31st Annual International Conference of the IEEE EMBS
Minneapolis, Minnesota, USA, September 2-6, 2009

Classification of the mechanomyogram: its potential as a multifunction access pathway

Natasha Alves and Tom Chau, *Member, IEEE*

***Abstract*—Although the mechanomyogram (MMG) has been demonstrated as a viable representation of muscle activity, its potential as a multifunction (>2) control signal has not yet been investigated. This study investigates the discriminability of multiple hand motions using multichannel forearm MMG. With nine able-bodied participants, MMG signals from six sites could be differentiated among eight classes of forearm muscle activity with a mean accuracy of 93±9% using 15 features selected by a genetic algorithm and classified by a linear discriminant analysis classifier. These results suggest that, with additional research, MMG may indeed become a usable control signal for multifunction access devices.**

***Index Terms*— Mechanomyogram, access pathway, assistive devices, control signal, Fisher ratio, genetic algorithm**

I. INTRODUCTION

Body-machine interface technologies enable individuals with physical disabilities to interact with their environment and regain some of the independence they have lost due to their disability. In these technologies, an individual mediates and controls a function of their access device by conscious control of physiological signals, such as brain activity or muscle activity. In this study, we investigate the potential of a multifunction muscle-interface that is controlled by mechanomyogram signals from forearm muscles.

Contracting muscles emit low frequency vibrations that can be measured by microphones or accelerometers on the surface of the skin. The mechanomyogram (MMG) is the superficial measurement of these vibrations. MMG is generated from gross lateral movement of the muscle at the initiation of a contraction, smaller subsequent lateral oscillations at the resonant frequency of the muscle, and dimensional changes of active muscle fibers [1].

Much of the work on muscle-interfaces has focussed on electromyogram(EMG)-based control of upper-limb prostheses [2], telephone interfaces [3] and computer interfaces[4]. In comparison to EMG, MMG has been understudied as a control signal. However, MMG, may have several advantages over EMG: it is not influenced by skin impedance changes, it is less sensitive to precise placement of sensors on the skin surface [1], the RMS power is high even at low contractions levels due to asynchronous firing of active motor units [5], and when compared to EMG, MMG provides a better estimation of the motor-unit activation strategy [6].

Since MMG provides information about the number and firing rates of recruited motor units during voluntary isometric contraction [7], it is expected that patterns of muscle activity will be reflected as discernable patterns in MMG signals. A pattern-recognition approach was therefore adopted to differentiate among MMG signals originating from multiple classes of muscle activity.

The success of the pattern recognition system is dependent on a signal representation that contains enough information to accurately discriminate among the forearm muscle activation patterns, yet is small enough to ensure processing speed and generalization. We propose the following stages in designing the MMG pattern-recognition system: representing the MMG signal as a feature vector; identifying individual discriminatory features by Fisher's ratio analysis [8]; selecting jointly discriminatory features using a Genetic Algorithm (GA) with classification accuracy as the criterion function, and evaluating the reduced feature set with a linear classifier. These steps are illustrated in Figure 1. The classifier's decision could subsequently be used as input to a multifunction controller for an access device.

II. METHODS

A. Data Collection

Nine healthy individuals (4 male, 5 female) aged 21±1 years with no previous history of musculoskeletal illness provided written consent to participate in the study.

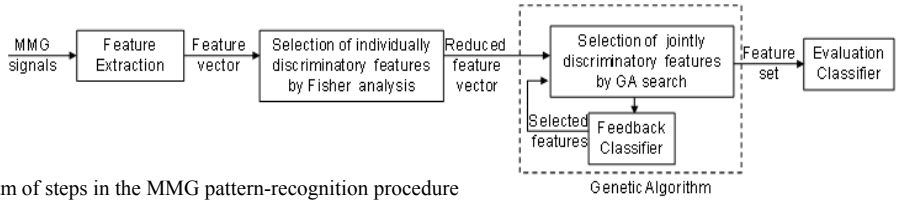

Figure 1: Block diagram of steps in the MMG pattern-recognition procedure

Participants were seated on a chair fitted with a custom arm-rest which supported the forearm at the wrist and elbow. Six MMG sensors, manufactured according to the method of Silva et al. [9], were affixed to the participants' dominant forearm over extrinsic hand muscles. The muscles monitored by the sensors were: the pronator teres, flexor carpi radialis, flexor carpi ulnaris, extensor digitorum communis, extensor carpi radialis longus and extensor carpi ulnaris. Each sensor was individually affixed with a small velcro strap. A custom LabView graphical user interface was used to start data acquisition and visually cue the participants to perform eight hand motions: hand open, hand close, wrist flexion, wrist extension, pronation, supination, adduction, and abduction. MMG data from the six muscle sites were sampled at a rate of 1KHz.

