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Removing ECG contamination from EMG recordings: A comparison of ICA-based and other filtering procedures

Nienke W. Willigenburg, Andreas Daffertshofer, Idsart Kingma, Jaap H. van Dieën *

Research Institute MOVE, Faculty of Human Movement Sciences, VU University, Amsterdam, The Netherlands

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ABSTRACT

Trunk muscle electromyography (EMG) is often contaminated by the electrocardiogram (ECG), which hampers data analysis and potentially yields misinterpretations. We propose the use of independent component analysis (ICA) for removing ECG contamination and compared it with other procedures previously developed to decontaminate EMG. To mimic realistic contamination while having uncontaminated reference signals, we employed EMG recordings from peripheral muscles with different activation patterns and superimposed distinct ECG signals that were recorded during rest at conventional locations for trunk muscle EMG. ICA decomposition was performed with and without a separately collected ECG signal as part of the data set and contaminated ICA modes representing ECG were identified automatically. Root mean squared relative errors and correlations between the linear envelopes of uncontaminated and contaminated EMG were calculated to assess filtering effects on EMG amplitude. Changes in spectral content were quantified via mean power frequencies. ICA-based filtering largely preserved the EMG's spectral content. Performance on amplitude measures was especially successful when a separate ECG recording was included. That is, the ICA-based filtering can produce excellent results when EMG and ECG are indeed statistically independent and when mode selection is flexibly adjusted to the data set under study.

1. Introduction

Trunk muscle electromyography (EMG) appears very suitable to study the activity of abdominal and back muscles, e.g., during postural control. The frequency content of trunk muscle EMG signals may provide information on fatigue development in these muscles. Unfortunately, trunk muscle EMG recordings are often contaminated by the electrocardiogram (ECG), which can hamper analysis (Butler et al., 2009) and may result in misinterpretations.

In trunk EMG recordings the heart rate can often be determined by mere visual inspection. Nonetheless it is difficult to remove the contamination algorithmically because of the ECG's complicated waveform, which is accompanied by a broad-band spectral distribution. This distribution covers many higher harmonics characterizing the ECG but also reflects the transient nature of the heart rate, which causes peaks at harmonics to broaden substantially. As a consequence, the ECG spectrum typically overlaps the spectral distribution of the EMG and disentangling the two forms a challenge.

ECG removal procedures used to date include high-pass filtering (HPF), usually employing finite impulse response or Butterworth filters with a cut-off frequency of about 30 Hz (Redfern et al., 1993; Drake and Callaghan, 2006). The overlap of ECG and EMG frequency content, however, causes such high-pass filtering (or other types of frequency filters like consecutive notch filters) to alter the frequency content of the EMG, affecting outcome measures like mean frequency and mean amplitude. We note that HPF-effects on amplitude can – in part – be compensated via proper normalization, assuming that the frequency distribution scales constantly over activation levels. Still, this is problematic in studies involving muscle fatigue or when measuring patients who cannot perform maximal voluntary contractions.

ECG contamination in EMG may also be removed via template matching approaches exploiting archetypical ECG waveforms. Unfortunately, the shape of the ECG waveforms strongly depends on electrode location, which limits success of conventional template detection. To avoid the need for generic archetypes, filtering by adaptive sampling (FAS) has been suggested (Aminian et al., 1988; Marque et al., 2005). If ECG is recognizable and can be isolated as individual waveform using a single epoch, it can be subtracted from the contaminated signal, resulting in a 'clean' EMG signal. This procedure has the potential advantage of leaving the spectral content of the actual EMG largely

* Corresponding author. Address: Research Institute MOVE, Faculty of Human Movement Sciences, Van der Boechorststraat 9, 1081 BT Amsterdam, The Netherlands. Tel.: +31 20 598 8501; fax: +31 20 598 8529.
E-mail address: j.van.dieen@vu.nl (J.H. van Dieën).

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unaffected, but the proper identification of ECG in EMG signals remains rather difficult, if at all feasible. Aminian and colleagues (1988) recommended recurrent application of a modified turning point algorithm to distinguish between (fast fluctuations in) EMG and (slower) ECG samples, in combination with a reference amplitude to detect R-peaks. Although this procedure can track changes in heartbeat over time, peak removal is limited by recurrent application of the modified turning point algorithm, since the highest peaks will be discarded.

To improve ECG removal from EMG recordings, Hof (2009) suggested to record a separate ECG signal simultaneously with the EMG recordings. By this, for each electrode location, a separate ECG template can be constructed based on the impulse responses to the ECG channel, which are fitted to a resting EMG recording. In fact, this procedure requires a simultaneous ECG recording and a measurement with minimal EMG activity of the trunk muscles. If these supplementary recordings are available, Hof's approach appears promising, though to our best knowledge the procedure has not been thoroughly evaluated, yet.

Here we advocate the use of adaptive filters based on multivariate assessments of EMG. This method is not new and found frequent application in particularly in the neurosciences, e.g., for artifact removal in the electro-encephalogram (EEG). EEG is often contaminated by various confounding signals, predominantly by eye-blinks. Capitalizing on the independence of EEG and eye-blinks and, by the same token, exploiting the multivariate nature of EEG, Makeig and colleagues (1996) suggested the use of independent component analysis (ICA). ICA decomposes a set of time series into a set of statistically independent or uncorrelated modes ('source signals'). This procedure is very similar to a principal component analysis (PCA) with the addition that the simple singular value decomposition of the covariance matrix in PCA is replaced by an optimization of the source signals' covariance and kurtosis.

We generally assume that the contaminating signal (here ECG) can in first approximation (1) be considered as merely superimposed onto the signal under study (here EMG) and (2) is independent thereof. For this case we expect ICA to result in subsets of modes that only contain contaminations and – more importantly – subsets of uncontaminated modes. A recent study indeed examined ICA-based ECG removal on a simulated data set of ECG-contaminated EMG signals (Mak et al., 2010). Results were promising, but about 25% of all ICA modes were identified as ECG-contaminated. Most probably this resulted in loss of EMG but, unfortunately, EMG amplitude or frequency outcome measures have not been reported. Also, the suggested procedure relied on a peak-detection algorithm used to identify ECG in the ICA modes, which limits the general applicability to EMG with low amplitude. In the present study we build on these early ideas and examined automatic ICA-based removal of ECG from EMG recordings by comparing it with the more traditional HPF and FAS as well as the aforementioned method by Hof (2009). To assess quantitative differences in both ECG removal and EMG preservation, we used artificially contaminated EMG recordings from peripheral muscles with different patterns and levels of activation. The ECG used for artificial contamination was recorded at 15 different electrode locations often used for trunk muscle EMG recordings, in order to mimic actual differences in ECG waveforms in trunk muscle EMG. ICA-based filtering was realized with and without the use of a separate ECG recording. We hypothesized that the methods requiring a separate ECG recording are in general superior to methods without the use of such a reference. From the latter, we further hypothesized ICA-based filtering to be more successful than both alternatives in removing ECG, because it is largely independent of signal-to-noise ratio (which is known to limit template matching) and because of its merely subtle effects on frequency content of the signals.

