EMG Signal Decomposition
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I. Introduction

Electromyography (EMG) is tool used to evaluate and record skeletal muscle electrical activity.[1] EMG signals have been applied to wide variety of fields including diagnosis, electrical stimulation, prosthesis control, human-machine interaction, and muscle fatigue analysis.[2] EMG involves an electromyograph instrument, which produces a record termed an electromyogram. EMG is used for biomedical and clinical applications to represent neuromuscular activities. Specifically, EMG measures electrical currents generated in muscles as a by product of contraction.[3] EMG records the sum of action potentials from the muscle fibers using electrodes.[4]

II. Physiology Background

EMG records muscle electrical signals. A muscle consists of bundles of specialized cells responsible for contraction and relaxation to generate forces and movements. There are three types of muscle tissue: skeletal muscle, smooth muscle, and cardiac muscle. EMG measures activity of the skeletal muscle, which supports movement of the skeleton. Impulses in the neurons, specifically motor neurons, to the muscle initiates the contraction of skeletal muscle. One motor neuron is able to supply stimulation to many muscle fibers. The EMG signal represents neuromuscular activities as the signal is dependent on the anatomical and physiological properties of the muscle and as the nervous system controls muscle activity, both contraction and relaxation. The nerve cell membrane is polarized in the resting state due to differences in the concentrations and ionic composition across the plasma membrane. In response to a stimulus from a neuron, depolarization of the muscle fiber occurs as the signal propagates along its surface. Both the depolarization and the movement of ions results in an electric field near each muscle fiber. Muscle tissue conducts electrical potentials and the signal is termed muscle action potential. From all the muscle fibers of a single motor unit, the combination of the muscle fiber action potentials is the motor unit action potential (MUAP). The MUAP is what is detected using the electrodes in EMG. However, through decomposition of the raw EMG signal using MUAP as the filter, one can visualize the individual MUAPs.[5]

III. EMG Signal

Before discussing the process and methods in EMG signal decomposition, it is important to cover the basic elements in an EMG signal: muscle fiber action potential (MFAP), motor unit action potential (MUAP), and motor unit action potential train (MUAPT). First, MFAP results from the propagation of an action potential along the excitable membrane of a muscle fiber. MFAP is dependent upon factors such as fiber diameter, action potential speed (conduction velocity), and location relative to detection electrode. However, fibers of a muscle are controlled together in groups termed motor units, which means individual MFAPs are not detected. Instead, the summation of all of a motor unit's MFAPs are detected. This summation is termed MUAP, which is often dependent on the location, relative to the detection electrode, and diameter of the closest few fibers. Furthermore, motor units need to continually fire to maintain or increase muscle generated force. During a sustained contraction, each motor unit produces multiple

MUAPs. One motor unit's collection of MUAPs is termed a motor unit action potential train (MUAPT).[6]

A. Factors and Concerns

There are a number of factors that can affect the EMG signal. Electrode characteristics, structure, and placement are major factors that involve shape of electrode, distance between electrodes, location of muscle electrode on muscle surface, and orientation of muscle fibers compared to the electrode. The active motor units, fiber type composition, motor firing rate, and other characteristics of muscle and nerve physiology also plays a role.

There are two main considerations or concerns when looking at the reliability of an EMG signal. One concern is the signal-to-noise ratio, which is the ratio of the energy in the EMG signals to the energy in the noise signals, defined as signals that are not part of desired EMG signal. Electrical noise can be categorized as inherent noise in electronics equipment, ambient noise from electromagnetic radiation, motion artifact from the electrode, and inherent instability of signal from the firing frequency of neurons. The second major concern is the distortion of the signal. The maximization of the quality of the EMG signal should focus on minimizing noise and distortion of the EMG signal, meaning avoiding unnecessary filtering and distortion of signal peaks and filters.[7]

