor unit after injury (axonal injury) are distinguishable [32, 39–41]. MUAPs from needle EMG are not only adequate in diagnosing neuropathy (nerve injury) but can also determine the severity of the neuropathic condition [41]. Abnormal motor units constitute polyphasic potentials, unlike diphasic or triphasic potentials that exist in healthy individuals. Polyphasic potentials are a result of nascent potentials and terminal collateral sprouting [40]. Rodriguez-Carreno et al. [6] reported MUAPs shape abnormality pertinent to the anatomical phenomena shown in **Table 1**. A study conducted on mice with amyotrophic lateral sclerosis (ALS) using single unit extracellular recording within the spinal cord and EMG revealed gait variability [32]. In ALS mice, the low frequency of motor neuron and irregularities in the motor burst were co-occurring with fractionated EMG.

Among patients with myopathy, short, small, long duration, polyphasic and early recruitment of MUAPs were observed [39]. Different myopathy disorder studies in relation to MUAP trains were conducted using needle EMG by Paganoni et al. [39]. In early phases of disorders due to loss in muscle fibers the compound muscle action potential amplitude is lower. The result was short, small and early recruitment of MUAPs, but in Lambert-Eaton Myasthenic Syndrome, higher CMAP amplitude was observed. The shapes of MUAPs also alter with chronicity. Instead of positive sharp wave and fibrillation in the needle EMG, a mixture of long and short duration of EMG is prevalent [39]. Use of sEMG in comparison to needle EMG for postural disorder is preferable. sEMG is very good at detecting kinesiological disorders such as myotonia, myoclonus and tremors [13]. It can further be decomposed into MUAPs with the PD (III) algorithm, or hybrid of K-means and convolution kernel compensation method.

5. Extraction of muscle synergies

Linear decomposition of multi-source EMG signal is another method to diagnose the alteration in EMG patterns of patients with gait disorders [5, 42]. The muscle synergy hypothesis can be employed to understand better the physiological aspects of gait disorders using a number of linear decomposition algorithms such

as principal component analysis (PCA), factor analysis (FA), independent component analysis (ICA), and non-negative matrix factorization algorithm (NNMF). Each algorithm is unique and extracts the synergy structure based on the assumption made on the synergy (e.g. orthogonality, non-negativity, statistical independence, etc.). After applying the factorization algorithm, the multi-electrode EMG signal is decomposed into the activation coefficients and synergies. The synergy vectors from the healthy group can be compared with a group suffering from the neurological or non-neurological disorder [43]. Statistical tests including cosine correlation, Pearson correlation or cluster analysis are generally used to compare the similarity and alterations in synergy structures [44, 45]. The application of a clustering algorithm for diagnosing gait disorder is discussed in a later section. Patients with thoracic spinal cord injury revealed lesser modules, higher co-contraction and, less directional tuning in relation to healthy individuals [46]. It is likely that the number of dimensional space was affected due to the choice of preprocessing [47]. A review cum research by Kieliba et al. [47] supported that increase in the cut off frequency of the filter decreases the variance, accounts for a particular component and increases dimensional space of synergies to be extracted. EMG acquired from children with cerebral palsy and from individual's post-stroke has shown that the choice of preprocessing (filtering, normalization) had an effect on the number of synergies and differentiation of physiological traits [48, 49]. **Figure 3** displays how the choice of low pass filter (10 and 20 Hz), a second-order Butterworth filter, effects the dimensional space. Filters are generally used to remove movement artifact. The principal component variance is higher for 10 than 20 Hz.

From a neurophysiological perspective, the recruitment of fewer spinal modules during movement is due to the loss of supraspinal inflow that results in simple muscle coordination (neuroadaptation). In upper extremities, the neuroadaptation was similarly perceived in the form of changes in the dimensional space of muscle synergy structures. Alteration of synergy structures was also present in patients with chronic stroke (upper extremity), and cerebral palsy [42, 43, 45, 50]. The linear envelopes extracted from the EMG data are subjected to MS extraction. The synergy hypothesis is well suited for capturing the physiological aspects of motor

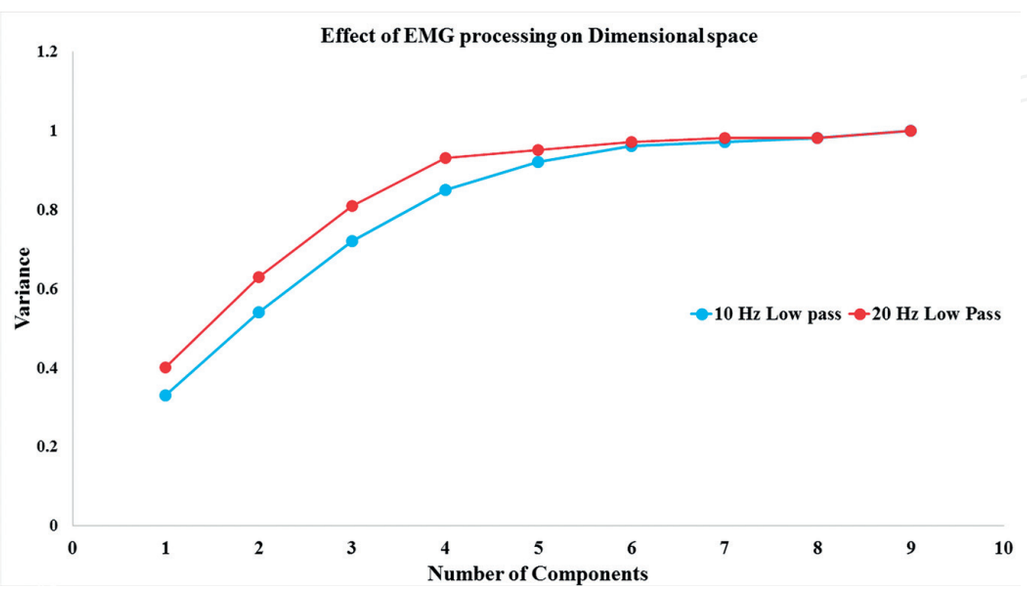

Figure 3.
A variance threshold ≥0.9 reveals five synergies for 10 Hz low pass filter and four synergies for 20 Hz low pass filter for 9-channel EMG data.

impairment [19]. In chronic stroke, merging and fractionation of synergies were observed. Merging of muscle synergies results in poor muscle coordination. In children with cerebral palsy, the dimensional space was smaller than it was in the control participants (unimpaired) [42]. However, the modules for cerebral palsy were higher for Duchenne muscular dystrophy (DMD) and typical developing (TD) children [43]. Rodriguez et al. revealed that fewer modules were recruited while walking on treadmill among Parkinson's patients. Thus, the size of dimensional space is crucial for the assessment of gait disorder such as cerebral palsy and Parkinson's [51, 52]. It is also important to properly choose preprocessing before analyzing the synergies as the dimensional space is sensitive to the preprocessing methods.

