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Review

Processing transcutaneous electromyography measurements of respiratory muscles, a review of analysis techniques

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ABSTRACT

Transcutaneous electromyography (tc-EMG) has been used to measure the electrical activity of respiratory muscles during inspiration in various studies. Processing the raw tc-EMG signal of these inspiratory muscles has shown to be difficult as baseline noise, cardiac interference, cross-talk and motion artefacts can influence the signal quality. In this review we will discuss the most important sources of signal noise in tc-EMG of respiratory muscles and the various techniques described to suppress or reduce this signal noise. Furthermore, we will elaborate on the options available to develop or improve an algorithm that can be used to guide the approach for analysis of tc-EMG signals of inspiratory muscles in future research.

1. Introduction

Electromyography (EMG) is a technique which measures the electrical activity generated by muscles (American Thoracic Society and European Respiratory Society, 2002). The electrical activity is generated by individual motor units, the smallest functional unit of a muscle, consisting of a terminal axon and the muscle fibers it innervates (Buchthal and Schmalbruch, 1980). At the moment an action potential is generated and a depolarization takes place at the neuromuscular junction, this generates a change in the motor unit potential. Subsequently, the muscle fibers are activated and contract (Putten, 2009). EMG can detect and register these changes in electrical activity.

EMG is utilized and studied in various medical fields such as clinical neurophysiology (Shaw and Bagha, 2012), rehabilitation, pulmonology (Duiverman et al., 2004) and intensive care medicine. After recording, amplification, and analysis of the muscle's electrical activity, the outcome can be used for clinical monitoring or diagnostic purposes in these medical fields (de Waal et al., 2017; Hutten et al., 2008, 2010a, 2010b; Koopman et al., 2018; Maarsingh et al., 2000, 2006; Prechtl et al., 1977).

The potential role of EMG in measuring electrical activity of the respiratory muscles has been increasingly studied in various populations ranging from healthy adult subjects to critically ill preterm infants treated at an intensive care unit (e.g. de Waal et al., 2018; Estrada et al., 2016; Iyer et al., 2017). Respiratory conditions such as muscle atrophy after prolonged mechanical ventilation in adults (Jonkman et al., 2017), apnoea of prematurity in preterm infants (Kraaijenga et al., 2017; Muller et al., 1979), but also increased demand of the inspiratory muscles in dyspnoeic infants (Maarsingh et al., 2006) and COPD patients (Duiverman et al., 2004), can be visualized and objectified with EMG of the inspiratory muscles. The diaphragm, the most important respiratory muscle for inspiration, is most often studied and in general the focus is on inspiratory muscle strength. Next to the diaphragm, the intercostal muscle activity is the second most studied inspiratory muscle in literature (Dos Reis et al., 2019).

Overall, three established EMG-modes are available to assess inspiratory muscle activity during respiration: intramuscular (im-EMG), trans-esophageal (te-EMG) and transcutaneous electromyography (tc-EMG). The first mode uses needle electrodes which are inserted directly into the muscle of interest to record the activity of individual motor units. During te-EMG a special catheter (or modified feeding tube) with incorporated electrodes is inserted in the esophagus where it detects the muscle activity at the level of the diaphragm (Beck et al., 1997; Luo et al., 2008). In contrast to these two techniques, tc-EMG is a non-invasive technique using surface electrodes placed on the skin. The electrodes are placed on the muscle of interest to measure the electrical activity detected through the skin. These features make tc-EMG interesting as a clinical tool.

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Despite its non-invasive features, the application of respiratory tc-EMG in a clinical or research setting is limited due to the difficulties in acquiring a continuous, noise-free tc-EMG signal in which noise is defined as any unwanted signal that is superimposed on the signal of interest. tc-EMG measures the summed spontaneous electrical activity that is generated by many motor units at once of the underlying muscle of interest, for example the diaphragm. This results in a signal with a good temporal but limited spatial resolution (Andrade et al., 2012). The tc-EMG signal has stochastic properties with a zero-mean distribution and a low signal-to-noise ratio (SNR). This low SNR is caused by a reduction of signal quality due to noise from other electrical hardware or the detection of neighboring muscle activity. The electrical activity of the heart is detected as well and this cardiac interference is the most important influencer of the tc-EMG signal quality, which hampers interpretation of respiration (Abbaspour and Fallah, 2014; Drake and Callaghan, 2006).

It is important to realize that this intrinsic cardiac noise cannot be prevented or removed prior to signal acquisition, but requires further signal processing, either in real-time or retrospectively. Only with a comprehensive analysis, a respiratory waveform can be acquired that is ready for clinical interpretation.

The need for additional processing steps has resulted in tc-EMG being used mainly as a research tool. Over the last decades several analysis techniques to process respiratory muscle tc-EMG signals have been studied and published. Some papers have been published reviewing tc-EMG measurement procedures or comparing different aspects of the signal analysis over the last decade (Chowdhury et al., 2013; Dos Reis et al., 2019; Drake and Callaghan, 2006; Hutten et al., 2010a, 2010b; Merletti et al., 2009). Dos Reis et al. recently published a systematic review outlining many different procedures to record tc-EMG of inspiratory muscles in adults (Dos Reis et al., 2019). They concluded that the diversity in procedures and analysis is substantial and that it is hard to objectively identify one optimal approach for the acquisition and processing of these signals. However, this and previous studies have not described the entire process in a single review covering all processing steps from a raw signal to the respiratory waveform. Combining the findings of these previous studies could contribute to the development of an optimized data analysis algorithm which facilitates implementation of tc-EMG in clinical practice.

Therefore, the aim of this narrative review is to describe the different sources of signal noise and their influence on the tc-EMG signal of respiratory muscles aiding inspiration, to summarize the available data analysis techniques to remove or reduce noise and construct a respiratory waveform based on inspiratory tc-EMG. Finally, this review will provide suggestions for future research in this field.

2. Sources of signal noise

Signal noise in tc-EMG can have different sources. Overall these noise sources can be categorized based on the different factors present during the recording: the environment, the subject, the electrodes, the interface between the electrodes and the subject's skin and the amplifier (i.e. the equipment). Table 1 summarizes common sources of signal noise and describes options to reduce the noise in these categories.

The interface between the skin and the electrodes is seen as the largest contributor of signal noise when measuring muscles' activity in a state of rest (Huigen et al., 2002). Preparing the measurement and using proper equipment is therefore paramount when recording tc-EMG. Analog filtering can be used to suppress low-frequency noise before digitisation. This could reduce the effect of disturbances to the interface (e.g. poor skin contact) which directly results in reduced signal quality. Noise can also be reduced by using a state-of-the-art amplifier with a high input impedance ($>$ 100 MOhm) at the frequencies of interest and a low bias current, thereby suppressing background noise and improving the SNR. Fortunately, these two factors (high input impedance and low bias current) often go hand in hand in modern signal amplifiers.

The SENIAM project (Surface Electromyography for the Non-Invasive Assessment of Muscles) provides general recommendations for tc-EMG measurements of 27 different muscles, including topics like preparation of the skin, inter-electrode distance (IED), electrode material, electrode shape and size and electrode fixation to reduce signal noises (Hermens et al., 2000). However, this project does not provide specific recommendations for tc-EMG recordings of respiratory muscles.

3. Signal analysis steps

Removal of extrinsic and intrinsic noise and interpretation of electrophysiological tc-EMG signals requires several steps, especially when looking at respiratory muscles. In this process the following steps are identified: pre-processing of the data, cardiac activity removal, motion artefact removal and the construction of the actual respiratory waveform. We will describe the processing of a raw respiratory muscle tc-EMG signal into a respiratory waveform.

3.1. Pre-processing

3.1.1. Offset removal and high frequency noise reduction

When recording respiratory muscle activity with skin electrodes interfering low frequencies can cause a baseline offset and drift of the raw signal. This offset can be caused by suboptimal skin preparation or an introduced bias current.

To remove this baseline offset and low frequency drift, a high-pass filter is used. It remains unclear which cut-off frequency should be used for this high-pass filter, because noise sources overlap in frequency content with the tc-EMG signal of interest (Levine et al., 1986; Lu et al., 2009). Cut-off frequencies used for high-pass filtering of tc-EMG vary between 5 and 30 Hz in literature (De Luca et al., 2010; Hermens et al., 2000; Merletti, 1999).

