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# A segmentation approach to long duration surface EMG recordings

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**Abstract**

The purpose of this study was to develop an automatic segmentation method in order to identify postural surface EMG segments in long-duration recordings. Surface EMG signals were collected from the cervical erector spinae (CES), erector spinae (ES), external oblique (EO), and tibialis anterior (TA) muscles of 11 subjects using a bipolar electrode configuration. Subjects remained seated in a car seat over the 150-min data-collection period. The modified dynamic cumulative sum (MDCS) algorithm was used to automatically segment the surface EMG signals. Signals were rejected by comparison with an exponential mathematical model of the spectrum of a surface EMG signal. The average power ratio computed between two successive retained segments was used to classify segments as postural or surface EMG. The presence of a negative slope of a regression line fitted to the median frequency values of postural surface EMG segments was taken as an indication of fatigue. Alpha level was set at 0.05. The overall classification error rate was 8%, and could be performed in 25 min for a 150-min signal using a custom-built software program written in C (Borland Software Corporation, CA, USA). This error rate could be enhanced by concentrating on the rejection method, which caused most of the misclassification (6%). Furthermore, the elimination of non-postural surface EMG segments by the use of a segmentation approach enabled muscular fatigue to be identified in signals that contained no evidence of fatigue when analysed using traditional methods.


*Keywords:* Electromyography; Fatigue; Segmentation

## 1. Introduction

The fatigue induced by long duration driving has long been identified as a potential safety problem [3,8,18]. The type of fatigue that has been studied has often been psychological in nature, although numerous articles have concentrated on sleep deprivation [19,20]. Although physical fatigue has been mentioned, there have been few studies in which physical fatigue has been recorded objectively, with most studies preferring a more qualitative, subjective approach.

One of the major objective tools that can be used to study fatigue is surface electromyography (EMG). The surface EMG signal has been used to study muscle activation, due to its non-invasive nature, ease of use, and the fact that it can provide a representation of the global level of muscle activity [5,7]. Furthermore, the compression of the surface EMG spectrum with fatigue can be used to detect fatigue onset and progression [2,16].

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Despite the wealth of information that can be gleaned from surface EMG signals, there are several problems concerning signal acquisition and interpretation in an ergonomic setting. Firstly, the magnitude of postural surface EMG signals may be as low as only 1–2% of maximal voluntary contraction (MVC) [6]. Such a low level of activation could make detection of postural muscle activation problematic, particularly if low signal-to-noise ratios were present. Indeed, postural surface EMG signals are well-known to be prone to problems of masking by movement artefact, bursts of unrelated muscle activity, as well as mechanical artefact due to vehicle vibration [4,15]. A further problem with postural surface EMG recordings is the long duration of data collection that is needed in order to accurately represent the ergonomic reality, and to identify muscle fatigue if it occurs. Given that contractions at 5% MVC require several hours before fatigue is observed [10], sitting in a car seat might take all day before an effect is noticeable.

One approach to the many problems outlined above is to automatically segment the recorded signals, and subsequently classify each segment. Such a technique is used to identify the different activities contained in the signals, and to retain only those segments corresponding to postural surface EMG. The aim of this study, therefore, was to develop an automatic segmentation method, in order to detect postural surface EMG segments in long duration recordings. The secondary aim of the study was to search for an evolution in the power spectra of these signals due to fatigue.

## 2. Methodology

### 2.1. Subjects

Eleven male subjects participated in the study. Subjects' mean (±SD) age, height and mass were $35.7 \pm 10.4$ years, $175.6 \pm 5.5$ cm, and $75.5 \pm 6.1$ kg, respectively. All subjects gave their written informed consent, and all experimental procedures were approved by the regional ethics committee (Reference: Consultative Committee for the Protection of Subjects in Biomedical Research, No. 94041, 27/09/94). No subjects reported any musculoskeletal or neurological conditions that precluded their participation in the study.

