* For the reference see also the last page

# Predicting Muscle Fatigue via Electromyography: A Comparative Study

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**Abstract**
This paper presents a comparison of some statistical and AI predictive techniques. The data used were electromyography (EMG) signals related to fatigue and rest conditions of certain arm muscles. Besides the building of some effective models for predicting muscle fatigue from EMG signals, this study indicates that a new data mining technique (the OCAT approach), which has been developed by some of the authors, has a lot of promise.

**Key Words:** Electromyography, comparison of prediction methods, neural networks, fuzzy membership, C-means, K-nearest neighbor, logistic regression, linear discriminant, data mining, Fourier transform.

## 1. General Problem Description

This paper presents the development, testing, and comparison of a number of models for the prediction of muscle fatigue associated with sustained muscle contraction. This study aimed at two goals. The first goal was to compare a number of predictive methods, especially a number of statistical techniques with some data mining methods. The second goal was to develop an accurate model for the prediction of muscle fatigue via electromyography.

An experimental study was conducted in order to evaluate the effects of heavy isometric loading (maximum and 80% of the maximum) on recorded electromyography (EMG) signals. Furthermore, this study investigated any possible effects of electrode orientation on the detection of muscle fatigue during heavy isometric loading. For the frequency domain analysis, the estimated power spectrum and its characteristic fractile frequencies were calculated. The estimated power spectrum, also known as the periodogram, was calculated as the modulus squared Fourier transform ([Garcia *et al.*, 1997] and [Waly, *et al.*, 1997]). The characteristic frequencies used in this study were 1, 5, 10, 25, 50, 75, 90, 95, 99 fractile frequency, and the peak frequency.

## 2. Experimental Data

The EMG data for this study were derived from 18 healthy male subjects with no history of musculoskeletal injuries. All subjects were selected on a voluntary basis from a student population. They represented a wide spectrum of body weights, heights, age, and muscle strengths. They ranged in age between 22 and 40 years with a mean value of 27.2 years. Their weights ranged from 53.2 *kg* to

105.9 *kg* (117 to 233 *lbs*) with a mean value of 75.86 *kg* (166.89 *lbs*). Their heights ranged from 160 *cm* to 187.5 *cm* (5'4" to 6'3") with a mean value of 172.5 *cm* (5'9").

The subjects were required to perform a static muscle effort corresponding to a predetermined load level. The load was applied to permit static contraction of the biceps brachii muscle. The load was placed in the dominant hand of each subject with the upper arm hanging freely in a neutral adducted position to the side of the body. The forearm was flexed at 90° at the elbow joint. The wrist was maintained in a straight neutral position with the hand supinated to support the load. The load consisted of a bar and two balanced weights attached to both sides of the bar. Two levels of loading were studied. These loads were set to the maximum amount of weight the individual can hold for a few (e.g., 3-5) seconds and 80% of the maximum weight. The maximum weight was determined on a separate day prior to the experimental sessions. The subjects were instructed to hold the weight, as described earlier, as long as possible. The EMG data were recorded from the biceps brachii muscle using two sets of electrodes simultaneously. One set was placed along the muscle fibers and the other across the muscle fibers. The electrodes used in this experiment were Beckman type, 11 *mm* silver/silver chloride surface electrodes. The EMG signals was recorded using an R611 Multichannel Sensormedics Dynograph via a type 9853A voltage/pulse/pressure coupler. The amplifier gain was adjusted to allow full utilization of the dynamic range of the A/D converter (+ 10 *volts*). A sampling rate of 512 *Hz* was used to digitize the EMG signals using a 12 bit A/D converter model *DT 2801-A*.

The EMG signals were recorded from the onset of the load under investigation until the subject could not hold the load anymore. A pre-processing of the EMG signals was conducted as described earlier. The window size used in this pre-processing was selected to be 512,000 per second based on the results of the first experiment. The EMG parameters were estimated for the first and last window in the recorded signal. Also, the EMG parameters were calculated at fixed periods of time as a percentage of the total time an individual was able to maintain the task of holding the load. The center of the EMG window used in the analysis was set at the selected fixed periods of time. These periods were selected at 5% through 95% of the total time with an increment of 5%.

## 3. Analysis of the EMG Data

Several statistical analyses were conducted to achieve the objectives of this study. The results summarized in section 3.1 and 3.2 lead up to the problem of predicting muscle fatigue based on the EMG parameters. This problem is addressed in section 4 using some statistical models and AI algorithms.

### 3.1. The Effects of Load and Electrode Orientation

The results obtained indicated that the time domain parameters did not change significantly for all the interactions and main effects of the three independent variables (load, electrode orientation and muscle condition of rest or fatigue). The frequency domain parameters were significantly affected by the main effects of electrode orientation and muscle condition. The load had no significant effect on these parameters. The effect of electrode orientation on the characteristic frequencies used in this investigation was more pronounced for the lower frequencies of the spectrum. Electrodes placed across the muscle fibers showed lower fractile frequencies compared to electrodes along the muscle fibers. The effect of electrode orientation was only significant for the lower fractiles with the exception of the 99-th fractile (peak frequency, 1, 5, 10, 25, and 99 fractile).