2. Methods

2.1. Data collection and pre-processing

2.1.1. Generating artificially ECG-contaminated EMG

Surface EMG activity of 16 peripheral muscles in the upper and lower extremities was recorded in a single subject (female, age 26, BMI 22) using a conventional, bipolar montage (Porti 17, TMS, Enschede, The Netherlands; 22 bits AD conversion after 20× amplification, input impedance >10^{12} Ω, CMRR >90 dB, 1000 samples/s, with online 10–400 Hz band-pass filtering). A single subject design (as also used by (Drake and Callaghan (2006)) was considered suitable for this methodological study, since signal characteristics of ECG and EMG are similar between subjects.

Electrodes (Ag/AgCl, inter-electrode distance 25 mm) were placed above selected arm and leg muscles according to SENIAM recommendations (Hermens et al., 2000); see Table 1, left column. During these EMG recordings the subject performed several tasks (30 s each) requiring different levels and patterns of activation; see Table 2 for an overview. Maximal voluntary contractions (MVCs) were performed against the experimenter's manual resistance for each muscle.

ECG was recorded during rest (lying supine) at 16 locations commonly used for recordings of trunk muscle activity (four back and four abdominal muscles bilaterally, see Table 1, right column; more details on electrode locations can be found in Willigenburg et al. (2010)). Visual inspection revealed only minimal EMG activity, implying that apart from some background noise largely isolated ECG signals were recorded. From here-on we therefore refer to these signals as ECG. Note that these 16 ECG channels differed from each other in that each signal represented a realistic ECG contamination at a specific trunk muscle. An occasional 50-Hz interference was removed using a conventional off-line notch filter (4th order bi-directional Butterworth, 49.5–50.5 Hz).

Table 1
Muscles from which EMG was recorded; odd and even channels refer to right and left muscles, respectively.

Channel	Limb EMG recordings during five tasks	ECG recordings at trunk muscle electrode locations during rest
1–2	m. rectus femoris	m. longissimus thoracis
3–4	m. vastus medialis	m. iliocostalis thoracis
5–6	m. biceps femoris	m. iliocostalis lumbalis
7–8	m. gastrocnemius lateralis	m. longissimus lumbalis
9–10	m. gastrocnemius medialis	m. rectus abdominis
11–12	m. tibialis anterior	m. obliquus externus anterior
13–14	m. biceps brachii	m. obliquus internus anterior
15–16	m. brachioradialis	m. obliquus externus lateralis

Table 2
Experimental tasks during which EMG of peripheral muscles was recorded.

Task	Activity	
	Lower extremity	Upper extremity
1	Upright stance	90° elbow flexion
2	Upright (15 s) to squatted (15 s) stance	Arms hanging down
3	Squatted (15 s) to toe (15 s) stance	Arms forward (15 s) to upward (15 s)
4	Rhythmic stepping	90° elbow flexion, arm sway
5	Various (randomly chosen) activities	Various (randomly chosen) activities

EMG signals of peripheral muscles did not contain any recognizable ECG contamination and were 10–400 Hz band-pass filtered off-line (2nd order bi-directional Butterworth). We then created artificially contaminated EMG recordings by superimposing the ECG signals (recorded at trunk muscle electrode locations during rest) on the EMG (of the active peripheral muscles). Superposition was implemented by adding channels 2–16 of the ECG to channels 2–16 of the uncontaminated limb EMG recordings (EMG_{uncon}), resulting in 15 contaminated EMG signals (EMG_{con}). Channel 1 of the ECG recordings served as a 'reference' ECG channel, which was used in the filtering procedures requiring a simultaneously recorded ECG signal; channel 1 of the EMG recordings was discarded. During 'real' trunk muscle EMG recordings, the reference ECG signal could be recorded on a bony area close to the heart, e.g. the sternum.

2.2. Data analysis

We employed three ECG removal techniques that do not require a reference ECG recording: 30-Hz high-pass filtering (EMG_{HPF}), filtering by adaptive sampling (EMG_{FAS}), and ICA-based filtering (EMG_{ICA}). In addition, we evaluated two methods for ECG removal including a simultaneously recorded ECG signal: Hof's procedure (EMG_{Hof}) and ICA-based filtering ($EMG_{ICA+ref}$).

2.2.1. HPF procedure

Most of the ECG's spectral power is located below 30 Hz. This concentration of the spectral distribution to low frequencies renders mere high-pass filtering the first choice for removal of ECG contamination. As recommended by Drake and Callaghan (2006), we therefore applied a 2nd order bi-directional high-pass Butterworth filter with cut-off frequency of 30 Hz to EMG_{con}, resulting in EMG_{HPF}.

2.2.2. FAS procedure

The FAS procedure builds on the fact that the variations in motor unit action potentials are much more rapid than those of the ECG. This difference in time scales allows for recognizing samples of ECG via a QRS-complex detection algorithm after recurrent (four times) application of the modified turning point algorithm (Aminian et al., 1988). Our QRS-detection algorithm used an average R-peak width of 20 ms and an R-peak amplitude threshold of four times the standard deviation of the raw EMG_{con}. Q and S were determined as local minima preceding and following the R-peaks. Linear interpolation of the so-detected QRS-samples were considered the 'pure' ECG, which was subtracted from EMG_{con}. This subtraction led to a decontaminated EMG, here referred to as EMG_{FAS}.

2.2.3. Hof's procedure

Hof's procedure (Hof, 2009) models the ECG contamination at different electrode locations as a filtered version of the reference ECG recording. The impulse responses of the ECG filters for each EMG channel are determined based on least squares fitting to a resting recording with minimal EMG activity. Subsequently, these filtered ECGs are subtracted from the actual EMG recordings yielding EMG_{Hof}. We note that we here did not implement a 'conventional' 20 or 30 Hz high-pass filtering as was included in Hof's original proposal in order to avoid limitations as in the HPF procedure above.