6. Frequency and time-frequency analysis

EMG power spectrum estimation methods can be categorized into parametric and nonparametric techniques. The spectral methods include fast Fourier transform (FFT), multitaper analysis and short-time Fourier transform (STFT) and wavelet transform. The difference between FFT and Wavelet Transformation is that FFT is localized to the frequency domain whereas the latter is localized to time-frequency analysis. Hu [53] recorded cortical and spinal somatosensory evoked potential (CSEP and SSEP), cortical motor evoked potential (CMEP) and spinal cord evoked potential (SCEP). The short time Fourier transformation was applied to the CSEP signal with a Hanning window [53]. The results revealed that the time-frequency analysis is a better marker for spinal injury than time domain analysis. The peak power after spinal injury had lesser energy with more dispersion in time-frequency scale.

The EMG time series signal can be analyzed in the frequency domain for the diagnosis of gait disorders. The frequency spectrum for EMG signals is in range of 0–500 Hz [54]. The FFT algorithm [55] computes the discrete Fourier transform (DFT) of EMG signal more efficiently. The FFT decomposes the EMG signals into periodic sine and cosine waves. We computed the FFT of EMG signal recorded from the Vastus Medialis (VM) during walking (**Figure 4**).

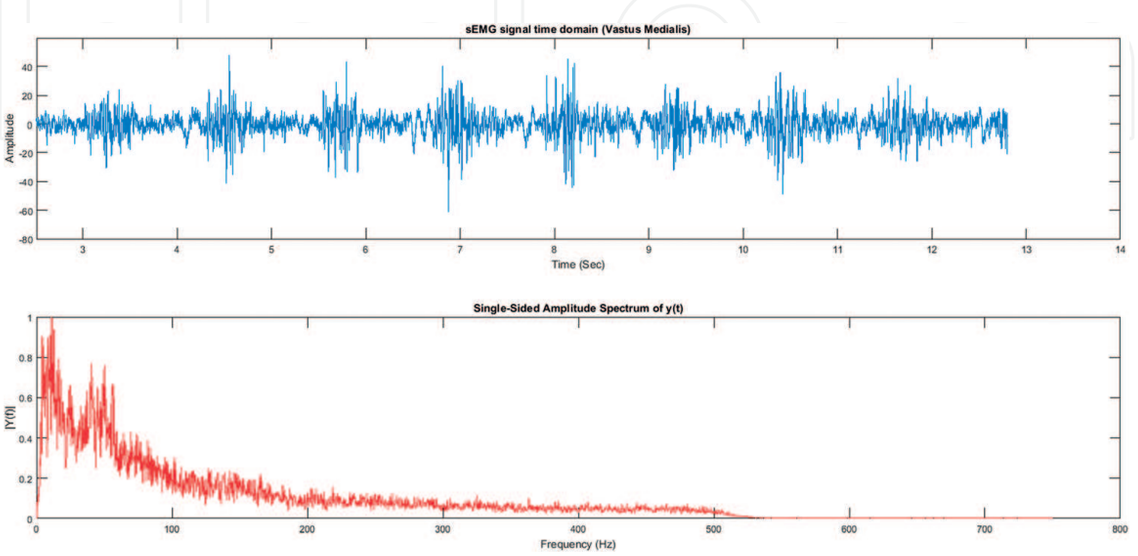

Figure 4.
(A) sEMG signal from VM during walking in time domain; (B) frequency domain representation of the signal using FFT.

The FFT allows computation of power spectra by squaring of FFT's magnitude [56]. In Parkinson disease, the spectral power of the signal has lower amplitude for the usual tremor than for the unusual tremor, which has peak amplitude of 4–6 Hz during an atypical tremor [15]. The signals associated with nonperiodic tremors are differentiable with FFT [57]. The EMG signal from neuropathic patients with SCI also exhibited distinct power spectrum density and amplitude in comparison to healthy individuals [58]. The application of FFT to the EMG envelope revealed muscle burst discharge in frequency domain ranging from 4 to 7 Hz [15]. Average power spectra computed from fractionated EMG of ALS mice by FFT was significantly higher than the control group. In the ALS group the spectra were skewed towards higher frequency content but single unit recordings revealed the absence of higher motor neuron (MN) frequencies or shortening of MN frequency in ALS mice [32], due to small type firing neurons improperly increasing firing frequency. This phenomenon results in co-contraction thus producing fractionated EMG. Co-contraction in muscles can also be observed in spinal cord injured patients [32]. In a study, EMG signals from lower limbs of dystonic and non-dystonic participants while walking were recorded. The non-dystonic participants were also patients suffering from other gait disorders. The power spectral density was computed using FFT with the Welch method of 50% overlap. The median power frequency (MdPF) and total power in low frequency were calculated for each muscle. The results revealed that MdPF for dystonic muscles had shifted to low frequencies and a concurrent increase in total power percentage in low-frequency range was observed [59]. Thus, frequency analysis of EMG signal not only provides us with distinction between normal and abnormal gait behavior but also specific gait abnormalities can be distinguished.

6.1 Short-time Fourier transform

Short-time Fourier transformation (STFT) is used to analyze a nonstationary signal in the frequency-domain. The signal is sliced and subjected to Fourier transform. Segmenting the signal is called time domain windowing, and the time localized signal is defined by $S_t(\tau) = S(\tau)h(\tau - t)$, where $h(t)$ is the window function centered at time t. The equation for STFT is given by (2).

$$S_t(\omega, t) = \frac{1}{\sqrt{2n}} \int S(\tau) h(\tau - t)\, e^{-i\omega t}.d\tau \tag{2}$$

Mitchell et al. [60] used cross time-frequency analysis to diagnose hypertension of the GM muscle. The study included 57 elderly people with 10 younger adults. Reduced Interference distribution (RID) was utilized to remove cross terms implementing time smoothing window and frequency smoothing window. A Hanning frequency smoothing window was chosen. In the study of gait, it is necessary to consider a time-localized cross-correlation between two signals, such as left and right muscle groups responsible for gait [60]. Hence, cross Wigner distribution (CWD) was selected to preserve the phase information. The results revealed statistical significance for several time-frequency parameters of sEMG between control group and persons with neuropathy, diabetes, osteoporosis, and arthritis patients [60]. STFT does not adopt an optimal time window or frequency resolution for non-stationary signals [7]. For the implementation of FFT and STFT the signals are considered to be stationary [8]. The problem or resolution can be overcome by continuous wavelet transform (CWT) [8]. Multitaper analysis is another and perhaps more efficient method for power spectral analysis to deal with non-stationary signals [61, 62].