Participants performed 80 repetitions of each of the eight motions in a pre-defined order. All movements originated from the resting position. Each motion was comprised of the full range of motion from the resting position to the target position, followed by 3 seconds of the hand being held in the target position. Participants were instructed to return their hand to a resting position for 3 seconds before being prompted to perform the next hand motion. To ensure that muscle fatigue was not an issue, participants were given adequate time to rest in between trials.

B. Signal pre-processing and feature measurement

The continuous streams of recorded MMG signals were subsequently spliced into individual 3-second recordings, each corresponding to one of the eight hand movements or rest. To attenuate the effects of movement, the signals were band-pass filtered with a cut-off frequency range of 5-100Hz [5].

The first 1000ms of each MMG signal was used for feature extraction. The time-domain signals were represented by a feature vector $\mathbf{A}_{D_{orig}\,xN}$, where D_{orig} is the initial feature dimensionality and N is the number of contraction samples. We measured a comprehensive set of 60 time-domain, frequency-domain and time-frequency domain features from each MMG channel. These features included RMS measures, peak and median frequencies, relative power in frequency bands, auto-regressive coefficients, moments about the mean, and wavelet coefficients. The features were concatenated for all six channels, yielding a feature vector $\mathbf{A}_{D_{orig}\,xN}$ (D_{orig}=360).

C. Feature pre-selection by Fisher Ratio Analysis

The initial feature vector $\mathbf{A}_{D_{orig}\;xN}$ consists of approximately N=640 samples (80 samples x 8 classes) of the D_{orig}=360 features (60 features x 6 channels). The first step in feature selection was to reduce the dimensionality by discarding non-discriminatory features.

Each feature in the feature vector was ranked according to its discriminatory power by evaluating its Fisher score $J_F(\mathbf{A}_d)$, where $1 \le d \le 360$. The Fisher score is a ratio of the between-class scatter $\mathbf{S_B}_d$ to the within-class scatter $\mathbf{S_W}_d$. For a multiclass problem, the Fisher criterion for the for the d^{th} feature vector $\mathbf{A}_d$ is given by,

$$J_F(\mathbf{A}_d) = \sum_{i=1}^{K-1} \sum_{j=i+1}^{K} p_i p_j (m_{i,d} - m_{j,d})^2 (p_i S_{i,d} + p_j S_{j,d})^{-1}$$

where, p_i is the priori probability of class i, and $m_{i,d}$ and $S_{i,d}$ are the mean and variance of feature d for class i, respectively [8].

For each participant, the Fisher score of each of the 360 features was computed, and the 100 linearly-independent features with the highest scores were retained. Combinations of features from this reduced feature set were used in the next step of feature selection.

D. Feature selection by the Genetic Algorithm

Selecting the optimal feature dimensionality is of paramount importance in pattern-recognition since it determines classifier accuracy and generalization. Since the size of the training set is small i.e. 64 samples per class when using 80% of the 80 hand movement samples, the upper limit on feature dimensionally should be D=14 according to [10], and may exceed D=20 if the features are correlated [11]. In this study, dimensionality was varied such that $4 \le D \le 15$, where D is an integer.

The genetic algorithm is an evolution-based optimization procedure where a solution, or chromosome, is represented as a finite sequence of 0's and 1's. Chromosomes are allowed to crossover and mutate. A finite set of solutions, the population, is evaluated by the optimization criterion function. A proportion of the best chromosomes are selected to breed a new population. The optimization process is carried out in iterations, called generations. In each generation, the new population is created through crossover, mutated and evaluated. In dimensionality reduction, the chromosome represents a subset of features, where the k^{th} bit denotes the presence or absence of the k^{th} feature. Each chromosome in the population is evaluated according to its classification accuracy. For a detailed description on GAs for feature selection, please refer to [12].