A cut-off frequency of 20 Hz for the high-pass filter has been suggested as the best compromise to remove low-frequency noise and limit the influence on tc-EMG signal amplitude (De Luca et al., 2010). This was studied in peripheral muscles in which spectral analysis showed that when the cut-off frequency was increased above 20 Hz an increased loss of tc-EMG signal occurred. This first step of high-pass filtering has been adopted for respiratory (Reilly et al., 2012, 2011; Smith et al., 2017) and trunk muscle tc-EMG as well (Redfern et al., 1993), however an application- and muscle dependent cut-off might be more appropriate, because the influence of signal noise depends on the location of the muscle(De Luca et al., 2010).

Besides the cut-off frequency a filter order has to be set as well, which determines the slope of the frequency response function of the filter at its cut-off frequency. A first order filter has only one frequency dependent component and the slope of the frequency response function is often not steep enough to suppress the noise. By increasing the order, the filter approximates the actual set cut-off frequency better, but this increased accuracy comes with an increased processing time.

Besides low-frequency noise, high frequency noise can be present as well. This type of noise is caused by the equipment itself or bias currents and can be reduced by an analog low-pass filter prior to digitization, although not all devices have this option (Maarsingh et al., 2000). When taking the frequency characteristics of an individual motor unit action potential into account, no tc-EMG signal of interest is estimated to be present at frequencies higher than 450–500 Hz (De Luca, 2006). Therefore a low-pass filter with a cut-off frequency in this range is often chosen to remove inherent high frequency noise (De Luca et al., 2010).

3.1.2. Power supply interference

Besides correcting for the baseline offset, signal drift and high frequency noise, the power supply interference or electrical interference from surrounding hardware needs to be filtered out as well. Most often

Table 1
Causes of signal noise and options to reduce noise in transcutaneous electromyography.

Contributing factor	Noise cause	Option(s) to reduce noise	Ref
Environment			
Power supply interference	• The tc-EMG equipment and electrodes can serve as an antenna picking up power supply interference or other electrical interference from neighbouring equipment as noise (50 or 60 Hz, depending on the country).	• Driven shielding of the cables ('guarding') and a high common mode rejection reduce interference.	(Chowdhury et al., 2013; De Luca et al., 2010; Maarsingh et al., 2000)
Subject			
Skin preparation	• Dead skin cells cause fluctuations of impedance at the electrode-skin interface, leading to a change in half-cell potential of the electrode. Due to the resulting bias current, noise is added to the signal.	• Skin preparation improves skin contact. Depending on the population of interest the skin can be cleaned or even shaved/scrubbed. • Use hardware with a high input impedance and low bias current, this reduces the effects of poor skin preparation.	(Clancy et al., 2002; Hermens et al., 2000; Merletti et al., 2009)
Subcutaneous tissue/ anatomy of the subject	• Fat, edema and other subcutaneous tissue reduce the sensitivity to detect muscle activity of covered muscles. It serves as a low-pass filter, decreasing signal amplitude and thereby reducing SNR (a relative increase of noise).	• Study of superficial muscles increase the sensitivity.	(Merletti et al., 2009)
Electrode placement/ inter-electrode distance (IED)	• Too small IED can increase noise in the signal recording. • Too large IED picks up a stronger signal but has a lower spatial resolution.	• Electrodes should be properly placed on top of the muscle of interest based on the muscle's anatomy. The EMG signal is picked up through the skin. • The use of a reference electrode can greatly reduce noise when placed at an electrically neutral spot (often bone).	(Beck et al., 1995; Dos Reis et al., 2019; Farina et al., 2002; Hakonen et al., 2015; Hermens et al., 2000; Staudenmann et al., 2010)
Motion artefacts/cross-talk	• Displacement of the electrode with respect to the studied muscle. • Changes in skin-electrode interface during contraction or relaxation. • Activity of other muscles is detected as well. (e.g. cardiac interference)	• Choose size and type of electrode carefully depending on which muscle and subject is studied.	(Beck et al., 1995; Chowdhury et al., 2013; Clancy et al., 2002; Hermens et al., 2000)
Electrode			
Type (*Hydrogel, wet, dry)*	• Wet: when not trained in using wet electrodes usage of this type electrode results in poor signal quality. When properly placed, the skin is saturated with the conductive fluid/paste resulting in less noise. • Dry electrodes can have higher electrode impedance and a higher susceptibility to motion artefacts. • Hydrogel electrodes are hydrophilic, which can dry the skin and cause the electrodes to come off (worsening interface noise).	• Wet: seems to produce less noise due to saturation of the skin. • Dry: similar accuracy as hydrogel when properly fixated. • Hydrogel: easier to apply and more available than the other two. Recommended because it improves stability of the signal over time.	(Hakonen et al., 2015; Hermens et al., 2000; Laferriere et al., 2011; Roy et al., 2007; Searle and Kirkup, 2000)
Material	• Electrode chemistry. Polarizable materials (e.g. platinum and carbon) can induce voltage noise in the presence of bias currents. • The adhesive of electrodes contains ionic salt (often chloride, as in the AgCl hydrogel electrode). The level of ionic salts determines the input impedance of the electrode and thus the recording. • The conductance and impedance of the material determines the susceptibility to noise.	• The electrode should have the lowest possible impedance. • Ag/AgCl electrodes are mostly used, because they are non-polarizable, cheap and have a proper skin interaction. • Carbon electrodes tend to be more robust against motion artefacts.	(Hakonen et al., 2015; Posada-Quintero et al., 2016)

(*continued on next page*)

Table 1 (*continued*)

Contributing factor	Noise cause	Option(s) to reduce noise	Ref
Size	• Larger electrodes collect signals from a larger area. This geometry results in picking up more noise signals as well.	• Optimize the size of the electrode to the muscle of interest.	(Merletti, 1999)
Configuration *e.g. monopolar/bipolar/ high density*	• A monopolar derivation is a single lead making it difficult to distinguish where potential noise comes from. • High density has a higher spatial resolution but this may be unnecessary, actually increasing noise.	• Use a reference electrode. This electrode serves as a return channel for bias current. This results in signal electrodes having effectively identical bias current noise which can be subtracted. • Use a systematic approach (similar to the SENIAM recommendations) when performing the measurement. • A bipolar derivation (two unipolar derivations subtracted) is more robust than monopolar, because it levels out noise by subtraction.	(Bingham et al., 2018; Staudenmann et al., 2010)
Amplifier			
Amplifier noise	• Every amplifier has a level of inherent stochastic signal noise.		
Amplifier gain	• Amplifier gain error occurs when the gain exceeds the dynamic range of the signal. It can result in signal 'distortion' causing artefacts in the recording.	• Equipment with adjustable amplifier gain enables the user to optimize the gain prior to the actual recording.	(Merletti et al., 2009)
Common-mode-rejection-ratio (CMRR)	• If the CMRR is too low, the measurement's quality deteriorates by picking up background noise as well.	• CMRR should be at least 100 dB at the frequencies that are deemed important in the specific measurement. CMRR should especially be high in a differential amplification. If the common is not suppressed, noise gets amplified.	(Clancy et al., 2002)
Quantization/digitization noise	• Digitizing the measurement with a sampling frequency which is too high results in picking up irrelevant noise frequencies. • A sampling frequency which is too low can introduce low frequency noise due to the under sampling of higher signal frequencies which are reflected as low frequencies (an effect known as 'aliasing').	• Choose the sampling frequency based on clear assumptions with respect to the frequency range of interest. • Use proper analog signal conditioning that eliminates noise sources with (expected) frequencies above half the sampling rate before digitization, to reduce the risk at aliasing.	(Clancy et al., 2002)

CMRR: Common-mode rejection ratio; SNR: signal to noise ratio; IED: inter-electrode distance.