6.2 The wavelet transform

Wavelet transform such as Multitaper is well suited for non-stationary signals. Wavelet transform elicits good localization of energy when the MUAP shape matches that of the wavelet [8]. Continuous wavelet transform (CWT) of bandpass filtered EMG showed alteration in the motor unit among stroke patients when a foot drop stimulator device was used (FDS) [63]. Energy localization below 100 Hz that resulted from foot drop was caused by slow motor unit recruitment. The neuromuscular activation improved with FDS. The time-frequency plot for Gastrocnemius showed that peak energy localization shifted from 50 to 100 Hz as a neuromuscular strategy [63]. Instantaneous mean frequency (IMNF) is the average frequency of power density spectrum of a signal and is computed from time-frequency distribution, $W(f, t)$ [63], where W is obtained from continuous wavelet transformation defined by (3) and (4).

$$IMNF(t) = \frac{\sum_{j=1}^{N} f_i W(f_i, t)}{\sum_{j=1}^{N} W(f_i, t)} \tag{3}$$

$$W(x, y) = \frac{1}{\sqrt{x}} \int_{-\infty}^{+\infty} y(t) \psi . \frac{(t - y)}{x} dt \tag{4}$$

In the above, x is the scaling factor that controls the width of the wavelet, y controls its location in time, ψ is the mother wavelet function and $y(t)$ is the signal. Instantaneous mean frequency can also be computed from the scalogram of CWT by its dimensional reduction. The scalogram has three dimensional space with time (x axis), frequency (y axis) and power (z axis) [63, 64]. In growing children, the higher IMNF level computed from scalogram revealed difference with respect to the children with cerebral palsy. The IMNF frequency component, unlike healthy children, decreased with age and maturation for children with cerebral palsy. IMNF also provided significant differences between the affected and unaffected site among stroke patients [63].

7. Feature extraction and classification

Time and frequency domain features of the EMG signal may be used to diagnose gait disorders. For example, an image processing technique can be used to detect pathological gait affected by abnormal firing of MUs [65]. Machine learning algorithms are important tools in detecting the pattern of normal and abnormal gait [66, 67]. They do so by making minimum assumptions about the data generating system, as it does not need a carefully controlled experimental design [9]. Application of machine learning algorithms to detect and classify gait disorders is suited to big data. Machine Learning is further divided into: (1) Supervised learning and (2) unsupervised learning. We will now discuss techniques to detect gait disorders using supervised and unsupervised learning algorithms.

7.1 Unsupervised learning

Unsupervised learning can be used to find structures in the EMG data. For example, cluster analysis has been used to identify alteration in the gait patterns, which are undetected by statistical tests. Patients with Parkinson's disease can be distinguished from a healthy individual by using cluster analysis of dimensionally

reduced feature vector [68, 69]. K-means clustering is a very common clustering technique that initially estimates K centroids randomly or selectively. The algorithm iterates between two steps, data assignment steps and updating centroid. The aim is to minimize objective function, which is given by (5).

$$V(j) = \sum_{j=1}^{k}\sum_{i=1}^{n} \|x_i - c_j\|^2 \quad (5)$$

where $V(j)$ is the objective function, n is the number of data points in *jth* cluster, k is the number of clusters and $\|x_i - c_j\|^2$ is the square of Euclidean distance.

The hypothesis of muscle synergies has been applied in several studies [44, 45, 70]. Unsupervised Learning helps in grouping identical synergies and can be helpful in diagnosing gait disorders. Kim et al. [70] identified synergies using iterative *K*-mean clustering and intraclass correlation. Hierarchical, model-based, fuzzy c means clustering has been employed to group gait patterns [69, 71–73]. Dolatabadi et al. [71] used mixture model clustering on spatiotemporal gait pattern to classify pathological gait. Pathological disorders such as cerebral palsy that show higher inter-stride variability can be analyzed with a hierarchical clustering method proposed by Rosati et al. [72]. Feature Fusion technique with Davies Bouldin Index (DBI) based on fuzzy C means algorithm was used in a trip/fall study [73]. The DBI can be used to evaluate the clustering algorithm. We have used K mean cluster analysis to cluster normal gait and gait with constraints, which are displayed in **Figure 5**.

7.2 Supervised learning

In supervised learning, the predictive models are based on the input and output data. Some of the widely used learning algorithms are decision trees, Bayesian networks, support vector machine, artificial neural networks, and linear discriminant analysis (LDA). After feature extraction and classification, the EMG time series can be modeled to control prosthetic or rehabilitative device. The fundamental approach to classification of EMG signal is shown in **Figure 6** [66].

The performance of different algorithms (SVM, LDA, MLP) in classifying gait disorders (Cerebral Palsy) was compared [74]. SVM classifier, compared to LDA and MLP, performed better when the analysis was done on kinematic data [74]. The normalization of the EMG data from different limb configurations increased

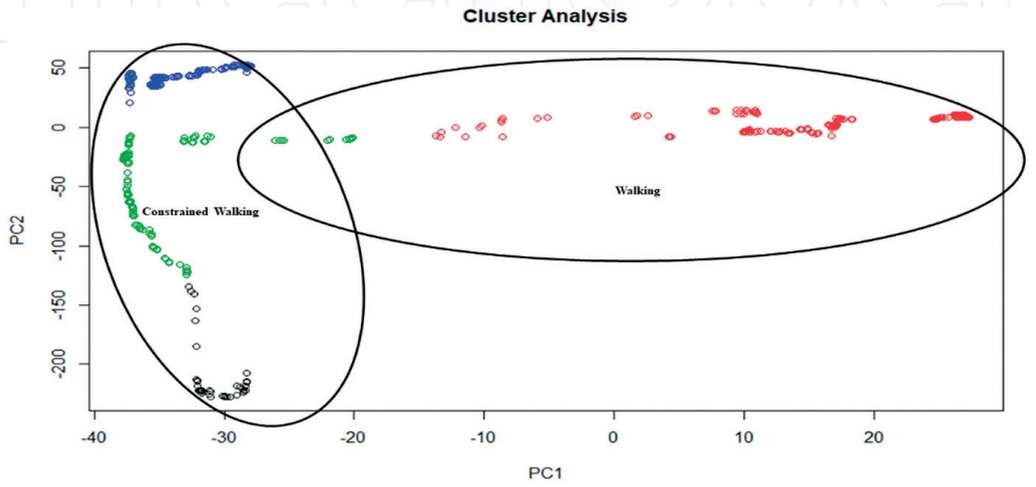

Figure 5.
A total of four clusters were chosen to group sEMG signal based on 93% variability in data within each cluster. The clusters were plotted for the first two principal components for walking with and without constraint.

