GENERALIZING A MULTIVARIABLE FATIGUE ESTIMATOR

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INTRODUCTION

Localized muscle fatigue has been described by De Luca [1] as a type of physiological fatigue induced by sustained muscular contraction and associated with a reduced capacity to maintain a given output force level. This reduction in ability is the result of changes in the physiological processes within the muscle. In order to assess the level of fatigue a muscle is experiencing, these changes must be somehow monitored and quantified. Directly tracking the physiological processes in a muscle as it performs a contraction is a very difficult and impractical task, however, monitoring the surface myoelectric signal (MES) is a non-invasive way to observe the electrical manifestations of the physiological events. Myoelectric parameters such as conduction velocity [2], mean and median frequency [1] and instantaneous mean frequency [3] have all been investigated in search of a myoelectric parameter which most accurately estimates fatigue. When muscle force and joint angle are constrained to be fixed for the duration of the contraction, hereon termed a static contraction, evaluation of the mean frequency (MF) has emerged as the gold standard for muscle fatigue assessment. However, under dynamic conditions, when muscle force and joint angle are unconstrained, other factors have an effect on the frequency content of the surface MES and therefore on its calculated MF. The most notable of these effects is the time-varying spatial filter which results as detectable motor units move relative to the detecting electrodes. [1] These confounding conditions make it very difficult to find a single parameter which can estimate fatigue under dynamic conditions.

To overcome these limitations, MacIsaac has developed a multivariable approach which considers multiple parameters extracted from the MES and uses an artificial neural network (ANN) to adapt a function which tracks fatigue. [4] This methodology, known as the mapping index (MI), requires baseline data collected from each participant in order to train the individual functions. Fatigue may then be estimated from subsequent data using the trained function. While this approach has yielded a significant improvement over MF when estimating fatigue under dynamic conditions, collecting baseline data in a practical context may not be feasible.

This work is an extension of MI and proposes a generalized function which is trained using baseline data from multiple individuals.

METHODOLOGY

The goal of this work was to compare the ability to estimate fatigue of the generalized mapping index (GMI) to that of MI and MF under static and dynamic contraction conditions. Five healthy participants, 2 female and 3 male, aged 25, 22, 19, 30 and 26 completed two sets of fatigue tests (baseline and test data). Each set consisted of three fatigue tests, one for each of static, cyclic and random contractions, totaling six tests per participant.

A third set of data consisting of static, cyclic and random data from four participants previously collected by MacIsaac [4] was added to the baseline data to train the GMI functions. The baseline data was used to train the individual functions according to the MI methodology and the test data was used to estimate fatigue using both the GMI and MI functions.

Fatigue Test Protocol

In order to maintain consistency among data sets, the testing protocol, apparatus and data acquisition system previously described by MacIsaac [4] was implemented. MES was collected from the right brachial biceps muscle as the participant performed the prescribed contraction with each participant using a weight of approximately 30% of maximum voluntary contraction at 130º joint angle. An ergometer attached to the apparatus allowed visual feedback to the participant in the form of an onscreen bar plot. By following as closely as possible a second, computer-generated bar plot, the user performed the desired contraction.

In order to confirm a fatiguing process, dynamic (cyclic and random) contractions were interrupted for the first ten seconds of each minute. During this time a static contraction was held at 90º joint angle and a MF calculation was done. A statistically significant negative slope of these readings was used to confirm that the muscle had fatigued.

Data Processing

The intermittent periods of static contraction, termed fatigue confirmation segments, were removed from the data. For static contractions, the first ten seconds of each minute was used and for dynamic contractions, the joint angle data was used to identify the appropriate portions. Fatigue was confirmed using a regression analysis of MF values, one per segment, each calculated from a periodogram estimated by averaging 0.5 s, 50% overlapped Hamming windows.

The remaining dynamic MES was segmented as follows: static and random data were divided into equal length 5 s. segments and cyclic data was segmented with one cycle per segment, beginning and ending at the minimum joint angle. While the cyclic segments were invariably different lengths, the period of the cyclic contraction was approximately 5 s.

Myoelectric parameters which form a feature vector that characterizes each segment were then extracted. The set of four time-domain parameters were those used by MacIsaac [4] and previously described by Hudgins [5]: mean absolute value, the number of zero crossings, the number of slope sign changes and the waveform length. These parameters are well suited to characterizing fatigue because they are easy to calculate and provide information about both the amplitude and frequency content of the MES, parameters that have been shown to vary with fatigue. [1]

Function Training

The individual functions were trained with the baseline data from a single fatigue test corresponding to the participant and contraction condition. A fully connected multi-layer perceptron (MLP) network with four input neurons and one output neuron was trained with a backpropagation algorithm as MacIsaac found this network architecture outperformed others. [4] The set of feature vectors was divided into training and validation data such that feature vectors from segments 1,3,5,.. formed the training data and feature vectors from segments 2,4,6,… formed the validation data. While training the MLP, the validation data was used to verify the progress of the training and to implement an early stopping criterion based on a sufficiently low output RMS error when comparing the network outputs to the desired outputs.

