# FEATURE EVALUATION FOR EMG-BASED LOAD CLASSIFICATION

**Anne Gu**
Department of Mechanical Engineering, University of Michigan
Ann Arbor, Michigan, USA

## ABSTRACT

Human-machine interfaces (HMIs) often have pattern recognition-based myoelectric control for rehabilitation purposes. In order to make this technology applicable in the real world, the control needs to be as robust as possible. For pattern recognition-based myoelectric control, feature selection is the preprocessing step that finds relevant data to improve robustness of a learning algorithm. A filter is a feature selection algorithm that uses only the inherent data characteristics to evaluate features. In this paper, thirty five time-domain and frequency-domain electromyography (EMG) features are evaluated using a univariate filter method in order to determine the feature most likely to produce the highest prediction accuracy in lifted load classification. The features are extracted from a database of raw surface EMG recordings from the lower back muscles. The EMG signals were recorded from nine healthy subjects while they performed a weight-lifting task with three different loads. For pre-lift and post-lift of a single subject, v-order (*V*) was the best feature. For pre-lift of nine subjects, frequency ratio (*FR*) was the best feature. The results from this study can provide helpful insight for the feature selection for EMG-based pattern recognition models.

**Keywords**: Feature Extraction, Univariate Filter, Pattern recognition, Electromyography (EMG) Signals, Lower Back, Human machine interfaces (HMIs), and Lifting

# 1. INTRODUCTION

With the recent development in machine learning in the past years, intuitive human-machine interfaces (HMIs) have become a point of interest. HMIs are used in many different fields including in the clinical and biomedical field. Surface electromyography (EMG) pattern recognition algorithms are common methods of control for HMIs for reliable user motion intent classification. Surface EMG signals are electrical activity of muscle fibers measured from the surface of the skin. EMG-based HMIs are especially prominent in the field of rehabilitation [5]. Examples of EMG-based HMIs include powered orthoses/exoskeletons, rehabilitation robotics, and powered prostheses [3]. One type of user intended motion that EMG pattern recognition algorithms can predict is when a user lifts a weight. An example of such an EMG-based HMI is a powered back orthosis that identifies what a person is lifting before the person lifts the weight and applies the correct amount of assistive torque on the lower back when the weight is lifted to prevent lower back pain.

# 2. BACKGROUND

EMG features are statistical properties of the EMG signal. EMG features can be grouped into two main categories: time-domain and frequency-domain [5]. Time-domain features provide information for onset detection, muscle contraction, and muscle activity detection [6]. Time-domain features also are easy to implement and can be done in real time. Frequency-domain features provide information about the frequency and power of the EMG signal. They are often used to study fatigue of muscles and recruitment pattern of motor units (MU) [2].

For successful load classification of surface EMG signals, there are three main aspects to consider: processing of data, feature extraction, and classification methods [5]. Raw surface EMG signals are processed according to the type of feature needed to be extracted. Features are extracted from the appropriately processed EMG signal. Based on the extracted features, a pattern recognition model recognizes the EMG signal patterns and classifies them into predefined load classes. Popular pattern recognition models include neural network, hidden Markov model, and support vector machine. Fig. 1 shows an overview of how load classification of surface EMG signals works.

The features inputted into a pattern recognition model, or classifier, are crucial factors of the accuracy and response time of the model. Feature selection is the preprocessing step that finds relevant features to improve robustness of a learning algorithm for pattern recognition-based myoelectric control. There are three main feature selection techniques: Filter methods, wrapper methods, and embedded methods. Filter methods measure how relevant a feature is based on the intrinsic properties of the data. Univariate filters, a type of filter method, are advantageous to use because they are computationally simple, fast, and independent of the classifier [7].

In this study, thirty five time-domain and frequency-domain electromyography (EMG) features, found in literature [1], are evaluated using multinomial logistic regression (MLR), a univariate filter, in order to determine the feature most likely to produce the highest prediction accuracy in lifted load classification. The results from this study will provide helpful insight into the feature selection for EMG-based pattern recognition models.