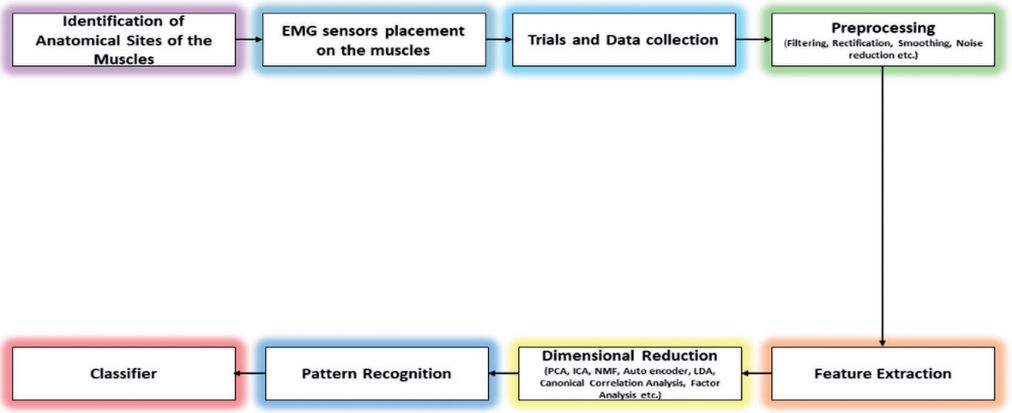

Figure 6.
Block diagram of an EMG Signal classification system.

classification accuracy [74, 75]. Feature level fusion is used to extract the feature space from daily life activities [73]. Patients with Parkinson's were classified with high accuracy using SVM with leave-one-out cross-validation [75]. Results from Nair et al. [76] suggest that least square kernel algorithm performed better than LDA, Neural Network, MLP and learning vector quantification (LVQ) for patients with arthritis. Decision Tree (DT) classifier used to classify toe walking gait disorder revealed three major toe-walking patterns [77]: (1) muscle weakness of TA and quadriceps and spasticity of Tibialis Surae; (2) severe spasticity of Tibialis Surae with limited range of ankle motion; and, (3) hamstring spasticity. The MLP, on the other hand, exhibited higher accuracy while classifying gait disorders associated with myopathy and neuropathy. Based on the literature studied, normalization, feature extraction and selection are important steps for accurately classifying gait disorders [75, 76].

Artificial neural networks (ANNs) are considered better at discovering nonlinear relationships in data. Ozsert et al. [78] classified biceps, frontalis and abductor muscles using ANN. The authors used wavelet transform for pre-processing the sEMG signal and an AR model to train the ANN. Senanayake et al. [79] used EMG RMS value and soft tissue deformation parameter (STDP) extracted from the video recordings to train a feed-forward-backward propagation neural network (FFBPN) to identify gait patterns. The proposed evaluation scheme improved classification accuracy between healthy and injured subject's gait patterns as Vastus Medialis and Lateralis revealed higher positive correlation between EMG and STDP for healthy individuals [79].

An adaptive neuro-fuzzy inference system (ANFIS) successfully diagnosed neurological disorders [8, 80]. In a number of studies, ANN and SVM worked well in diagnosing the gait pathology [7, 8, 71, 81]. Naik et al. [82] decomposed needle EMG from brachial biceps with ensemble empirical mode decomposition (EMD). The authors used Fast ICA and LDA classifier with majority voting to diagnose healthy participants from ALS, and myopathic individuals [82]. The algorithm of Naik et al. [83] for walking, sitting and standing tasks, achieved 86% classification accuracy for participants with and 96% without knee pathology. ICA via entropy bound minimization, time domain feature extraction, and feature selection with fisher score were performed prior to LDA classification. Ai et al. [30] used fused accelerometer and EMG data to discriminate among four participants including an amputee; more amputees in the study could provide better insight of the suggested technique [30].

There is no perfect machine learning algorithm to detect gait disorders. Signal processing techniques for feature extraction and selection, and standardization of the time series play a crucial role in enhancing classification accuracy. We also see

consistent improvement in the existing models with increased classification accuracy [84]. ANN classifier has some deficiencies, such as high training process time and overfitting. Extreme Machine Learning algorithm (EML) improves on these anomalies at no cost to classification accuracy [8]. SVM accuracy was low for eight

Classifier	Authors	Year	Conditions	Classification	Performance
Neural networks	Senanayake et al.	2014	Soft tissue deformation	Gait pattern identification between healthy and injured	Accuracy = 98%
	Nair et al.	2010	Osteoarthritis	EMG of healthy and osteoarthritis	Accuracy = 89.4 ± 11.8%
	Nair et al.	2010	Rheumatoid arthritis	EMG of healthy and rheumatoid arthritis	Accuracy = 57 ± 1 8%
	Kamruzzaman and Begg.	2006	Cerebral palsy	Gait pattern identification using stride length and cadence	Accuracy = 94.87%
LDA	Naik et al.	2018	Knee pathology	Movement classification for healthy and patients with knee pathology	Accuracy = 86% (Unhealthy) and 96% (Healthy)
	Nair et al.	2010	Rheumatoid arthritis	EMG of healthy and rheumatoid arthritis	Accuracy = 72 ± 20%
	Ai et al.	2017	Normal and amputated	Movement-based classification for normal and amputee subject	Accuracy = 95.6 ± 2.2%
	Kamruzzaman and Begg.	2006	Cerebral palsy	Gait pattern identification using stride length and cadence	Accuracy = 93.59%
SVM	Kamruzzaman and Begg.	2006	Cerebral palsy	Gait pattern identification using stride length and cadence	Accuracy = 96.8%
	Kugler et al.	2013	Parkinson	Differentiate between healthy and Parkinson patients by auto-step segmentation	Specificity = 90% and Sensitivity = 90%
	Ai et al.	2017	Normal and amputated	Movement-based classification for normal and amputee subject	Accuracy = 98.1 ± 1.6%
	Xi et al.	2018	Fall	Gait recognition for daily life activities including Fall	Accuracy = 100%
Decision tree	Armand et al.	2006	Toe Walking disorders	Identification of ankle kinematic patterns for toe walkers	Accuracy = 81%

Classifier	Authors	Year	Conditions	Classification	Performance
Least square Kernel Algorithm	Nair et al.	2010	Rheumatoid arthritis	EMG of healthy and rheumatoid arthritis	Accuracy = 91%
	Nair et al.	2010	Osteoarthritis	EMG of healthy and osteoarthritis	Accuracy = 97%

Table 2.
EMG classification methods.

daily life activities including falling. The accuracy for detecting trip fall improved with weighted genetic algorithm [73]. A wide variety of time domain, frequency domain, and time-frequency domain features, and optimization techniques provide multiple options to enhance the classification accuracy of gait diagnosis. The performance of each algorithmic class discussed in this review with respect to the abnormal physiological condition is shown in **Table 2**.