2.2.4. ICA-based filtering procedure

ICA is a multivariate statistical approach to (blind) source separation (Jutten and Hérault, 1991). The multivariate input data consisted of the aforementioned 15 contaminated EMG signals; EMG_{con}. As said the ICA-based filtering procedure was realized in the absence of an additional reference but also with an additional reference ECG (as in Hof's approach). In the latter case an amplified[1] ECG signal (channel 1) was used as 16th input EMG channel. In the first case, i.e. without external reference, we created a reference channel via averaging the 15 contaminated input EMG signals after 8–18 Hz band-pass filtering.

For ICA decomposition we used the so-called FastICA algorithm (Hyvärinen and Oja, 2000, version 2.1, from http://research.ics.tkk.fi/ica/fastica) with a symmetric decorrelation approach and PCA eigenvectors as initial guess. The optimization employed a fixed-point algorithm with cubic non-linearity. In the resulting ICA modes, ECG was identified by a tailor-made detection algorithm (soon available via http://www.upmove.org/misc). In a nutshell, we first enhanced possible ECG peaks in the ICA projection by setting all values within a small range around the mean to zero, second we computed the power spectral densities and selected those modes that displayed pronounced higher harmonics of the ECG base frequency which had to cover at least 5% of the total power of the mode. The so-defined ICA_{ECG}-modes were removed by zeroing the corresponding coefficients of the mixing matrix prior to reconstructing the 16-dimensional data set from which the leading 15 signals represented decontaminated EMG signals, referred to as EMG_{ICA} and $EMG_{ICA+ref}$.

2.3. Filter performance

2.3.1. EMG amplitude

Linear envelopes were obtained by application of a 2.5 Hz (1st order bi-directional) low-pass filter to the Hilbert amplitudes (i.e., modulo of the corresponding analytic signal) of the various EMG signals (Bruns, 2004). Amplitudes were normalized to %MVC. With the HPF procedure, HPF was also applied to the MVC recordings to correct for the loss of EMG with low frequency content (<30 Hz). Root mean squared relative errors (*RMSRE*) and correlation coefficients (R) of the linear envelopes of EMG_{con}, EMG_{FAS}, EMG_{HPF}, EMG_{ICA}, EMG_{Hof} and $EMG_{ICA+ref}$ with respect to the linear envelopes of EMG_{uncon} were calculated. *RMS* error was defined as the *RMS* of the difference between the linear envelopes of EMG_{uncon} and the differently filtered EMGs for each channel. To correct for differences in EMG activation levels between channels within tasks, *RMSRE* was calculated by dividing *RMS* errors by the mean amplitude of EMG_{uncon} over the task for each channel.

2.3.2. EMG frequency

Spectral analysis of EMG_{uncon}, EMG_{con} and the five differently filtered EMG signals (EMG_{HPF}, EMG_{FAS}, EMG_{ICA}, EMG_{Hof} and $EMG_{ICA+ref}$) was performed using Welch's averaged periodogram method (Hamming window size 5 s with 50% overlap between consecutive windows). From these power spectral densities, we calculated the mean power frequency (*MPF*). Note that EMG_{con} will underestimate *MPF* with respect to EMG_{uncon}, whereas HPF will (obviously) result in an overestimation of *MPF*. Since the other filtering procedures can result in errors in both directions, which could theoretically cancel out, we calculated the absolute difference with respect to MPF_{uncon}. The absolute difference between the uncontaminated MPF_{uncon} and MPF_{con}, MPF_{FAS}, MPF_{HPF}, MPF_{ICA}, MPF_{Hof} and $MPF_{ICA+ref}$ divided by MPF_{uncon} resulted in six different *MPF* relative error (*MPFRE*) values for each channel and task.

2.3.3. Bootstrapping procedure

To assess robustness of the filtering results, we applied a bootstrapping procedure. Specifically, all calculations were repeated using 50 surrogates by means of random combinations of the

[1] Amplifying the 'reference' ECG guaranteed that it always dominated at least one of the ICA modes.

EMG channels of 15 muscles and the ECG signals recorded at 15 locations on the trunk. By this, ECG signals with distinct amplitudes and QRS-complexes were superimposed on EMG signals with different amplitudes and activation patterns, resulting in a variety of amplitude ratios between EMG and ECG which is also found in 'real' contaminated EMG. The current method did not allow for further statistical comparison of the filtering procedures, since a fundamental assumption for statistical testing was violated: the samples are not independent.

2.3.4. Trunk muscle EMG example

In addition to the quantitative evaluation of filter performance, we further tested the different techniques on 'real' ECG contaminated trunk muscle EMG recordings. Obviously, the lack of a 'gold standard' in such a data set does not allow for quantification of filter performance. However, a figure with examples of ECG removal by HPF and the ICA-based procedure was included to allow for visual inspection of filtering results.

3. Results

3.1. An example

We first illustrate our ICA-based filtering approach using signals of task 3 (squatted to toe stance). Fig. 1 shows the 16 ICA modes that resulted from decomposition of 15 EMG_{con} and one constructed 'reference ECG' signal. Mode 16 (right lower panel) not only had the highest coefficient for the constructed ECG channel in the mixing matrix, but also met both criteria of equidistance and relative power at the heart frequency (and its harmonics) and was therefore removed prior to reconstructing the signals.

Fig. 2 shows in gray the reconstructed EMG_{ICA} based on the remaining 15 modes of Fig. 1. EMG_{ICA} was superimposed onto EMG_{con} in black, revealing that ECG contamination largely disappeared with limited loss of EMG. Only in channel 5 some amplitude loss at the higher activation level was observed. Note that with an external reference ECG the ICA-filter generally performed better than without that reference; apparently a simultaneously recorded ECG signal provided a better ECG reference signal than the 'reference' signal (right lower panel) constructed by averaging over EMG channels.

A closer look at the linear envelopes and power spectra of the (un)contaminated versus the filtered EMG signals of channel 2 allowed for an in-depth assessment of approaches (Fig. 3). The upper panel demonstrates the effect of ECG contamination (black) on the original EMG recording (gray). Although all procedures (in black in the lower panels) reduced ECG contamination, differences in filter performance were clearly visible.

