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Removing ECG noise from surface EMG signals using adaptive filtering

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ABSTRACT

Surface electromyograms (EMGs) are valuable in the pathophysiological study and clinical treatment for dystonia. These recordings are critically often contaminated by cardiac artefact. Our objective of this study was to evaluate the performance of an adaptive noise cancellation filter in removing electrocardiogram (ECG) interference from surface EMGs recorded from the trapezius muscles of patients with cervical dystonia. Performance of the proposed recursive-least-square adaptive filter was first quantified by coherence and signal-to-noise ratio measures in simulated noisy EMG signals. The influence of parameters such as the signal-to-noise ratio, forgetting factor, filter order and regularisation factor were assessed. Fast convergence of the recursive-least-square algorithm enabled the filter to track complex dystonic EMGs and effectively remove ECG noise. This adaptive filter procedure proved a reliable and efficient tool to remove ECG artefact from surface EMGs with mixed and varied patterns of transient, short and long lasting dystonic contractions.

The surface electromyograms (EMGs) represent a superposition of electrical activity from motor unit action potentials located subcutaneous to the detecting electrodes. EMGs provide valuable information relating to peripheral and central motor function and has been widely adopted in the study of motor function and movement disorders including dystonia [3,7–9,16,28,29,31]. Dystonia is a clinical syndrome characterised by twisting, abnormal posture, repetitive movements and pain resulting from sustained muscle contractions. Surface EMGs have previously been applied quantitatively to assess muscular activity in dystonia and to study its pathophysiological features [3,11]. In the surface EMGs of dystonic patients we have found that there is short bursting activity superimposed on sustained tonic activity [12,31]. Recently, novel measures suggest that patients with a dominant bursting pattern of EMG activity have quicker and better improvement after pallidal deep brain stimulation (DBS), an invasive stereotactic neurosurgical procedure [12,13,28]. It has been suggested that the dystonic activity may be due to over-synchronised pallidal oscillations at 3–20 Hz range [17], however clear separation of the mechanisms responsible for bursting and sustained muscular activation remains illusive [16]. These findings were limited by contamination of the EMG recordings, due in part to ECG artefact, which were especially pronounced in EMGs from the shoulder and neck muscles in patients with cervical dystonia.

Surface EMGs obtained from patients with dystonia are inherently non-stationary due to unstable and mixed symptoms which contain substantial levels of noise [3,8,28]. There are also several prominent artefactual sources which require consideration. These include motion artefacts, power line interference and electrocardiogram (ECG) coupling. The first two types of noise can easily and satisfactorily be removed using high-pass or digital filters [19,21,24–26,33]. Notch filters can remove power line interference from the recorded surface EMG signals very effectively [19], whilst high-pass filters with a cutoff frequency between 2 and 20 Hz may be used for removing movement induced artefacts [24–26,33]. The separation of ECG from surface EMG recordings proves a more problematic task due to their inherent overlap in frequency and temporal domains. Several studies have reported procedures for ECG noise removal from surface EMGs by applying high-pass filters, subtraction or gating operation methods [2,4,14,22]. Redfern et al. investigated the influence of adjusting the cutoff frequency of a high-pass filter and suggested that a cutoff frequency of approximately 30 Hz seemed optimal in balancing ECG removal with excessive EMG degradation [22]. A subtraction procedure, as presented in [2,4], provides an alternative solution by detecting and aligning QRS complexes, averaging the aligned activity and subtracting the averaged artefacts from EMGs via a least-square fit. The efficacy of this procedure relies on the accuracy of QRS

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complex detection and the degree of stationarity of the ECG signals which are not always stereotypic and time-invariant. The gating method provides a simplistic yet potentially effective method of ECG artefact removal. The method does suffer however from losing the portions of the EMGs which overlap with QRS complexes in amplitude [2]. Recently, more sophisticated signal processing algorithms, including the application of nonlinear state-space projections [15], wavelet-threshold denoising [32], independent components analysis (ICA) [23] and combinations of Neural-ICA and wavelet transforms [1] have been used for artefact suppression in surface EMGs. To achieve optimal denoising performance, the relative characteristics of ECG and EMG signals, i.e., the frequency overlap, non-stationarity, varied temporal shape and low signal-to-noise ratio (SNR), should be taken into consideration.