8. Future trends

The computational methods reviewed in this study have evolved over several decades and continue to do so. For example, ANOVA test's inability to detect visually observable waveform due to abnormal gait behavior had been improved with wfANOVA test [20]. Apart from factorization algorithms and PCA, artificial neural

EMG method	Pros	Cons
Visual inspection of raw EMG	1. Lower computational burden 2. Takes advantage of experience	1. Relies on experience only, hence chances of error 2. Limited theoretical basis
EMG envelope/ onset detection	1. EMG onset can reveal altered muscle activity (e.g., freezing episodes in Parkinson's)	1. Impacted by a number of parameters, hence may not be reliable
Frequency and time-frequency analysis	1. Provides quantitative information in frequency and time-frequency domain 2. Specific Gait abnormalities can be distinguished (suitable for SCI patients) 3. Provides additional features like MdPF, IMNF for further classification 4. Provides algorithmic options that sidestep stationarity issues	1. Added processing time and computational burden 2. Assumption of stationarity is made for some FFT tools
MUAP decomposition	1. An abnormality in MUAP's shape reveals altered motor behavior 2. Requires less processing for Needle EMG	1. Harder to decompose sEMG signal 2. Computational cost is high for sEMG
Muscle synergy decomposition	1. Recovers dominant spatio-temporal profiles in EMG signal 2. Useful in certain disorder diagnosis (Cerebral Palsy, stroke, SCI, etc.) 3. Computational cost is dependent on the type of factorization algorithm	1. Preprocessing of EMG signal impacts the dimensional space for synergy extraction 2. Choice of algorithm alters the results, i.e., assumption on the type of synergies need to be made

Table 3.
Pros and cons of EMG processing techniques discussed.

network were implemented for synergy extraction [5]. New time and frequency domain features and hybrid methods for feature selection have been developed and introduced over the years [67]. In these examples, the conventional techniques were enhanced or detection of gait disorders. There is a consistent effort to augment current computational techniques and improve the EMG based detection methods for motor behavior abnormalities. Optimization algorithms, feature level fusion, and advances in computational methodology point to a future for detecting intricate EMG patterns EMG associated with abnormal gait behavior in machine learning. Recently, application of deep learning algorithms to detect abnormal EMG patterns appears more promising [85], and performs well with EMG acquired directly from the muscles. The main issue in clinical application of deep learning is its real-time implementation. The development of powerful graphics processing unit (GPU) and faster training algorithms will likely resolve such issues in near future.

In conclusion, in this article we reviewed the existing literature on EMG processing techniques from simple thresholding to complex computation algorithms and their application in detecting gait disorders. The pros and cons of the techniques discussed are summarized in **Table 3**. Besides discussing these techniques in detail, our study cites pertinent literature where these techniques were successfully used to detect gait abnormalities. This study clearly points towards the recent trend in assessing gait disorders from EMG data using an intelligent system. Examples of such systems using supervised and unsupervised learning were also reviewed.

Author details

Rajat Emanuel Singh[1], Kamran Iqbal[1*], Gannon White[2] and Jennifer K. Holtz[2]

1 College of Engineering and Information Technology, University of Arkansas at Little Rock, Arkansas, USA

2 School of Counseling, Human Performance, and Rehabilitation, University of Arkansas at Little Rock, Arkansas, USA

*Address all correspondence to: kxiqbal@ualr.edu

References

[1] Luca CJ. Physiology and mathematics of myoelectric signals. IEEE Transactions on Biomedical Engineering, BME. 1979;**26**(6):313-325. DOI: 10.1109/tbme.1979.326534

[2] Konard P. The ABC of EMG: A Practical Introduction to Kinesiological Electromyography. USA: Noeraxon Inc.; 2005. Version 1.0

[3] Luca CJ. The Wartenweiler memorial lecture the use of surface electromyography in biomechanics. Journal of Biomechanics. 1994;**27**(6):724. DOI: 10.1016/0021-9290(94)91124-x

[4] Stifani N. Motor neurons and the generation of spinal motor neuron diversity. Frontiers in Cellular Neuroscience. 2014;**8**:293. DOI: 10.3389/fncel.2014.00293

[5] Singh RE, Iqbal K, White G, Hutchinson TE. A systematic review on muscle synergies: From building blocks of motor behavior to a neurorehabilitation tool. Applied Bionics and Biomechanics. 2018;**2018**:3615368. DOI: 10.1155/2018/3615368

[6] Rodriguez-Carreno I, Gila-Useros L, Malanda-Trigueros A. Motor unit action potential duration: measurement and significance. In: Ajeena I editor. Advances in Clinical Neurophysiology, ISBN: 978-953-51-0806-1, Ch 7. 2012. DOI: 10.5772/50265

[7] Raez MBI, Hussain MS, Mohd-Yasin F. Techniques of EMG signal analysis: detection, processing, classification and applications. Biological Procedures Online. 2006;**8**:11-35. DOI: 10.1251/bpo115

[8] Chowdhury RH, Reaz MBI, Ali MABM, Bakar AAA, Chellappan K, Chang TG. Surface electromyography signal processing and classification techniques. Sensors (Basel, Switzerland). 2013;**13**(9):12431-12466. DOI: 10.3390/s130912431

[9] Bzdok D, Altman N, Krzywinski M. Points of significance: Statistics versus machine learning. Nature Methods. 2018;**15**(4):233-234. DOI: 10.1038/nmeth.4642

[10] Iniesta R, Stahl D, McGuffin P. Machine learning, statistical learning and the future of biological research in psychiatry. Psychological Medicine. 2016;**46**(12):2455-2465. DOI: 10.1017/S0033291716001367

[11] Dietz V. Degradation of neuronal function following a spinal cord injury: Mechanisms and countermeasures. Brain. 2004;**127**(10):2221-2231. DOI: 10.1093/brain/awh255

[12] Malone A, Meldrum D, Gleeson J, Bolger C. Electromyographic characteristics of gait impairment in cervical spondylotic myelopathy. European Spine Journal. 2013;**22**(11):2538-2544. DOI: 10.1007/s00586-013-2928-9