### 2.2. Experimental protocol

The experimental protocol has already been described in detail in a previous publication [9]. Each subject was tested once in each of four experimental configurations, which consisted of two types of car seat, both with and without vibration. For reasons of commercial sensitivity, the seat models can not be disclosed, and henceforth will be identified only as comfortable (C: fitted to a top of the range model) and uncomfortable (fitted to an entry-level car). The seats were considered by the car manufacturer to be, subjectively, their most and least comfortable models. All testing was performed on a vibration platform, with subjects allowed to adjust their seat position at the start of the test until they were comfortable.

An experimental duration of two and a half hours was chosen after pilot testing, with subjects required to remain seated throughout the experiment. Data collection was divided into seven periods, which were separated by measurement of performance measures and the administration of a discomfort questionnaire [9].

### 2.3. Electromyography

Surface EMG signals were collected bilaterally from the cervical erector spinae (CES), erector spinae (ES), external oblique (EO), and tibialis anterior (TA) muscles using a bipolar electrode configuration and an inter-electrode distance of 20 mm. Disposable surface electrodes (3M Ag/AgCl, Red DotTM model 2237 electrodes, 3M Health Care, St. Paul, MN, USA) were applied to the skin after the electrode site had been cleaned with alcohol and shaved. All parameters of the electrode placements and configurations conformed to the SENIAM recommendations for surface EMG data collection [11]. Surface EMG signals were pre-amplified in two stages for a total gain of 80 dB, with a band-pass of 20–2000 Hz. Surface EMG recordings were sampled at 840 Hz, with an anti-aliasing filter of 350 Hz.

### 2.4. Segmentation algorithm

The computer used for the segmentation algorithm had a Pentium II processor with a speed of 266 MHz. All segmentation was performed using a custom-built software written in C (Borland Software Corporation, CA, USA) after an initial development in MATLAB (Mathworks Inc, Natick, MA, USA).

A segment was considered to be a section of the EMG signal that differed in content from adjacent sections of the signal. The method used for segment detection is based on an analysis of the local properties of signals [14]. This method is based on the cumulative sum algorithm (CUSUM), a statistical approach that consists of exploiting local differences in log-likelihood ratios [1]. The CUSUM is known to be one of the best algorithms for detection when parameters are known [1], as well as enabling the detection of both energy and spectral changes in the signal when used in conjunction with auto-regressive (AR) modelling. However, the CUSUM algorithm is unable to detect spectral changes when parameters are unknown. An initial modification of the algorithm, the dynamic cumulative sum (DCS), has been shown to be effective for detection of changes in signals of long duration such as postural muscle activity or uterine EMG [13]. Unfortunately, the DCS algorithm is affected by the choice of the window widths used in the detection process, and also fails to detect changes when two hypotheses are very close together. In order to deal with the problems of the DCS, the algorithm was further modified to produce the modified dynamic cumulative sum (MDCS: see Fig. 1).

In the case of an AR model, the MDCS is expressed as:

$$\mathrm{MDCS}(H_{\mathrm{a}}^{j}, H_{\mathrm{b}}^{j}) = \sum_{i=1}^{j} \hat{s}_i \sum_{i=1}^{j} \frac{1}{2}\left[\ln\frac{(\hat{\sigma}_{\mathrm{a}}^{i})^2}{(\hat{\sigma}_{\mathrm{b}}^{i})^2} + \frac{(\varepsilon_{\mathrm{a}}^{i})^2}{(\hat{\sigma}_{\mathrm{a}}^{i})^2} - \frac{(\varepsilon_{\mathrm{b}}^{i})^2}{(\hat{\sigma}_{\mathrm{b}}^{i})^2}\right],$$

where $\hat{\sigma}_{\mathrm{b}}^{i}$ is the estimation of the standard deviation of the innovation of the AR model "before"; $\varepsilon_{\mathrm{b}}^{i}$ is the prediction error at instant $i$ calculated by the parameters of the AR model "before"; $\hat{\sigma}_{\mathrm{a}}^{i}$ is the estimation of the standard deviation of the innovation of the AR model "after"; $\varepsilon_{\mathrm{a}}^{i}$ is the prediction error at instant $i$ calculated by the parameters of the AR model "after"; and $j$ is the current moment in time.

