J Med Syst (2015) 39:167
DOI 10.1007/s10916-014-0167-1

MOBILE SYSTEMS

Super Wavelet for sEMG Signal Extraction During Dynamic Fatiguing Contractions

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Received: 27 April 2014 / Accepted: 19 November 2014 / Published online: 3 December 2014

Abstract In this research an algorithm was developed to classify muscle fatigue content from dynamic contractions, by using a genetic algorithm (GA) and a pseudo-wavelet function. Fatiguing dynamic contractions of the biceps brachii were recorded using Surface Electromyography (sEMG) from thirteen subjects. Labelling the signal into two classes (Fatigue and Non-Fatigue) aided in the training and testing phase. The genetic algorithm was used to develop a pseudo-wavelet function that can optimally decompose the sEMG signal and classify the fatigue content of the signal. The evolved pseudo wavelet was tuned using the decomposition of 70 % of the sEMG trials. 28 independent pseudo-wavelet evolution were run, after which the best run was selected and then tested on the remaining 30 % of the trials to measure the classification performance. Results show that the evolved pseudo-wavelet improved the classification rate of muscle fatigue by 4.45 percentage points to 14.95 percentage points when compared to other standard wavelet functions ($p < 0.05$), giving an average correct classification of 87.90 %.

Keywords Genetic algorithms · Localised muscle fatiguen · EMG · Wavelet analysis · Pseudo wavelets

This article is part of the Topical Collection on *Mobile Systems*

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Introduction

Electrical signal detected during muscle contraction is called the myoelectric signal. Some properties of this signal represent myoelectrical manifestation of muscle fatigue [1]. Surface electromyography (sEMG) signals give useful information about transformations in the muscle, which is used for localised muscle fatigue analysis [2–4]. Manifestation of muscle fatigue is usually investigated in terms of signal amplitude, muscle fibre conduction velocity (MFCV) and the frequency content of the signal. During non-isometric contractions (muscle length and tension change) the characteristic of the signal amplitude and the frequency content of the signal are affected by several factors [5], such as the position of active detectable motor units with respect to the electrodes, different limb states (e.g., joint angles) and the non-stationary nature of sEMG signal. These factors directly affect sEMG signal properties and may interfere with the detection of localised muscle fatigue.

Research on sEMG signals found that the onset of muscle fatigue correlate with changes in amplitude and median frequency (Med F) [6]. One study detected that a significant decline in the signal's Instantaneous Median Frequency (IMDF) is the manifestation of fatigue occurrence [7].

The discrete wavelet transform (DWT) is a joint time-frequency technique. This method has been applied in research on dynamic contractions to analyze muscle fatigue [8], and to estimate the power spectrum of sEMG signals [9, 10]. Analysis of the sEMG spectrum in dynamic contractions demonstrate a strong correlation between the onset of fatigue and the reduction of the Med F [11] and that a decline in CV reflects muscle fatigue [12]. Dimitrov et al. presented a new spectral index with a much higher sensitivity than traditional EMG parameters for isometric and dynamic contractions [13] that will aid in the analysis of sEMG signals.

Guglielminotti and Merletti hypothesised that if the wavelet analysis is selected to fit with the shape of the motor unit action potential (MUAP), the WT would give the best energy location in a time-scale [14]. Kumar et al. stated that the STFT does not give an optimal time or frequency resolution for the non-stationary signal, although the relatively short time windows may trace spectral variations with time [15]. The WT, comprised of numerous WFs, can be used to decompose the sEMG signal. The output of the power transform domain is calculated and thus functions as a deciding parameter in selecting the most appropriate WF to give the highest contrast between sEMG cases. It has been shown that it is possible to detect muscle fatigue status by determining the Sym4 or Sym5 WFs and decomposing the signal at levels 8 and 9 (out of 10 levels). 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 [15].