[13] Pullman SL, Goodin DS, Marquinez AI, Tabbal S, Rubin M. Clinical utility of surface EMG: report of the therapeutics and technology assessment subcommittee of the American Academy of Neurology. Neurology. 2000;**55**:171-177

[14] Burridge J, Wood D, Taylor P, Mclellan D. Indices to describe different muscle activation patterns, identified during treadmill walking, in people with spastic drop-foot. Medical Engineering & Physics. 2001;**23**(6):427-434. DOI: 10.1016/s1350-4533(01)00061-3

[15] Perumal SV, Sankar R. Gait monitoring system for patients with Parkinsons disease using wearable sensors. In: 2016 IEEE Healthcare

Innovation Point-Of-Care Technologies Conference (HI-POCT). 2016. DOI: 10.1109/hic.2016.7797687

[16] Domingo A, Sawicki GS, Ferris DP. Kinematics and muscle activity of individuals with incomplete spinal cord injury during treadmill stepping with and without manual assistance. Journal of Neuroengineering and Rehabilitation. 2007;**4**:32. DOI: 10.1186/1743-0003-4-32

[17] Banks CL, Huang HJ, Little VL, Patten C. Electromyography exposes heterogeneity in muscle co-contraction following stroke. Frontiers in Neurology. 2017;**8**:699. DOI: 10.3389/fneur.2017.00699

[18] Nieuwboer A, Dom R, Weerdt WD, Desloovere K, Janssens L, Stijn V. Electromyographic profiles of gait prior to onset of freezing episodes in patients with Parkinsons disease. Brain. 2004;**127**(7):1650-1660. DOI: 10.1093/brain/awh189

[19] Lukhanina E, Karaban I, Berezetskay N. Diagnosis of Parkinsons disease by electrophysiological methods. In: Dushanova J editor. Diagnostics and Rehabilitation of Parkinsons Disease, Ch 2. 2011. DOI: 10.5772/17761

[20] McKay JL, Welch TDJ, Vidakovic B, Ting LH. Statistically significant contrasts between EMG waveforms revealed using wavelet-based functional ANOVA. Journal of Neurophysiology. 2013;**109**(2):591-602. DOI: 10.1152/jn.00447.2012

[21] PhysioNet. Available online: http://www.physionet.org [Accessed: July 1, 2018]

[22] Bar-On L, Aertbeliën E, Molenaers G, Desloovere K. Muscle activation patterns when passively stretching spastic lower limb muscles of children with cerebral palsy. PLoS One. 2014;**9**(3):e91759. DOI: 10.1371/journal.pone.0091759

[23] Morey-Klapsing G, Arampatzis A, Brüggemann GP. Choosing EMG parameters: Comparison of different onset determination algorithms and EMG integrals in a joint stability study. Clinical Biomechanics. 2004;**19**(2):196-201. DOI: 10.1016/j.clinbiomech.2003.10.010

[24] Solnik S, DeVita P, Rider P, Long B, Hortobágyi T. Teager–Kaiser operator improves the accuracy of EMG onset detection independent of signal-to-noise ratio. Acta of Bioengineering and Biomechanics/Wroclaw University of Technology. 2008;**10**(2):65-68

[25] Tenan MS, Tweedell AJ, Haynes CA. Analysis of statistical and standard algorithms for detecting muscle onset with surface electromyography. PLoS One. 2017;**12**(5):e0177312. DOI: 10.1371/journal.pone.0177312

[26] Staude G, Flachenecker C, Daumer M, Wolf W. Onset detection in surface electromyographic signals: A systematic comparison of methods. EURASIP Journal on Advances in Signal Processing. 2001;**2001**(2):867853. DOI: 10.1155/s1110865701000191

[27] Hodges P. A comparison of computer-based methods for the determination of onset of muscle contraction using electromyography. Electroencephalography and Clinical Neurophysiology. 1996;**101**(6):511-519. DOI: 10.1016/s0013-4694(96)95190-5

[28] Bonato P, Dalessio T, Knaflitz M. A statistical method for the measurement of muscle activation intervals from surface myoelectric signal during gait. IEEE Transactions on Biomedical Engineering. 1998;**45**(3):287-299. DOI: 10.1109/10.661154

[29] Lidierth M. A computer based method for automated measurement of the periods of muscular activity from an EMG and its application to locomotor EMGs. Electroencephalography

and Clinical Neurophysiology. 1986;**64**(4):378-380. DOI: 10.1016/0013-4694(86)90163-x

[30] Ai Q, Zhang Y, Qi W, Liu Q, Chen AK. Research on lower limb motion recognition based on fusion of sEMG and accelerometer signals. Symmetry. 2017;**9**(8):147. DOI: 10.3390/sym9080147

[31] Amplitude Analysis: Normalization of EMG to Maximum Voluntary Contraction (MVC). May 09, 2017. Retrieved from: https://www.delsys.com/emgworks-analysis-techniques-using-emgscript/

[32] Hadzipasic M, Ni W, Nagy M, Steenrod N, McGinley MJ, Kaushal A, et al. Reduced high-frequency motor neuron firing, EMG fractionation, and gait variability in awake walking ALS mice. Proceedings of the National Academy of Sciences of the United States of America. 2016;**113**(47):E7600-E7609. DOI: 10.1073/pnas.1616832113

[33] Condliffe EG, Jeffery DT, Emery DJ, Gorassini MA. Spinal inhibition and motor function in adults with spastic cerebral palsy. The Journal of Physiology. 2016;**594**(10):2691-2705. DOI: 10.1113/JP271886

[34] Fang J, Agarwal G, Shahani B. Decomposition of EMG signal by wavelet spectrum matching. In: Proceedings of the 19th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. Magnificent Milestones and Emerging Opportunities in Medical Engineering (Cat. No.97CH36136). 1997. DOI: 10.1109/iembs.1997.756598

[35] De Luca CJ, Chang S-S, Roy SH, Kline JC, Nawab SH. Decomposition of surface EMG signals from cyclic dynamic contractions. Journal of Neurophysiology. 2015;**113**(6):1941-1951. DOI: 10.1152/jn.00555.2014

[36] Nawab SH, Chang S-S, De Luca CJ. High-yield decomposition of surface EMG signals. Clinical Neurophysiology: Official Journal of the International Federation of Clinical Neurophysiology. 2010;**121**(10):1602-1615. DOI: 10.1016/j.clinph.2009.11.092

[37] Luca CJ, Adam A, Wotiz R, Gilmore LD, Nawab SH. Decomposition of surface EMG signals. Journal of Neurophysiology. 2006;**96**(3):1646-1657. DOI: 10.1152/jn.00009.2006