The MDCS has two major advantages over the original methods. First, it is fast, and thus well adapted to long-duration signal processing. Second, the MDCS does not require a priori knowledge of the events to be detected, provided that these events can be represented by an auto-regressive (AR) process. In order to ensure that the MDCS method is automatic, it is necessary to develop an adaptive method to define the value of the various thresholds implied in the segmentation process. This method of automatic determination of the thresholds was performed using distribution of the Kullback–Leibler information in the signal.

### 2.5. Segment classification

The segmentation algorithm divided the EMG signals into segments by cutting the signal at points where the algorithm considered there to be a change in the content of the signal, due to either a process change or a superimposed event. After this segment detection step, it was necessary to classify segments, in order to retain only those segments containing postural surface EMG signals. The reason for the change from one segment to another could have been due to an increase in noise level, the presence of a burst of EMG activity, or a total absence of EMG activity. It was also possible to have two adjacent segments classified as postural EMG.

Segment classification was performed as a two-step process: first, those segments that did not contain surface EMG were identified and rejected; second, those segments containing postural surface EMG activity were identified and retained. All segment classification was performed using MATLAB.

#### 2.5.1. Rejection of non-EMG segments

The spectrum of an EMG signal acquired by surface electrodes has a typical form whose characteristics depend on the type of EMG activity, as well as on methodological factors such as the type of electrodes used, inter-electrodes distances, etc. The typical surface EMG spectrum can also be modified according to other events present in the recording, such as superimposed noise or external events. The rejection method used was a regression technique, whereby the real spectrum was normalised, before comparison with an exponential mathematical model $S(f) = \beta f^{\gamma} \mathrm{e}^{-\alpha f}$ (see Fig. 2). The exponential model used was found to be superior to that of the more traditional model of Shwedyk [21] when used to classify a sample of 50 EMG segments and 50 noisy segments. These segments were obtained by randomly selecting segments from the recorded signals until 50 segments of each type were obtained. The classification of these segments was performed by an expert. The resultant ROC curves can be seen in Fig. 3.

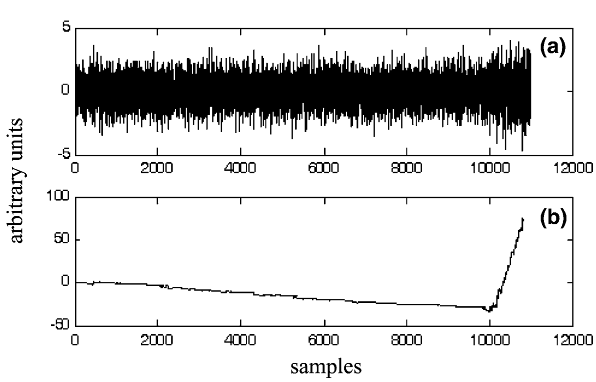


Fig. 1. Evolution in the MDCS around a change point at 10,000. (a) Surface EMG signal; (b) evolution in the MDCS.

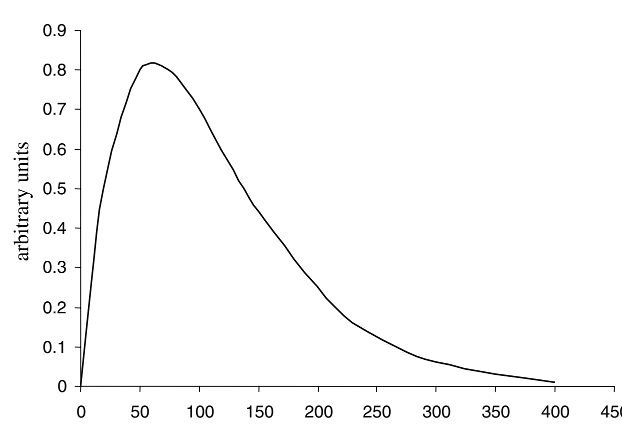


Fig. 2. The exponential function used for segment classification (0–420 Hz).

### 2.5.2. Rejection of non-postural surface EMG segments

The second part of the classification procedure was used to differentiate between those segments containing postural surface EMG (low levels of muscle activation, with a correspondingly small amplitude EMG signal) and bursts of surface EMG related to movements (high levels of muscle activation, with a correspondingly high amplitude EMG signal). In order to identify these two events, a heuristic process was used that took into account the characteristics of the two signal types. The two most important parameters used to identify these types of segments were the segment duration and the average power ratio computed between two successive segments.