The Weiner and Kalman filters have revolutionised control theory, spawning numerous variants including adaptive modifications, and have been used in our recent neurophysiological investigations [5]. Adaptive filters for noise cancellation were developed to optimally estimate signal components embedded in noisy environments without requiring explicit *a priori* knowledge [30]. Adaptive filters adjust their parameters based on the statistical properties of the inputs which permit real-time adaptation to track dynamic changes in the signal and noise components. A few studies have applied adaptive filter techniques to remove ECG noise from surface EMGs. The least-mean-square (LMS) filter has previously been applied to remove ECG contamination [18]. However, significant residual ECG artefacts were apparent in this study due to a reference signal derived directly from the contaminated EMGs by band-pass filtering. Moreover, due to a relatively slow convergence rate, the LMS algorithm is less capable of improving signal-to-noise ratio in rapidly varying environments; this is a common feature of dystonic muscular activity which shows mixed transient, short and long lasting contraction patterns [3]. In this paper, an adaptive noise cancellation (ANC) filter based on the recursive-least-squares (RLS) algorithm was developed for removing ECG artefact from surface EMGs recorded in patients with cervical dystonia. An ECG signal recorded from a separate channel was used as a reference signal. Simulated signals were used to evaluate the efficiency and effectiveness of the method through SNR measures and coherence analysis. Six patients with cervical dystonia were recruited, providing simultaneous ECG and surface EMG recordings.

The experiment was approved by the local research ethics committee and informed consent was obtained from two healthy subjects and six patients diagnosed with primary cervical dystonia. For dystonic patients, surface EMGs were recorded using disposable adhesive Ag/AgCl electrodes (H27P, Kendall-LTP, MA, USA) placed bilaterally over symptomatic trapezius and sternocleidomastoid muscles. Single channel lead II ECG was simultaneously recorded as a reference signal for adaptive filtering. In the two healthy control subjects, single channel lead II ECG was also recorded as a reference signal. Signals were simultaneously recorded from bilateral trapezius muscles during rest and head-rotational movement. Signals were amplified using isolated CED 1902 amplifiers (1000×), filtered at 0–1000 Hz and digitised using CED 1401mark II at a sampling rate of 2500 Hz (Cambridge Electronic Design, Cambridge, UK), displayed online and recorded onto a harddisk using Spike2 software (Cambridge Electronic Design, Cambridge, UK). ECG artefacts from the left trapezius muscle of healthy controls at rest were mixed with ECG free surface EMGs from right trapezius during head-rotation to generate simulated contaminated EMG signals. This procedure allowed ECG contaminated EMG signals to be simulated with varying SNRs. A 10 s segment of EMGs (recorded or simulated) were selected from each subject. All signals were digitally resampled at 1000 Hz prior to further processing. The signals were pre-processed using a notch filter (centred at 50 Hz) to remove power line interference and a high-pass filter at 15 Hz (12th-order Chebyshev Type I filter) to remove motion artefacts. The pre-processed signals were then filtered with an adaptive noise cancellation filter utilising an RLS algorithm.

The recorded or simulated contaminated EMGs ($EMG_1(n)$) are modelled as a combination of clean EMGs ($EMG_0(n)$) and ECG noise ($ECG_0(n)$), i.e.,

$$EMG_1(n) = EMG_0(n) + ECG_0(n) \tag{1}$$

The ECG component, $ECG_0(n)$, is then estimated by modelling the reference signal of a separate channel lead II ECG ($ECG'(n)$) via a finite impulse response digital filter, i.e.,

$$ECG'_0(n) = \sum_{i=0}^{L-1} w_i^*(n) ECG'(n-i) \tag{2}$$

with L the filter order, $w_i(n)$ the filter coefficients and $ECG'_0(n)$ the estimated ECG noise signal. Asterisk denotes complex conjugation.