IV. EMG Recording

EMG is recorded using electrodes placed on the muscle. Two types of electrodes can be used to get the muscle signal: invasive and non-invasive. With non-invasive electrodes, the signal is a sum of all the muscle fiber action potentials in the muscles below the skin. There are also invasive electrodes, done using a wire or needle electrodes placed directly in the muscle.[8] Different electrodes offer different information about fibers of a motor unit. For example, to obtain detailed information, relating to spatial or temporal characteristics, about the fibers, signal should be acquired with small, selective detection surface electrodes such as MN, CN, SFN, or wire electrodes. On the other hand, for overall size and motor unit spatial characteristics, signals should be acquired with a large, non-selective surface electrodes, to get what is termed a macro signal. The micro signal received from the selective detection surface electrode is what can be decomposed to understand the individual MUAPTs.[9] For the micro signal, adequate sharpness and signal-to-noise ratio allows proper discrimination between MUAPs and the background noise and between different MUAPs. Thus, sharpness and signal-to-noise ratio is important for accurate decomposition that can be obtained when the electrode is positioned close to the fibers of active motor units. The simultaneously acquired macro signal can be analyzed using triggered averaging techniques after decomposing the micro signal into its constituent MUAPTs and extracting the firing pattern information of the active motor units.[10] Overall, the type of the electrode, electrode positioning, and characteristics of muscle fiber and contraction affect the decomposability of the acquired signal. The selection of sampling rate is also important to avoid loss of information or oversampling.[11]

Electrical activity measured by the muscle electrodes and the ground electrode is fed into an amplifier. By subtracting the ground electrode signal from the muscle electrode signal, the amplifier is able to eliminate electrical noise that causes random voltages giving the raw EMG recording.[12] A differential amplifier is usually the first with additional amplification stages afterwards if needed. [13]

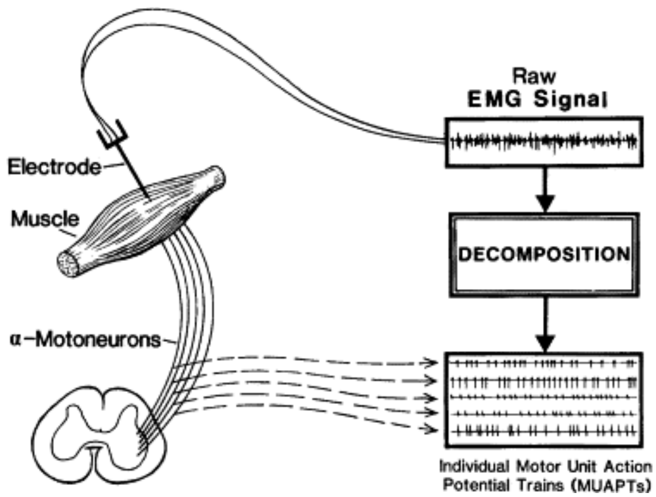

Fig. 1. Diagram portraying the process of EMG signal decomposition in identifying the MUAPTs in the EMG recording (from DeLuca et al.[14]).

V. EMG Signal Decomposition

After EMG recording, the EMG signal must go through the process of EMG signal decomposition to get information on MUAPs as described. Through EMG signal decomposition, an EMG signal is resolved into its component MUAPTs.[15] Fig. 1 illustrates the process from the raw EMG signal to discovering the individual motor unit action potential trains (MUAPTs). Various methods and algorithms are used for EMG signal decomposition and vary for both surface and intramuscular EMG signals. According to Merletti and Farina, decomposition requires two steps: detecting action potentials termed segmentation and recognizing detected action potentials as members of a class termed classification.[16] Decomposition techniques can be categorized as manual and automatic. Manual methods are tedious and often inaccurate. Automatic methods, on the other hand, involve digital signal processing and pattern recognition techniques to extract MUAPs and sort them into MUAPTs. Automatic EMG signal decomposition can be comprised of these steps: signal preprocessing, signal segmentation and MUAP detection, alignment, feature extraction, clustering and supervised classification of detected MUAPs, and analysis. These MUAPTs that are part of the EMG signal are indicators of the temporal behavior and morphological layout of motor units that occur during muscle contraction. This information can contribute to neuromuscular disorder diagnosis and in overall understanding of neuromuscular systems.[17]