There are numerous ways to classify the sEMG signals, although the non-stationary nature of the signals make classification more complicated [16]. Common classification methods are Principal Component Analisis (PCA) [17] and support vector machine (SVM) [18]. Another common method for sEMG classification is to measure the Euclidean distance between the MUAPs waveform; where a shimmer is generated in the representation of time-triggered and non-overlapping MUAPs [19]. The shimmer is influenced by external factors, such as background noise and noise from offsets. In addition, the shimmer of the MUAP is affected by the variance within a class as well as the distance between the classes. A recent study developed a classification method for sEMG signals based on discrete harmonic wavelet packet transform (DHWPT) [20]. Firstly, the relative energy of sEMG signals in each frequency band was extracted using DHWPT, and, secondly, a GA selected appropriate features that reduced the feature dimensionality. Various research has used different classification techniques for SEMG signals in localised muscle fatigue, such as genetic programming and genetic algorithms [21–25], statistical analysis [26–28], as well as classification methods to predict and detect fatigue by using neural networks [29, 30] or linear discriminant analysis (LDA) [31]. A variation of these techniques have been adapted in this research where the genetic algorithm utilises a pseudo-wavelet as the feature extraction method for classifying (using LDA) fatigue content in the sEMG signal.

Methods

This study used wavelet analysis to overcome the stochastic and transitory nature of the sEMG signals emanating from dynamic contractions. A genetic algorithm was selected to evolve an optimal solution by tuning a pseudo-wavelet function for its optimal decomposition of sEMG targeted in extracting muscle fatigue content. In addition, the evolved pseudo-wavelet was validated and compared with other common wavelet transforms. The term 'pseudo-wavelet' is used here to indicate that the evolved wavelet-like function is not required to meet the necessary conditions (e.g., admissibility and regularity) to be formally described as a wavelet [24]. Pseudo-wavelets are thus a convenient joint time-frequency tool aimed specifically at pattern recognition.

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).

To evaluate the Maximum Dynamic Strength (MDS) percentage for each participant we used the average of three 100 % MDS measurements on three different days to ensure correct estimation. The 100 % MDS measurements for each subject were determined by the one-repetition maximum (1RM), where the subjects managed to keep the correct technique while executing the repetition with the heaviest possible load on a preacher biceps curl machine. In other words 100 % MDS is equal to 1RM. Determining each subject's 100 % MDS allowed estimating the correct loading MDS (40 % MDS and 70 % MDS) across subjects when conducting the trials.

After establishing the MDS for each subject the trials where carried out. After the warm-up period, all the thirteen participants carried out 3 trials of non-isometric exercises with 40 % Maximum Dynamic Strength (MDS) and 3 trials of 70 % MDS with a one week resting period between trials to ensure full recovery from the biceps fatigue, giving a total of 104 trials. Only one trial was performed per day for each subject in order to avoid injury.

sEMG electrodes (Biometrics Ltd., Model SX230W) were placed on the participant's biceps brachii's lower belly, avoiding the estimated innervation zone and toward the distal tendon to acquire sEMG reading. These electrodes were chosen due to their high quality, designed with an input impedance of more than 10^{15} ohms. A goniometer (Biometrics Ltd.) was placed on the lateral side of the arm to measure the elbow angle and arm oscillation.

The myoelectric signal was recorded using one two-channel Single Differential (SD) electrodes (Biometrics Ltd.), (both placed on the biceps brachii with a distance of 2 cm [3]) with A/D conversion at 2000 samples/s. The sEMG signals underwent a rectification and filtering process. The signals were filtered with a dual pass Butterworth filter of order 5, with the pass band being between 10 and 500 Hz. All movement aspects were recorded simultaneously and are described in the subsection below.

The test bed set up for one of the conducted trials is shown in Fig. 1.

Labelling the signals

The acquired sEMG signals were divided into Fatigue and Non-Fatigue epochs. The first few repetitions were considered as Non-Fatigue as the subject felt "fresh", while the last few repetitions before the subject could not continue the sustained task, were labelled as Fatigue epoch [15]. This meant that for the signal analysis the first rep was labelled as Non-Fatigue and the last full repetition was labelled as Fatigue. The labelling of the sEMG signal was utilised to tune the evolved pseudo-wavelet as well as for training and testing the classifier.

Wavelet decomposition

In a wavelet transform there are various standard mother wavelet functions utilised for decomposing a signal, such as Daubechies, Symmlet, Mexican Hat, Morlet etc. The wavelets can be used for different signals, but previous research has recommended guidelines to select the most suited wavelet [32], such as Db4 is appropriate for signals using feature extractions and linear approximation with more than four samples, but Db6 is more suited for a signal approximated by a quadratic function over the support of six; coiflet6 is used for data compression results [32]. To select the most appropriate wavelet, the properties of the wavelet function and the characteristic of the signal should be analysed and matched for specific data sets.