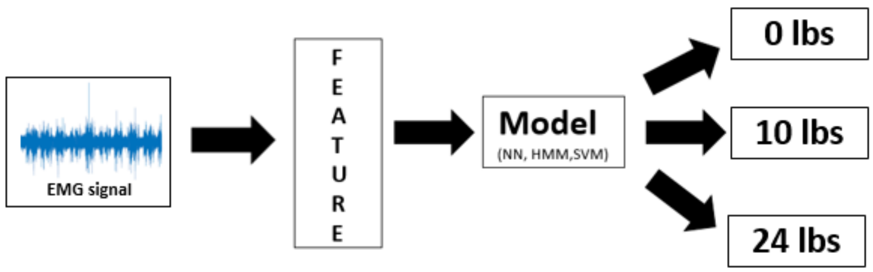


**Figure 1.** Overview of load classification of surface EMG signals. Raw surface EMG signals are processed according to the type of feature needed to be extracted. Features are extracted from appropriately processed EMG signal. Based on the extracted features, a pattern recognition model recognizes the EMG signal patterns and classifies into predefined load classes. Popular pattern recognition models include neural network, hidden Markov model, and support vector machine.

## 3. DATA COLLECTION

The dataset used to evaluate the proposed EMG features was taken from lower back EMG sensors from nine healthy subjects. Placement of lower back EMG sensors are shown in Fig. 2C. These signals were recorded and sampled at a sampling rate of 1200 Hz with the Trigno Wireless EMG system. The EMG data was collected as the subjects lifted three weight classes, 0, 10, and 24 lbs, from a table on a force plate when prompted by a screen (Fig. 2B). To simulate lifting 0 lbs, or no weight, subjects lifted light aluminum-covered sticks. Each subject lifted each weight class ten times. The weight classes can be seen in Fig. 2A. Subjects also did two repetitions of isometric back extension while lying on a roman chair at a 45° angle. From this task, the maximum EMG baseline for the lower back muscles was taken in order to normalize

EMG data for time-domain features. A diagram illustrating this isometric back extension can be seen in Fig. 2D.