A. EMG Signal Preprocessing

EMG signal preprocessing is done to the raw EMG signal and improves MUAP detection and classification, the essence of decomposition. EMG signal preprocessing involves filtering the signal to remove background noise and low-frequency information.[18] Generally, bandpass filtering and low-pass differentiators shorten MUAPs duration, leading to reduced temporal overlap and thus reduced number of superimposed waveforms. In addition, they reduce the amplitude of the many similarly-shaped MUAPs of different motor units that do not have fibers close to the electrode. Essentially, filtering has the ability to remove non-discriminative, low frequency information (noise), which reduces the variability of the MUAP shapes and thus makes differentiating between the MUAPs of different motor units easier.[19]

B. EMG Signal Segmentation and MAUP Detection

The next step is to detect all of the MUAPs generated by motor units that occur during signal acquisition. However, since motor units with no fibers close to the detection surface will have low amplitude, it is important to only select and detect those MUAPs that can be effectively assigned to the correct MUAPT. This segmentation of the signal is difficult as any detected section can represent an isolated MUAP, a superposition of MUAPs from multiple motor units, a portion of a single MUAP, or noise. Various methods have been designed to be able to segment the signal into sections to understand which are significant MUAPs. The basis of these methods is defining some detection threshold based on statistical analysis of the signal. Three commonly used characteristics used to set the detection threshold value are maximum absolute value, mean absolute value, and root mean square value of the signal.[20] The thresholds mentioned for detection can be set to select for MUAPs with a fixed set of characteristics or can be determined by analyzing the signal and noise components of the micro-EMG signal. The latter approach can be done with noise-based thresholds or thresholds based on the largest signal component. According to Stashuk, most methods for the segmentation step align detected waveforms using peak values of either the raw or slope signal. In most algorithms, when the signal produces a statistic value above the threshold value, the fixed section is selected and is further interpreted for MUAP classification. This is called a threshold-crossing technique where the raw or filtered signal is scanned for peaks that exceed the threshold, marking those set of peaks as candidate MUAP positions. Other methods select variable length sections. Detection methods can be applied to the raw signal or to bandpass filtered micro signal as referenced in the EMG Signal Preprocessing section above. Additionally, some detection methods are based on amplitude, while others use a combination of both slope and amplitude thresholds.[21]

C. Alignment

After MUAPS are detected, they must be aligned before further analysis. This alignment can be done using local peak values of either the raw or filtered signal or using methods based on discrete Fourier transforms. Due to time quantization errors, discrete Fourier transforms to interpolate between samples and a Nyquist sampling rate allow for more accurate alignment.[22]

D. Feature Extraction

In detecting action potential from the EMG signal, the focus is on characteristics that differentiate the action potential shapes from background noise and. Techniques to identify MUAPS from each motor unit action potential train contained in the EMG signal can be categorized as visual inspection or automatic identification with a computer. Automatic identifications are based on feature extraction. In general, a set of features should be chosen that gives a high discriminate ability among detected MUAPs. The values of these combined features is termed the feature space. This part of the process is termed feature extraction for pattern recognition. Features are the characteristics of the MUAPs used for this representation.

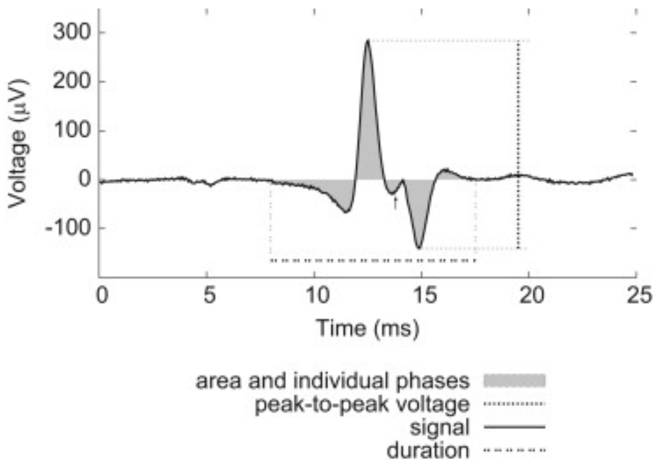

Fig. 2. Illustration of a general MAUP with several features outlined that would occur in the feature extraction process (from Yousefi & Hamilton-Wright[23]).