The pseudo-wavelet evolved in this study utilises scaling function (phi) coefficients that are the most suitable to find the optimal shape for our application. The goal was to evolve a custom-made wavelet-like shape suitable for join-time frequency decomposition for muscle fatigue detection in the sEMG signal. The GA first evolved random values for the scaling function coefficients, then ten coefficients for phi was chosen.

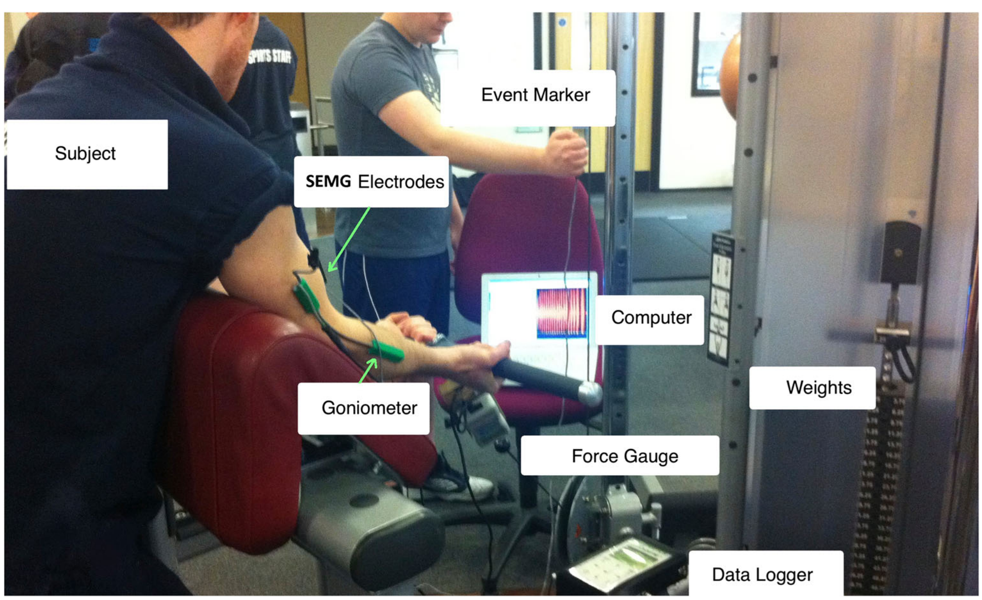

Fig. 1 Experimental set-up showing one of the trials

Genetic algorithms

Genetic Algorithms (GA) can be used for solving linear and nonlinear problems by utilising different operators, e.g. crossover, mutation and selection operations applied to each individual in the population to explore the optimal solution is the state space [33]. Presumably, by using a GA to adapt a standard wavelet, or to evolve a pseudo-wavelet, an optimal solution will be generated that finds the shape of a (pseudo)wavelet for improved, data-specific joint-time frequency decomposition that detects muscle fatigue within the sEMG signal.

The steps taken for the initialisation and running of the GA are displayed as a flow chart in Fig. 2, while the parameter settings for the GA runs are shown in Table 1.

Solution representation

The solution representation was utilised to determine the optimal wavelet by using standard wavelet functions, including Symlet, Mexican hat and Daubechies. In this research we selected a scaling function (phi) coefficients from 1 to 19 for the evolved pseudo-wavelet, while it is common to chose a scaling function from 1–10. According to Kumar et al.the muscle fatigue content lays between scale 9 and 10 [15], while in this study it was chosen for the GA to have a wide scaling function (1–19) to find the most optimal scale for class discrimination.