In this study, a 100-dimensional feature vector, previously reduced by Fisher analysis, is further reduced to D-dimensional feature sets ($4 \le D \le 15$). The solutions for each dimensionality were found from GA searches comprising of 100 generations, each with a population of 1000 chromosomes, a 50% cross-over rate, and a 30% mutation rate. The optimization criterion here was the average eight-class classification rate of the selected features on the training data using five-fold cross validation with a linear discriminant analysis (LDA) classifier. For each dimensionality, the search consisted of six runs of the GA for randomly selected initial populations. The best feature-set over all the runs was selected for subsequent evaluation of the MMG classifier.

E. Error estimation

Fisher's LDA classifier was employed for performance evaluation since it is simple to train and has proved to be reliable even for a small number of training samples if the number of features is not too large [10]. Pattern recognition performance was evaluated using five-fold cross-validation. For each participant, the feature-set suggested by the GA was used to train and test the LDA classifiers offline.

III. Results

Figure 2 is an example of a typical MMG signal recorded from sensors on the surface of a forearm showing the transient and steady-state components accompanying a hand movement. The transient signal lasts for approximately 600ms. MMG signals spliced at 1000ms from the initiation of contraction were classified, and the accuracies for discriminating among eight classes of forearm muscle activity were evaluated. Table 1 shows the classification accuracies for each participant, reported as the average accuracy over the five folds used in cross-validation. The highest mean accuracy across all participants was 93±9% when D=15. Participant #1 consistently produced the best results, with average accuracies up to 97±1%. In contrast, the classification accuracies for Participant #2 and #9 were below 90% regardless of feature dimensionality.

Accuracies initially increase by at least 2% for each increment in dimension, and the advantage of increased dimensionality eventually plateaus, showing no significant differences for 9≤ D≤ 15 (p=0.05). On comparing the individually selected feature set recommended by the GA for each participant, it was observed that some features, such as the cepstral coefficients [13], were common to most participants. Classification accuracies of 88±7% were attained for the 8-class problem (D=15) using cepstral features alone.

Table 1: Classification accuracies

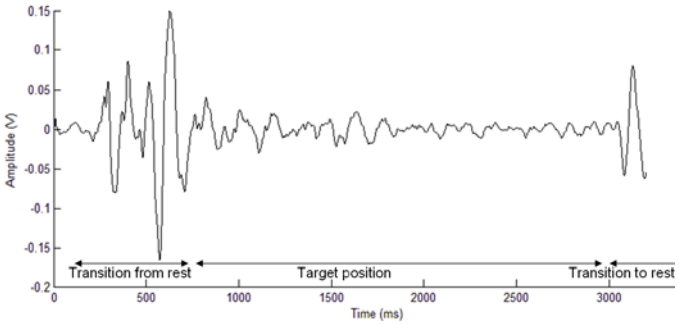

Figure 2. Typical MMG from a forearm muscle during hand movement.

IV. Discussion

A. Features

While the feature-sets were not common among participants, the GA was useful in suggesting common discriminatory features that may be useful when training time is an issue. Many of the GA-selected features stemmed from cepstral coefficients, which have been important for speech and speaker recognition applications [13]. The frequent inclusion of these features in the GA-selected feature set may indicate differences in the spectral patterns of MMG signals generated during different classes of forearm muscle activity.

B. Feature Dimensionality

For a finite sample size, classification accuracy is known to increase to a maximum and subsequently decline as dimensionality increases [14]. Lower dimensionality is associated with greater generalization, and hence greater credibility. As dimensionality is increased, classification accuracy increases sharply until D=6 at which point there is a gradual increase until D=9. For D>9, the increase in accuracy is insignificant until D=15. This suggests that at least 10 features are required for good separability among the classes. Since the peaking phenomenon was not observed, the maximum classification accuracy may be attained for D>15. However, the increase in dimensionality may not be warranted given the small training sample size.