In general, a set of features should be chosen that gives a high discriminate ability among detected MUAPs. The values of these combined features are termed the feature space. This part of the process is termed feature extraction for pattern recognition. Features are the characteristics of the MUAPs used for this representation. Factors to consider to represent an object (MUAP) for pattern recognition include number of features, computational effort, signal to noise ratio, variance of each feature, feature correlation, discrimination power of feature representation, sensitivity of the representation to waveform alignment, effect of MUAP superpositions on the feature values, and MUAP shape variability on the feature values.[24] A number of features have been used to represent MUAPs for signal decomposition including: morphological statistics (e.g. peak-to-peak voltage, number of phases, duration, number of turns), Fourier transformation coefficients to represent the frequency domain, coefficients obtained from other transformations (e.g. a wavelet basis), the time samples of the band-pass filtered signal and the time samples of the low-pass differentiated signal. In EMG signal decomposition, MUAPs are represented as a feature values vector to be able to measure the similarity of detected MUAPs and properly classify them into MUAPTs. Different features have been used to determine detected MUAPs and improve the EMG signal decomposition processing time and accuracy.[25] In addition to the ones described above, other features include peak amplitude, rise time, area, or other MUAP wave form characteristics, or signal space representation, which comprises correlation, matched filter, template, or square-error separation techniques.[26] Other variables are signal derivatives, power spectrum, and Fourier coefficients of transform (e.g. wavelet transform), wavelet coefficients, and principal components of wavelet coefficients. [27] These features vary in effectiveness and computational need. Fig. 2 shows a general MUAP with a set of example features that can be used to analyze the signal.

As mentioned, there are many MUAP features that can be extracted from the EMG signal through decomposition. Certain features that are commonly used to classify EMG signals include: duration, peak-to-peak amplitude, number of phases, turns, and area. Duration is defined as the time between the onset and termination of a MUAP. Peak-to-peak amplitude is defined as the difference between the maximal and minimal peak values for the MUAP. The number of phases refers to the number of baseline crossing plus 1. A turn is defined as a positive or negative peak that is separated from a previous and a following peak of opposite polarity by some threshold voltage. The area refers to the MUAP area, which is calculated by integrating the rectified MUAP over its duration. Other features based on combinations of these features can be constructed such as spike, spike duration, firing rate, and firing variability. These features act as an input to a classification system.[28]

1. Principal Component Analysis (PCA)

PCA, known for its conceptual simplicity, its application in a number of commercial packages, its ease to program, is a widely used statistical procedure for finding patterns in high dimensional data. PCA serves as a way to identify patterns in the data and highlighting their similarities and differences. PCA offers another advantage as it allows the data to be compressed, by reducing the number of dimensions, where the data is then projected onto this smaller set.[29] Particularly for EMG signals, PCA allows for the decomposition of the EMG signal waveforms in a small set of basis waveforms that capture most of the relevant features of the source EMGs. PCA defines a low-dimensional space on which the original EMG activation patterns can be represented as vectors. The principal components are the factors that define the most of the dataset variance. PCA is based on the concepts of covariance, a measure of how much two variables change together shown in Fig. 3a, and correlation, a measure of the linear relationship between the two variables shown in Fig. 3b. A positive correlation (or covariance) indicates that two variables have similar trends while negative indicates that the two variables have specular trends. If unrelated, the value is equal to zero. A significant point is that correlation, unlike covariance is not influenced by the oscillations in amplitude of the two variables but by their temporal relationship.

$$\mathbf{cov}(X, Y) = E\{[X - E(X)][Y - E(Y)]\}$$

Fig. 3a. Equation of covariance where E is the mean value.

$$\mathbf{cor}(X, Y) = \mathbf{cov}(X, Y)/[\mathbf{sd}(X)\ \mathbf{sd}(Y)]$$

Fig. 3b. Equation of correlation where sd is the standard deviation (from Bosco[30]).

