Optimal Elbow Angle for Extraction of sEMG and MMG Signals During Dynamic Fatiguing Contractions

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ABSTRACT

Electromyography (sEMG) and Mechanomyography (MMG) signals of the biceps muscle acquired from thirteen subjects undertaking fatiguing dynamic contraction. Both the sEMG and MMG signals were divided into Non-Fatigue and Fatigue segments. A genetic algorithm generated elbow angles which best distinguished (using DBI) between Non-Fatigue and Fatigue contents of the signal. Determining the optimal elbow angle for feature extraction utilised in the evolutionary process was based on 70% of the conducted trials (both sEMG and MMG). The best individual evolution run was selected based on the optimal elbow angle for separation between the fatigue classes, before testing the classification performance on the remaining on 30% of the data. The results were compared to eight parameters to measure the classification performance. Results consistently show that the pseudo-wavelet generated the highest classification results of the fatigue content in both signal modalities; however, the sEMG signal performed better than the MMG signals.

Keywords

Genetic Algorithms, Localised Muscle Fatigue, Electromyography, Mechanomyography, Wavelet analysis, Pseudo-wavelets, Elbow Angle

1. INTRODUCTION

There are different techniques to detect muscle fatigue; however, mechanomyography (MMG) and surface electromyography (sEMG) have been widely researched review. In MMG it is the mechanical signal from the surface of a contracting muscle that is measured, i.e., movement of the muscle fibres create vibrations that are recorded orizio. Electrical signal detected during muscle contraction is called the myoelectric signal. Some properties of this signal represent myoelectrical manifestation of muscle fatigue [1].

A goniometer can be used as an indicator of localised muscle fatigue, and albeit it can be used in isolation to determine muscle fatigue, it is often used in conjunction with other methods (such as sEMG and MMG). When conducting a sustained task (static or dynamic), fatigue occurrence will cause a drop in the joint angle to a certain threshold. Masuda *et al.* investigated this fatigue threshold in the knee at a 90° joint angle during static and dynamic contractions by merging features inferred from the sEMG signals with goniometer and temperature data [2]. Ravier *et al.* utilised a goniometer for a comparison of shifts in the elbow angle at 100° for static contractions in the biceps brachii to demonstrate the changes in the median frequencies of the EMG signal at fatigue occurrence [3].

Manifestation of muscle fatigue of the sEMG signal is often researched using signal amplitude, muscle fibre conduction velocity (MFCV) and the frequency content of the signal when analysing the sEMG signal [4, 5, 6, 7, 2, 8, 9]. MMG signal detection can be applied to muscle activity in both dynamic and isometric contractions. Research on localised muscle fatigue in dynamic contractions has investigated changes in the MMG amplitude during fatigue [10, 11, 12, 13, 14, 15].

Due to the stochastic nature of the sEMG and MMG signal from dynamic contractions, wavelet functions has been suggested as a preferred method for signal analysis. The wavelet transform (WT) decomposes a signal into numerous multi-resolution components [16, 17], which can be used to detect and characterise the short time components within a non-stationary signal, providing information regarding the signal's time-frequency. Studies on muscle fatigue have utilised WFs for sEMG signals [18, 19, 20, 21] and MMG signals [22, 23, 24, 25, 26]. Kumar *et al.* discussed the effectiveness of decomposing the EMG signal to measure its power in order to identify muscle fatigue as an automated process [18].

Previous studies have applied various classification techniques for SEMG signals in localised muscle fatigue that may also be utilised in studies using MMG signals [27, 28]. These include genetic programming and genetic algorithms [29, 30, 31, 32], statistical analysis [33, 34, 35], as well as classification methods to predict fatigue by using neural networks [36] or linear discriminant analysis (LDA) [37].

A variation of these techniques have been adapted in this research where the GA utilises a pseudo-wavelet as the feature extraction method for finding the optimal angle for clas-

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sification of fatigue content in the sEMG and MMG signal.

2. METHODS

The pseudo-wavelet was used as a feature extraction method by the GA to find the optimal elbow angle that best separate between Non-Fatigue and Fatigue segments of the recorded signals (both sEMG and MMG). The pseudo-wavelet developed in this research uses scaling function (phi) coefficients that are best suited to find the optimal shape for our application. The aim was to develop a custom-made wavelet-like shape suitable for join-time frequency decomposition for muscle fatigue detection. Random values for the scaling function coefficients were first used that were evolved by the GA.

2.1 Data Recording and Pre-processing

Thirteen athletic, healthy male subjects (mean age 27.5 +/- 3.6 yr) volunteered for this research. The study was approved by the University of Essex's Ethical Committee and all subjects signed an informed consent form prior to taking part in the study.