	No. of features											
	4	5	6	7	8	9	10	11	12	13	14	15
Participant												
1	85 ± 2	88 ± 4	91 ± 2	93 ± 1	94 ± 2	95 ± 2	95 ± 2	96 ± 3	96 ± 1	97 ± 1	97 ± 1	97 ± 1
2	64 ± 3	68 ± 6	72 ± 8	76 ± 3	78 ± 4	79 ± 3	79 ± 3	82 ± 6	82 ± 4	83 ± 1	84 ± 2	84 ± 6
3	80 ± 1	82 ± 2	86 ± 2	88 ± 2	89 ± 4	91 ± 2	91 ± 5	92 ± 2	93 ± 3	92 ± 4	93 ± 1	93 ± 4
4	75 ± 2	81 ± 3	84 ± 3	85 ± 1	87 ± 2	89 ± 3	90 ± 2	90 ± 2	91 ± 2	92 ± 3	92 ± 2	92 ± 2
5	81 ± 4	86 ± 2	88 ± 2	91 ± 2	93 ± 2	94 ± 3	94 ± 2	95 ± 2	95 ± 2	96 ± 1	97 ± 2	97 ± 1
6	83 ± 3	87 ± 3	89 ± 1	92 ± 3	93 ± 2	94 ± 2	94 ± 2	95 ± 2	96 ± 3	96 ± 1	96 ± 2	97 ± 1
7	74 ± 4	78 ± 3	80 ± 4	83 ± 1	86 ± 3	86 ± 3	89 ± 3	89 ± 2	90 ± 1	89 ± 2	91 ± 3	91 ± 3
8	77 ± 3	82 ± 5	84 ± 4	86 ± 1	89 ± 2	89 ± 2	91 ± 3	92 ± 1	92 ± 1	94 ± 2	94 ± 3	94 ± 1
9	67 ± 5	70 ± 5	74 ± 5	77 ± 5	79 ± 3	82 ± 4	82 ± 4	84 ± 2	84 ± 4	85 ± 5	87 ± 2	86 ± 3
Average Accuracy	76 ± 9	81 ± 12	84 ± 12	86 ± 7	88 ± 8	89 ± 8	90 ± 9	91 ± 8	91 ± 8	92 ± 8	93 ± 6	93 ± 9

Results are reported as mean±std values for each participant over all five folds of cross-validation. Mean±SD accuracies over all participants are shown.

C. Classifier

At each generation of the GA, the classifier had to be trained and evaluated at all points in the population. We selected thee LDA classifier since it has low training and evaluation complexity ($O(D^2N)$). Since the GA employs an LDA classifier in its feedback loop, there is a greater tendency for the GA to select features that are linearly separable. However, the classes of hand-function in the GA-selected feature space may only be partially linearly separable. This may be the cause of lower classification accuracies reported for Participants #2 and 9. The use of non-linear classifiers, such as radial basis networks, may provide better accuracies in some cases.

D.MMG signal duration

The MMG signal itself is a low frequency signal, with the dominant frequency lying below 20Hz [15]. It may therefore be unreasonable to expect small durations of the signal (less than 500ms) to yield reliable classification results. The one-second of data required for classification may lead to response delays that may not be suitable for applications such as prosthesis control. Since there is a trade-off between response time and classification accuracy, the classifier design should be customized to the speed and accuracy requirements of the user and the application. An individual without a reliable access pathway may be tolerant to response delays greater than 1s when controlling their communication aid or environment control unit.

E. Limitations and future work

Since MMG is affected by motion artefact, its measurement is only meaningful in well-controlled environments. In this study, although the measurement sites were stationary, a sensor comprising of a coupled microphone-accelerometer pair was used to record MMG, and could provide a method for source separation in the presence of extraneous movement [16].

While trials on able-bodied participants are common in determining the feasibility of access solutions, able-bodied performance may not always be relevant to the performance of the severely disabled. Concerns for the target population include the ability to produce multiple activation patterns, the minimum muscle force required for discernable MMG signals, and the ability of the data recorder to verify the integrity of the training-set when the muscle activation pattern does not accompany observable physical movement.

The proposed pattern-recognition paradigm requires further development, such as real-time data acquisition, segmentation, feature extraction and classification, before it can be considered for practical use.