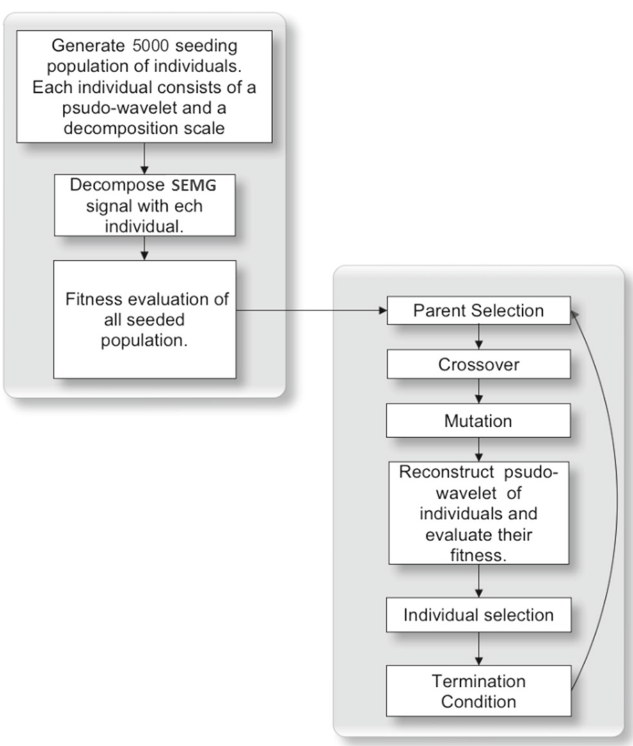

Fig. 2 Flowchart of the pseudo-wavelet evolution

Table 1 Parameter settings for the GA runs

Parameter	Value
Independent runs	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

Fitness function

A fitness function in the GA is used to find the optimal solution in the search space. The modified Davies Bouldin Index (DBI) was selected in this study in the fitness function as it is a simple and effective index. Data cluster linear overlap was calculated applying the modified DBI [34] by deceding the propotion of intracluster spread to intercluster centroid distance. A good class separation was expressed by smaller DBI values.

The joint-time frequency decomposition by the pseudo-wavelet was achieved for every scale (1–19) and extracted in one second intervals to calculate the DBI between the two classes (i.e., Fatigue and Non-Fatigue). This resulted in minimising the DBI, which aided the evolutionary processes. Furthermore, it permitted the fitness function to increase the separation between the two classes. Normally the fitness function works by maximisation, using a hill climbing method; however, in this research the DBI was changed into negative numbers, letting the fitness function use the hill climbing method by trying to bring the (now) negative DBI closer to zero.

Validation/ classification

Linear Discriminant Analysis (LDA) classifier was used as this method is simple, well established and requires few computational resources. The input for the training and testing of the LDA classifier utilised the decomposed sEMG signal from the pseudo-wavelet. Similar to the evolutionary process, the classifier was trained utilising 70 % the trials and tested with the remaining 30 % of the trials.

The performance of the evolved pseudo-wavelet was compared with other common wavelet functions. In order to obtain a meaningful comparison, 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.

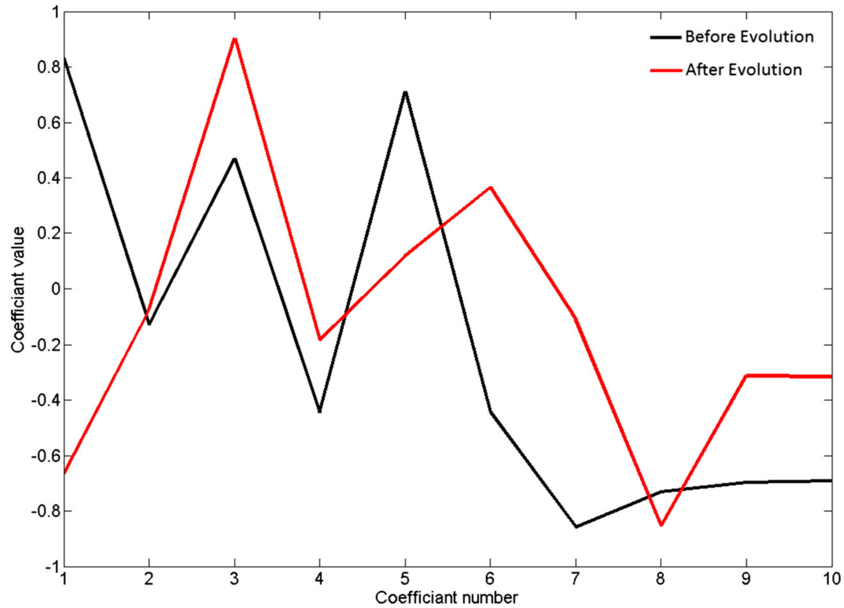

Fig. 3 Pseudo-wavelet before and after evolution

Results

There are three main interesting findings in this research. Firstly, the GA selected the optimal wavelet for sEMG classification and secondly, the optimal scale for decomposing the sEMG signal was selected. Thirdly, the classification performance of the evolved pseudo-wavelet proved to be better than traditional wavelet functions for sEMG classification.