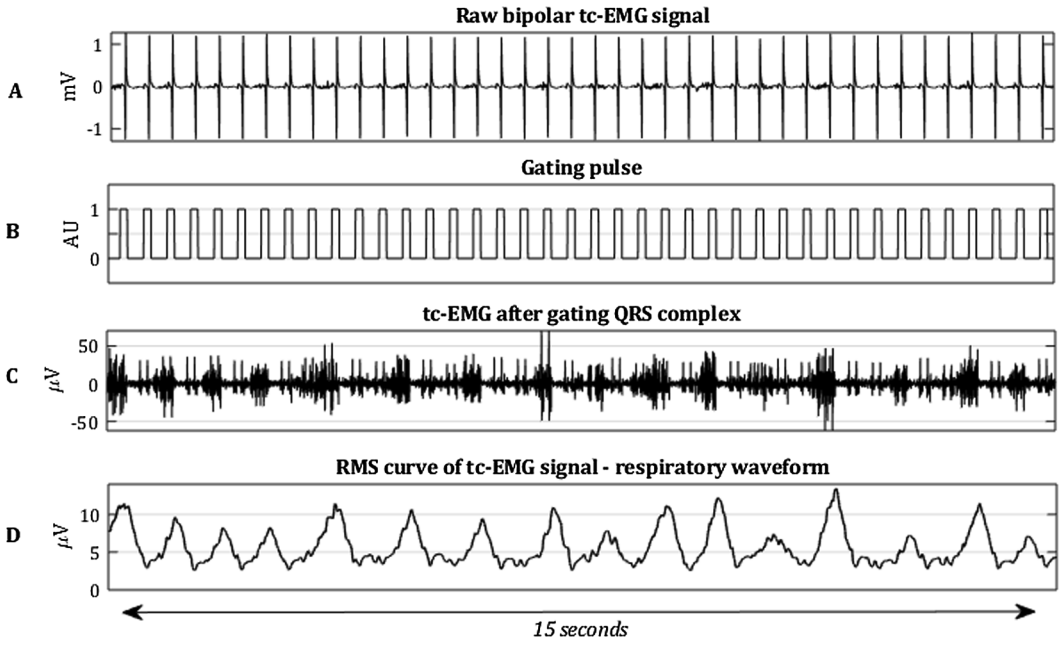

Fig. 1. Illustration of the analysis steps that need to be performed in order to retrieve a respiratory waveform. A: The raw bipolar electromyography derivation, B: detection and marking the QRS complexes and generating a gating pulse, C: EMG signal after gating and filling of the gates with a copy of previous data, D: root-mean-square (RMS) curve of the gated signal showing the respiratory pattern of a preterm infant. Signals based on data acquired by the research group of the authors. AU: arbitrary units, mV: millivolt, μV: microvolt.

a notch filter or a comb filter is used to remove this interference (50 or 60 Hz depending on the country). A notch filter has a narrow frequency band-stop that filters out the power supply interference. A comb filter is a combination of multiple notch filters in which higher harmonics of the original noise frequency can be removed (Chowdhury et al., 2013; Glover, 1977; Raez et al., 2006).

3.2. Cardiac activity removal

The large difference in signal strength between the electrical activity of the heart (electrocardiogram (ECG) in the order of millivolts) and the respiratory muscles (in the order of microvolts) makes retrieval of the respiratory tc-EMG signal challenging. For correct identification of respiration the impact of cardiac activity should be reduced while preserving the signal of the respiratory muscle activity. The method of choice to remove the cardiac interference is important because remaining ECG components can influence the amplitude and therefore the interpretation of the recorded tc-EMG activity (Butler et al., 2009). Several algorithms to deal with the cardiac activity have been published and will be briefly discussed.

1. Frequency domain filtering of cardiac activity

The cardiac interference, with its clear QRS complex, can be described as a set of frequency components which could be filtered out using a digital filter. High-pass filtering has been described to suppress cardiac interference in the respiratory tc-EMG signal, for example by Redfern et al. who compared 10, 30 and 60 Hz cut-off to remove the ECG (Redfern et al., 1993). High-pass filtering can suppress the influence of the P-waves, T-waves and the QRS complex. This approach is debatable, since the frequency content of ECG and tc-EMG overlap and filtering the QRS complex out dampens the respiratory tc-EMG amplitude in the process, removing information of interest (O'Brien et al., 1983; Schweitzer et al., 1979).

2. Adaptive filtering

Adaptive filters, also referred to as adaptive noise cancellation (ANC) filters, use a technique in which the filter settings are dynamic and can be changed based on the signal characteristics. These properties allow filtering of signal disturbance with specific characteristics that are not known in advance or which can change over time. The timing and frequency of the heartbeat can vary and this variability is incorporated in the adaptive filter. An adaptive filter has two inputs: a primary input (the disturbed signal) and a reference input (e.g. the sampled noise, in this case a separate ECG tracing (Hof, 2009)). The statistical properties of the inputs are used to adapt the filter characteristics constantly to minimize the filter error (Lu et al., 2009; Marque et al., 2005).

Two common types of adaptive filters are used for the removal of cardiac interference: the least mean squares (LMS) filter and the recursive least squares (RLS) filter. Both have been used in research but comparison is difficult. The LMS has a slower convergence rate and showed significant residual ECG artefacts in peripheral muscles, when using a band-pass filtered raw signal sampled noise (Marque et al., 2005). However, Yacoub and Raoof (2008) tested the LMS filter on tc-EMG of the diaphragm and synthesized a noise input that could be used for the ECG removal process of this important respiratory muscle. They concluded that the LMS approach showed good ability to reduce ECG noise in this specific muscle. The characteristics of the RLS filter tend to make it more adaptive to signals with rapidly changing features than the LMS (Lu et al., 2009). Ortega et al. (2017) used a RLS filter to remove an artificially introduced ECG interference from a diaphragm tc-EMG signal in post-operative ventilated adults. They showed that the RLS filter was able to reduce cardiac noise in this respiratory activity recording. Although RLS has a faster convergence, it comes with a high computational cost, also due to the fact that RLS assumes the data is stochastic (and is whitened at the input), while LMS uses deterministic inputs. Overall, RLS tends to filter noise a bit better (Ortolan et al.,

Table 2
Characteristics of techniques to reduce cardiac interference from tc-EMG.

Technique	Computational cost	Introduced time delay (ms)	Real-time analysis	Adaptive algorithm
1. Filtering	+	< 50*	+	No
2. Adaptive filtering	+ + +	> 200	Not described	Yes
3. Gating	+ +	50–150	+	Yes
4. Subtraction	+ + +	50–250	+	Yes
5. ICA	+ + + +	Unknown	Not described	Offline
6. wICA	+ + + + +	Unknown	Not described	Offline

ICA: independent component analysis; wICA: wavelet ICA; ms: milliseconds.
* Depends on the filter order.

2003), since a lower filter order can be used in RLS than in LMS, when filtering general noise. However, a direct comparison of LMS and RLS for the removal of ECG in respiratory tc-EMG has not been described yet.

3. Gating

Gating is a frequently used method to remove the QRS complexes from tc-EMG tracings of the respiratory muscles (O'Brien et al., 1987; Prechtl et al., 1977). First, the high R-peaks of the QRS complex are identified with a level detector. Next, a pulse generator marks the QRS complexes (see Fig. 1, second graph). These pulses have a standardized (gating) width which varies within the range of 50–100 ms (Bartolo et al., 1996b; Maarsingh et al., 2000), but also larger intervals (e.g. 380 ms (Levine et al., 1986)) have been described. The pulse train is aligned with a delayed (around 40 ms) tc-EMG recording to allow for time to detect the peaks of the QRS complex and construct the pulse train. At the generated pulses the QRS complexes, together with all other EMG activity, are cut out of the signal. All signal is lost in these periods and these 'gates' need to be filled. How to do that is a matter of debate. Some studies use a constant value (e.g. zero (Drake and Callaghan, 2006) or the mean of a previous segment (Prechtl et al., 1977)) while others use more dynamic options (e.g. running average (Koopman et al., 2018; Maarsingh et al., 2000) or a copy of previous data, see Fig. 1, third graph). No studies were found that compared all different options to fill the gates.

4. Template subtraction

The template subtraction technique to remove cardiac interference is a mixture of adaptive filtering and gating. First, the R-peak is detected either manually or threshold-based, similar to the gating technique (Bloch, 1983). Next, a template is made of the QRS complex by averaging multiple QRS complexes (a window around the R-peak) (Levine et al., 1986). Template derivation can be 'learned' from a test measurement and used throughout the measurement or two 'parallel' pathways can be used in which case the template is based on the average of several past heart beats. The latter approach makes the analysis more adaptive to changing circumstances but adds time delay. The offset of the template is adaptive (Levine et al., 1986) and a least squares algorithm can be used to adjust height and width of the template during the data analysis (Bartolo et al., 1996a). When the template is properly scaled, it is aligned with the detected peaks and subtracted from the tc-EMG signal (Abbaspour and Fallah, 2014).