V. Conclusion

The results of this study verify the hypothesis that MMG signals reflect multiple distinctive patterns of muscle activity. Multi-site MMG signals generated during multiple forearm activation patterns are discernable with high accuracy using simple classifiers and prudently selected features. This suggests that MMG could potentially be used as an alternative control signal to EMG where the latter is contraindicated.

Acknowledgements

This work was supported in part by the Ontario Graduate Scholarship and Natural Sciences and Engineering Research Council of Canada.

References

[1] C. Orizio, "Muscle sound: bases for the introduction of a mechanomyographic signal in muscle studies," *Crit. Rev. Biomed. Eng.,* vol. 21, pp. 201-243, 1993.

[2] K. Englehart and B. Hudgins, "A robust, real-time control scheme for multifunction myoelectric control," *IEEE Transactions on Biomedical Engineering ,* vol. 50, pp. 848-854, 2003.

[3] Y. L. Chen, J. S. Lai, J. J. Luh and T. S. Kuo, "SEMG-controlled telephone interface for people with disabilities," *J. Med. Eng. Technol.,* vol. 26, pp. 173-176, Jul-Aug. 2002.

[4] C. N. Huang, C. H. Chen and H. Y. Chung, "Application of facial electromyography in computer mouse access for people with disabilities," *Disabil. Rehabil.,* vol. 28, pp. 231-237, Feb 28. 2006.

[5] P. Madeleine, P. Bajaj, K. Sogaard and L. Arendt-Nielsen, "Mechanomyography and electromyography force relationships during concentric, isometric and eccentric contractions," *J. Electromyogr. Kinesiol.,* vol. 11, pp. 113-121, Apr. 2001.

[6] K. Akataki, K. Mita and M. Watakabe, "Electromyographic and mechanomyographic estimation of motor unit activation strategy in voluntary force production," *Electromyogr. Clin. Neurophysiol.,* vol. 44, pp. 489-496, Dec. 2004.

[7] C. Orizio, D. Liberati, C. Locatelli, D. De Grandis and A. Veicsteinas, "Surface mechanomyogram reflects muscle fibres twitches summation," *J. Biomech.,* vol. 29, pp. 475-481, Apr. 1996.

[8] M. Loog, R. P. W. Duin and R. Haeb-Umbach, "Multiclass linear dimension reduction by weighted pairwise Fisher criteria," *IEEE Transactions on Pattern Analysis and Machine Intelligence ,* vol. 23, pp. 762-766, 2001.

[9] J. Silva and T. Chau, "Coupled microphone-accelerometer sensor pair for dynamic noise reduction in MMG signal recording," *Electronics Letters,* vol. 39, pp. 1496-1498, 2003.

[10] S. J. Raudys and A. K. Jain, "Small sample size effects in statistical pattern recognition: recommendations for practitioners," *IEEE Transactions on Pattern Analysis and Machine Intelligence ,* vol. 13, pp. 252-264, 1991.

[11] J. Hua, Z. Xiong, J. Lowey, E. Suh and E. R. Dougherty, "Optimal number of features as a function of sample size for various classification rules," *Bioinformatics,* vol. 21, pp. 1509-1515, Apr 15. 2005.

[12] Siedlecki W. and Sklansky J., "A note on genetic algorithms for large-scale feature selection," *Pattern Recogn.Lett.,* vol. 10, pp. 335-347, 1989.

[13] B. S. Atal, "Effectiveness of linear prediction characteristics of the speech wave for automatic speaker identification and verification," *J. Acoust. Soc. Am.,* vol. 55, pp. 1304-1322, Jun. 1974.

[14] A. K. Jain, R. P. W. Duin and J. Mao, "Statistical pattern recognition: a review," *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 22, pp. 4-37, 2000.

[15] C. Orizio, R. Perini, B. Diemont, M. Maranzana Figini and A. Veicsteinas, "Spectral analysis of muscular sound during isometric contraction of biceps brachii," *J. Appl. Physiol.,* vol. 68, pp. 508-512, Feb. 1990.

[16] J. Silva and T. Chau, "A Mathematical Model for Source Separation of MMG Signals Recorded With a Coupled Microphone-Accelerometer Sensor Pair," *IEEE Transactions on Biomedical Engineering,* vol. 52, pp. 1493-1501, 2005.