HPF did not entirely remove ECG-peaks and, as expected, caused a substantial overestimation of the *MPF*. Moreover, EMG_{HPF} amplitude at higher activity levels was slightly underestimated, despite application of the same HPF to the MVC data used for normalization. Also, some EMG around the transition from high to lower activation level was lost. FAS reduced ECG peak height at the low EMG activation level, but failed to recognize all QRS-complexes at higher EMG activity levels. FAS furthermore resulted in a slight overestimation of the EMG amplitude at higher activation levels and in a substantial underestimation of the *MPF*, due to low frequencies originating from the QRS-template construction. After ICA-based filtering without the use of a reference ECG signal, residuals of ECG peaks were clearly present, but, in contrast with HPF and FAS, the power spectrum of EMG_{ICA} largely resembled that

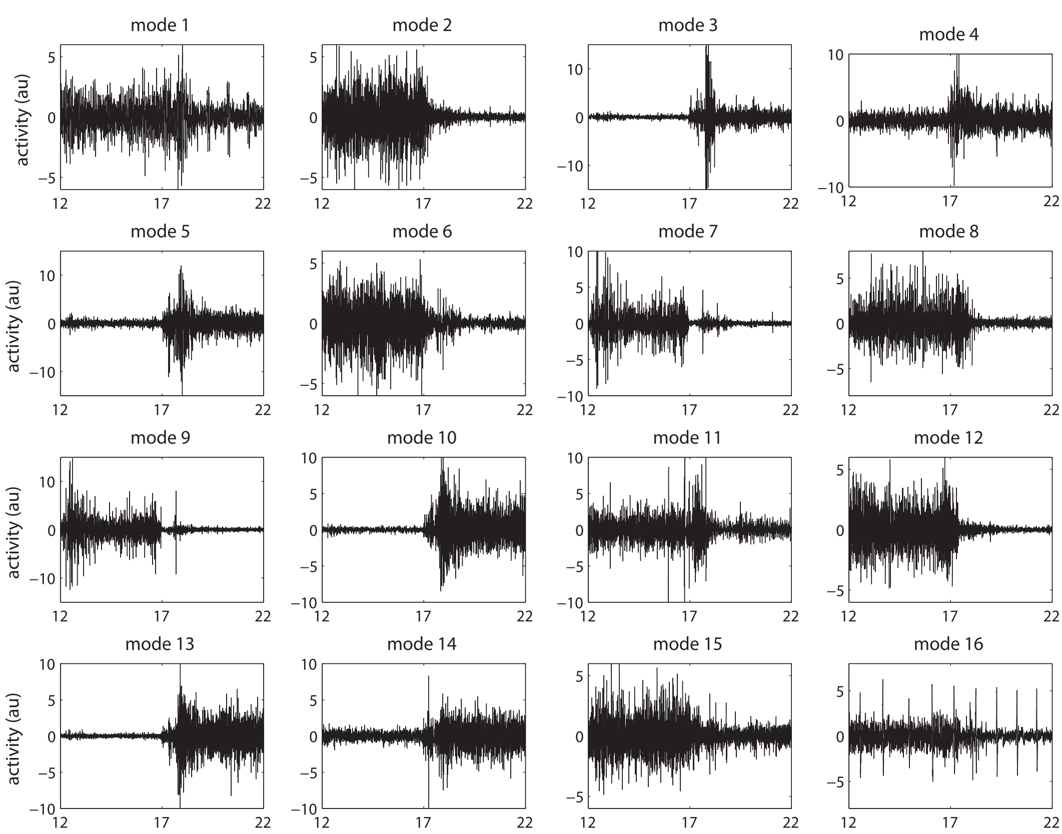

Fig. 1. ICA modes after decomposition of EMG_{con} without reference ECG recording for task 3. Activity level on the *y*-axis is in arbitrary units (au) reflecting normalization of the data prior ICA decomposition. The *x*-axis is limited to 10 of the 30 s and this order of ICA modes was prior to sorting. Note that ECG was largely isolated in mode 16, which indeed became the first mode after sorting and was detected as ICA_{ECG}-mode.

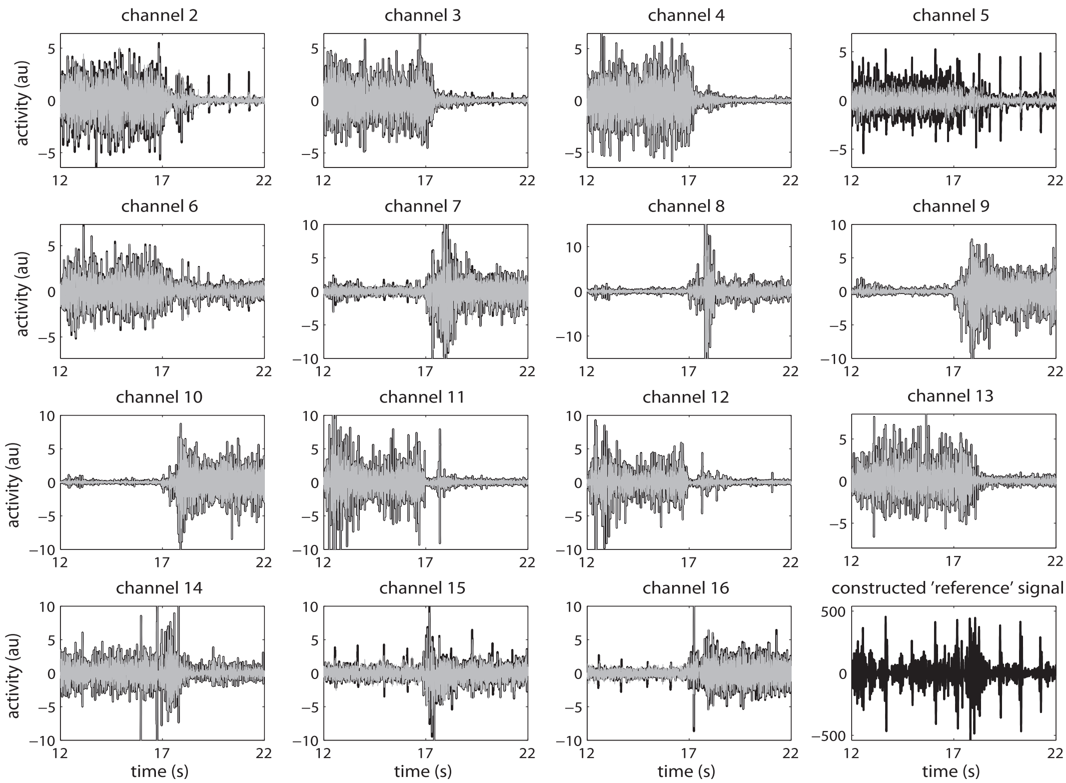

Fig. 2. EMG_{con} in black bold lines and $EMG_{ICA+ref}$ in gray thin lines for all channels (see Table 1 for an overview of the EMG and ECG origins). In the right lower corner the 'reference' ECG constructed by averaging over EMG signals is shown. Note that removal of ICA_{ECG} mode 16 (see Fig. 1) resulted in successful ECG removal for all channels but also caused some amplitude loss in Ch 5.

of EMG_{uncon} yielding almost equal *MPFs*. The slight underestimation of EMG amplitudes at high EMG activity levels with ICA probably resulted from some common EMG other than ECG that was present in the ICA_{ECG}-mode (see mode 16 in Fig. 1). Both procedures based on a separate ECG reference recording were very successful in removing ECG while keeping EMG almost perfectly intact.