5. Independent component analysis

A more complex method to remove cardiac interference is independent component analysis (ICA), a technique based on blind source separation. It separates components of a signal by assuming the signals are non-Gaussian and its sources are statistically independent from each other (Mak et al., 2010). This technique can only be performed when multivariate, multi-channel data is available.

The ICA algorithm estimates a vector of signal sources and a mixing matrix, linking the sources to retrieve the original signal. When independent signal sources are found containing ECG noise, they can be zeroed out in the mixing matrix. Reconstruction of the signal (inverse ICA) then results in a signal without (most of) the cardiac interference (Taelman et al., 2007).

When the difference in power between the ECG and tc-EMG becomes smaller, a separate ECG channel can aid in separating tc-EMG from ECG. Willigenburg et al. tested this technique in a healthy subject and measured 16 peripheral muscles (Willigenburg et al., 2012). ECG was recorded separately and the noisy tc-EMG signals were imported in the ICA algorithm. They showed the ability of this technique to remove ECG interference, with and without use of an extra ECG channel. The removal improved when a separate ECG channel was added that could underline the independence of the different signal sources. This, however, does require more measurement electrodes during the recording. Till now, this technique has only been used in methodological studies using constructed data and not in clinical studies or in a real-time application for tc-EMG. As a result the introduced time delay has not been described, which might be of importance for potential real-time analysis.

6. Wavelet analysis

A more advanced technique which can be used for the denoising of continuous signals is wavelet analysis or wavelet transformation. Wavelet transformation is a combination of time and frequency aspects to describe a continuous signal consisting of a set of scaled 'mother wavelets'. This approach describes a signal as the wavelet components it exists of and with this approach the number of signals that is measured can be reduced. Zhan et al. (2010) tested a wavelet-based adaptive filter for the removal of ECG interference and found that the wavelet-based filter could accurately remove the ECG from the tc-EMG signal. The power spectrum of the 'clean' tc-EMG and the processed EMG (after the filter) showed great similarity. However, this comparison could be made because tc-EMG and ECG were simulated signals that were summed to construct a noisy tc-EMG signal and then do the analysis. Results on real-life data analysis when using this filter have not been described.

Additional to wavelet analysis being used in adaptive filtering it has also served as an add-on to conventional ICA (Taelman et al., 2007). Taelman et al. combined wavelet transformation and ICA and called it wavelet ICA (wICA). The original signal is transformed into individual wavelet components which can be introduced to the ICA algorithm. Components including ECG characteristics can be removed. Taelman et al. studied this technique for cardiac activity removal in trunk muscles and showed that it could indeed remove QRS artefacts. However, decisions on what kind of wavelet to use are still arbitrary and a separate ECG channel might still be needed to improve the removal.

3.2.1. *Comparison of cardiac filtering techniques*

Some of the cardiac filtering techniques have been compared with each other. Factors like the computational cost, mathematical

complexity and introduced time delay of the analysis can guide the decision to choose one specific method. It must be emphasized that any technique that requires detection of the QRS complex introduces a time delay in signal processing which may limit its use in real-time recording. Based on the described literature Table 2 provides a short overview of the six described methods.

It is important to realize that removal of cardiac interference results, per definition, in tc-EMG signal loss. Some studies have indicated that this tc-EMG data loss is redundant considering the removal of a large (ECG) artefact (Bartolo et al., 1996a). However, this may not be true in patients with higher heart rates, making gating heart rate (and often age) dependent. For example, when a subject has a heart rate of 120 beats per minute, and a gating window of 380 ms is used (Levine et al., 1986; Schweitzer et al., 1979) every second of tc-EMG recording loses 760 ms of data. This can result in too much of the signal being discarded.

In practice gating is described as a fast computable algorithm and is often used in clinical studies. Subtraction has a higher computational burden but is deemed to provide smoother data in the time domain compared to filling the gates with constant values. Both techniques can be used in real-time. Downsides of the subtraction technique are that it has to be done for each recording individually to optimize the template (Taelman et al., 2007). The shape and size of the QRS complex might differ over time and poor alignment can increase noise. Multiple scaling parameters are necessary to fit the template to the data. Direct comparison of gating and template subtraction (while using a different tc-EMG acquisition technique) showed no statistical significant differences with respect to the spectral characteristics of the signal (Bartolo et al., 1996a; Drake and Callaghan, 2006; Levine et al., 1986; Redfern et al., 1993). As a consensus, it has been argued that in case of higher heart rates (> 160/min) subtraction is the preferred technique, due to the substantial amount of data loss with gating at higher heart rates (Bartolo et al., 1996b; Levine et al., 1986). Whether filling with continuous data, instead of a constant, during gating improves the gating technique has not clearly been described.

ICA has not been tested in prospective clinical studies yet, but it has been compared to filtering of cardiac activity. Using ICA with a separate ECG recording performed better, when compared to high-pass filtering, especially when the tc-EMG amplitude increased. However, ICA has a high computational cost which would make it difficult to use ICA for real-time removal of cardiac interference. So far ICA only seems suitable for retrospective (off-line) data analysis.

Removal of cardiac interference based on wavelet analysis was compared with template subtraction and showed good performance (Taelman et al., 2007). When a separate ECG channel was added, the removal resembled the standard (template subtraction) even better (evaluated by visual inspection). Von Tscharner et al. changed the implementation of the wICA algorithm by using a different kind of wavelet and compared the ECG removal with a fourth order high-pass Butterworth filter (cut-off 30 Hz (Drake and Callaghan, 2006)). Similar accuracy of ECG removal was found but spectral analysis showed that filtering affected the lower tc-EMG frequencies more than the wICA did (non-significant) (von Tscharner et al., 2011).

3.3. Motion artefacts

Besides the cardiac interference, motion artefacts need to be removed from the raw tc-EMG signal to optimize interpretation of the data (see Table 1). Motion artefacts are large in magnitude (in the order of millivolts and larger), hard to predict and can vary largely in shape, making it very difficult to remove these artefacts. Therefore, interpretation of the signal during a motion artefact is not reliable since these artefacts have a large influence on the resulting waveform (Fratini et al., 2009). For this reason segments of the recording with large amplitude motion artefacts are often completely removed or discarded (de Waal et al., 2017).

Most movement artefacts originate from larger muscle groups becoming active during the measurement of a specific muscle or due to the subject being moved itself, e.g. during nursing. A double-differential electrode configuration can be used to reduce the effect of these motion artefacts. This technique uses two bipolar derivations, which are subtracted from each other (Broman et al., 1985; Frahm et al., 2012). As a result, common noise potentials are removed, thereby suppressing cross-talk from other muscles. However, this double-differential technique does require more electrodes and an extra processing step (van Vugt and van Dijk, 2001). Besides movement artefacts caused by neighbouring muscles, the movement of the measured muscle itself under the electrodes can have its effect as well. To correct for these physiological signal shifts, a multiple electrode set-up can be used to find the focus of electrical muscle activity (Lansing and Savelle, 1989).

3.4. Respiratory waveform derivation

When the cardiac activity and motion artefacts are removed from the tc-EMG signal of the respiratory muscles, a last step of signal processing is needed to construct a respiratory tc-EMG waveform. This can be done in different ways, based on signal strength or on signal complexity.

3.4.1. General signal strength

A tc-EMG recording can both show negative and positive deflections, because a difference in voltage is measured between two (or more) electrodes. Many tc-EMG studies perform half- or full-wave rectification to provide a resultant of total muscle activity which is always a positive value (Devaprakash et al., 2016; Merletti, 1999; Raez et al., 2006). Half-wave rectification discards all negative data while full-wave rectification uses the absolute value of each data point, both ensuring no negative samples remain in the tc-EMG record (Raez et al., 2006). Next to the standard rectification two methods are often used (in the time domain) to provide a continuous signal of general muscle activity: the root-mean-square (RMS) and the average rectified value (ARV) (González-Izal et al., 2012), calculated as:

$$RMS = \sqrt{\frac{1}{n}\sum_{n} x_n^2} \mid ARV = \frac{1}{n}\sum_{n} |x_n|$$

x_n represent the values of the tc-EMG signal with n being the number of samples used per step.