The participants, all non-smokers, were seated on a 'preacher' biceps curl machine to ensure stability and biceps isolation while performing biceps curl tasks. The participants reached physiological fatigue and was encouraged during the trial to reach the complete fatigue stage (unable to continue the exercise).

The MMG signal was recorded using a 3-axis accelerometer (Biometrics, ACL300 (range +/- 10G).. A flexible electrogoniometer (Biometrics Ltd.) was placed on the lateral side of the arm to measure the elbow angle and arm oscillations. For the sEMG electrodes (Biometrics Ltd., Model SX230W) were placed on the participant's biceps brachii'and a goniometer (Biometrics Ltd.) was placed on the lateral side of the arm to measure the elbow angle and arm oscillation.

The recorded signals were divided into Fatigue and Non-Fatigue epochs. This information was later utilised to train and test the classifier.

2.2 Genetic Algorithms

The genetic algorithm was also utilised to find the optimal elbow angle for both the sEMG and MMG signals, by using the pseudo-wavelet as a feature extraction method (see further explanations in the section on evolved elbow angle selection below). Out of the trials, 70% were used for the testing phase, while the remaining 30% were utilised in the testing phase. This method was applied to both the sEMG and the MMG signals.

Table 1 displays the parameter setting for the GA runs.

The evolved pseudo-wavelet uses scaling function (phi) coefficients from 1 to 19, having a wide range to determine the most optimal scale for class discrimination. The modified Davies Bouldin Index (DBI) was chosen in the fitness function, due to the DBIs simplicity and effectiveness [38]. Smaller DBI values indicate better class separation. The joint-time frequency decomposition by the pseudo-wavelet was obtained for every scale (1-19) and extracted in one second intervals to determine the DBI between the two classes (i.e., Fatigue and Non-Fatigue). This again helped the evolutionary processes by intending to minimise the DBI, which then allows the fitness function to increase the separation between the two classes.

Table 1: Parameter settings for the GA runs

Parameter	Value
Independent runs	25-28
Population size	5000
Maximum number of generations	20
Mutation probability	10%
Crossover probability	90%
Selection type	Tournament, size 5
Termination criterion	Maximum number of generations

2.3 Evolved elbow angle selection

To find the optimal elbow angle for fatigue detection in the biceps brachii, the GA used the pseudo-wavelet as the feature extraction technique. The pseudo-wavelet used as a feature extraction has been developed in previous research [32, 28, 27]. A window of both the recorded sEMG and MMG signal was selected based on the starting elbow angle and the ending elbow angle. The starting and ending elbow angle (a window) was decided by the evolutionary process of the GA through testing the separation (DBI) of the two stages of fatigue (Fatigue and Non-Fatigue). The starting and ending angles that generated the best separation of the signals were later utilised in the classification stage.

2.4 Feature Extraction Techniques

The GA used different feature extraction methods for comparison purposes, such as Higher-Order statistics (HO2 and HO3), Mean Frequency (MF), Median Frequency (MDF), Power Spectrum Density (PSD), Root Mean Square (RMS), Daubechies 4 (Db4) and Mexican Hat (Mex H).

3. VALIDATION/ CLASSIFICATION

For a comparison between the evolved pseudo-wavelet and other commonly used wavelet functions, LDA (linear discriminant analysis) was chosen. The decomposed signal from the pseudo-wavelet was the input for the training and testing phase of the LDA classifier. As was the case in the evolutionary process, the classifier was trained using 70% the trials, followed by testing with the remaining 30% of the trials. It must be noted that the decomposition scale value of the eight compared standard wavelet functions (see Wavelet Decomposition above) matched the decomposition scale value of the evolved pseudo-wavelet function, enabling a meaningful comparison.

Establishing the optimal elbow angle for feature extraction used in the evolutionary process was also based on 70% of the conducted trials for training purpose for both the sEMG and MMG signals. The best run containing the best separation value was selected and then tested on the remaining 30% of the data to measure the classification performance. For a comparison between the evolved pseudo-wavelet and other feature extraction methods, LDA (linear discriminant analysis) was also selected. The various features extracted from the different signals were the input for the training and testing phase of the LDA classifier.

4. RESULTS

This study has several interesting findings. Using the GA to select the optimal wavelet for fatigue classification was successful for the two different signal detection methods. The GA was also able to find the optimal scale for signal decomposition, although the scale differed from sEMG and MMG signals In addition, the classification performance of the pseudo-wavelet outperformed the classification of the other traditional wavelets for both signal acquisition techniques. The GA selected the optimal wavelet dependent upon the solution representation, where it finds the improvements based on the fitness function of the final evolved population with the best DBI scoring.

