2021 43rd Annual International Conference of the
IEEE Engineering in Medicine & Biology Society (EMBC)
Oct 31 - Nov 4, 2021. Virtual Conference

Onset and Offset Detection of Respiratory EMG Data Based on Energy Operator Signal

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Abstract— **Onset and offset detection of electromyography (EMG) data is an important step in respiratory muscle coordination assessment. Impaired respiratory coordination can indicate breathing disorders and lung diseases. In this paper, we present an algorithm for onset and offset timing detection of real-world EMG signals from respiratory muscles, which are contaminated with electrocardiogram (ECG) artifacts. The algorithm is based on the Energy Operator signal, has a low computational cost, and includes a filtering procedure to remove ECG artifacts from EMG. Analysis of EMG signals from 2 respiratory muscles of 5 participants' data shows high agreement between the algorithm and manual method with a mean difference between two methods of 0.0407 seconds.**

Clinical Relevance— **ECG artifacts in respiratory muscles are a barrier to the reliable onset and offset detection of their EMG signals. We developed and described a method that filters out ECG artifacts from respiratory EMG signals, and efficiently detects onset and offset. To the best of our knowledge, this is the first paper to discuss algorithmic onset and offset detection of EMG signals, collected from scalene and sternocleidomastoid inspiratory muscles, and contaminated with ECG artifacts.**

I. INTRODUCTION

Respiratory muscles are continuously activated throughout life to generate breathing. Although the diaphragm is the major breathing muscle in healthy people, several more muscles contribute in a well-coordinated manner [1]. Other primary inspiratory muscles recruited during quiet breathing are the scalenes and the parasternal intercostals [2] whereas accessory inspiratory muscles contribute to higher levels of ventilation (e.g., during exercise). The sternocleidomastoid is one of the most prominent accessory muscles of inspiration [2, 3].

Respiratory muscle coordination can be assessed by EMG timing of the onset and offset of activation of several respiratory muscles (e.g., scalenes and sternocleidomastoid). This coordination among onset and offset of respiratory muscle activation is impaired in people with lung diseases [4, 5] and those needing mechanical ventilation to breathe [6]. Early detection of abnormal respiratory muscle coordination may enable more effective treatment, possibly minimizing mechanical ventilation that could optimize recovery.

The most common approach for onset and offset detection of EMG data is based on a visual inspection and manual search [7]. These techniques are subjective, time-consuming, and are intended for small datasets. Results can be imprecise and highly dependent on raters' experience. One of the most important limitations of detecting respiratory muscle EMG onset and offset is ECG noise. Due to its proximity to the heart, respiratory muscle EMG signals are highly contaminated by the QRS complex, which many times appear exactly at onset or offset of muscle activation, constituting a barrier to reliable detection. Many different methods and algorithms have been proposed for EMG onset detection [8-17]. Most methods have been tested on simulated or low-noise EMG signals. Methods dealing with filtering ECG artifacts are scarce and, to the best of our knowledge, have not been used in the onset and offset detection context. Other limitations are a primary focus only on onset detection and computationally demanding algorithms.

In this paper, we analyzed real-world EMG signals, acquired using surface electrodes from a primary (scalene) and an accessory (sternocleidomastoid) inspiratory muscles that were contaminated with ECG artifacts. We first filtered out ECG artifacts using the Least-Mean-Square adaptive filter and subsequently applied an Energy-Operator-based algorithm with low computational complexity to reliably detect the onset and offset of EMG signals. Our results are based on EMG data collected from 2 respiratory muscles of 5 participants and with an average of 163 breaths in one signal.

II. RELATED WORK

In this section, we review the most common approaches for the onset detection of EMG signals, both simulated and acquired from body muscles.

Tenan et al. [8] evaluated several standard and statistical algorithms to detect activation onset in both real and simulated EMG signals with a known onset time. Standard algorithms included linear envelope, Teager-Kaiser Energy Operator (TKEO) [9, 10], and sample entropy [11]. Statistical techniques included time series mean/variance, sequential and batch processing of parametric and nonparametric tools, and Bayesian changepoint analysis [12, 13]. Their results indicate that Bayesian changepoint algorithms showed the best performance among other tested methods. However, the authors examined only the case when one muscle onset needs to be detected in the EMG time series.

Two studies used TKEO to improve onset detection [9, 10]. However, Li et al. [9] validated the method based on simulated EMG data. Solnik et al. [10] tested the method on real EMG signal (collected from vastus lateralis) and explored the effect of signal-to-noise ratio (SNR) on onset detection. Their main finding is that TKEO significantly improved the detection of EMG onset, independently of SNR. However,

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978-1-7281-1178-0/21/$31.00 ©2021 IEEE

their analysis is based on short 4-second duration EMG signals and limited to the detection of one onset point.

Drapala et al. [14] proposed a two-stage method for EMG onset detection where the first stage provided a rough estimation of EMG onset, while the second stage was focused on a precise, local search to detect the onset. When tested on real surface EMG recordings from the right and left-hand muscles, high accuracy, and algorithm without any threshold parameters were attained. However, this method has high computational costs and is intended for off-line implementations only.