3.2. Overall results

The *RMSREs* for EMG_{con}, and the five differently filtered signals with respect to EMG_{uncon} are shown in Fig. 4 for the five different tasks, averaged over channels. From the procedures without reference ECG recording, HPF substantially reduced *RMSRE* in tasks 1 and 2. In upright stance, with relatively low level and small variations of muscle activation, ICA without external reference performed equally well and in task 3, which contained more substantial levels of muscle activation, only the ICA version reduced *RMSRE*. None of the methods without reference ECG recording was successful in tasks 4 and 5, where *RMSREs* were similar to or even larger than *RMSRE* of EMG_{con}. Both procedures that required a reference ECG recording (Hof and ICA plus external reference) succeeded in reducing *RSMRE* in all tasks, but in particular performed better than the other methods in tasks 3, 4 and 5.

As mentioned earlier, the robustness of filter performances was tested with a bootstrapping procedure evaluating 50 random combinations of EMG and ECG channels. Averaging over 15 channels and these 50 combinations respectively, resulted in means and standard deviations of *RMSRE*, *MPFRE* and *R* as shown in Fig. 5. Average *RMSREs* were comparable to the results for the single combination of channels presented in Fig. 4. HPF was at least equally successful to both procedures that required a separate ECG channel in tasks 1 and 2. The large mean and standard deviation of RMSRE for ICA in the absence of an external reference in task 1 indicated that filter performance was not robust. Apparently, ECG removal was successful in some combinations of EMG and ECG (as in Fig. 4), but not in other combinations. Interestingly, in tasks 3 and 5, ICA without reference was the only method without a reference recording that resulted in (slightly) reduced *RMSRE* compared to EMG_{con}.

Obviously, HPF affected the EMG's spectral content, resulting in large overestimations of *MPF* (Fig. 5). Both procedures relying on a reference ECG signal resulted in low *MPFRE* for all tasks, implying that they left the EMG's frequency content largely unaffected. When no separate ECG recording was used, *MPFRE* was lowest with the ICA (without reference) procedure. Correlations (lower panel) were generally high, but some differences between filtering procedures can be observed, especially in task 1.

3.3. Trunk muscle EMG

Fig. 6, shows an example of HPF and ICA (without and with external ECG recording) in 'real' ECG-contaminated trunk muscle EMG recordings. Note that, in general, all filtering procedures reduced ECG contamination. However, some differences between procedures are clearly visible: residual ECG peaks remained after HPF (middle and right panel), whereas the complete removal of ECG peaks appeared to coincide with some loss of EMG amplitude for ICA without external reference ECG (middle panel). Best results were obtained when an external ECG recording was included in the ICA-based filtering procedure (lower panel).

4. Discussion

We evaluated the use of ICA for removal of ECG contamination from EMG recordings. The procedure was implemented with and

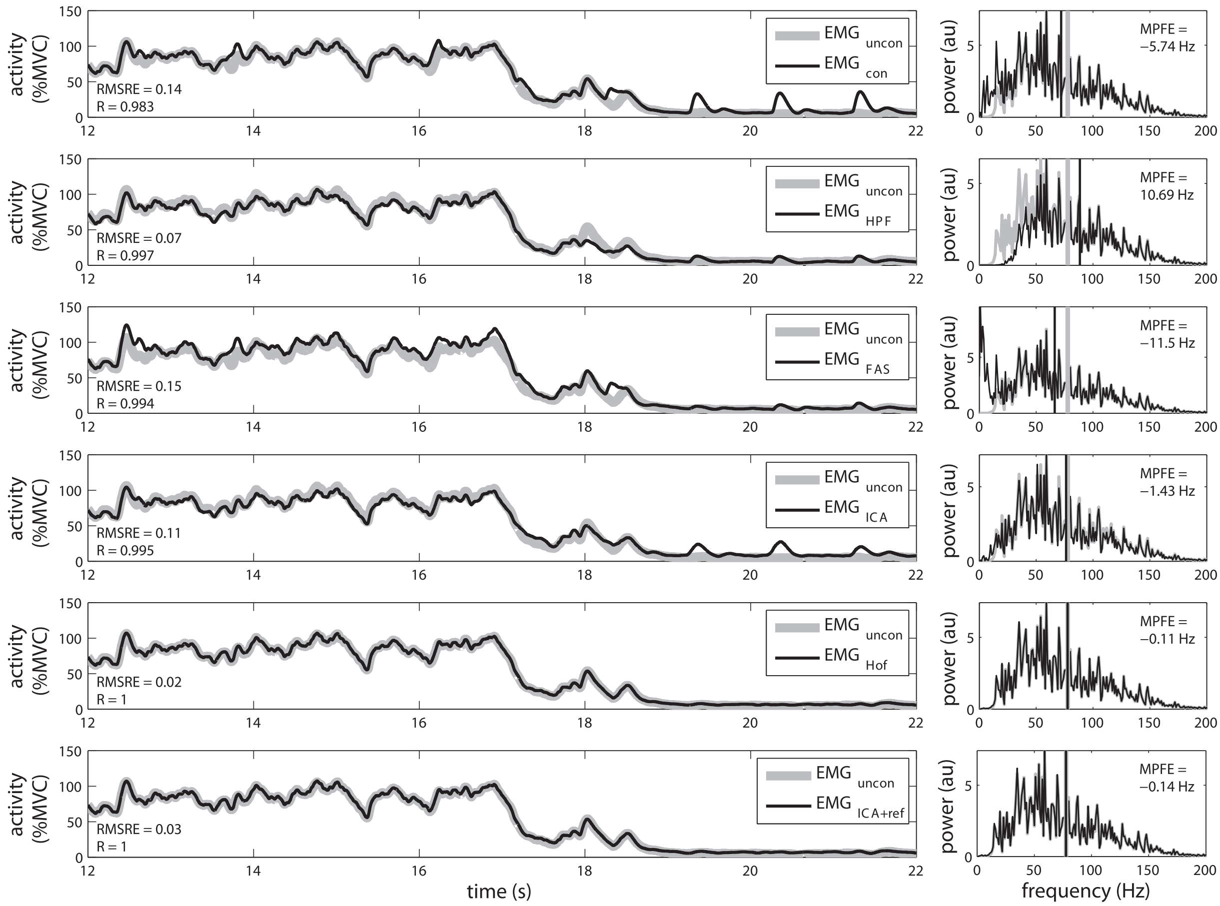

Fig. 3. Linear envelopes of the original EMG of channel 2 during task 3 in bold gray in the left panels. In black, linear envelopes are shown for (a) EMG_{con} (b) EMG_{HPF} (c) EMG_{FAS}, (d) EMG_{ICA}, (e) EMH_{Hof} and (f) $EMG_{ICA+ref}$ and *RMSRE* and correlation values are presented in the left lower insets. Power spectra are shown in the right panels, with the vertical lines representing *MPFs* and errors (*MPFEs*) indicated in the right upper insets. Note that *MPFEs* were later divided by MPF_{uncon} for further analysis.