These amplitude derivations can both be used for signal interpretation (González-Izal et al., 2012). The RMS is used more often because it represents signal power, while ARV represents the area under the signal and does not have a clear physiological meaning (De Luca, 1997). However, the calculation of ARV is less influenced by remaining isolated spikes (e.g. from cardiac interference), while the RMS can still show these artefacts, making ARV more robust to noise.

3.4.2. Fixed sample entropy

A relatively new way of retrieving a respiratory signal from a tc-EMG tracing is based on a long existing method: entropy analysis. Entropy measures can describe the complexity of nonstationary biomedical signals, like tc-EMG, over time. The ECG, due to its origin, has a different level of complexity than the tc-EMG signal and its periodic behavior is of less influence on the overall entropy of the signal (Naik et al., 2011; Zhang et al., 2016). Therefore an entropy calculation bypasses the need for an ECG removal procedure while still being able to obtain a respiratory waveform.

Recently, several studies investigated the use of fixed sample entropy (fSampEn) on tc-EMG data (Estrada et al., 2017, 2016b; Sarlabous et al., 2014). This technique is a variation of the normal sample entropy and measures how much a given sample is similar to m (the embedding dimension, often set at 1 (Sarlabous et al., 2014)) samples prior to that point. The estimated level of similarity depends on the tolerance

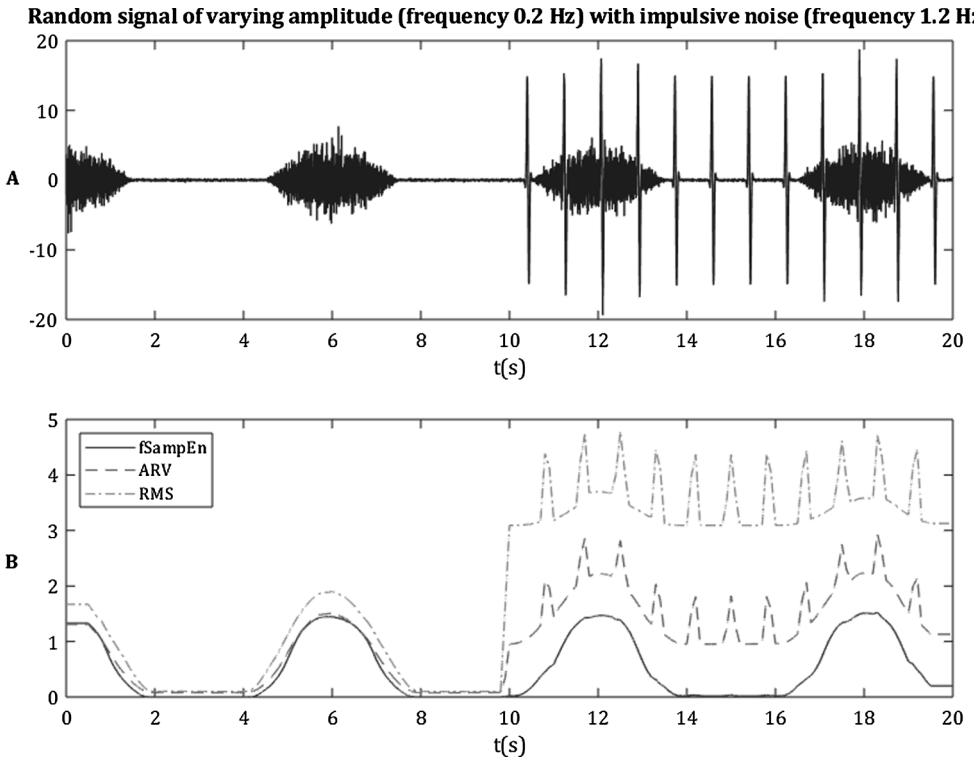

Fig. 2. A generated random signal with impulsive noise where fixed sample entropy (fSampEn), root-mean-square (RMS) and average rectified value (ARV) have been calculated. It illustrates that the fSampEn approach is not influenced by the impulsive noise. Graph redrawn from Estrada et al. with permission of the author (Estrada et al., 2015).

parameter (*r*). The tolerance is often set at a standard deviation (or a fraction of the standard deviation) of the signal. A high fSampEn value means that the signal is very unpredictable and therefore complex, while lower values indicate very regular data (Sarlabous et al., 2014). Cardiac activity is a sharp and repetitive short artefact, and therefore entropy analysis tends to be less influenced by cardiac activity, because the non-cardiac data parts get more weight in the analysis based on their variability. The calculations are performed over a moving time window (e.g. 1 sec (Estrada et al., 2017)), which induces a time delay of this more complex technique. Whether this delay counteracts the gained time of not using an ECG removal algorithm, is unknown. Nevertheless, Estrada et al. (2015) found that fSampEn showed a more accurate performance to derive a respiratory waveform in presence of cardiac artefacts than ARV and RMS (see Fig. 2).

4. Discussion

In this narrative review the sources of signal noise in tc-EMG and the different steps in the signal analysis techniques to process tc-EMG have been described. Based on the literature found of this technique, respiratory tc-EMG seems to be a promising clinical tool to assess inspiratory muscle activity.

4.1. The meandering road to the clinic

How to choose the optimal method to analyze respiratory tc-EMG recordings remains difficult, but it is undisputed that an optimal measurement set-up is essential.

Without proper documentation of the way the measurements are conducted, the reported output could be incorrectly interpreted. Results might be generalized while in practice they only agree with a specific method or device and the variation in protocols is substantial (Dos Reis et al., 2019).

When respiratory tc-EMG is used for cardiorespiratory monitoring, the cardiac component is relatively straight forward. Monitoring heart rate with tc-EMG can be done with high accuracy (Kraaijenga et al., 2015) based on a QRS detection algorithm (for example the Pan-Tompkins algorithm (Pan and Tompkins, 1985)) and does not need extensive processing of the data. Respiratory monitoring with tc-EMG, however, is more complex with the need for post-processing of recorded data before respiration can be evaluated. Removing the cardiac interference has been described extensively and can often be implemented with limited time delays. However, although QRS complex removal is targeted, studies do not describe how to deal with additional ECG noise such as the P and T-wave in the cardiac cycle. Of course frequency domain filtering can suppress this interference but this is described more as a side issue than the aim of filtering itself. On top of that, the width of the window that is gated/subtracted is rather arbitrarily determined. Because the shape and size of the QRS complex can differ between subjects and placements of electrodes the gating window should definitely be optimized.

Presenting the tc-EMG data as a respiratory waveform is needed for clinical feature extraction (the actual breath-by-breath parameters). Single breath parameters like amplitude, peak activity, tonic (end-expiratory) muscle activity and area under the curve are common parameters to report when using respiratory tc-EMG in clinical studies (e.g. Kraaijenga et al., 2016). Changes over time, i.e. trend or long-term variability analysis, of these parameters might be useful to detect clinical deterioration (de Waal et al., 2017; Zannin et al., 2018). However, the method used to construct the respiratory waveform may also influence its interpretation. RMS, ARV, ICA and entropy analysis can all be used to acquire a respiratory waveform, but when reporting the outcome parameters, one must clearly state which method was used.

4.2. Proposals for future research

Most current studies describe analysis techniques that were tested in a simulated bench setting, an animal model, or the adult population. Those reporting tc-EMG recordings in infants, used algorithms adopted from adult literature. No study has yet compared different groups of subjects (infants, children and adults), and tested multiple analysis algorithms (e.g. for QRS removal) in real-life data. More comparative studies on the effectiveness of these analyses are therefore needed to

allow for clinical implementation of tc-EMG measurements of respiratory muscles in different populations.

Furthermore, no clear software algorithm to automatically detect and remove motion artefacts has been described. Depending on the characteristics of the artefacts, development of such an algorithm might be possible, based on the use of signal strength thresholds or frequency characteristics.