In order to provide a complete set of training data, the desired outputs must accompany the set of training and validation inputs. It was assumed that fatigue progressed in a linear, monotonically decreasing fashion beginning at 1 (no fatigue) at the start of the contraction and ending at 0 (completely fatigued) at the end of the contraction. While the true nature of the progression of fatigue remains largely unknown, the linear assumption is sufficient to demonstrate the feasibility of the MI and GMI methodologies.

When training a generalized function, the same MLP ANN architecture was used. Considering the previously collected data and newly collected baseline data as a single large set of baseline data from nine participants, the function which will estimate fatigue for a particular participant and contraction type was trained using the baseline data of the other eight participants under the same contraction conditions. Multiple data sets were combined into a single large training set by concatenating the individual training sets, each complete with corresponding targets. A single validation set was formed similarly.

Estimating Fatigue

With the GMI and MI functions trained, they were then used to estimate fatigue from the test data. A fatigue estimate is comprised of the sequence of outputs from the trained function when presented with the myoelectric feature vectors from the test data in chronological order. A comparison of results was then made where the figure of merit for fatigue assessment was the signal to noise ratio (SNR) defined as:

$$SNR = \frac{R}{E_{RMS}} = \frac{\max[\hat{s}(n)] - \min[\hat{s}(n)]}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}[s(i) - \hat{s}(i)]^2}} \qquad (1)$$

where s(n) is the fatigue estimate and ŝ(n) is the line of best fit of s(n).

RESULTS

Figure 1 shows a sample of MI, GMI and normalized MF fatigue estimates from the test data under static, cyclic and random contraction conditions. These results were typical of all subjects. Figure 2 shows the SNR values of the fatigue estimates averaged across participants. To compare the various indices of fatigue, a Bland and Altman analysis [6] was completed. Table 1 lists the 90% confidence intervals for the mean bias between pairs of measurements under each contraction condition. If a mean bias of zero is not within the given confidence interval, then it can be inferred that the measurements are statistical different.

Examination of Table 1 leads to the conclusion that there was a significant difference between GMI and MF under all contraction conditions and that there was no significant difference between GMI and MI, nor between MI and MF under all contraction conditions.

DISCUSSION

From the statistical analysis it can be concluded that GMI performs as well as MI under all contraction conditions. That is, functions trained from the baseline data of other individuals can estimate fatigue as well as those trained from the baseline data of the individual.