### 3.2. The Effects of Muscle Condition, Load, and Electrode Orientation

The first and last window of the recorded EMG signals were used to represent the muscle at a resting condition and the fatigue state respectively. The EMG indices were the dependent variables. The independent variables were the muscle condition (rest or fatigue), load, and electrode orientation. The effect of muscle fatigue was significant for all the characteristic frequencies used. A significant shift toward lower frequencies was observed, however the amount of shift in these frequencies was higher for the sub-maximum load. Also, it is worth noting that the shift in these frequencies was not linear across the spectrum. Therefore, monitoring a single characteristic frequency may not be adequate for the quantification of the spectrum shift.

## 4. A Comparative Analysis of the EMG Data

Since there are numerous prediction methods in statistics and AI (including the newer ones which are based on data mining techniques) an important goal of this study was to use the derived EMG data to compare the prediction accuracy of some of these methods. Of particular interest was to compare a new method which is called the OCAT (One Clause At a Time) approach [Deshpande and Triantaphyllou, 1998]. Besides the OCAT approach, other methods were Fisher's linear discriminant analysis, logistic regression, a neural network approach, fuzzy c-means and fuzzy k-nearest neighbor approaches.

As we explain in more detail in our papers and in the description section of our data mining home page (http://cda4.imse.lsu.edu or: http://www.imse.lsu.edu/vangelis), the OCAT (One Clause At a Time) approach forms two sets of rules: the positive and the negative rules. As result of this, classifying a new (i.e., unclassified) observation will result in one of the following three outcomes: the classification will be either correct, or incorrect, or will be an undecided case. To provide a common ground to compare our results to those obtained using the other methods, we decided to fix the number of undecided cases (in the testing data) to that obtained by the OCAT approach. As a result, we could find the accuracy, on the same number of actual classifications, for each method.

To determine which cases should be deemed undecided for each of the various other methods, we expanded an interval symmetric about the respective cut-off value. This lead to a unique set of undecided cases and hence a unique classification accuracy on the remaining cases. A symmetric interval is reasonable when the underlying classification function is monotone and symmetric. Note that a classification function is monotone in the sense that once the function has been determined, each variable has a monotone effect on the classification. That is, each variable will either have a non-negative effect or non-positive effect (not both) on the outcome. In all of the methods except the neural network, symmetry and monotonicity are reasonable assumptions. This is probably the most apparent in the logistic regression model and the fuzzy models with their respective intuitive probability and membership value interpretations. The hyperplane that separates the two groups in linear discriminant analysis is obviously monotone. In addition, Fisher's linear classification rule assumes equal variance-covariance matrices, which results in symmetric probabilities of misclassification. Even though the sigmoid transfer function, used in individual neurons, is monotone, the overall network of neurons is not monotone when it has hidden layers. Despite of this fact, our network had a single hidden layer, and the symmetric interval was computed on the single output neuron.

We split the dataset into a training and a testing set, and the classification functions were derived for each method on the training set. Due to the unsupervised nature of the fuzzy c-means algorithm, it was trained and tested on the testing data. The OCAT approach achieved 100% accuracy on the training data by definition and, for this particular data split, labeled 20 of the test cases as undecided. To find the interval corresponding to a fixed number of undecided cases for the other methods, it was only necessary to find one of its borders (because of symmetry and the middle point is given). To find an appropriate upper border point we performed a binary search, until we found an interval that captured 20 testing data points. The results of prediction analyses are summarized in table 1.

**Table 1.** Summary of the Prediction Results

| Method Used | Accuracy on Data Set (in %) Training Data | Testing Data |
|---|---|---|
| **Linear Discriminant Analysis:** | **86.0** | **84.8** |
| **Logistic Regression:** | **87.5** | **84.8** |
| **Neural Network:** | **85.4** | **80.4 to 89.1** |
| **Fuzzy *C*-Means:** | **n/a** | **69.6** |
| **Fuzzy *K*-Nearest Neighbors** | | |
| **(when $K = 5$):** | **100.0** | **82.6** |
| **(when $K = 10$):** | **100.0** | **82.6** |
| **The OCAT Approach:** | **100.0** | **89.1** |

## 5. Concluding Remarks

The analyses reported in this paper indicate that the model derived by using the new data mining (i.e., the One Clause At a Time or OCAT) approach is the most accurate one. Analyzing EMG data on muscle fatigue is important in its own right (e.g., [Garcia *et al.*, 1997] and [Waly, *et al.*, 1997]). Furthermore, this comparative study indicates that the OCAT approach has some potential when it is compared with some of the existing prediction approaches. Clearly, more similar studies are required before one can fully assess the merits and potential of the new approach.

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Proceedings of the
25th International Conference on

# Computers
# &
# Industrial Engineering

March 29-31, 1999
New Orleans, Louisiana

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