The classification of these segment types was based on the comparison of the power ratio to a threshold. When the ratio was small, the segment was classified as postural; otherwise the segment was classified as "phasic". In terms of segment duration, a segment length of 10 s was considered to be the maximum length for a non-postural segment. Segments longer than 10 s corresponded to long voluntary contractions, which were contrary to the instructions given to the subjects at the start of the experiment.

The detection procedure started with the first tonic segment, which was considered to be the first segment of low power and short duration. Power ratios were then calculated between this segment and the two adjacent segments. If the preceding segment was postural and the ratio between the current segment and the preceding segment less than a pre-determined threshold, this segment was classified as postural EMG. However, if the ratio was greater than the threshold, the segment was given a preliminary classification of non-postural. The power ratio was then calculated with the subsequent segment. If the ratio was still greater than the threshold, this segment was definitively classified as non-postural. The optimal threshold was calculated by using ROC curves of a range of thresholds for known samples (50

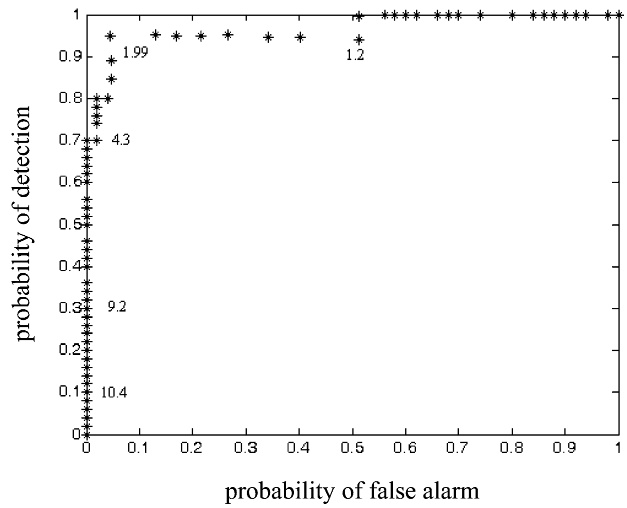


Fig. 4. ROC curve for the threshold optimisation for detection of non-postural EMG segments. The statistic used was the power ratio between two adjacent segments. A threshold of 1.99 provided the best compromise for classification.

postural and 50 non-postural EMG segments). The results of the threshold optimisation can be seen in Fig. 4. The statistic used was the power ratio between two segments. It can be seen that a threshold equal to 2 (1.99) provided the best compromise for classification.

## 2.6. Muscular fatigue

Those segments that were classified as postural surface EMG were retained for subsequent analysis. The median frequency of the surface EMG signal has been shown to decrease with fatigue [2], and it was this parameter that was calculated for all remaining surface EMG segments. Only those signals in which over 50% of the data for a given data period were classified as postural surface EMG were included in the analysis. It should be noted that the term data period refers to a