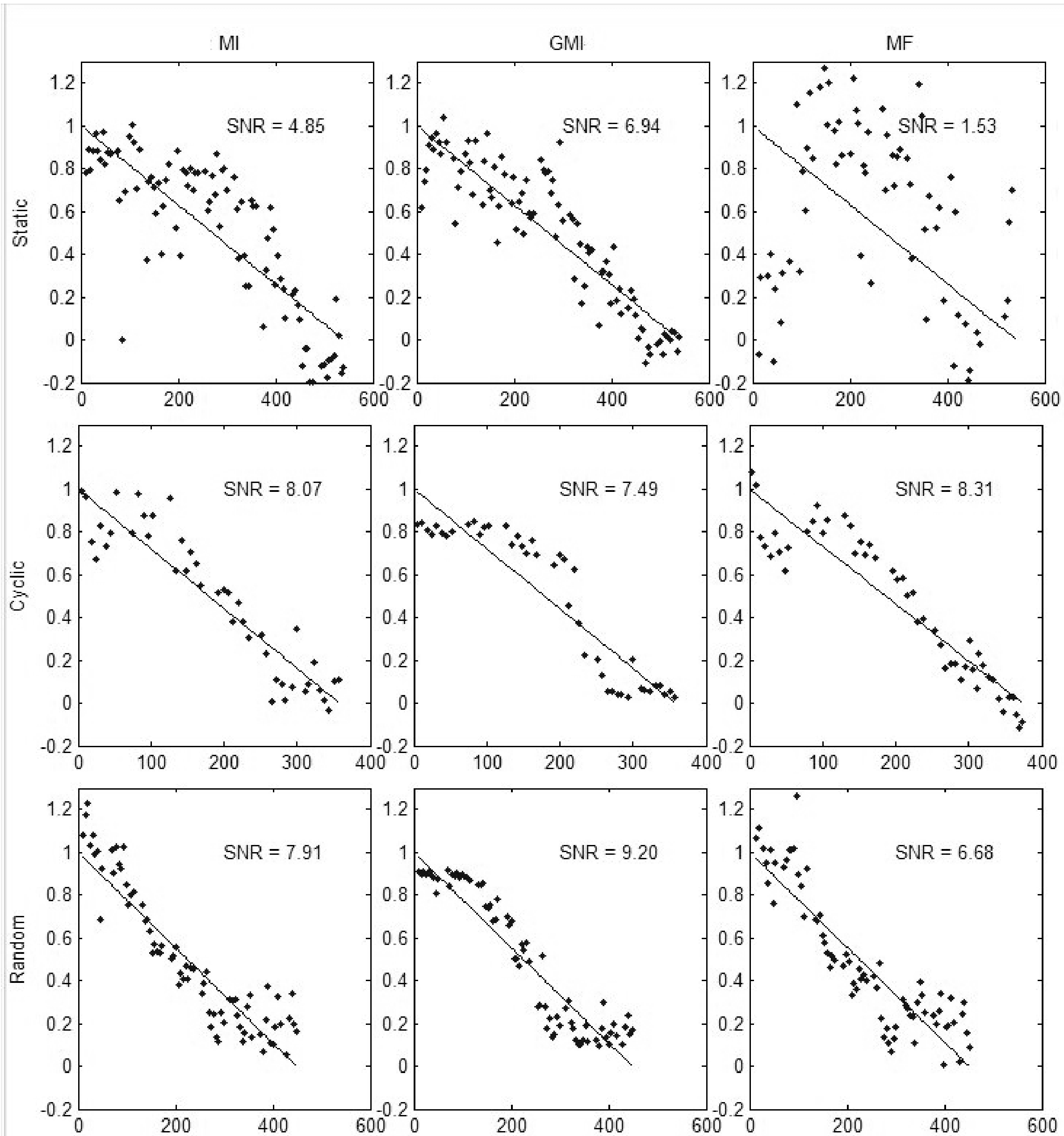

Figure 1: GMI, MI and normalized MF fatigue estimates from test data of participant 7 under static, cyclic and random contraction conditions

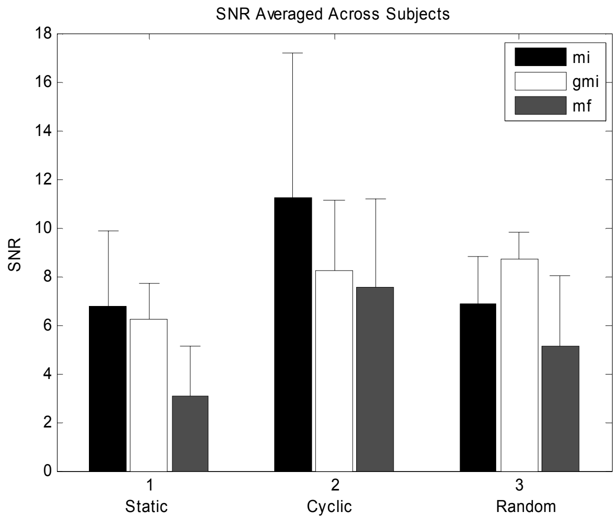

Figure 2: Signal to noise ratios averaged across participants for MI, GMI and MF fatigue estimates from test data.

Table 1: Bland and Altman mean bias 90% confidence intervals for comparing GMI, MI and MF fatigue estimates.

Contraction Conditions	**Mean bias 90% confidence interval**			
	Indices compared		***Lower bound***	***Upper bound***
Static	MI	GMI	-1.44	1.90
	MI	MF	-0.555	7.92
	GMI	MF	0.798	6.10
Cyclic	MI	GMI	-3.36	6.98
	MI	MF	-0.936	8.30
	GMI	MF	0.109	3.64
Random	MI	GMI	-3.23	1.40
	MI	MF	-1.44	4.95
	GMI	MF	0.563	4.77

Inspection of the confidence intervals comparing MI to MF shows that several nearly exclude zero. It is possible that with further investigation using a larger number of participants that a statistically significant difference might be found

It was observed in many subjects (and visible in Figure 1) that fatigue often appears not to progress in a linear manner but often follows a curvi-linear or piece-wise linear path. This suggests that the use of non-linear targets when tuning the functions bears further investigation.

It was also noted in some subjects that MF estimates were highly variable, leading to a low SNR while MI and GMI were unaffected. It is believed that this emphasizes the strength of the multivariable approach to fatigue estimation, allowing other parameters to be emphasized when one appears less correlated with fatigue.

The MI and GMI methodologies have yet to be thoroughly optimized. Ongoing research is examining richer feature sets such as those extracted from the time-frequency representation of the MES. Other parameters such as the segment length and the selection of targets, as previously mentioned, are also under investigation. It is hoped that with further honing of this methodology that a significant improvement over MF will be achieved at a confidence level of at least 95%.

CONCLUSION

This work has shown the ability to train a generalized function to estimate fatigue from the data of different individuals. This represents substantial progress toward the development of a clinically viable tool for localized muscle fatigue assessment under dynamic contraction conditions.

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