The first step to perform a PCA on an EMG is to compute either the covariance or correlation coefficient of the dataset variables, EMG signals. Finding common temporal features among EMG signals is most important in EMG decomposition so the correlation matrix, as described above, is used as it is influenced only by temporal relationships. The PCA extracts from the correlation matrix: the eigenvectors, the eigenvalues, the principal components or factor scores which represent the waveforms associated to each eigenvector/eigenvalue, and the weighting coefficients which represent the Pearson correlation coefficients between the principal components and each original EMG waveform. The principal component waveforms extracted using the above method statistically represent the common features across the dataset. Orthogonal and oblique rotations are algorithms that are done to further understand the significance.[31]

E. Clustering and Classification of Detected MUAPs

EMG signal decomposition consists of the processes of identification and classification of action potentials of individual motor units from the EMG recording. Classification is challenging due to the overlapping in time and frequency of action potentials generated by different motor units and the variability in the shape of the action potentials from the same motor unit.[32] To classify the detected action potentials, action potentials produced by the same motor unit should have more similarity in shape that those produced by different motor units. This difference in shape can be quantified (feature space) for comparison. The detected MUAPs (done in EMG Signal Segmentation and MAUP Detection) are then represented using a vector for pattern recognition described in the Feature Extraction section. The first classification step involves action potentials that do not overlap in time. For resolving superimposed action potentials, there are two basic strategies, the sequential approach and the modeling approach.[33]

Clustering of detected MUAPs involves the partitioning a set of objects into a number of groups or clusters. A clustering algorithm applied to the EMG signal decomposition has the goal of determining the correct number of motor units contributing significant MUAPs to the composite signal (i.e. the number of significant MUAPTs) and of assigning as many MUAPs as possible to their correct MUAPT so that the mean MUAP shape of each contributing motor unit can be determined. It is important the clustering algorithm is accurate to have the most successful classification results. Thus, often times superimposed MUAPs are ignored or not all detected MUAPs are assigned to ensure accuracy. Instead, the clustering algorithm should only consider discovering all of the MUAPTs that significantly contribute to the signal and make sure to minimize erroneous classifications.

Clustering is based on the measure of similarity or dissimilarity between MUAP shapes. Different measures are used. To measure dissimilarity, the most common measure is called the Euclidean distance which involves a formula with the dimensional pattern of the MUAP. Most clustering algorithms that are employed for EMG signal decomposition are based on single-linkage or nearest-neighbor concepts. In complete-linkage techniques, two most similar objects are combined into one cluster and then replaced by their mean shape. The distance matrix is then recalculated with the reduced number of objects and the process is repeated until only a single object (cluster) remains. Using a threshold of dissimilarity, a number of clusters will be created with all of the objects represented by the remaining means for each respective cluster. In the single-linkage technique, however, cluster membership is based on the single closest individual object not on the cluster mean. This clustering technique is also called nearest-neighbor clustering. This type of clustering does not depend on order, but requires that all the data be considered at once which is computationally taxing. This type also relies on defining threshold values for cutting the dendrogram, what is created from joining objects and recalculating the matrix, to determine the number of clusters.

An alternate to these hierarchical techniques is partitioning methods. K-means and ISODATA are examples of partitioning methods, while sequential clustering, such as leader-based clustering, is a special kind. Partitioning methods create a clustering set partition that minimizes a specified objective function, often the squared error. For this technique, the number of clusters must be decided and their initial means must be selected. Then, each object is assigned to the cluster with the most similar. Afterwards, the mean value of each cluster is updated either after each assignment or at the end of a pass. The cluster means become stable after multiple passes through the data. In partitioning methods, the order of object classification changes the results, but since only one object is considered at a time, the computational complexity is reduced. As mentioned above, a variety of clustering algorithms are used for EMG signal decomposition that are based on the single-linkage or nearest-neighbor concepts. Others use partitioning methods such as K-means and the leader-based approach explained previously. Distance normalization and threshold adjustment are common for larger MUAPs. Classification decisions also involve MUAP shape and firing pattern information in addition to basic clustering algorithms. According to Stashuk, one of the most important aspects when analyzing clustering algorithms is defining thresholds used for cutting dendograms to determine the number of clusters or for making classification decisions.[34]

The objective of clustering and classification of the MUAPs detected during signal segmentation is to groups the MUAPs into sets of MUAPTs. Each MUAPT represents the activity corresponding to a motor unit that contributed to a number of MUAPs in a composite signal. Each MUAPT should have a consistent motor unit firing pattern and the MUAPs, assigned through clustering and classification, to a MUAPT should be more similar to each other than to a different MUAPT. The clustering techniques described above are followed by classification and often done in multiple iterations until either the extracted MUAPTs are stable or a termination criteria is met. Supervised classification uses information from the clustering algorithms mentioned above. So, MUAPs are assigned to their associated trains based on the information about the possible MUAPTs provided by the clustering results. After deriving MUAP shapes and motor unit firing patterns from clustering, classification of unassigned MUAPS to the extracted MUAPTs is done based on these statistics and the statistics are updated. [35]