Another observation of the results was the correlation between the shape of the wavelet and the optimal scale. The shape of the wavelet affects the selection of the optimal scale that best discriminate between Fatigue and Non-fatigue content of the signals. This finding falls in line with Kumar et al.'s [18] result that certain wavelet functions at certain scales can best contrast between Fatigue and Non-Fatigue, although in their case the results was only based on sEMG signals. In the present study, the GA selected the optimal scale based on the wavelet function, which eliminated human subjective choice of the recommended wavelet functions for fatigue content analysis. By using the DBI, the GA selected the optimal scale for decomposing the signals. The optimal scale finds the highest separability between the fatigue classes (Fatigue and Non-Fatigue).

Figure 1 and Figure 2 illustrate a scatter plot 1a and 2aof the selected joint angles by all the GA runs. Additionally, Figure 1b and Figure 2b display a histogram of the joint elbow angles, where the frequency of joint elbow angles selected by all the GA runs are shown.

Figure 1: A scatter plot and a 3D histogram of elbow joint angles that was selected by 26 evolutionary runs from the sEMG signals

(a) A scatter plot of elbow angles selected by the GA. (larger dots indicate better separation)

(b) 3D histogram of elbow joint angles selected by all the GA runs

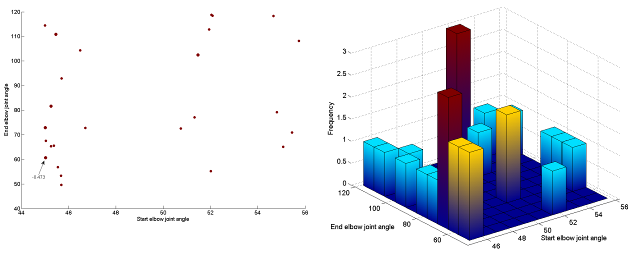
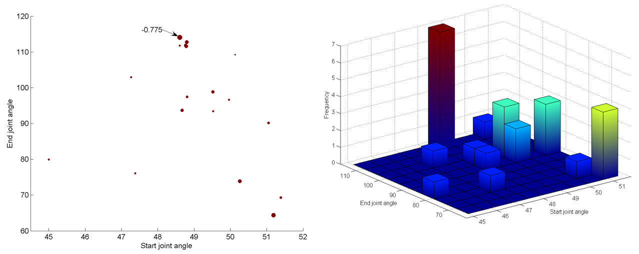


Figure 2: A scatter plot and a 3D histogram of elbow angles that was selected by 26 evolutionary runs from MMG signals

(a) A scatter plot of elbow angles selected by the GA. (larger dots indicate better separation)

(b) 3D histogram of elbow angles selected by the GA



The classification performance for the 13 subjects using the 9 various parameters is displayed in Table 2 and Table 3. The findings demonstrate that the elbow joint angles selected by the GA facilitated a classification of the two classes (Non-Fatigue and Fatigue) with remarkable performance based on the different features, giving a range from 72.95% and to 87.90% classification performance for the sEMG signal and ranging from 52.74% and up to 80.63% classification of the MMG signal. In addition, the pseudo-wavelet was the parameter that obtained the best classification average, with the lowest standard deviation. The average classification accuracy for the pseudo-wavelet was substantially higher than the average classification accuracy for the other feature extraction techniques. The parameter that gave the second highest average classification was also a wavelet, which was Db4 for the sEMG signal and Mexican Hat for the MMG signal.

Table 2: Classification performance of sEMG signals

Subjects	HO2	HO3	Mean freq	Median Freq	PSd	RMS	Db4	Mexican Hat	PW
1	83.58	83.58	88.06	82.84	80.60	88.29	86.57	17.16	90.99
2	94.89	91.97	94.89	89.05	90.51	96.35	93.43	90.51	94.16
3	79.69	76.56	78.91	66.41	74.22	78.91	85.16	69.53	85.94
4	68.52	67.28	82.72	74.07	64.20	82.72	83.95	80.25	88.27
5	74.12	71.93	80.70	73.25	71.49	79.39	83.77	79.39	81.58
6	86.79	88.68	91.51	83.96	86.79	89.62	90.57	84.91	93.40
7	75.17	73.15	83.89	79.19	71.14	83.22	77.18	83.89	82.55
8	73.33	74.81	71.11	65.19	75.56	73.33	79.26	71.11	87.41
9	91.18	89.71	88.24	85.29	91.18	92.65	94.12	89.71	92.65
10	71.19	68.64	83.05	74.58	69.49	81.36	85.59	77.97	86.44
11	59.46	63.06	63.96	66.67	62.16	67.57	81.98	67.57	93.69
12	53.44	53.05	62.60	53.82	56.49	64.50	64.12	53.05	83.59
13	69.14	69.14	82.72	79.01	66.67	83.95	82.10	83.33	82.10
Average	75.42	74.74	80.95	74.87	73.88	81.68	83.68	72.95	87.90
st.dev	11.87	11.32	9.81	9.88	10.83	9.25	7.72	19.65	4.67