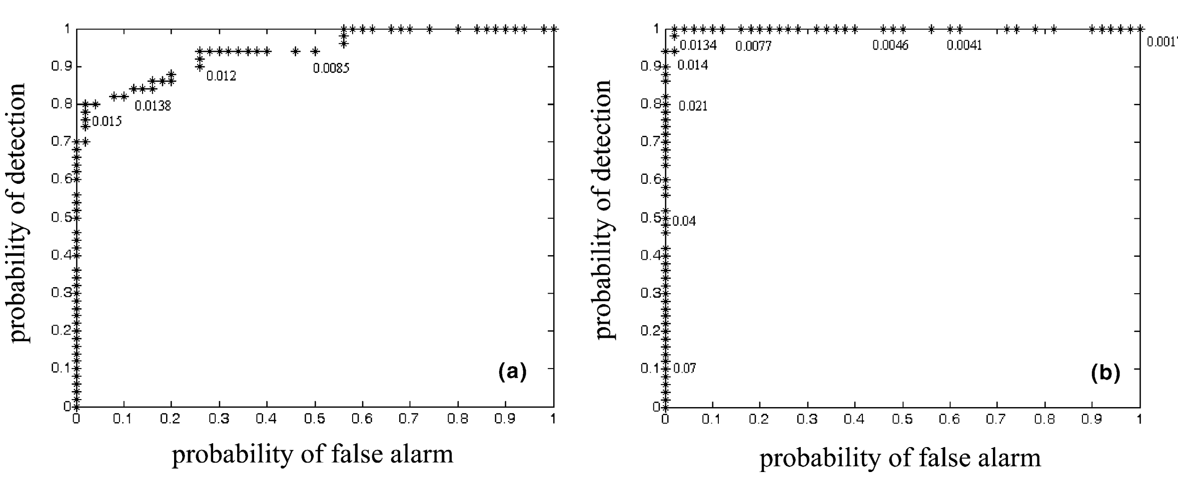


Fig. 3. Comparison of the Shwedyck model and the exponential model using ROC curves computed from the distances between real and modelled spectra. (a) Shwedyck; (b) exponential.

continuous period of data collection in between the performance tests. Median frequencies were also calculated for the surface EMG signals before any segmentation or classification had taken place using a moving one-second window, without overlap. A line of best fit was then calculated for the median values using regression analysis. The slope of the regression line was taken as a measure of the presence of fatigue. To avoid a possible effect of the pause during the testing procedure [9], the slope of each of the seven data periods of the experimental configuration was calculated separately. The slopes of the median frequency calculated for postural surface EMG segments were compared with those of the non-segmented surface EMG data.

### 2.7. Statistical analysis

Statistical analyses were performed with the Statistical Package for Social Sciences (SPSS Inc., Chicago, IL, USA). Data was checked for univariate outliers using Z-scores [22]. Analysis of variance was used to test for differences between conditions. The independent variables were vibration (present or absent) and seat type, while the dependent variable was the slope of the regression line for the median frequency data. $\alpha$ levels were set at $p < 0.05$. Data were expressed as means ± SD.

## 3. Results

### 3.1. Algorithm comparison

The performance of the MDCS method was compared with that of the DCS method using simulated data, which comprised 1000 segments of white noise with a variance change from 1 to 2, and 1000 segments without a change. As the ROC curves shown in Fig. 5 demonstrate, the modified MCDS algorithm improves the detection quality.

### 3.2. Segment classification

The algorithm was able to perform the automatic segmentation and classification procedure at a speed of 25 min for each 150 min signal. The 25 min was comprised of 5 min for the segmentation and 20 min for the classification algorithm.

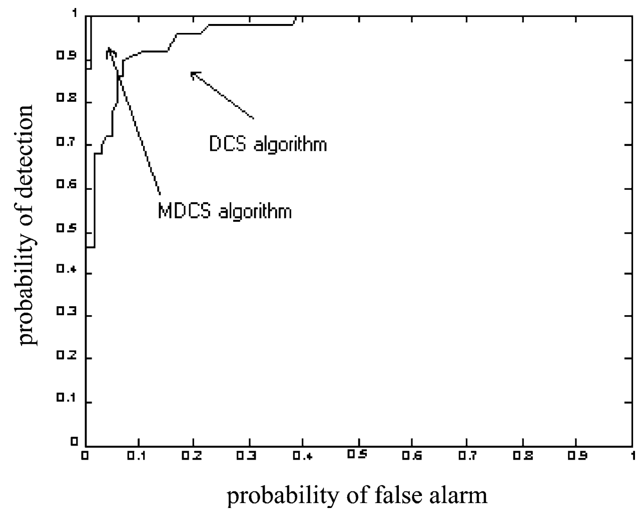


Fig. 5. Comparison of DCS and MDCS methods by ROC curves computed from simulated data.

The performance of the rejection test was measured by an expert, who either accepted or reclassified the segments rejected by the algorithm after having examined the spectrum of each segment. The performance of the rejection algorithm is presented in Table 1. This first classification step, which rejected non-surface EMG segments, had an error rate of just over five percent (false negative and false positive results combined), with no differences observed between experimental conditions.