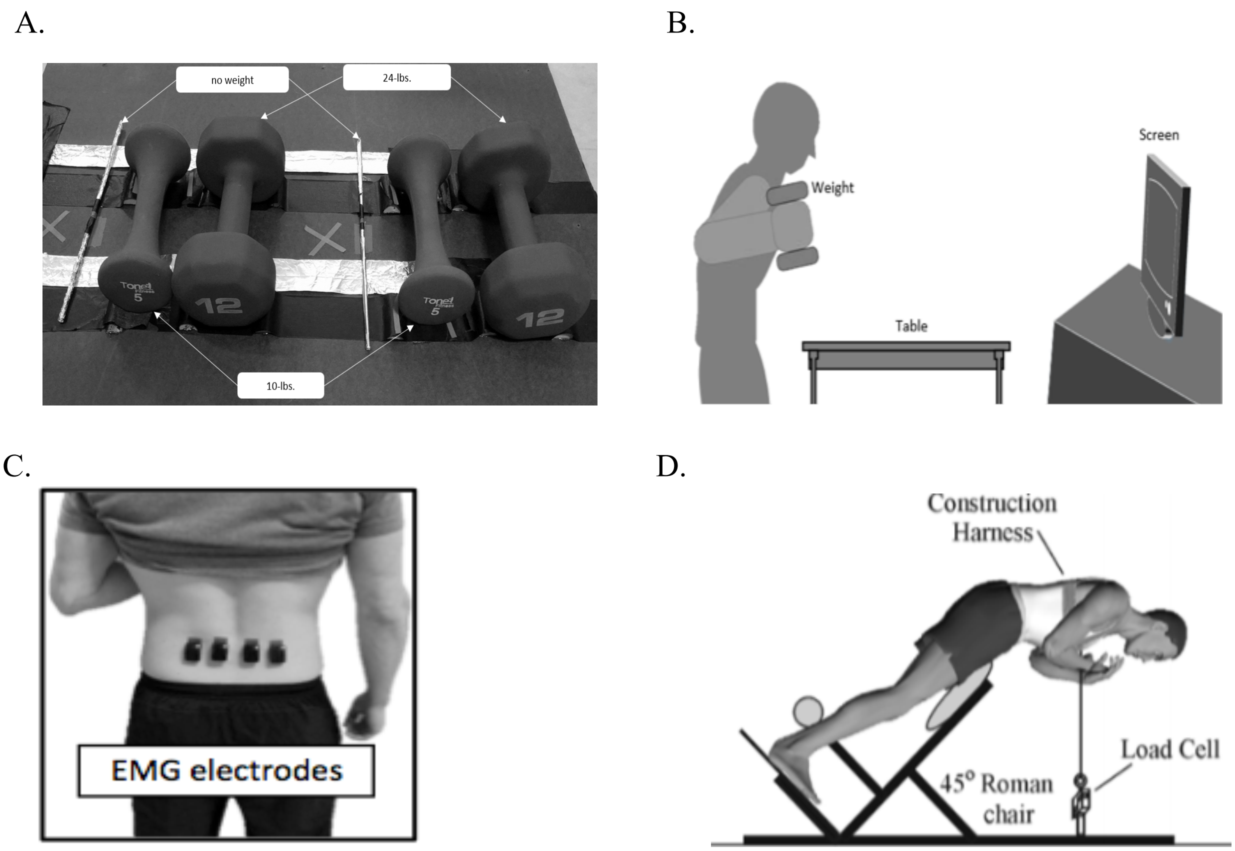


**Figure 2**. Experimental apparatus and placement of EMG sensors. (A) Placement of the three classes of weights, 0, 10, and 24 lbs, on table. Lifting no weight is simulated by having the subjects pick up light aluminum-covered sticks. (B) Diagram illustrates a subject lifting weights from a table on a force plate when prompted by a screen. (C) Placement of EMG electrodes on the lower back. (D) Picture of subject doing two repetitions of isometric back extension while lying on a roman chair at a 45° angle. These pictures are reprinted with permission of Deema Totah.

## 4. DATA ANALYSIS

Data analysis for feature evaluation consists of three main steps. These steps are segmentation and pre-processing of data, feature extraction, and feature evaluation.

*4.1 Segmentation of EMG data*

Segmentation of raw EMG data into known classes (0,12 and 24 lbs) is a necessary step to improve accuracy and response time of feature extraction. EMG data was segmented using threshold detection from the force plate data. Lift time is defined as the instant at which the weights are off the table, as seen in Fig. 3 with a red circle. An example of using threshold detection from the force plate data of one subject to find lift times can be seen in Fig. 4, where the black circles indicate lift detection times of 10 lbs and blue circles indicate the lift detection times of 24 lbs. Once lift times are detected, the EMG data is segmented into its respective weight class with a segment length of approximately 12 seconds.

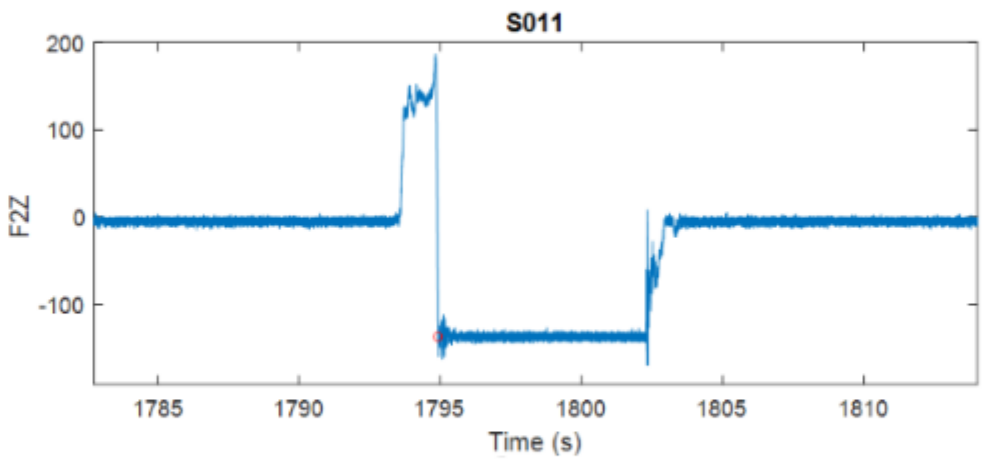


**Figure 3.** Force plate data of subject 11 lifting a weight class. Lifting occurs when the mean threshold value for the weight class in the force plate data is first reached. The red circle indicates the time at which lifting occurs.