The denoised EMGs ($EMG'_0(n)$) are defined as the difference between the input to the filter, i.e., the contaminated EMGs, and the output of the filter, i.e., the estimate of ECG noise. The difference represents the residual of the ANC filter.

$$\begin{aligned} EMG'_0(n) &= e(n) = EMG_1(n) - ECG'_0(n) \\ &= EMG_1(n) - \sum_{i=0}^{L-1} w_i^*(n) ECG'(n-i) \end{aligned} \tag{3}$$

Accordingly, the cost function at sample n is defined as the summation of weighted least-square-errors

$$\xi(n) = \sum_{i=1}^{n} \lambda^{n-i} |e(i)|^2 + \delta \lambda^n ||\mathbf{w}(n)||^2 \tag{4}$$

where λ is a forgetting factor close to or equal to 1, δ is a positive real value defined as a regularisation parameter. We define $\mathbf{w}(n)$ as a coefficient vector of the FIR filter at time n,

$$\mathbf{w}(n) = [w_0(n), w_1(n), \ldots, w_{L-1}(n)]^T \tag{5}$$

with T the transpose operator.

The RLS algorithm adaptively updates the coefficient vector to minimise a cost function, the summation of weighted least-square-errors.

The algorithm is initialised with $\mathbf{w}(0) = 0.$ and $\mathbf{P}(0) = \delta^{-1}\mathbf{I}$, with $\mathbf{I}$ the identity matrix. For each sample, $n = 1, 2, \ldots$, we then compute

$$\mathbf{u}(n) = [ECG'(n), ECG'(n-1), \ldots, ECG'(n-L+1)]^T \tag{6}$$

$$\boldsymbol{\pi}(n) = \mathbf{P}(n-1)\mathbf{u}(n) \tag{7}$$

$$\mathbf{k}(n) = \frac{\boldsymbol{\pi}(n)}{\lambda + \mathbf{u}^H(n)\boldsymbol{\pi}(n)} \tag{8}$$

$$\alpha(n) = EMG_1(n) - \mathbf{w}^H(n-1)\mathbf{u}(n) \tag{9}$$

$$\mathbf{w}(n) = \mathbf{w}(n-1) + \mathbf{k}(n)\alpha^*(n) \tag{10}$$

$$\mathbf{P}(n) = \lambda^{-1}\mathbf{P}(n-1) - \lambda^{-1}\mathbf{k}(n)\mathbf{u}^H(n)\mathbf{P}(n-1) \tag{11}$$

where H is the *Hermitian* transpose operator.

Performance of the ANC filter is now evaluated on the simulated noisy EMG signals from the healthy subjects. Performance is evaluated according to SNRs, power spectra and coherence analysis.

The SNR of the denoised EMG is used to evaluate the overall improvement of signal quality and is defined as

$$\mathrm{SNR} = 10\,\log_{10} \frac{\mathrm{var}(EMG_0)}{\mathrm{var}(EMG_0 - EMG'_0)} \tag{12}$$

Var is the variance operator.

Power spectra of the uncontaminated clean EMGs and EMGs denoised through ANC filtering are obtained by Welch's method, with 10-s EMG signals segmented into 50% overlapping sections. A Hamming window of 1024 data points is used to reduce the variance of the resulting spectral estimate.

Coherence computed between clean and denoised EMGs provides a quantitative measure of denoising performance in the frequency domain. Greater denoising performance results in higher coherence values.

The coherence between two signals EMG_0 and $ECG'_0(n)$ is given by

$$\mathrm{Coh}(f) = \frac{|P_{EMG_0 EMG'_0}(f)|^2}{P_{EMG_0}(f) P_{EMG'_0}(f)} \quad (13)$$

where $P_{EMG_0 EMG'_0}(f)$ the cross-spectral density between EMG_0 and $ECG'_0(n)$, with $P_{EMG_0}(f)$ and $P_{EMG'_0}(f)$ their respective auto-spectra.