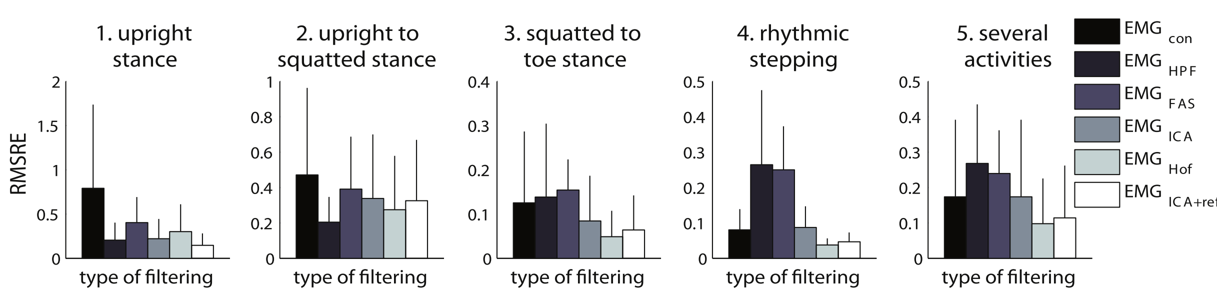

Fig. 4. *RMSRE* for the different filtering procedures (colored bars) for the five different tasks, averaged over channels. Error bars represent SDs over channels. Note that the scaling between tasks differs in order to emphasize differences between filtering procedures. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

without the use of a simultaneously recorded reference ECG signal and its performance (ECG removal as well as EMG preservation) was compared to three previously reported methods for ECG removal (HPF, FAS, and Hof's procedure). In terms of amplitude estimates, HPF was at least equally successful as both procedures that required a reference ECG recording (Hof and ICA plus reference) in tasks with low (variation in) EMG activity levels. In tasks with larger (variations in) EMG activation, the procedures that require a reference ECG recording performed substantially better in reducing *RMSRE*. By and large, FAS displayed limited success, underscoring the challenge when defining and detecting QRS templates in inherently noisy EMG data sets. Since none of the methods performed optimal at all outcome measures, the choice for a method to remove ECG should be made dependent on the type of signals and the circumstances under which data are recorded and, of course, on the type of outcome measures one is interested in.

The HPF procedure resulted in large overestimations of *MPF*, while ICA was more successful in preserving spectral content when no reference ECG was available. The procedures using a reference ECG recording come with a significant advantage as they preserve the EMG's full spectral content, here demonstrated by *MPFs* largely resembling those of EMG_{uncon}. That is, when focusing on frequency

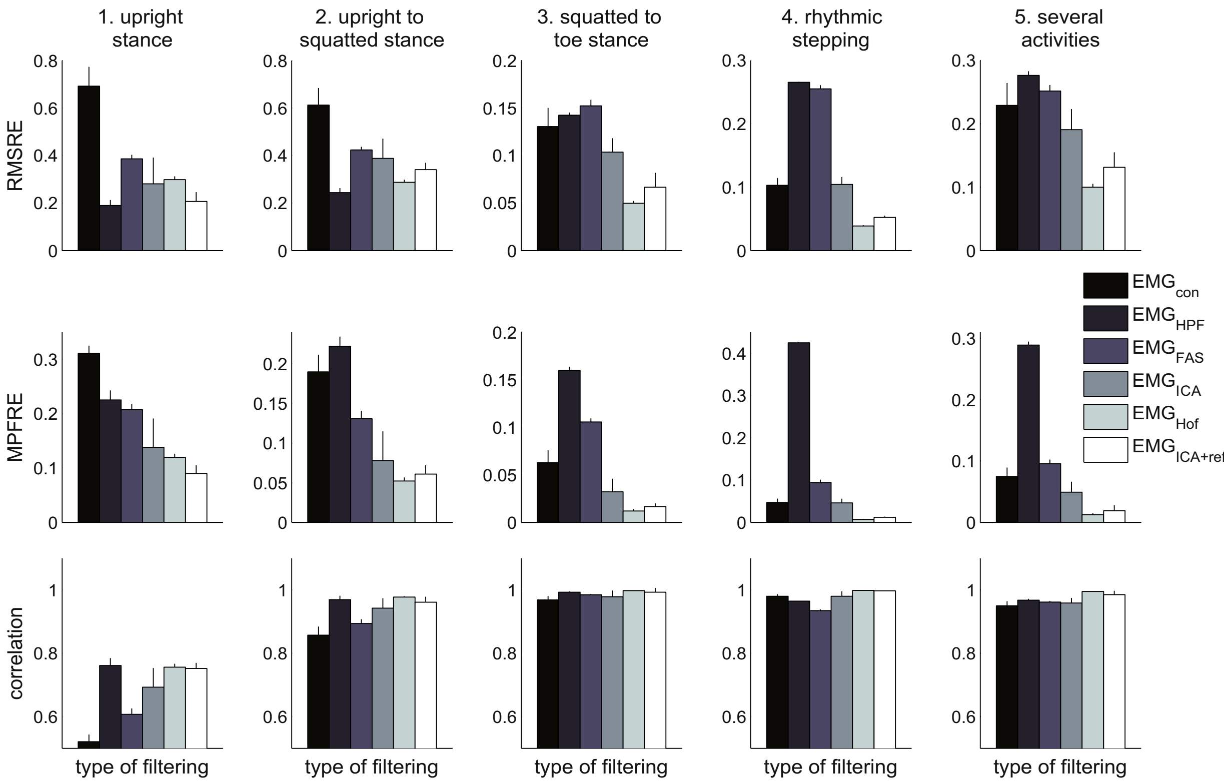

Fig. 5. *RMSRE*, *MPFRE* and *R* for EMG_{con}, EMG_{HPF}, EMG_{FAS}, EMG_{ICA}, EMG_{Hof} and $EMG_{ICA+ref}$ with respect to EMG_{uncon}. Averages and SD over 50 random surrogate combinations of EMG and ECG recordings; again the scaling differs between tasks.

measures, either ICA-based ECG removal or Hof's procedures should be preferred – recall that the latter requires more supplementary recordings. When no reference ECG signal is available, ICA can improve estimations of *MPF* when compared to EMG_{con}, except for activation patterns that are rhythmic at approximately the frequency of the heartbeat as in our task 4. When a separate ECG recording is available, ICA is preferred whenever activation levels are fairly low (as with upright stance in task 1), while Hof's procedure resulted in similar or even slightly better estimates for data sets with larger (variations in) muscle activation.