Once adequate signal processing is achieved, more research is needed on how to incorporate tc-EMG in clinical practice. Besides monitoring respiratory rate and heart rate (Kraaijenga et al., 2015), monitoring respiratory activity might also be used in assessing the effect of altering respiratory support in the process of weaning or perhaps to trigger a ventilator based on spontaneous breathing effort recorded by tc-EMG. Visual inspection might suggest that entropy analysis provides a smooth waveform that could be used for triggering. However, its processing time might be too long to efficiently trigger a ventilator. Nevertheless, it would be interesting to investigate the different kinds of respiratory waveform construction (RMS, ARV, entropy) as means to trigger a ventilator. In that way tc-EMG might become a non-invasive and low-cost alternative to the neurally adjusted ventilator assist (NAVA, Ferreira et al., 2017; Oda et al., 2018) mode. NAVA uses te-EMG to trigger the ventilator based on the patient's effort but this mode is only available on a single type of ventilator.

In conclusion, the diversity in the current literature with respect to the different options in tc-EMG data analysis should not hamper future research. On the contrary, it can be used as a drive to make a large contribution to the generalizability of data analysis and data publication in this field. With all clinical possibilities to implement tc-EMG, the analysis should be tailor-made, based on system requirements, the patient population and the setting in which tc-EMG is used.

Contributor statement

RvL wrote the first version of the manuscript.
RvL, GH, CdW, PD, AK and FdJ modified the manuscript.
All authors agreed to submission of the manuscript.
RvL submitted the paper.

Declaration of Competing Interest

The authors declared that there is no conflict of interest.

References

Abbaspour, S., Fallah, A., 2014. Removing ECG artifact from the surface EMG signal using adaptive subtraction technique. J. Biomed. Phys. Eng. 4, 33–38.

American Thoracic Society, European Respiratory Society, 2002. ATS/ERS Statement on respiratory muscle testing. Am. J. Respir. Crit. Care Med. 166, 518–624. https://doi.org/10.1164/rccm.166.4.518.

Andrade, A.O., Soares, A.B., Nasuto, S.J., Kyberd, P.J., 2012. EMG decomposition and artefact removal. Comput. Intell. 1–26. https://doi.org/10.5772/50819.

Bartolo, A., Dzwonczyk, R.R., Roberts, C., Goldman, E., 1996a. Description and validation of a technique for the removal of ECG contamination from diaphragmatic EMG signal. Med. Biol. Eng. Comput. 34, 76–81. https://doi.org/10.1007/BF02637025.

Bartolo, A., Roberts, C., Dzwonczyk, R.R., Goldman, E., 1996b. Analysis of diaphragm EMG signals: comparison of gating vs. subtraction for removal of ECG contamination. J. Appl. Physiol. 80, 1898–1902.

Beck, J., Sinderby, C., Lindström, L., Grassino, a., 1997. Diaphragm interference pattern EMG and compound muscle action potentials: effects of chest wall configuration. J. Appl. Physiol. 82, 520–530.

Beck, J., Sinderby, C., Weinberg, J., Grassino, a., 1995. Effects of muscle-to-electrode distance on the human diaphragm electromyogram. J. Appl. Physiol. 79, 975–985. https://doi.org/10.1152/jappl.1995.79.3.975.

Bingham, A., Jelfs, B., Arjunan, S.P., Kumar, D.K., 2018. Identifying noisy electrodes in high density surface electromyography recordings through analysis of spatial similarities. Conf. Proc. IEEE Eng. Med. Biol. Soc. 2325–2328.

Bloch, R., 1983. Subtraction of electrocardiographic signal from respiratory electromyogram. J. Appl. Physiol. 55, 619–623.

Broman, H., Bilotto, G., Luca, C.J.D.E., 1985. A note on the noninvasive estimation of muscle fiber conduction velocity. IEEE Transact. Biomed. Eng. 5, 341–344.

Buchthal, F., Schmalbruch, H., 1980. Motor unit of mammalian muscle. Physiol. Rev. 60, 90–142. https://doi.org/10.1152/physrev.1980.60.1.90.

Butler, H.L., Newell, R., Hubley-Kozey, C.L., Kozey, J.W., 2009. The interpretation of abdominal wall muscle recruitment strategies change when the electrocardiogram (ECG) is removed from the electromyogram (EMG). J. Electromyogr. Kinesiol. 19, e102–e113. https://doi.org/10.1016/j.jelekin.2007.10.004.

Chowdhury, R., Reaz, M., Ali, M., Bakar, A., Chellappan, K., Chang, T., 2013. Surface electromyography signal processing and classification techniques. Sensors 13, 12431–12466. https://doi.org/10.3390/s130912431.

Clancy, E.A., Morin, E.L., Merletti, R., 2002. Sampling, noise-reduction and amplitude estimation issues in surface electromyography. J. Electromyogr. Kinesiol. 12, 1–16. https://doi.org/10.1016/S1050-6411(01)00033-5.

De Luca, C.J., 2006. Electromyography. Encycl. Med. Devices Instrum. 98–109.

De Luca, C.J., 1997. The use of surface electromyography in biomechanics. J. Appl. Biomech. 13, 135–163 Article-id:2515246.

De Luca, C.J., Gilmore, L.D., Kuznetsov, M., Roy, S.H., 2010. Filtering the surface EMG signal: movement artifact and baseline noise contamination. J. Biomech. 43, 1573–1579. https://doi.org/10.1016/j.jbiomech.2010.01.027.

de Waal, C.G., Hutten, G.J., de Jongh, F.H., van Kaam, A.H., 2018. The effect of minimally invasive surfactant therapy on diaphragmatic activity. Neonatology 114, 76–81. https://doi.org/10.1159/000487916.

de Waal, C.G., Hutten, G.J., Kraaijenga, J.V., de Jongh, F.H., van Kaam, A.H., 2017. Electrical activity of the diaphragm during nCPAP and high flow nasal cannula. Arch. Dis. Child. – Fetal Neonatal Ed. https://doi.org/10.1136/archdischild-2016-312300.

Devaprakash, D., Weir, G.J., Dunne, J.J., Alderson, J.A., Donnelly, C.J., 2016. The influence of digital filter type, amplitude normalisation method, and co-contraction algorithm on clinically relevant surface electromyography data during clinical movement assessments. J. Electromyogr. Kinesiol. 31, 126–135. https://doi.org/10.1016/j.jelekin.2016.10.001.

Dos Reis, I.M.M., Ohara, D.G., Januário, L.B., Basso-Vanelli, R.P., Oliveira, A.B., Jamami, M., 2019. Surface electromyography in inspiratory muscles in adults and elderly individuals: a systematic review. J. Electromyogr. Kinesiol. 44, 139–155. https://doi.org/10.1016/j.jelekin.2019.01.002.

Drake, J.D.M., Callaghan, J.P., 2006. Elimination of electrocardiogram contamination from electromyogram signals: an evaluation of currently used removal techniques. J. Electromyogr. Kinesiol. 16, 175–187. https://doi.org/10.1016/j.jelekin.2005.07.003.

Duiverman, M.L., van Eykern, L.A., Vennik, P.W., Koëter, G.H., Maarsingh, E.J.W., Wijkstra, P.J., 2004. Reproducibility and responsiveness of a noninvasive EMG technique of the respiratory muscles in COPD patients and in healthy subjects. J. Appl. Physiol. 96 (5), 1723–1729. https://doi.org/10.1152/japplphysiol.00914.2003.

Estrada, L., Torres, A., Sarlabous, L., Jane, R., 2015. EMG-derived respiration signal using the fixed sample entropy during an Inspiratory load protocol. Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS 2015 1703–1706. https://doi.org/10.1109/EMBC.2015.7318705.

Estrada, L., Torres, A., Sarlabous, L., Jané, R., 2017. Influence of parameter selection in fixed sample entropy of surface diaphragm electromyography for estimating respiratory activity. Entropy 19, 10–14. https://doi.org/10.3390/e19090460.

Estrada, L., Torres, A., Sarlabous, L., Jane, R., 2016. Onset and offset detection of the neural respiratory activity in surface diaphragm electromyography using fixed sample entropy: a pilot study in healthy subjects. IEEE J. Biomed. Heal. Informat. 2194. https://doi.org/10.1109/JBHI.2017.2672800.

Estrada, L., Torres, A., Sarlabous, L., Jané, R., 2016b. Improvement in neural respiratory drive estimation from diaphragm electromyographic signals using fixed sample entropy. IEEE J. Biomed. Heal. Informatics 20, 476–485. https://doi.org/10.1109/JBHI.2015.2398934.