Fig. 1 displays the results of denoising of the simulated noisy EMGs by ANC filtering. Results are presented in both the time and frequency domains. ECG artefacts recorded from left trapezius of a healthy subject (Fig. 1a) at rest were scaled and added to ECG free EMGs obtained from the right trapezius (Fig. 1b) to generate the simulated contaminated EMGs (Fig. 1c). Displayed are results from a simulated EMG contaminated at an SNR level of −4.71 dB. A lead II ECG simultaneously recorded at rest was used as a reference signal with simulated EMGs as the input to the ANC filter (Fig. 1d). The denoised EMGs (Fig. 1e) were computed as the residual of the ANC filtering, with minimal observable ECG artefact remaining. The clean EMGs (Fig. 1b) and the denoised EMGs (Fig. 1e) had similar spectra.

The performance of the ANC filter was then evaluated using coherence analysis under varying filter and signal characteristic parameters, i.e., the SNR of the simulated EMGs, filter order, forgetting factor and regularisation factor. Noise and filtering affected mainly frequencies between 15 and 50 Hz. The performance of the ANC filter was then related to the SNR of the contaminated EMGs. As expected, a high SNR resulted in superior performance. With the SNR reduced from −4.71 to −9.15 dB there was slight decrease in coherence. When the SNR reduced further, coherence dropped markedly (Fig. 2a). Very low filter orders (around 2) resulted in poor performance. When the order of the filter was increased above nine, coherence stabilised at levels close to one (Fig. 2b). The ANC filter was very sensitive to the forgetting factor. When this factor changed from 1 to 0.98, the coherence decreased dramatically (Fig. 2c). The regularisation factor had little effect on ANC filter performance (Fig. 2d).

Fig. 3 displays the SNR of the denoised EMGs under equivalent parameter modulation. Fig. 3a shows that the SNR of the denoised EMGs increased from −11.10 to 11.09 dB with decreasing SNR of the contaminated EMGs from −15.17 to −4.71 dB. The SNR of the denoised EMGs increased by 4 dB when the SNR of the contaminated EMGs was −15.17 dB, with an increase of 15.8 dB when the SNR of the contaminated EMGs was −4.71 dB. Here a filter order of 12 and a forgetting factor of 0.999 were used. Low filter orders provide poor filtering performance and low SNR. When the filter order was increased beyond nine, the SNR of the denoised EMGs became stable (Fig. 3b). Here, a forgetting factor of 0.999 and a SNR of −4.71 dB of contaminated EMGs were used. The performance of the filter was sensitive to the forgetting factor. The SNR of the denoised EMGs varied between 5.53 and 11.09 dB with several forgetting factor values. A value of 0.999 provided the best performance (Fig. 3c). Here a filter order of 12 and −4.71 dB contaminated EMGs were used. The regularisation factor slightly increased SNR from 11.0 to 11.23 dB when changed from 0.03 to 0.7 (Fig. 3d). Therefore a combination of parameters of a filter order of 12, a forgetting factor of 0.999 and a regularisation factor of 0.1