Remarkably, residuals of ECG peaks often remained after HPF (Figs. 3 and 6). When ECG peaks have to be removed entirely, e.g., in order to detect onset of muscle activation), this method may not suffice. Both procedures using a separate ECG recording were better in completely removing ECG traces. If no reference ECG is available and full ECG removal has a high priority, then ICA should be considered, as Fig. 6 shows complete removal in a signal where residual peaks remained after HPF. Moreover, the proposed criteria for identification of ICA_{ECG}-modes could be adjusted, to tune the ICA-based procedure for specific purposes. For instance, if complete peak removal has priority over preserving EMG, the 5% power criterion may be decreased or even omitted.

The two methods employing a reference ECG signal largely succeeded in removing ECG while preserving EMG amplitude and frequency content in all tasks. Whereas ICA plus external reference performed better in task 1, Hof's procedure appeared more successful in the other tasks. Since Hof's procedure also requires less calculation time, can be applied when only a small number of recordings is available, and provides deterministic results, it might be preferred over ICA, which can only be applied to multivariate data sets and provides results that may not be entirely reproducible, due to the here-applied optimization procedure in the ICA decomposition. More important, if independence of EMG and ECG cannot be guaranteed, by construction the ICA-based filter has limited performance. In our example, in the absence of a separate ECG recording, ICA decomposition often resulted in more than one mode, which not only contained ECG, but also some (common mode) EMG. This emphasizes the importance of carefully chosen criteria for identification of ICA_{ECG}-modes, which can vary over data sets. Optimizing criteria for ICA_{ECG}-mode detection for different data sets and purposes is beyond the scope of the current study. Despite these 'limitations', however, the present results do indicate the potential benefits of an ICA-based filtering as it can clearly improve the validity of EMG outcome measures compared to currently used methods.

In the present study, we determined the MVC normalization factor from uncontaminated EMG signals. As contamination was realized in terms of a superposition, the normalization meant that the sum of two signals (i.e. ECG recorded at trunk muscle electrode locations superimposed to EMG recordings of arm and leg muscles) was scaled to the maximum of one of these signals and not the maximum of their sum. By this, normalization could affect the ratio of ECG amplitude between channels generating some bias in our assessments. We note that we chose for the individual normalization to %MVC as the use of non-normalized data might have penalized the HPF method due to the loss of power below 30 Hz. Another limitation is that we applied ICA-based filtering in one specific way, while alternatives are also suggested. For instance, Von Tscharner et al. (2011) proposed a method for ICA-based ECG removal using non-linearly scaled wavelets, which may be an effective method as well.

Our test protocol revealed important differences between procedures for ECG removal. This resulted in recommendations for choosing the optimal technique given a specific data set and outcome measure of interest, which can improve interpretation of contaminated trunk muscle EMG. ICA-based filtering does not provide

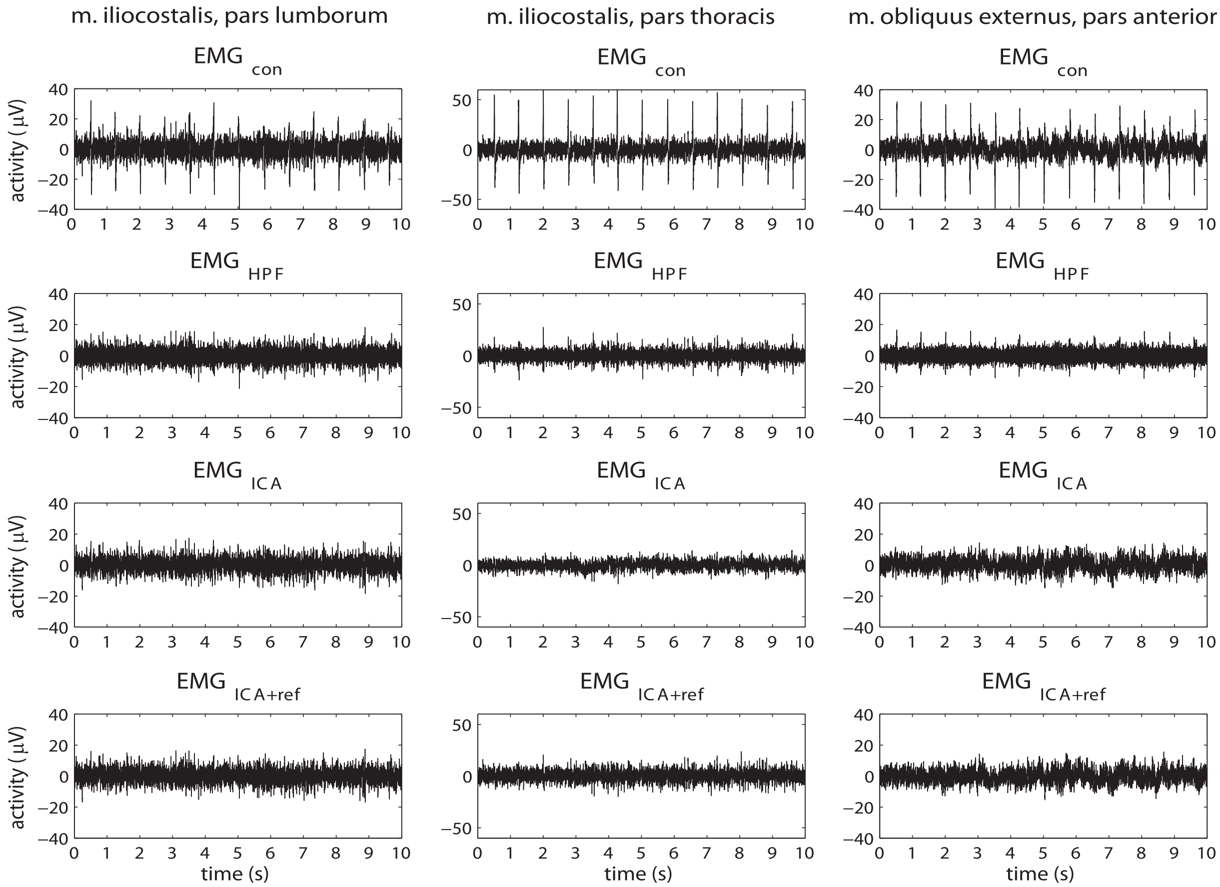

Fig. 6. Example of 'real' ECG contaminated trunk muscle EMG recordings. Contaminated EMG of three trunk muscles in the upper panel. The lower panels show the same recording after HPF filtering, after ICA-based filtering without external reference ECG and after ICA-based filtering with inclusion of a separate ECG recording.

a solution to all possible artifacts but, if implemented properly, forms a welcome and promising addition to EMG preprocessing.