[38] Ning Y, Zhu X, Zhu S, Zhang Y. Surface EMG decomposition based on K-means clustering and convolution kernel compensation. IEEE Journal of Biomedical and Health Informatics. 2015;**19**(2):471-477. DOI: 10.1109/JBHI.2014.2328497

[39] Paganoni S, Amato A. Electrodiagnostic evaluation of myopathies. Physical Medicine and Rehabilitation Clinics of North America. 2013;**24**(1):193-207. DOI: 10.1016/j.pmr.2012.08.017

[40] Feinberg J. EMG: Myths and facts. HSS Journal. 2006;**2**(1):19-21. DOI: 10.1007/s11420-005-0124-0

[41] Chung T, Prasad K, Lloyd TE. Peripheral neuropathy—Clinical and electrophysiological considerations. Neuroimaging Clinics of North America. 2014;**24**(1):49-65. DOI: 10.1016/j.nic.2013.03.023

[42] Steele KM, Rozumalski A, Schwartz MH. Muscle synergies and complexity of neuromuscular control during gait in cerebral palsy. Developmental Medicine and Child Neurology. 2015;**57**(12):1176-1182. DOI: 10.1111/dmcn.12826

[43] Goudriaan M, Shuman BR, Steele KM, Van den Hauwe M, Goemans N, Molenaers G, et al. Non-neural muscle weakness has limited influence on complexity of motor control during gait. Frontiers in Human

Neuroscience. 2018;**12**:5. DOI: 10.3389/fnhum.2018.00005

[44] Cheung VCK, Piron L, Agostini M, Silvoni S, Turolla A, Bizzi E. Stability of muscle synergies for voluntary actions after cortical stroke in humans. Proceedings of the National Academy of Sciences of the United States of America. 2009;**106**(46):19563-19568. DOI: 10.1073/pnas.0910114106

[45] Roh J, Rymer WZ, Beer RF. Evidence for altered upper extremity muscle synergies in chronic stroke survivors with mild and moderate impairment. Frontiers in Human Neuroscience. 2015;**9**:6. DOI: 10.3389/fnhum.2015.00006

[46] Milosevic M, Yokoyama H, Grangeon M, Masani K, Popovic MR, Nakazawa K, et al. Muscle synergies reveal impaired trunk muscle coordination strategies in individuals with thoracic spinal cord injury. Journal of Electromyography and Kinesiology. 2017;**36**:40-48. DOI: 10.1016/j.jelekin.2017.06.007

[47] Kieliba P, Tropea P, Pirondini E, Coscia M, Micera S, Artoni F. How are muscle synergies affected by electromyography pre-processing? IEEE Transactions on Neural Systems and Rehabilitation Engineering. 2018;**26**(4):882-893. DOI: 10.1109/tnsre.2018.2810859

[48] Banks CL, Pai MM, McGuirk TE, Fregly BJ, Patten C. Methodological choices in muscle synergy analysis impact differentiation of physiological characteristics following stroke. Frontiers in Computational Neuroscience. 2017;**11**:78. DOI: 10.3389/fncom.2017.00078

[49] Shuman BR, Schwartz MH, Steele KM. Electromyography data processing impacts muscle synergies during gait for unimpaired children and children with cerebral palsy. Frontiers in Computational Neuroscience. 2017;**11**:50. DOI: 10.3389/fncom.2017.00050

[50] Roh J, Rymer WZ, Perreault EJ, Yoo SB, Beer RF. Alterations in upper limb muscle synergy structure in chronic stroke survivors. Journal of Neurophysiology. 2013;**109**(3):768-781. DOI: 10.1152/jn.00670.2012

[51] Tang L, Li F, Cao S, Zhang X, Wu D, Chen X. Muscle synergy analysis in children with cerebral palsy. Journal of Neural Engineering. 2015;**12**:046017. DOI: 10.1088/1741-2560/12/4/046017

[52] Rodriguez KL, Roemmich RT, Cam B, Fregly BJ, Hass CJ. Persons with Parkinson's disease exhibit decreased neuromuscular complexity during gait. Clinical Neurophysiology: Official Journal of the International Federation of Clinical Neurophysiology. 2013;**124**(7):1390-1397. DOI: 10.1016/j.clinph.2013.02.006

[53] Hu Y. Prevention of spinal cord injury with time-frequency analysis of evoked potentials: An experimental study. Journal of Neurology, Neurosurgery & Psychiatry. 2001;**71**(6):732-740. DOI: 10.1136/jnnp.71.6.732

[54] DeLuca CJ. Fundamental Concepts in SEMG signal Acquisition. DelSys Inc Tutorial; 2003. https://delsys.com/Attachments_pdf/download/tutorials/01_fundamental-concepts-in-emg-signal-acquisition.pdf (accessed on 25 Dec 2018)

[55] Good IJ. Introduction to Cooley and Tukey (1965). An algorithm for the machine calculation of complex Fourier series. In: Kotz S and Johnson N editor. Breakthroughs in Statistics Vol III. New York: Springer; 1997. pp. 201-216. DOI: 10.1007/978-1-4612-0667-5_9

[56] Press WH et al. Sec. 13.4: Power spectrum estimation using the FFT. In:

Numerical Recipes in C. 2nd ed. New York: Cambridge University Press; 1992

[57] Grimaldi G, Manto M. Neurological tremor: Sensors, signal processing and emerging applications. Sensors. 2010;**10**(2):1399-1422. DOI: 10.3390/s100201399

[58] Sadikoglu F, Kavalcioglu C, Dagman B. Electromyogram (EMG) signal detection, classification of EMG signals and diagnosis of neuropathy muscle disease. Procedia Computer Science. 2017;**120**:422-429. DOI: 10.1016/j.procs.2017.11.259

[59] Go SA, Coleman-Wood K, Kaufman KR. Frequency analysis of lower extremity electromyography signals for the quantitative diagnosis of dystonia. Journal of Electromyography and Kinesiology: Official Journal of the International Society of Electrophysiological Kinesiology. 2014;**24**(1):31-36. DOI: 10.1016/j.jelekin.2013.11.002

[60] Mitchell P, Krotish D, Shin Y, Hirth V. Cross time-frequency analysis of gastrocnemius electromyographic signals in hypertensive and nonhypertensive subjects. EURASIP Journal on Advances in Signal Processing. 2010;**2010**(1):206560. DOI: 10.1155/2010/206560

[61] Babadi B, Brown EN. A review of multitaper spectral analysis. IEEE Transactions on Biomedical Engineering. 2014;**61**(5):1555-1564. DOI: 10.1109/tbme.2014.2311996