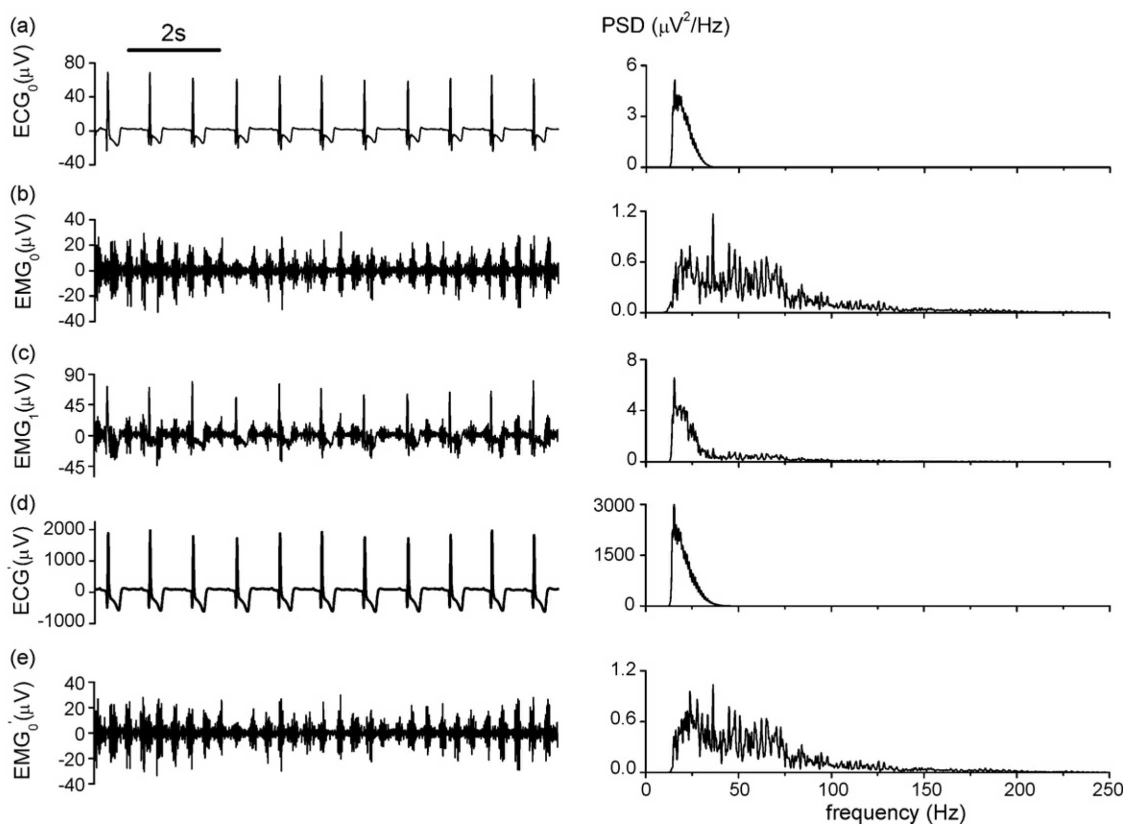

Fig. 1. The ECG artefacts (a) were mixed with clean EMGs (b) to simulate contaminated surface EMGs (c). A separate lead II ECG (d) was recorded as a reference signal and the denoised EMGs (e) was obtained by filtering the contaminated EMGs using adaptive filter. The spectra of ECG and EMG signals were on the right column.