The GA chose the optimal wavelet dependent upon the solution representation, in which it detects improvements based on the fitness function of the final evolved population with the best DBI scoring. This is shown in Fig. 3, where superimposed shapes of original randomly produced pseudo-wavelets with the final pseudo-wavelet at the end of a typical evolutionary process.

An interesting finding of these results was the relationship between the shape of the wavelet and the optimal scale. The shape of the wavelet affects the choice of the optimal scale that gives the best discrimination between Fatigue and Non-Fatigue content of the sEMG signal. This result is similar to Kumar et al.'s [15] finding that some wavelet functions at various scales better contrast between Fatigue and Non-fatigue.

In this research, the GA selected the optimal scale according to the wavelet function, which eliminated human

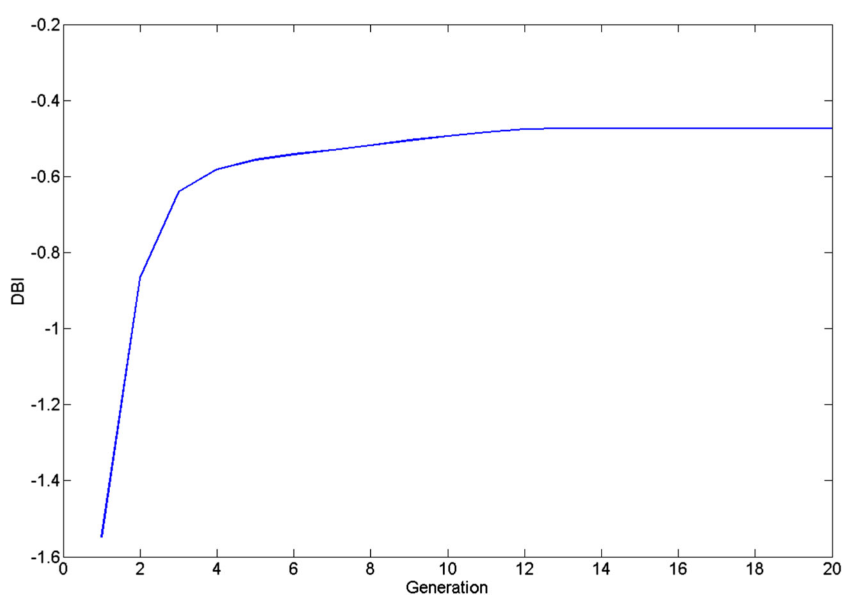

Fig. 4 Generation fitness during the GA

subjective choice of the most suited wavelet functions for fatigue content analysis. By using the DBI, the GA choose the optimal scale for decomposing the sEMG signals. The highest separability between the fatigue classes (Fatigue and Non-Fatigue) is found by the optimal scale. Figure 4 displays the improvements in the pseudo-wavelet population fitness (values closer to zero indicate improved fitness) attained by one of the GA runs in optimising the pseudo-wavelet function and the most optimal scale.

The GA was initialised using 5000 individuals with randomly seeded coefficients. In the first generation the GA run was generated with relatively good solutions averaging a transformed DBI of -1.547. When continuing with the evolutionary process the fitness enhanced for this particular scenario and obtained its optimal range of -0.4730 DBI, around the 14th generation.

The GA initialisation and GA run were completed 28 times utilising a variation of epochs each time to safeguard optimal coverage of the GA search space. In Table 2 all the 28 independent GA runs are presented. The table shows that there is a consistency in the results from each GA run.

The optimal scale for the best GA run is 11, which gives an exceptional separability of -0.4730. This shows that the