The second step of the classification procedure was the identification of the postural surface EMG segments. As with the rejection step, performance of the algorithm was measured against that of an expert. The results of the classification procedure are shown in Table 2. The overall error rate in the classification step of 1.8% was evenly spread between false positives and false negatives. There was a slight decrease in the error rate when the experimental condition included vibration ($p < 0.05$).

A detailed example of a segmented signal can be seen in Fig. 6. The original signal contains rejected segments, postural surface EMG segments, as well as bursts of

Table 1
Performance of the rejection procedure (non-EMG segments) compared with expert opinion

| Experimental configuration | Number of segments rejected | Number of rejected segments found to contain EMG | Error rate (%) |
|---|---|---|---|
| Vibration, Seat C | 1051 | 52 | 5.6 |
| Vibration, Seat U | 1017 | 51 | 5.0 |
| Without vibration, Seat C | 1151 | 69 | 6.0 |
| Without vibration, Seat U | 1276 | 82 | 6.4 |
| Total | 4495 | 254 | 5.7 |

Errors are the combined figures for false negative and false positive results.

Table 2
Performance of the classification procedure (postural surface EMG segments) compared with expert opinion

| Experimental configuration | Number of segments detected | Number of segments misclassified | Error rate (%) |
|---|---|---|---|
| Vibration, Seat C | 650 | 7 | 1.1 |
| Vibration, Seat U | 595 | 7 | 1.2 |
| Without vibration, Seat C | 634 | 17 | 2.7 |
| Without vibration, Seat U | 645 | 15 | 2.3 |
| Total | 2524 | 46 | 1.8 |

non-postural surface EMG activity. The spectrum of each segment is also presented.

### 3.3. Muscular fatigue

Those segments that were classified as containing postural surface EMG were analysed for a fatigue effect. The number of possible data periods that could have been analysed was 616 for each muscle (seven periods, four configurations, bilateral recordings, for 11 subjects). The number of periods retained for analysis was 61 for TA (10% of the number of possible periods), 162 for EO (26%), 224 ES (36%), and 340 CES (55%).

There were no significant differences between the bilateral recordings from any muscle, therefore data were pooled for each muscle. Analysis of variance revealed that the slope of the regression lines for the TA, EO, and CES muscles did not differ significantly from zero, neither before nor after segmentation. Thus,