Farina, D., Cescon, C., Merletti, R., 2002. Influence of anatomical, physical, and detection-system parameters on surface EMG. Biol. Cybern. 86, 445–456. https://doi.org/10.1007/s00422-002-0309-2.

Ferreira, J.C., Diniz-Silva, F., Moriya, H.T., Alencar, A.M., Amato, M.B.P., Carvalho, C.R.R., 2017. Neurally Adjusted Ventilatory Assist (NAVA) or Pressure Support Ventilation (PSV) during spontaneous breathing trials in critically ill patients: a crossover trial. BMC Pulm. Med. 17, 1–9. https://doi.org/10.1186/s12890-017-0484-5.

Frahm, K.S., Jensen, M.B., Farina, D., Andersen, O.K., 2012. Surface EMG crosstalk during phasic involuntary muscle activation in the nociceptive withdrawal reflex. Muscle Nerve 46, 228–236. https://doi.org/10.1002/mus.23303.

Fratini, A., Cesarelli, M., Bifulco, P., Romano, M., 2009. Relevance of motion artifact in electromyography recordings during vibration treatment. J. Electromyogr. Kinesiol. 19, 710–718. https://doi.org/10.1016/j.jelekin.2008.04.005.

Glover, J.R., 1977. Adaptive noise canceling applied to sinusoidal interferences. IEEE Trans. Acoust. 25, 484–491. https://doi.org/10.1109/TASSP.1977.1162997.

González-Izal, M., Malanda, A., Gorostiaga, E., Izquierdo, M., 2012. Electromyographic models to assess muscle fatigue. J. Electromyogr. Kinesiol. 22, 501–512. https://doi.org/10.1016/j.jelekin.2012.02.019.

Hakonen, M., Piitulainen, H., Visala, A., 2015. Current state of digital signal processing in myoelectric interfaces and related applications. Biomed. Signal Process. Control 18, 334–359. https://doi.org/10.1016/j.bspc.2015.02.009.

Hermens, H.J., Freriks, B., Disselhorst-Klug, C., Rau, G., 2000. Development of recommendations for SEMG sensors and sensor placement procedures. J. Electromyogr. Kinesiol. 10, 361–374. https://doi.org/10.1016/S1050-6411(00)00027-4.

Hof, A.L., 2009. A simple method to remove ECG artifacts from trunk muscle EMG signals. J. Electromyogr. Kinesiol. 19, e554–e555. https://doi.org/10.1016/j.jelekin.2008.11.007.

Huigen, E., Peper, A., Grimbergen, C.A., 2002. Investigation into the origin of the noise of surface electrodes. Med. Biol. Eng. Comput. 40, 332–338. https://doi.org/10.1007/BF02344216.

Hutten, G.J., Van Eykern, L.A., Latzin, P., Kyburz, M., Van Aalderen, W.M., Frey, U., 2008. Relative impact of respiratory muscle activity on tidal flow and end expiratory volume in healthy neonates. Pediatr. Pulmonol. 43, 882–891. https://doi.org/10.1002/ppul.20874.

Hutten, G.J., Van Eykern, L.A., Latzin, P., Thamrin, C., Van Aalderen, W.M., Frey, U., 2010. Respiratory muscle activity related to flow and lung volume in preterm infants compared with term infants. Pediatr. Res. 68 (4), 339–343. https://doi.org/10.1203/PDR.0b013e3181eeeaf4.

Hutten, G.J., van Thuijl, H.F., van Bellegem, A.C.M., van Eykern, L.A., van Aalderen, W.M.C., 2010b. A literature review of the methodology of EMG recordings of the diaphragm. J. Electromyogr. Kinesiol. 20, 185–190. https://doi.org/10.1016/j.jelekin.2009.02.008.

Iyer, N.P., Dickson, J., Ruiz, M.E., Chatburn, R., Beck, J., Sinderby, C., Rodriguez, R.J., 2017. Neural breathing pattern in newborn infants pre- and postextubation. Acta Paediatr. 1–6. https://doi.org/10.1111/apa.14040.

Jonkman, A.H., Jansen, D., Heunks, L.M.A., 2017. Novel insights in ICU-acquired respiratory muscle dysfunction: implications for clinical care. Crit. Care 21, 1–7. https://doi.org/10.1186/s13054-017-1642-0.

Koopman, A.A., Blokpoel, R.G.T., van Eykern, L.A., de Jongh, F.H.C., Burgerhof, J.G.M., Kneyber, M.C.J., 2018. Transcutaneous electromyographic respiratory muscle recordings to quantify patient–ventilator interaction in mechanically ventilated children. Ann. Intensive Care 8. https://doi.org/10.1186/s13613-018-0359-9.

Kraaijenga, J.V., Hutten, G.H., de Waal, C.G., De Jongh, F.H., Onland, W., Kaam, A.H., 2017. Classifying apnea of prematurity by transcutaneous electromyography of the diaphragm. Neonatology. https://doi.org/10.1159/000484081.

Kraaijenga, J.V., Hutten, G.J., De Jongh, F.H., Van Kaam, A.H., 2015. Transcutaneous electromyography of the diaphragm: a cardio-respiratory monitor for preterm infants. Pediatr. Pulmonol. 50, 889–895. https://doi.org/10.1002/ppul.23116.

Kraaijenga, J.V., de Waal, C.G., Hutten, G.J., de Jongh, F.H., van Kaam, A.H., 2016. BMJ, Diaphragmatic activity during weaning from respiratory support in preterm infants. Archives of Disease in Childhood - Fetal and Neonatal Edition. https://doi.org/10.1136/archdischild-2016-311440.

Laferriere, P., Lemaire, E.D., Chan, A.D.C., 2011. Surface electromyographic signals using dry electrodes. IEEE Trans. Instrum. Meas. 60, 3259–3268. https://doi.org/10.1109/TIM.2011.2164279.

Lansing, R., Savelle, J., 1989. Chest surface recording of diaphragm potentials in man. Electroencephalogr. Clin. Neurophysiol. 72, 59–68. https://doi.org/10.1016/0013-4694(89)90031-X.

Levine, S., Gillen, J., Weiser, P., Gillen, M., Kwatny, E., 1986. Description and validation of an ECG removal procedure for EMGdi power spectrum analysis. J. Appl. Physiol. 60, 1073–1081.

Lu, G., Brittain, J.S., Holland, P., Yianni, J., Green, A.L., Stein, J.F., Aziz, T.Z., Wang, S., 2009. Removing ECG noise from surface EMG signals using adaptive filtering. Neurosci. Lett. 462, 14–19. https://doi.org/10.1016/j.neulet.2009.06.063.

Luo, Y.M., Moxham, J., Polkey, M.I., 2008. Diaphragm electromyography using an oesophageal catheter: current concepts. Clin. Sci. 115, 233–244. https://doi.org/10.1042/CS20070348.

Maarsingh, E.J.W., Oud, M., Van Eykern, L.A., Hoekstra, M.O., Van Aalderen, W.M.C., 2006. Electromyographic monitoring of respiratory muscle activity in dyspneic infants and toddlers. Respir. Physiol. Neurobiol. 150, 191–199. https://doi.org/10.1016/j.resp.2005.05.029.

Maarsingh, E.J.W., van Eykern, L.A., Sprikkelman, A.B., Hoekstra, M.O., Van Aalderen, W.M.C., 2000. Respiratory muscle activity measured with a noninvasive EMG technique: technical aspects and reproducibility. J. Appl. Physiol. 88, 1955–1961.

Mak, J.N.F., Hu, Y., Luk, K.D.K., 2010. An automated ECG-artifact removal method for trunk muscle surface EMG recordings. Med. Eng. Phys. 32, 840–848. https://doi.org/10.1016/j.medengphy.2010.05.007.

Marque, C., Bisch, C., Dantas, R., Elayoubi, S., Brosse, V., Pérot, C., 2005. Adaptive filtering for ECG rejection from surface EMG recordings. J. Electromyogr. Kinesiol. 15, 310–315. https://doi.org/10.1016/j.jelekin.2004.10.001.

Merletti, R., 1999. Standards for reporting EMG data. J. Electromyogr. Kinesiol. 9.

Merletti, R., Botter, A., Troiano, A., Merlo, E., Minetto, M.A., 2009. Technology and instrumentation for detection and conditioning of the surface electromyographic signal: state of the art. Clin. Biomech. 24, 122–134. https://doi.org/10.1016/j.clinbiomech.2008.08.006.