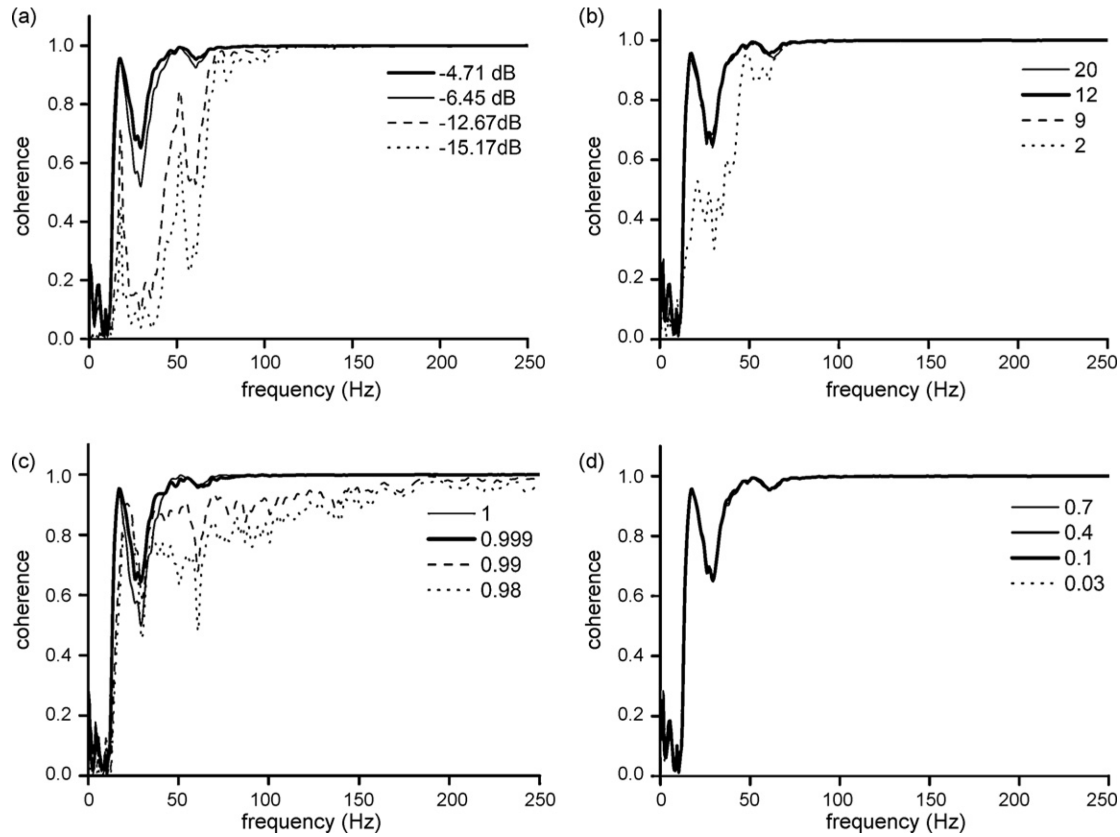

Fig. 2. Coherence between the clean and denoised EMGs was computed when different parameters of adaptive filter were applied, i.e., signal-to-noise ratio (SNR) of the contaminated EMGs (a), filter order (b), forgetting factor (c) and regularisation factor (d).