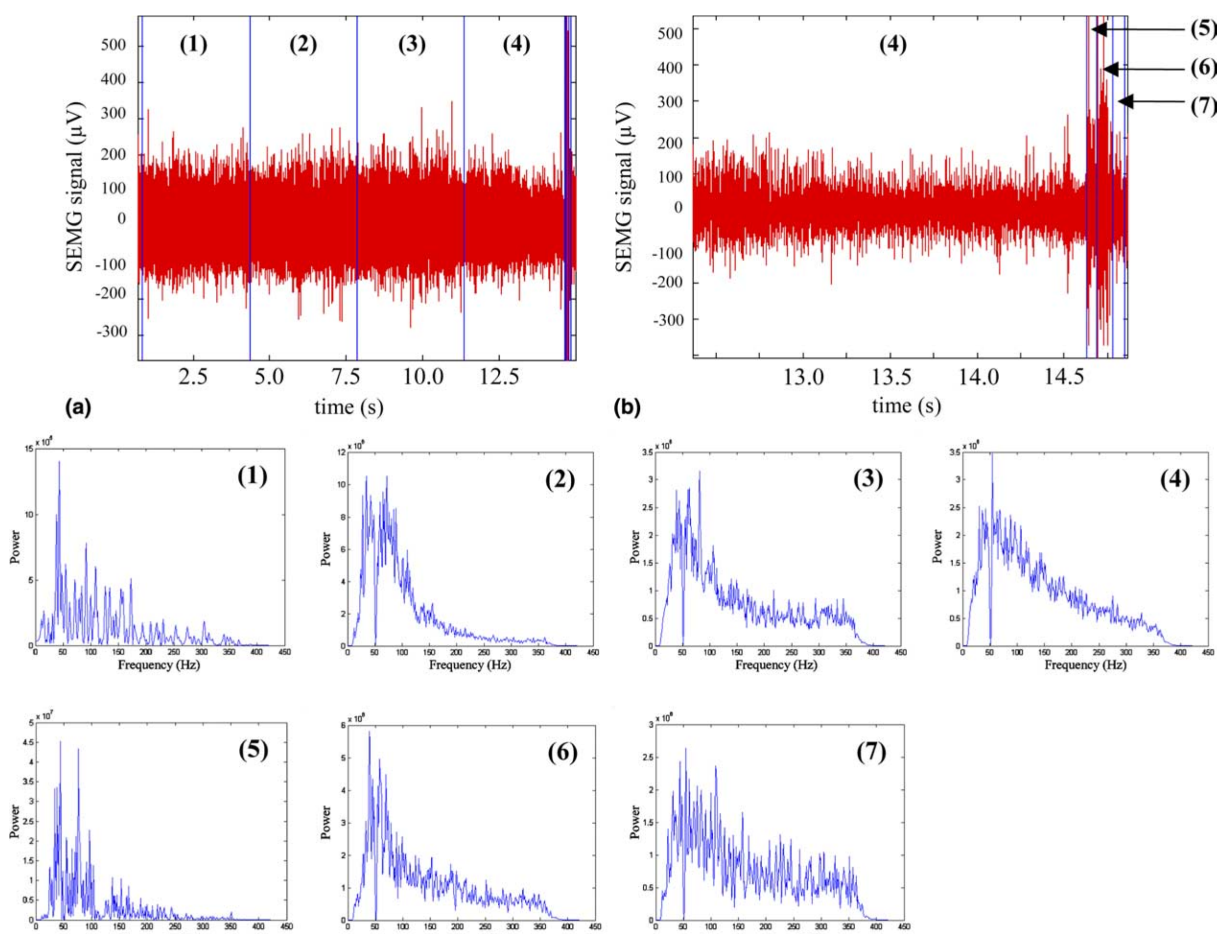


Fig. 6. An example of a segmented signal. (a) Segments 1–4; (b) zoom of segment 4 and segments 5–7. Vertical lines indicate the limits of each segment. The spectra of all seven segments are shown in the second part of the figure. The segments were classified as follows: rejected (1,5); postural surface EMG (2,3,4,6,7).

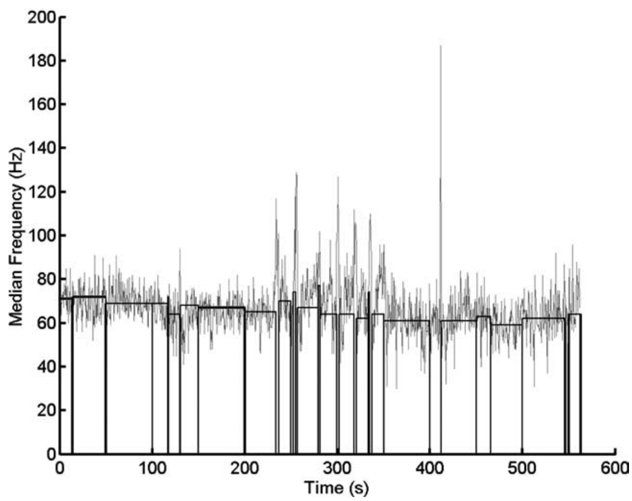


Fig. 7. An example of median frequency data before and after the segmentation and classification procedures. The bars correspond to the median frequencies of the postural surface EMG segments, while the line represents the median frequencies obtained from a non-segmented signal.

there was no evidence of fatigue for these muscles. In contrast, the slope of the regression line for the ES muscle did differ significantly from zero for the segmented signals ($p < 0.05$). Analysis of contrasts for the ES muscle revealed that only the uncomfortable seat without vibration had a significantly negative slope ($p < 0.05$). There were no effects of the other experimental conditions. In respect to the non-segmented surface EMG signals, no effect of fatigue was observed, even after statistical outliers had been removed. In order to examine whether the lack of effect was due to the large variance caused by the use of 1-s windows, median frequencies were calculated for both 5 and 10 s windows for ES muscle. No effect of fatigue was observed for the increased window length. An example of median frequency data before and after the segmentation/classification procedure can be seen in Fig. 7.