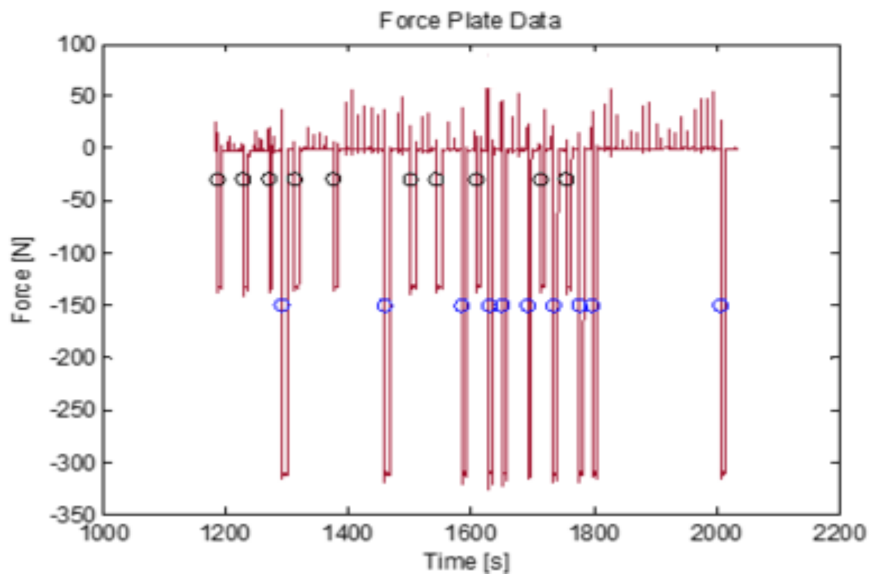


**Figure 4.** Example of using threshold detection of 10 and 24 lbs from the force plate data to segment the raw EMG signal. Black circles indicate the lift detection times of 10 lbs and blue circles indicate the lift detection times of 24 lbs. These lifting times are used to segment the EMG data.

*4.2 Pre-processing of data for time-domain features*

Pre-processing of data for time-domain features involves filtering and normalizing the segmented data. The data is first filtered using two 5th order Butterworth filters, which consist of a 20-300 Hz band pass filter and 59 - 61 Hz band stop filter. After applying the Butterworth filter, the data is de-meaned, rectified, and applied with a low-pass filter with a cutoff frequency of 4 Hz to get a linear envelope of the signal.

Because EMG signals are unique to each subject, the processed data need to be normalized in order to compare subjects to each other. The normalization method proposed is percent maximum voluntary contraction (MVC) and can be seen in Eq. 1 where *EMG signal* in *% MVC* is the processed time-domain EMG data and *maximum EMG baseline*, obtained by the isometric contraction tasks.

$$\%MVC = \frac{EMG\ signal}{maximum\ EMG\ baseline} \times 100 \tag{1}$$

### *4.3 Pre-processing of data for frequency-domain features*

Pre-processing of data for frequency-domain features involves filtering out noise from the segmented data. Before evaluating the frequency-domain features, the raw EMG signal was filtered with a band stop filter around 60 Hz to remove electrical noise. Once the raw EMG signal is filtered, the data is transformed into a fast Fourier transform (FFT). FFTs provided power and frequency information of the filtered signal. Once EMG segments are transformed, frequency-domain features can be extracted.

### *4.4 Feature extraction and feature evaluation*

Thirty five time-domain and frequency-domain EMG features, found in literature with defined parameters [1], were extracted from a single-EMG channel. Of the thirty five features, twenty three were time-domain features and twelve were frequency-domain features.

To evaluate features, multinomial logistic regression (MLR) is used as a univariate filter, a technique to evaluate the "goodness" of a feature based on a heuristic merit. The data input into MLR was the extracted feature values and its associated class (represented in binary using a one-vs-all strategy). 70% of the data of one subject was used to train the MLR model and 30 % of the data was used to test the trained MLR model. Data for one subject consisted of 30 lifts, 10 for each weight class. Out of the 19 subjects that we had, we used nine subjects for the multi-subject feature evaluation. For the multi-subject data, 67% was used to train the MLR model and 33 % was used to test the trained MLR model. Training and testing data for nine subject was split by subject. Using the test data set, the MLR model outputted the probabilities for each of the classification classes. The highest probability was taken and labeled as the output label in binary and compared to the class identification binary matrix to determine classification accuracies of each feature.

## 5. RESULTS

For feature evaluation of subject 11, two 100 ms window, pre-lift and post-lift, were investigated. Pre-lift was defined as the 100 ms time frame before lift time. Post-lift was defined as the 100 ms time frame after lift time. The pre-lift time window was investigated because it was the ideal window of interest for a pattern recognition model to predict a user's intention of lifting a load. The post-lift time window was investigated to provide insight on feature classification performance when varying time windows.

The top ten performing features for subject 11 at pre-lift can be seen in Fig. 5. V-order ($V$) was the top performing feature with a classification accuracy of 88.9%. Time-domain features are predominant amongst the top ten performing features. Time-domain features seem to do better than the frequency-domain in classification accuracy in pre-lift. The top ten performing features for subject 11 at post-lift can be seen in Fig. 6. The feature with the highest classification accuracy was *V* with an accuracy of 67.8%. Time-domain features are predominant amongst the top ten performing features.