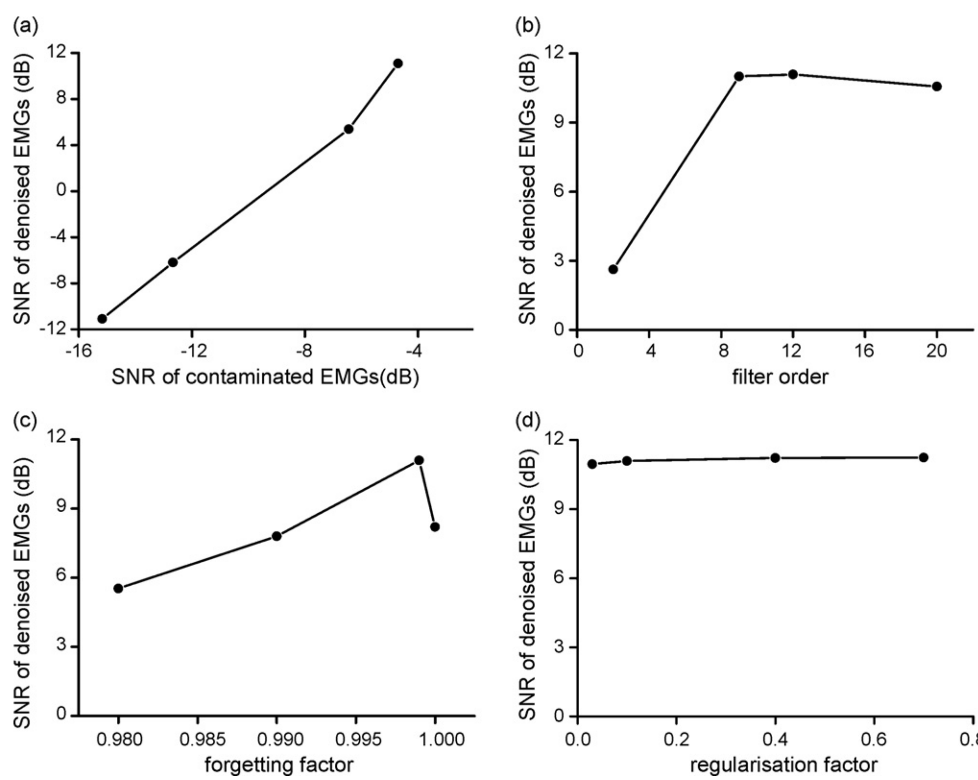

Fig. 3. The SNR of the denoised EMGs was computed when different parameters of adaptive filter were applied. (a) The increase of SNR of the denoised EMGs was positively correlated to the SNR of the contaminated EMGs. (b) The SNR of the denoised EMGs became stable when the filter order was larger than 9. (c) The filter performance was sensitive to the forgetting factor and value of 0.999 achieved the highest SNR. (d) The regularisation factor had little influence on the SNR of the denoised EMGs.