Muller, N., Gulston, G., Cade, D., Whitton, J., Froese, A.B., Bryan, M.H., Bryan, A.C., 1979. Diaphragmatic muscle fatigue in the newborn. J. Appl. Physiol. 46, 688–695. https://doi.org/10.1152/jappl.1979.46.4.688.

Naik, G.R., Arjunan, S., Kumar, D., 2011. Applications of ICA and fractal dimension in sEMG signal processing for subtle movement analysis: a review. Australas. Phys. Eng. Sci. Med. 34, 179–193. https://doi.org/10.1007/s13246-011-0066-4.

O'Brien, M.J., van Eykern, L.A., Oetomo, S.B., Van Vught, H.A., 1987. Transcutaneous respiratory electromyographic monitoring. Crit Care Med. 15, 294–299. https://doi.org/10.1097/00132586-198804000-00008.

O'Brien, M.J., van Eykern, L.A., Prechtl, H.F.R., 1983. Monitoring respiratory activity in infants – a non-intrusive diaphragm EMG technique. Non-Invasive Measurements.

Oda, A., Kamei, Y., Hiroma, T., Nakamura, T., 2018. Neurally adjusted ventilatory assist in extremely low-birthweight infants. Pediatr. Int. 60, 844–848. https://doi.org/10.1111/ped.13646.

Ortega, I.C.M., Valdivieso, A.M.H., Lopez, J.F.A., Villanueva, M.Á.M., Lopez, L.H.A., 2017. Assessment of weaning indexes based on diaphragm activity in mechanically ventilated subjects after cardiovascular surgery. A pilot study. Rev. Bras. Ter. Intensiva 29, 213–221. https://doi.org/10.5935/0103-507X.20170030.

Ortolan, R.L., Mori, R.N., Pereira, R.R., Cabral, C.M.N., Pereira, J.C., Cliquet, A., 2003. Evaluation of adaptive/nonadaptive filtering and wavelet transform techniques for noise reduction in EMG mobile acquisition equipment. IEEE Trans. Neural Syst. Rehabil. Eng. 11, 60–69. https://doi.org/10.1109/TNSRE.2003.810432.

Pan, J., Tompkins, W.J., 1985. A real-time QRS detection algorithm. IEEE Trans. Bio-Med. Eng. Eng. BME-32 230–236. https://doi.org/10.1109/TBME.1985.325532.

Posada-Quintero, H.F., Rood, R.T., Burnham, K., Pennace, J., Chon, K.H., 2016. Assessment of carbon/salt/adhesive electrodes for surface electromyography measurements. IEEE J. Transl. Eng. Heal. Med. 4. https://doi.org/10.1109/JTEHM.2016.2567420.

Prechtl, H.F.R., Van Eykern, L.A., O'Brien, M.J., 1977. Respiratory muscle EMG in newborns: a non-intrusive method. Early Hum. Dev. 1, 265–283. https://doi.org/10.1016/0378-3782(77)90040-8.

Putten, M. Van, 2009. Essentials of Neurophysiology. Springer.

Raez, M.B.I., Hussain, M.S., Mohd-Yasin, F., Reaz, M., Hussain, M.S., Mohd-Yasin, F., 2006. Techniques of EMG signal analysis: detection, processing, classification and applications. Biol. Proced. Online 8, 11–35. https://doi.org/10.1251/bpo115.

Redfern, M.S., Hughes, R.E., Chaffin, D.B., 1993. High-pass filtering to remove electrocardiographic interference from torso EMG recordings. Clin. Biomech. 8, 44–48. https://doi.org/10.1016/S0268-0033(05)80009-9.

Reilly, C.C., Jolley, C.J., Elston, C., John, M., Rafferty, G.F., 2012. Measurement of parasternal intercostal electromyogram during an infective exacerbation in patients with cystic fibrosis. Eur. Respir. J. 40, 977–981. https://doi.org/10.1183/09031936.00163111.

Reilly, C.C., Ward, K., Jolley, C.J., Lunt, A.C., Steier, J., Elston, C., Polkey, M.I., Rafferty, G.F., Moxham, J., 2011. Neural respiratory drive, pulmonary mechanics and breathlessness in patients with cystic fibrosis. Thorax 66, 240–246. https://doi.org/10.1136/thx.2010.142646.

Roy, S.H., de Luca, G., Cheng, M.S., Johansson, A., Gilmore, L.D., de Luca, C.J., 2007. Electro-mechanical stability of surface EMG sensors. Med. Bio. Eng. Comput. 45, 447–457.

Sarlabous, L., Torres, A., Fiz, J.A., Jané, R., 2014. Evidence towards improved estimation of respiratory muscle effort from diaphragm mechanomyographic signals with cardiac vibration interference using sample entropy with fixed tolerance values. PLoS One 9. https://doi.org/10.1371/journal.pone.0088902.

Schweitzer, T.W., Fitzgerald, J.W., Bowden, J.A., Lynne-Davies, P., 1979. Spectral analysis of human inspiratory diaphragmatic electromyograms. J. Appl. Physiol. 46, 152–165.

Searle, A., Kirkup, L., 2000. A direct comparison of wet, dry and insulating bioelectric recording electrodes. Physiol. Meas. 21, 271–283. https://doi.org/10.1088/0967-3334/21/2/307.

Shaw, L., Bagha, S., 2012. Online EMG signal analysis for diagnosis of neuromuscular diseases by using PCA and PNN. Int. J. Eng. Sci. Technol. 4 (10), 4453–4459.

Smith, L., Reilly, C.C., MacBean, V., Jolley, C.J., Elston, C., Moxham, J., Rafferty, G.F., 2017. Physiological markers of exercise capacity and lung disease severity in cystic fibrosis. Respirology 22, 714–720. https://doi.org/10.1111/resp.12954.

Staudenmann, D., Roeleveld, K., Stegeman, D.F., van Dieen, J.H., 2010. Methodological aspects of SEMG recordings for force estimation – a tutorial and review. J. Electromyogr. Kinesiol. 20, 375–387. https://doi.org/10.1016/j.jelekin.2009.08.005.

Taelman, J., Van Huffel, S., Spaepen, A., 2007. Wavelet-independent component analysis to remove electrocardiography contamination in surface electromyography. Annu. Int. Conf. IEEE Eng. Med. Biol. – Proc. 682–685. https://doi.org/10.1109/IEMBS.2007.4352382.

van Vugt, J.P., van Dijk, J.G., 2001. A convenient method to reduce crosstalk in surface EMG. Clin Neurophysiol 112, 583–592. https://doi.org/10.1016/S1388-2457(01)00482-5.

von Tscharner, V., Eskofier, B., Federolf, P., 2011. Removal of the electrocardiogram signal from surface EMG recordings using non-linearly scaled wavelets. J. Electromyogr. Kinesiol. 21, 683–688. https://doi.org/10.1016/j.jelekin.2011.03.004.

Willigenburg, N.W., Daffertshofer, A., Kingma, I., van Dieën, J.H., 2012. Removing ECG contamination from EMG recordings: a comparison of ICA-based and other filtering

procedures. J. Electromyogr. Kinesiol. 22, 485–493. https://doi.org/10.1016/j.jelekin.2012.01.001.
Yacoub, S., Raoof, K., 2008. Noise removal from surface respiratory EMG signal. Int. J. Comput. Inf. Eng. 2 (2), 227–234.
Zannin, E., Veneroni, C., Dellacà, R.L., Corbetta, R., Suki, B., Tagliabue, P.E., Ventura, M.L., 2018. Effect of continuous positive airway pressure on breathing variability in early preterm lung disease. Pediatr. Pulmonol. 53, 755–761. https://doi.org/10.1002/ppul.24017.
Zhan, C., Yeung, L.F., Yang, Z., 2010. A wavelet-based adaptive filter for removing ECG interference in EMGdi signals. J. Electromyogr. Kinesiol. 20, 542–549. https://doi.org/10.1016/j.jelekin.2009.07.007.
Zhang, X., Ren, X., Gao, X., Chen, X., Zhou, P., 2016. Complexity analysis of surface EMG for overcoming ECG interference toward proportional myoelectric control. Entropy 18. https://doi.org/10.3390/e18040106.

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