Conflict of interest

The authors declare that no financial and personal relationships with other people or organizations have inappropriately influenced the content of the work reported in this paper.

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References

Aminian K, Ruffieux C, Robert P. Filtering by adaptive sampling (FAS). Med Biol Eng Comput 1988;26(6):658–62.
Bruns A. Fourier-, Hilbert- and wavelet-based signal analysis: are they really different approaches? J Neurosci Methods 2004;137(2):321–32.
Butler HL, Newell R, Hubley-Kozey CL, Kozey JW. The interpretation of abdominal wall muscle recruitment strategies change when the electrocardiogram (ECG) is removed from the electromyogram (EMG). J Electromyogr Kinesiol 2009;19(2):e102–13.
Drake JDM, Callaghan JP. Elimination of electrocardiogram contamination from electromyogram signals: an evaluation of currently used removal techniques. J Electromyogr Kinesiol 2006;16(2):175–87.
Hermens HJ, Freriks B, Disselhorst-Klug C, Rau G. Development of recommendations for SEMG sensors and sensor placement procedures. J Electromyogr Kinesiol 2000;10(5):361–74.
Hof AL. A simple method to remove ECG artifacts from trunk muscle EMG signals. J Electromyogr Kinesiol 2009;19(6):e554–5.
Hyvärinen A, Oja E. Independent component analysis: algorithms and applications. Neural Netw 2000;13(4–5):411–30.
Jutten C, Hérault J. Blind separation of sources, part I: an adaptive algorithm based on neuromimetic architecture. Signal Process 1991;24(1):1–10.
Mak JNF, Hu Y, Luk KDK. An automated ECG-artifact removal method for trunk muscle surface EMG recordings. Med Eng Phys 2010;32(8):840–8.
Makeig S, Jung TP, Bell AJ, Sejnowski TJ. Independent component analysis of electroencephalographic data. Adv Neural Inf Process Syst 1996;8:145–51.
Marque C, Bisch C, Dantas R, Elayoubi S, Brosse V, Perot C. Adaptive filtering for ECG rejection from surface EMG recordings. J Electromyogr Kinesiol 2005;15(3):310–5.
Redfern MS, Hughes RE, Chaffin DB. High-pass filtering to remove electrocardiographic interference from torso EMG recordings. Clin Biomech 1993;8(1):44–8.
Von Tscharner V, Eskofier B, Federolf P. Removal of the electrocardiogram signal from surface EMG recordings using non-linearly scaled wavelets. J Electromyogr Kinesiol 2011;21(4):683–8.
Willigenburg NW, Kingma I, van Dieën JH. How is precision regulated in maintaining trunk posture? Exp Brain Res 2010;203(1):39–49.

Nienke Willigenburg (1984) studied Human Movement Sciences at VU University in Amsterdam from 2002 to 2007. One of her research projects resulted in a paper on fatigue-related changes in motor unit synchronization. After graduation, she worked as a teacher at The Hague University for a year. In 2008, she started a PhD project on motor control in low back pain patients. Specifically, Nienke studies differences in kinematics and muscle activation between low back pain patients and healthy controls when trunk control is challenged.

Andreas Daffertshofer is professor of neural dynamics at the Faculty of Human Movement Sciences of the VU University, Amsterdam. He received the PhD degree in theoretical physics from Stuttgart University, Stuttgart, Germany, in 1996. His primary interest is in complex dynamics in biological systems and its formal and conceptual assessment in terms of nonlinear dynamics and synergetics. He has been engaged in various studies on the stability and variability of coordinated movement in relation to its neuromuscular control. With the background in statistical physics and dynamical systems, he appropriated various methods for the analysis of multivariate signals for movement data as obtained from kinematic, electromyographic, and encephalographic recordings (e.g., principal or independent components in the vicinity of macroscopic, qualitative changes in coordination). His current theorizing in motor control includes the interplay of deterministic and stochastic aspects of neural dynamics, modeling of mirror movements, phase transitions in rhythmic movements and accompanying patterns of cortical activity, and more general aspects of neural synchronization.

Idsart Kingma is an assistant professor at the Faculty of Human Movement Sciences of the VU University, Amsterdam where he is teaching courses on ergonomics and biomechanics. He has an MSc in human movement sciences and he finished his PhD on the biomechanics of lifting in 1998. Currently, his main research interests are mechanical aspects of low back loading and neuromuscular control of joint stability. He was (co-)author of over 100 papers in international scientific journals and he serves on the editorial board of the Journal of Electromyography and Kinesiology.

Jaap H. van Dieën worked as a researcher in physical ergonomics at the Institute for Agricultural Engineering in Wageningen, the Netherlands from 1986 to 1996. He obtained a PhD from the Faculty of Human Movement Sciences at the VU University, Amsterdam, The Netherlands in 1993 and has been affiliated to this faculty since 1996. In 2002, he was appointed as full professor. Jaap H. van Dieën is the director of MOVE-AGE a joint doctorate program of three European universities on ageing and mobility. In addition, he leads a research group focusing on mechanical aspects of ageing and musculoskeletal disorders. His main research interest regards the effects of task demands, fatigue, ageing, and disorders on joint load and stability. Jaap H. van Dieën has (co-)authored over 180 papers in international scientific journals. He was an editor of the European Journal of Applied Physiology, and currently is section editor of Human Movement Sciences and serves on the editorial advisory board of the Journal of Electromyography and Kinesiology and the editorial boards of Clinical Biomechanics, Manual Therapy, IIE Transactions on Occupational Ergonomics and Human Factors and the Journal of Back and Musculoskeletal Rehabilitation. Jaap H. van Dieën has been the treasurer of ISEK since 2006.