Table 3: Classification performance of MMG signals

Subjects	Ho2	Ho3	Mean freq	Median Freq	Psd	RMS	Mexican Hat	PW
Subject 1	39.01	58.24	57.69	68.68	46.15	47.80	59.20	87.36
Subject 2	67.42	71.35	91.01	70.79	80.34	89.33	81.12	83.92
Subject 3	38.46	63.74	56.59	69.23	66.48	62.09	58.62	79.89
Subject 4	40.62	60.93	81.46	60.93	78.15	79.47	78.73	81.34
Subject 5	44.76	33.47	34.27	52.02	72.18	29.03	76.13	77.78
Subject 6	32.98	70.21	75.53	77.66	74.47	75.53	70.45	70.45
Subject 7	39.64	71.07	60.71	72.86	43.93	45.36	82.59	92.31
Subject 8	49.02	72.06	75.00	66.18	75.00	25.00	52.28	70.56
Subject 9	84.34	89.16	90.36	89.16	85.54	85.54	86.67	88.00
Subject 10	64.66	74.44	58.65	70.68	53.38	54.14	87.30	84.92
Subject 11	65.31	64.29	69.39	64.29	60.20	59.18	75.58	74.42
Subject 12	49.64	46.04	55.76	53.96	56.83	53.60	60.23	67.18
Subject 13	69.16	69.16	71.03	76.64	58.88	66.36	75.82	90.11
Average	52.69	64.93	67.50	68.70	65.50	59.42	72.67	80.63
st.dev	15.74	13.73	15.78	9.87	13.33	19.99	11.55	8.11

5. DISCUSSION

Wavelet analysis was utilised to take into account the stochastic and transitory nature of the sEMG and MMG signal from fatiguing dynamic contractions. A genetic algorithm was chosen as the method to evolve an optimal solution by tuning a pseudo-wavelet function for its optimal decomposition of signals targeted in extracting muscle fatigue content.

In this study a GA successfully determined the optimal elbow angles by utilising a window giving the highest separability between fatigue and Non-Fatigue segments of both the sEMG and the MMG signal. Utilising signals from dynamic contractions gives a consistent movement of the elbow angle, which was overcome by choosing a window of optimal elbow angle. Using the GA for selecting the optimal window is a far better solution than subjectively choosing one specific elbow angle degree.

The GA runs gave different separation indexes. Results show that for the sEMG signal emanating from dynamic contractions the fatigue content is in the smallest elbow angles, a consistent finding with the previous literature [39, 40, 41]. For the MMG signal the best run had the widest range of the starting and ending joint angle, although this finding is not consistent throughout the different runs. Even the runs with smaller elbow angles produced good classification results between the two fatigue classes (Fatigue and Non-Fatigue.

The sEMG signal is consistently outperforming the classification results from the MMG signal, the reason being that the MMG signal is very chaotic and is not the preferred method for signal analysis from fatiguing dynamic contractions [42, 43]. For both the sEMG and the MMG signals, the classification performance of the pesudo-wavelet outperformed the classification of the other comparable features, demonstrating great consistency through both signal detection methods. The feature obtaining the second best classification results was a wavelet function (Db4 and Mexican Hat) for sEMG and MMG signals. A reason may be the stochastic nature of the signals, which wavelet functions are assumed to accommodate better than other feature extraction methods [44, 18, 45, 25, 26, 27, 28].

The methodology in this research is presenting a new approach, although the pseudo-wavelet previously have presented great classification results of fatigue content from both isometric [32]and dynamic contractions [28, 27]. There is little research on finding the optimal elbow angle, and in most research the assumed preferred angle is 90 degrees [2]. However, although the results of this approach is promising for the biceps brachii, the method may not be applicable to other muscle groups. Further research is therefore needed on establishing the optimal joint angle classification performance of the GA on other muscles groups from fatigue dynamic contractions recorded with sEMG and MMG signals.

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