VI. Advancements in EMG Signal Processing: Machine Learning

Recent advancements in new signal processing techniques, mathematical models, and computational ability have allowed advanced EMG detection and analysis methods. Various mathematical and machine learning techniques such as Artificial Neural Networks (ANN), Probabilistic model algorithms, Metaheuristic and Swarm intelligence algorithms, and other hybrid algorithms are now being employed to characterize EMG signals. Learning algorithm is defined as an adaptive method by network computing units to realize the target or desired behavior. Machine learning involves learning to predict from samples of target behaviors or past observations of data.[36]

A. Artificial Neural Networks (ANN) Approach

ANN is a technique that is used for pattern recognition in high-dimensional parameter space and is a method of mapping input parameters to an output variable. ANN has been the focus of interest in the field of EMG classification. ANN are used as a novel approach for the automatic classification of EMG features. Major advantages of ANN are its ability to learn from examples, its approach vagueness and uncertainty, common to EMG signals, and its generalization skill, useful when dealing with high dimensional input spaces. ANNs have been applied to the diagnosis of neuromuscular disorders with its ability to learn from large data sets even with high feature variability.[37] Features of MUAPs extracted such as duration, amplitude, and phases allow differentiation of disorders. However, with increasing muscle force, the EMG signal shows an increase in the number of activated MUAPs recruited at increasing firing rates, which makes classification extremely difficult.[38] In ANN, the neural network is trained to adjust the connection weights, of links between neurons, in order to produce the desired mapping. With EMG signals, the feature vectors are applied as an input to the network and the network adjusts its variable parameters, the weights, to get the relationship between the input patterns and outputs. There are many types of ANNs including improved backpropogation networks (IBPN), radial basis networks (RBN), and learning vector quantization networks (INQ).[39]

1. Wavelet Neural Networks (WNNs)

ANN is employed in WNNs, which combines the learning ability of ANN and the time-frequency localization characteristic of wavelets in wavelet decomposition. WNN has a major advantage for MUAP classification with its ability to train quickly through heuristics and its capability of non-stationary signals.[40] WNN is based on wavelet transform, where a discrete wavelet function is used as the node activation function. The wavelet space is used as characteristic space of pattern recognition. First, multidimensional wavelets are defined. The wavelet nodes are then specifically trained to approximate only the “wave-like” components in the function. For solving the pattern classification problem, an ANN back-propagation training algorithm can be used. The data is first divided into a training set and a test set using the selection of network input parameters. The classification scheme of 1-of-C coding is then used to classify the signal into one of the output categories. [41] For each type of EMG signal, a corresponding output class is assigned. ANN inputs are represented in the feature vector set and the corresponding class, using coding, comprises the ANN outputs. For example, if the output classes is three, the ANN has three outputs, which produce a code for each class . The outputs are represented by basis vectors. An example is given below.

[0.9 0.1 0.1]=awake
[0.1 0.9 0.1]=drowsy
[0.1 0.1 0.9]=sleep

Each dummy variable is given the value 0.1 except the one corresponding to the correct category that is given the 0.9 value. The output vector associated to the modified input vector xk, k=1, 2,…, K is noted yk, with K the number of EEG signals. A set of K input/output pairs $D=\{xk, yk \mid k=1, 2,\ldots, K\}$ is available from coding. As described above, this data set is divided into two subsets, training set and test set.

(1) $D_{\text{train}}=\{xk, yk|k=1, 2,\ldots, K_{\text{train}}\}$ is used to perform the ANN training which consists of the determination of the ANN connection weights.

(2) $D_{\text{test}}=\{xk, yk|k=1,2,\ldots,K_{\text{test}}\}$ is used to validate off-line classification ability and quality of the ANN once the training has been completed.

The input and desired data will be repeatedly presented to the network during training.[42]

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