For nine subjects, features were evaluated at the pre-lift time window. The top ten performing features of nine subjects at pre-lift can be seen in Fig. 7. The feature with the highest classification accuracy was frequency ratio (*FR*) with an accuracy of 77.8%. Frequency-domain features are predominant amongst the top ten performing features.

For pre-lift and post-lift of subject 11, v-order (*V*) was the best feature. Post-lift feature classification accuracies of the top ten features are lower than pre-lift features'. It was interesting to note that histogram (*HIST*) and *FR* were in the top ten features of both the single and nine subject for pre-lift. Descriptions of the top performing features, *V*, *FR*, and *HIST*, can be found in the appendix.

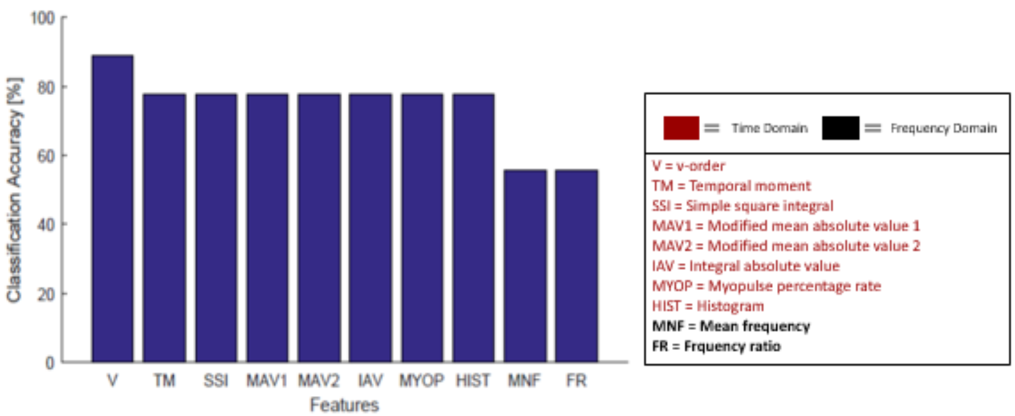


**Figure 5.** Top ten features of subject 11 at pre-lift, a 100 ms time window. The feature with the highest classification accuracy was v-order (*V*) with an accuracy of 88.9%. Time domain features are predominant amongst the top ten performing features. The time-domain features seemed to do better than the frequency-domain in classification accuracy.

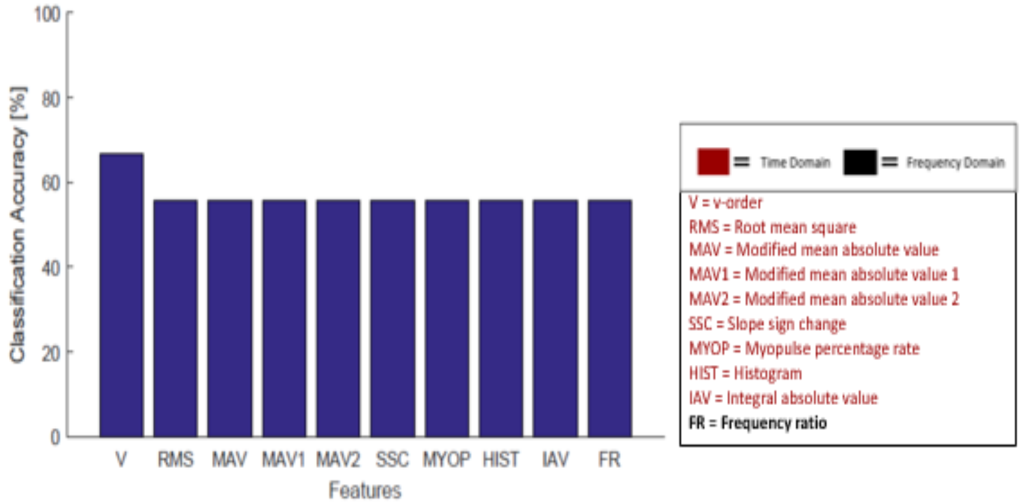


**Figure 6.** Top ten performing features of subject 11 at post-lift, a 100 ms time window. The feature with the highest classification accuracy was v-order (V) with an accuracy of 67.8%. Time-domain features are predominant amongst the top ten performing features.