Table 2 Twenty eight independent runs, showing the best individual

Best Indiv.	Coef 1	Coef 2	Coef 3	Coef 4	Coef 5	Coef 6	Coef 7	Coef 8	Coef 9	Coef 10	Scale	DBI
1	-0.864242	-0.242692	-0.931535	0.970248	0.246149	0.307375	-0.482074	-0.236434	0.983014	-0.760280	13	-0.491357
2	-0.236883	-0.502742	-0.194891	0.133722	0.676452	-0.797571	0.282683	0.256545	-0.416643	-0.067256	12	-0.483028
3	-0.082564	-0.543043	-0.836032	-0.544158	0.712949	0.930792	-0.180848	-0.584468	-0.016217	-0.476172	9	-0.485659
4	-0.923337	-0.063500	-0.122325	-0.185331	0.457136	0.347545	-0.788585	0.084199	0.351236	-0.810014	12	-0.485556
5	0.753819	0.917448	-0.176081	0.272940	-0.762004	-0.139448	0.435891	0.561613	-0.876146	-0.186043	10	-0.487483
6	-0.631399	-0.172173	-0.404954	-0.980757	0.943872	0.424935	-0.651820	0.293014	0.424031	0.617494	10	-0.491348
7	-0.876100	0.369932	-0.986108	0.656329	0.975698	-0.278396	-0.325693	-0.431663	0.530142	-0.443914	18	-0.493658
8	-0.446154	0.664486	-0.120145	-0.582775	0.830775	-0.493821	-0.395023	0.727275	-0.483121	-0.169820	16	-0.482704
9	0.773883	-0.518824	0.302386	-0.009532	-0.102918	-0.864620	0.388080	0.879412	0.801164	0.687968	13	-0.481972
10	0.227648	0.657091	0.707375	-0.158750	-0.625373	-0.114292	-0.719970	-0.766579	0.052077	-0.268672	3	-0.491937
11	-0.027224	0.928522	-0.729980	-0.240958	0.397727	-0.933038	0.543298	0.407653	0.669037	-0.462206	13	-0.475065
12	-0.618332	-0.080158	-0.730077	-0.375686	-0.909700	0.741772	0.144389	-0.655820	-0.135600	0.503826	1	-0.502978
13	0.588203	-0.814357	-0.359604	-0.763271	0.988322	0.157596	-0.284911	0.628369	0.224851	0.715838	4	-0.473747
14	0.547887	0.094344	-0.379070	-0.390996	0.628189	-0.567994	-0.797560	0.925749	0.439768	0.621294	10	-0.477569
15	-0.844267	0.866437	0.966678	0.049007	-0.674025	0.554753	-0.490083	-0.846132	0.175440	0.499542	4	-0.503437
16	0.346696	-0.503485	0.846013	0.507443	-0.933680	-0.102870	-0.294352	0.716410	0.331767	0.088780	16	-0.490912
17	0.356000	-0.224109	0.177374	0.316610	-0.530817	-0.347085	-0.178003	-0.082243	-0.347782	0.424249	3	-0.497717
18	0.309638	-0.434519	0.123595	-0.211702	0.689527	-0.651123	0.619346	-0.512927	0.852247	-0.306339	5	-0.481241
19	-0.971619	-0.210740	0.925958	0.756288	-0.779561	-0.358697	-0.429445	0.503069	0.145364	0.850787	16	-0.477890
20	0.111428	-0.235536	0.037306	-0.280862	-0.148421	0.670382	0.715589	-0.297703	0.847876	0.378478	6	-0.499018
21	-0.666214	-0.075309	0.903201	-0.183658	0.118085	0.365698	-0.111721	-0.853810	-0.312184	-0.315055	11	-0.473083
22	0.179040	-0.569012	0.700382	0.364073	-0.515999	0.076844	-0.051081	-0.441670	-0.984128	-0.840472	3	-0.504836
23	0.335504	-0.777735	0.328649	0.079035	0.611148	-0.638632	-0.528389	0.742692	0.919256	-0.892442	10	-0.490000
24	0.251042	0.613452	-0.652309	-0.732583	0.562082	0.171122	-0.101100	0.914875	-0.852659	0.785641	12	-0.498207
25	-0.695683	0.722936	-0.241893	0.337429	-0.014934	-0.846905	0.645762	-0.280293	0.614628	0.640743	20	-0.494014
26	0.774403	0.261807	-0.414799	-0.458481	-0.878473	-0.678152	-0.973922	-0.499812	0.922923	0.341972	1	-0.491499
27	-0.286343	-0.132542	0.972987	-0.917948	0.067086	0.286025	0.727677	0.045059	-0.797328	0.611004	3	-0.499535
28	-0.511974	-0.621935	0.499750	0.983238	-0.597065	0.787013	-0.101725	0.081020	0.882579	-0.185861	5	-0.505663
Average	-0.111684	-0.022355	0.007566	-0.056824	0.051151	-0.071100	-0.120842	0.045621	0.176628	0.056538	9	-0.489683
Std.	0.577925	0.542192	0.625187	0.539702	0.662496	0.561823	0.501322	0.584623	0.615143	0.560494	5	0.009648

Coef = Coefficient

GA is capable of separating the sEMG signals from the two different classes (Fatigue and No-Fatigue) while using an optimal wavelet..