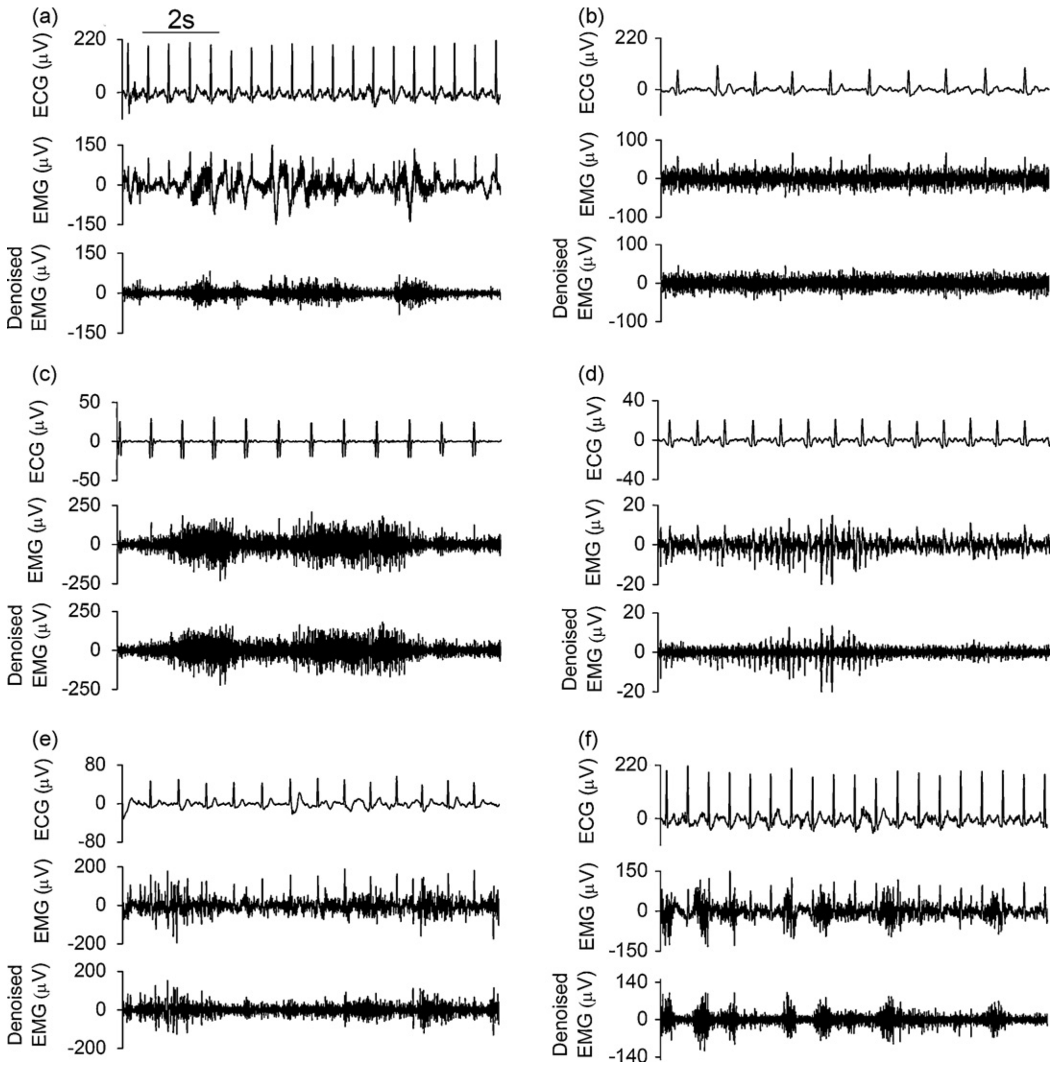

Fig. 4. ECG and surface EMGs of trapezius muscles were simultaneously recorded from six patients with cervical dystonia (top and middle, a–f). The ECG artefacts were significantly attenuated by adaptive filtering (bottom, a–f).

was used for denoising EMGs from patients with cervical dystonia.

Surface EMGs were recorded from the trapezius muscles of six patients with cervical dystonia (middle, Fig. 4a–f) with simultaneously recorded ECG as reference signal to the ANC filter (top, Fig. 4a–f). The denoised EMGs are displayed together (bottom, Fig. 4a–f). Surface EMGs recorded across the patient population showed a range of ECG noise contamination levels. There was high noise in (a) and (e) but the noise was low in (b) and (d) of Fig. 4. After filtering using ANC, there were no perceivable ECG artefacts present in any of the six denoised EMGs.

Several factors may influence the performance of an adaptive filter, for instance the filter structure, rate of convergence, robustness, etc. The RLS algorithm iteratively computes the updated estimate of the filter coefficients upon the arrival of new data. The convergence rate of the RLS algorithm is typically ten times faster than that of the LMS algorithm due to whitening of the input data [10]. The RLS algorithm will therefore naturally perform better for signals with rapidly changing features, such as dystonic EMGs which are known to possess complex patterns of activation. Adjusting the forgetting factor permits control over the convergence rate. Decreasing the forgetting factor results in faster convergence but an associated increase in fluctuations of filter coefficients. The RLS algorithm naturally provides a fast convergence rate so as to render tuning by the forgetting factors redundant in the specific case of denoising surface EMGs. When the recorded EMGs have a relatively high SNR, a forgetting factor very close to one proves sufficient. In our study, the regularisation parameter had no significant influence on the effectiveness of filtering ECG noise from EMGs (Fig. 3d). A value of 0.1 was selected in this study. As the robustness of the algorithm is signal dependant, when the SNR decreases, the performance of the filter worsens, but still achieves respectable performance even when the SNR is below −5 dB.

The level of ECG contamination in EMGs is highly dependant on the placement of EMG electrodes which is often dictated through selection of the pathological muscle group. ECG contamination in EMGs may be minimised by common-mode rejection at the recording site by careful placement of bipolar recording electrodes along the axis of heart if possible. Little significant ECG contamination has been reported in EMGs obtained from limb muscles in generalised dystonia [17]. Such contamination may become more severe in segmental dystonia where truck muscles are affected, for instance, the rectus abdominis, external oblique or erector spinae muscles. As the ANC filter based on a RLS algorithm can adaptively track the filter coefficients according to the input signals, it should maintain similar performance when applied to a variety of muscle groups.

This adaptive filter was effective and efficient for noise cancellation of surface EMGs. Such a filter could be used in other linear or nonlinear situations. Also they can be used for system identification, inverse modelling and predictive coding analysis [10] to elucidate the mechanisms of neuromuscular coupling or the basal ganglia-thalamo-cortical network in movement disorders and motor control [6,20,27,29].

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