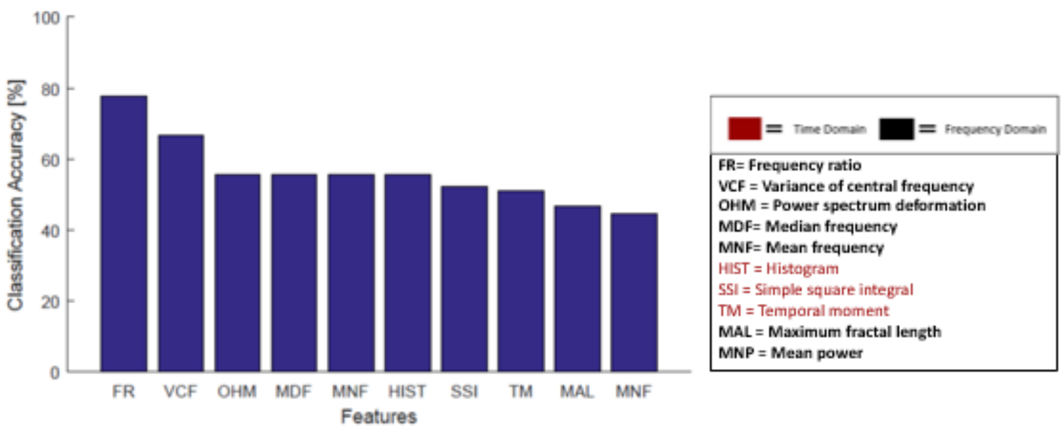


**Figure 7.** Top ten performing features of nine subjects at pre-lift, a 100 ms time window. The feature with the highest classification accuracy was frequency ratio (*FR*) with an accuracy of 77.8%. Frequency-domain features are predominant amongst the top ten performing features.

## 6. DISCUSSION

Based on the results we obtained, the single feature with the highest prediction accuracy in lifted load classification for subject 11 was *V* and the single best performing feature of nine subjects was *FR*. However, because EMG signals vary from person to person, we cannot conclusively say that *V* was the best feature for any single subject. Cross-validation of training and testing data is needed in order to produce results that are independent of the order of the training and testing data are used in the MLR model. Once the data is cross-validated, a practical application of these results include being able to fine tuning EMG pattern recognition algorithms for reliable user intent load classification to a specific person or to a general population.

Future work will extend to using a multivariate filter for single feature evaluation. One of the disadvantages to using a univariate filter method is that feature redundancy is not considered. In Yu *et al*, a feature is considered good if it is relevant to the EMG data but has low correlation to other features [8]. In order to meet this definition, features can be evaluated using a multivariate filter. In addition to finding the single best feature with a multivariate filter, finding an optimal set of features for lifted load classification could further improve robustness of EMG pattern recognition algorithms.

## 7. CONCLUSION

In this study, we evaluated thirty five time-domain and frequency-domain EMG features using a univariate filter method in order to determine the feature most likely to produce the highest prediction accuracy in lifted load classification. Our preliminary results include that for pre-lift and post-lift of a single subject, v-order ($V$) was the best feature and for pre-lift of nine subjects, frequency ratio ($FR$) was the best feature. However, cross-validation of testing and training data is needed in order to definitively say what the best feature for a single and multiple subjects are. Future work will extend to using a multivariate filter for single feature evaluation and finding an optimal set of features for lifted load classification to try to further improve robustness of EMG pattern recognition algorithms.

## ACKNOWLEDGMENTS

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## APPENDIX

**V-order (*V*)**

A time-domain feature that estimates of the exerted muscle force. The mathematical definition is that it is the absolute value of EMG signal to the *V*-th power. In this study, *V* was set to 3. *N* is the length of the EMG signal. *V* feature is defined as

$$V = \left( \frac{1}{N} \sum_{i=1}^{N} x_i^v \right)^{\frac{1}{v}}.$$

**Frequency ratio (*FR*)**

A frequency-domain feature that distinguishes between contraction and relaxation of muscle using the ratio between the low frequency and the high frequency components of the EMG signal. FR is defined as

$$\mathrm{FR} = \sum_{j=\mathrm{LLC}}^{\mathrm{ULC}} P_j \Big/ \sum_{j=\mathrm{LHC}}^{\mathrm{UHC}} P_j,$$

**Histogram (*HIST*)**

A time-domain feature that provides information of the frequency with which the EMG signal reaches various amplitudes. Histogram divides elements in the EMG signal into *B* equally spaced segments and returns a number of signal elements for each segment. In this study, *B* was set to 3.

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