## 4. Discussion

The segmentation method used provided satisfactory results in terms of the accuracy of classification, which was greater than 98%. However, when the classification error of 1.8% was combined with the larger rejection error of 5.7%, only 92% of postural surface EMG segments were correctly identified. The rejection algorithm chosen, which used an analytical model of the surface EMG spectrum, needs to be modified in order to improve rejection performance.

Those segments that were inappropriately rejected tended to contain mechanical artefacts. Such segments were classified as surface EMG, rather than being rejected, due to the form of the mechanical artefacts, which resembled that of surface EMG, although at much lower frequencies. Although these mechanical artefacts affected only narrow frequency bands, and did not create a large enough error of fit to be rejected, such artefacts are likely to affect the calculation of spectral parameters, particularly the median and deciles. Therefore, if such segments are retained and are present in any subsequent spectral analysis, there is a risk that erroneous conclusions may be drawn.

The classification algorithm provided better results than the rejection algorithm. However, this algorithm was designed purely for surface EMG signals, and can not, therefore, be applied to generic biomedical signals.

In terms of the segmentation algorithm, despite its low error rate, the algorithm does have some limitations. First, the algorithm is unable to detect segments of very small duration (less than 0.24 s). Such a limitation did not have an effect on the current application, as only the long postural segments were analysed. Thus, the influence of these short segments was greatly reduced.

In terms of the utility of the method, muscular fatigue was able to be identified in signals in which such an assessment was not possible using conventional methods. The signals contained considerable levels of noise, including mechanical artefact due to vibration. Although the level of noise introduced by the electrode-skin contact was not measured, a recent study reported that impedance levels up to 55 kΩ had no effect on median frequency estimates [12]. Despite the presence of such high noise levels, as well as bursts of surface EMG activity, only those segments that contained postural surface EMG were analysed, thus enabling the identification of muscular fatigue. The segmentation method developed in this study would be useful for other long-duration recordings of postural surface EMG signals.

In respect to the absence of muscular fatigue in the TA, EO, and CES muscles, two explanations seem likely. First, the TA and EO muscles were not sufficiently active during the protocol used, with less than 30% of the data considered to be postural surface EMG. As such, these muscles were excluded from the fatigue analysis. The majority of the segments excluded for these muscles were considered to be non-EMG activity, indicating a complete lack of activity for the greater part of the 150 min protocol. As such, it would have been expected that these muscles would not have become fatigued during the trial. In respect to the CES muscles, greater levels of surface EMG activity were observed than for the other muscles. Accordingly, a large number of segments from this muscle were classified as containing bursts of surface EMG activity related to voluntary movements of the head. In many cases, over 50% of a data period was rejected, making it impossible to draw conclusions.

In addition to the issues outlined above, further problems arise when interpreting the fatigue data found in the present study. Although it has widely been reported that changes in spectral parameters during isometric contractions reflect underlying changes in muscle activation due to fatigue [2,16], doubt has been cast on the validity of such findings at low contraction levels [23]. Westgaard and De Luca observed motor unit substitution in the trapezius muscle during long-duration contractions at low intensity (4% MVC). The spectral changes are usually interpreted as being due to a decrease in muscle fibre conduction velocity [17]. In terms of moderate to high intensity isometric contractions, such an explanation seems plausible. However, were the finding to hold true for other postural muscles, it would not be possible to infer the presence of fatigue when changes in median frequency occurred. Analysis of spectral data for low-intensity postural muscle activity should, therefore, be treated with caution.

The time taken to run the algorithm offers the possibility of performing real-time analysis of postural surface EMG signals. The 25 min taken to analyse each 150 min signal would allow six surface EMG signals to be analysed in real time during the protocol. Given that the time taken to reject and classify the segments was 80% of the total processing time, any enhancements to the algorithms should focus on these areas.

## 5. Conclusion

The method used in this study was effective in terms of both segmentation and classification, with a low error rate of less than 8% obtained. This error rate could be enhanced by concentrating on the step related to the rejection of non-EMG segments, which caused most of the misclassification. Furthermore, the elimination of non-postural surface EMG segments by the use of a segmentation approach enabled muscular fatigue to be identified in signals that contained no evidence of fatigue when analysed using traditional methods.

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