In the classification of the sEMG signals, both the optimal wavelet and the optimal scale were used. The classification performance with the developed pseudo-wavelet was 87.905 %. In comparison to other commonly used wavelet functions, the pseudo-wavelet could better classify the sEMG signal, with an average of 81.61 % ($p < 0.05$) vs. 83.67 % for DB4, which was the second best wavelet function.

Table 3 presents a classification comparison of the evolved wavelet with eight traditional wavelet functions in decomposing the sEMG signal, which shows the classification capabilities of the evolved pseudo-wavelet. Classification performance of all thirteen subjects with the unseen test data sets indicates that the evolved pseudo-wavelet function has outperformed all of the other wavelets, with an improvement ranging from 4.45 percentage points (P-W and DB4) to 14.95 percentage points (P-W and Mexican Hat) between the pseudo-wavelet and the highest and lowest average percent for the other wavelets. This is giving an average of 87.90 %. In addition, the average for all the other wavelets combined gives 81.61 % with significance of ($p < 0.05$). By studying the standard deviation across the classification averages, the evolved wavelet produced the lowest values, which may be due to its consistency in classification across subjects. To ensure consistency in the comparison all the wavelet functions, including the pseudo-wavelet, used scale 11. Figure 5 displays graphically the classification performance (in %) seen in Table 3.

Discussion

In this paper a pseudo-wavelet function was created and an optimal scale was found by the genetic algorithm that specifically improves the classification of localised muscle fatigue using sEMG signals. The evolved pseudo-wavelet improved the classification of muscle fatigue when compared to other wavelet functions. Results show that using the GA to evolve a pseudo-wavelet can produce exceptional classification performance, when specifically optimised to decompose the sEMG signal, retaining the fatigue content in the signal.

Using sEMG as a signal acquisition technique has been warned against for localised muscle fatigue on dynamic contractions [5], yet several studies have used it and found that sEMG signal detection is still a reliable technique for fatiguing dynamic contractions [11–13, 35]. Wavelets are a suited method for signal analysis as it takes into account the non-stationary nature of the sEMG signals from dynamic contractions [36]. Several studies has utilised wavelets to decompose the sEMG signal in muscle fatigue research [8, 14, 15]. The results in this study adds to this finding, as it shows that the pseudo-wavelet outperformed other common wavelets when it comes to the classification of sEMG signals. Additionally, all the other wavelets used for comparison purposes gives high classification performance, which shows that utilising wavelets are an appropriate method for sEMG signal classification from fatiguing dynamic contractions.

The optimal scale for decomposing the fatigue content of the sEMG signal was 11. This is a higher level than

Table 3 Classification Results (P-W = Pseudo-wavelet)

Subjects	Db5 %	Db4 %	Db3 %	Db2 %	Sym5 %	Sym4 %	Sym3 %	Mexican Hat %	P-W %
Subject 1	85.821	86.567	84.328	85.075	83.582	83.582	84.328	17.164	90.991
Subject 2	93.431	93.431	94.891	94.161	92.701	92.701	94.891	90.511	94.161
Subject 3	85.156	85.156	82.813	79.688	87.500	85.156	82.813	69.531	85.938
Subject 4	83.951	83.951	84.568	83.333	85.185	84.568	84.568	80.247	88.272
Subject 5	82.895	83.772	81.579	80.263	82.018	82.456	81.579	79.386	81.579
Subject 6	91.509	90.566	91.509	91.509	91.509	91.509	91.509	84.906	93.396
Subject 7	78.523	77.181	78.523	78.523	77.852	77.852	78.523	83.893	82.550
Subject 8	76.296	79.259	78.519	74.815	75.556	73.333	78.519	71.111	87.407
Subject 9	94.118	94.118	94.118	94.118	95.588	95.588	94.118	89.706	92.647
Subject 10	83.898	85.593	85.593	83.051	82.203	84.746	85.593	77.966	86.441
Subject 11	81.081	81.982	74.775	71.171	82.883	81.982	74.775	67.568	93.694
Subject 12	66.031	64.122	62.595	62.214	61.832	62.595	62.595	53.053	83.588
Subject 13	82.099	82.099	82.716	80.864	79.630	81.481	82.716	83.333	82.099
Average	83.447	83.677	82.810	81.445	82.926	82.889	82.810	72.952	87.905
Std.	7.494	7.721	8.535	9.017	8.628	8.540	8.535	19.646	4.675

