Journal of Electromyography and Kinesiology 22 (2012) 485–493

Contents lists available at SciVerse ScienceDirect

Journal of Electromyography and Kinesiology

journal homepage: www.elsevier.com/locate/jelekin

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

ARTICLE INFO

Article history:
Received 5 August 2011
Received in revised form 7 December 2011
Accepted 3 January 2012

Keywords:
Electromyography
Electrocardiogram
Independent component analysis
Artifact removal
Decontamination

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).

1050-6411
doi:10.1016/j.jelekin.2012.01.001

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 $>10^{12}\ \Omega$, 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