[62] Van Vugt MK, Sederberg PB, Kahana MJ. Comparison of spectral analysis methods for characterizing brain oscillations. Journal of Neuroscience Methods. 2007;**162**(1-2):49-63. DOI: 10.1016/j.jneumeth.2006.12.004

[63] Pilkar R, Ramanujam A, Nolan KJ. Alterations in spectral attributes of surface electromyograms after utilization of a foot drop stimulator during post-stroke gait. Frontiers in Neurology. 2017;**8**:449. DOI: 10.3389/fneur.2017.00449

[64] Lauer RT, Pierce SR, Tucker CA, Barbe MF, Prosser LA. Age and electromyographic frequency alterations during walking in children with cerebral palsy. Gait & Posture. 2010;**31**(1):136. DOI: 10.1016/j.gaitpost.2009.09.015

[65] Ren X, Huang H, Deng L. MUAP classification based on wavelet packet and fuzzy clustering technique. In: 2009 3rd International Conference on Bioinformatics and Biomedical Engineering. 2009. DOI: 10.1109/icbbe.2009.5163091

[66] Nazmi N, Abdul Rahman MA, Yamamoto S-I, Ahmad SA, Zamzuri H, Mazlan SA. A review of classification techniques of EMG signals during isotonic and isometric contractions. Sensors (Basel, Switzerland). 2016;**16**(8):1304. DOI: 10.3390/s16081304

[67] Mwadulo MW. A review on feature selection methods for classification tasks. International Journal of Computer Applications Technology and Research. 2016;**5**(6):395-402. DOI: 10.7753/ijcatr0506.1013

[68] Rissanen SM, Kankaanpää M, Meigal A, Tarvainen MP, Nuutinen J, Tarkka IM, et al. Surface EMG and acceleration signals in Parkinson's disease: Feature extraction and cluster analysis. Medical & Biological Engineering & Computing. 2008;**46**(9):849-858. DOI: 10.1007/s11517-008-0369-0

[69] Mulroy S, Gronley J, Weiss W, Newsam C, Perry J. Use of cluster analysis for gait pattern classification of patients in the early and late recovery phases following stroke. Gait & Posture. 2003;**18**(1):114-125. DOI: 10.1016/s0966-6362(02)00165-0

[70] Kim Y, Bulea TC, Damiano DL. Novel methods to enhance precision and reliability in muscle synergy identification during walking. Frontiers in Human Neuroscience. 2016;**10**:455. DOI: 10.3389/fnhum.2016.00455

[71] Dolatabadi E, Mansfield A, Patterson KK, Taati B, Mihailidis A. Mixture-model clustering of pathological gait patterns. IEEE Journal of Biomedical and Health Informatics. 2016;**5**:1297-1305. DOI: 10.1109/JBHI.2016.2633000

[72] Rosati S, Agostini V, Knaflitz M, Balestra G. Muscle activation patterns during gait: A hierarchical clustering analysis. Biomedical Signal Processing and Control. 2017;**31**:463-469. DOI: 10.1016/j.bspc.2016.09.017

[73] Xi X, Tang M, Luo Z. Feature-level fusion of surface electromyography for activity monitoring. Sensors. 2018;**18**(2):614. DOI: 10.3390/s18020614

[74] Kamruzzaman J, Begg R. Support vector machines and other pattern recognition approaches to the diagnosis of cerebral palsy gait. IEEE Transactions on Biomedical Engineering. 2006;**53**(12):2479-2490. DOI: 10.1109/tbme.2006.883697

[75] Kugler P, Jaremenko C, Schlachetzki J, Winkler J, Klucken J, Eskofier B. Automatic recognition of Parkinsons disease using surface electromyography during standardized gait tests. In: 2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). 2013. DOI: 10.1109/embc.2013.6610865

[76] Nair SS, French RM, Laroche D, Thomas E. The application of machine learning algorithms to the analysis of electromyographic patterns from arthritic patients. IEEE Transactions on Neural Systems and Rehabilitation Engineering. 2010;**18**(2):174-184. DOI: 10.1109/tnsre.2009.2032638

[77] Armand S, Watelain E, Roux E, Mercier M, Lepoutre F. Linking clinical measurements and kinematic gait patterns of toe-walking using fuzzy decision trees. Gait & Posture. 2007;**25**(3):475-484. DOI: 10.1016/j.gaitpost.2006.05.014

[78] Ozsert M, Yavuz O, Durak-Ata L. Analysis and classification of compressed EMG signals by wavelet transform via alternative neural networks algorithms. Computer Methods in Biomechanics and Biomedical Engineering. 2011;**14**(6):521-525. DOI: 10.1080/10255842.2010.485130

[79] Senanayake SM, Triloka J, Malik OA, Iskandar M. Artificial neural network based gait patterns identification using neuromuscular signals and soft tissue deformation analysis of lower limbs muscles. In: 2014 International Joint Conference on Neural Networks (IJCNN). 2014. DOI: 10.1109/ijcnn.2014.6889899

[80] Khezri M, Jahed M. A neuro-fuzzy inference system for sEMG-based identification of hand motion commands. IEEE Transactions on Industrial Electronics. 2011;**58**(5):1952-1960. DOI: 10.1109/tie.2010.2053334

[81] Xie H-B, Guo T, Bai S, Dokos S. Hybrid soft computing systems for electromyographic signals analysis: A review. Biomedical Engineering Online. 2014;**13**:8. DOI: 10.1186/1475-925X-13-8

[82] Naik GR, Selvan SE, Nguyen HT. Single-channel EMG classification with ensemble-empirical-mode-decomposition-based ICA for diagnosing neuromuscular disorders. IEEE Transactions on Neural Systems and Rehabilitation Engineering. 2016;**24**(7):734-743. DOI: 10.1109/tnsre.2015.2454503

[83] Naik GR, Selvan SE, Arjunan SP, Acharyya A, Kumar DK, Ramanujam A,

et al. An ICA-EBM-based sEMG classifier for recognizing lower limb movements in individuals with and without knee pathology. IEEE Transactions on Neural Systems and Rehabilitation Engineering. 2018;**26**(3):675-686. DOI: 10.1109/tnsre.2018.2796070

[84] Singh RE et al. Gait phase discrimination during kinematically constrained walking on slackline. Accepted in IEEE International Conference on Control and Automation. July 16-19, 2019, Edinburgh, Scotland

[85] Phinyomark A, Scheme E. EMG pattern recognition in the era of big data and deep learning. Big Data and Cognitive Computing. 2018;**2**(3):21. DOI: 10.3390/bdcc2030021