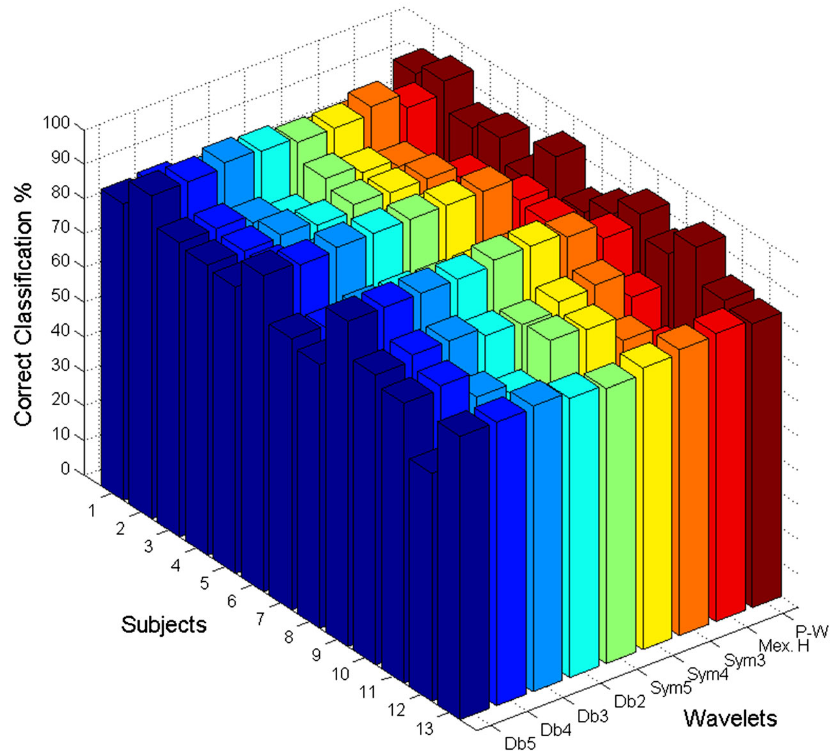

Fig. 5 Graphical representation of the Classification performance (in %) (P-W = Pseudo-wavelet)

Kumar et al.'s finding, where the fatigue content was found at scale 8 and 9, out of 10 levels, for Sym4. The reason the optimal scale is different in this research is due to the GA utilising a scale of 1-19 in selecting the most optimal scale, while Kumar et al's research only used 10 levels. Another factor influencing the selection of the scale is the wavelet function utilised. The GA selected the pseudo-wavelet, which is a wavelet-like function that is a joint time-frequency tool, while Kumar et al.'s research utilised Sym4. There are no specific rules for which wavelet is most suited for classifying fatigue content of the sEMG signal, but a selection needs to take into consideration the properties of the WF and the sEMG signal characteristics for the data sets. In this research it was the GA that selected the most suited wavelet function, and hence, the pseudo-wavelet was selected. The performance of the GA in finding the optimal scale is worth noting for future research, where the sEMG signals emanate from fatiguing dynamic contractions.

Classifying sEMG signals from fatiguing dynamic contraction is more complicated due to the non-stationary nature of the signal [16]. Various classification methods can be applied, but as mentioned above, wavelets take the stochastic nature of the sEMG signal into consideration. A similar study was carried out by Wang et al. where DHWPT was used to classify the sEMG signals. He used the GA to select the feature that would reduce dimensionality That research used a similar method applied to this study where the GA selected the feature that would best classify the fatigue content from the sEMG signal. The results here proved similarities to a previous study by Almulla et al., where this classification technique proved successful in classifying the sEMG signal emananting from fatiguing isometric contractions [24]. This shows that the methodology developed in this paper, as in the previous research, gives excellent classification results.

Conclusion

This study was able to classify the fatigue content using sEMG signals from fatiguing dynamic contractions. The classification results of the pseudo-wavelet proved to be better than other traditional wavelet functions, which would indicate that this methodology is useful for future research on sEMG signal classification for localised muscle fattigue from dynamic contractions.

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