Many algorithms presented in the systematic review [15] performed well in detecting onset in simulated and good quality surface EMG signals with high SNR. Furthermore, most algorithms are focused on the detection of one onset point for each separate signal [8, 10]. However, capturing EMG onset of respiratory muscles is challenging due to the proximity of the heart and the presence of ECG artifacts in EMG signals. Additionally, our EMG signals had on average 163 breaths with one onset and one offset point for each breath, which resulted in a high number of points for detection.

We propose an efficient threshold-based algorithm for the detection of multiple onset and offset points, which includes adaptive filtering to remove ECG contamination from EMG signals of respiratory muscles. The proposed algorithm uses the Energy Operator signal and has a low computational cost with high potential for real-time implementations.

III. DATA COLLECTION

The Institution's Ethical Review Board approved all experimental procedures involving human subjects. The data collection protocol is detailed in Derbakova et al. [16]. In brief, 5 non-smoking healthy adults (3 males) aged 23-25 years were tested. After the skin was prepared and cleaned with alcohol, EMG surface electrodes were placed over the scalenes and sternocleidomastoid (more details in [16]).

While in half-lying, maximum inspiratory pressures were measured at residual volume (full expiration) according to the standard procedure [17, 18]. Next, a constant-load inspiratory threshold loading test was performed at 50% of the maximum inspiratory pressure until task failure (Figure 1).

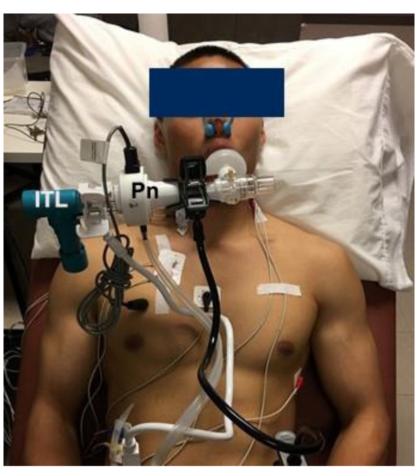


Figure 1. Participant in half-lying breathing in against an inspiratory threshold load imposed by a spring-loaded device (ITL). A pneumotach (Pn) measured inspiratory flow.

During this test, participants were cued by an audiotape to breathe at an inspiratory:expiratory cycle of 2:4 seconds and to target 45% to 55% of their maximum inspiratory pressure by keeping their inspiratory pressure within a horizontal shaded bar observed on a computer monitor. The load was imposed by a spring-loaded threshold device (POWERBreatheTM, Classic, England, UK) connected to a two-way non-rebreathing valve (Hans Rudolph, Kansas City, MO) in line with a mouthpiece. Task failure was defined as the point when the participant failed to meet the target on three consecutive breaths or stopped the test. Throughout the inspiratory threshold loading test, ECG, inspiratory flow, and EMG of the scalene and sternocleidomastoid (ADInstruments bioamplifier) were acquired at 1000 Hz (PowerLab; ADInstruments, Colorado Springs, CO).

IV. METHODS

A. Algorithm for Onset and Offset Detection

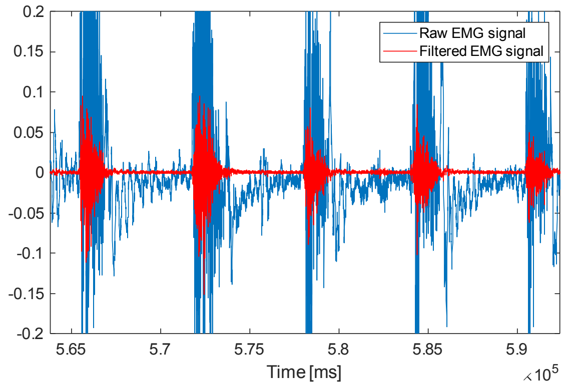
The first step in EMG signal processing was filtering to remove ECG artifacts, and for this task, adaptive filters have previously shown good performance [19, 20]. As recommended by Haykin [21], we used Least-Mean-Square (LMS) adaptive filter to remove ECG noise from surface respiratory EMG signals. We tried several values of the parameters and found the following values that worked for our dataset: filter order of 8 and cut-off frequency 5 Hz (high-pass Butterworth filter) for all signals, while step size was differed across signals, and ranged from 0.01 to 1. Raw and filtered EMG signals are presented in Figure 2a. The second step was the calculation of Energy Operator signal ($\psi(x(t))$, Equation 1) and TKEO from filtered signal [22]. In Equation 1, $x(t)$ is EMG signal in time t. Energy signals are flatter in-between the EMG parts in comparison to filtered EMG signal, which improves the detection of the onset and offset points. Although previously TKEO was used as a step toward the onset detection [9, 10], we selected the Energy Operator signal (Figure 2b), because of flatter parts in-between the EMG sections when compared to the TKEO, which would lead to better performance in detection of the onset and offset points.

$$\Psi(\mathrm{x(t)}) = \left(\frac{dx}{dt}\right)^2 + x(t)\left(\frac{d^2x}{dt^2}\right) \tag{1}$$

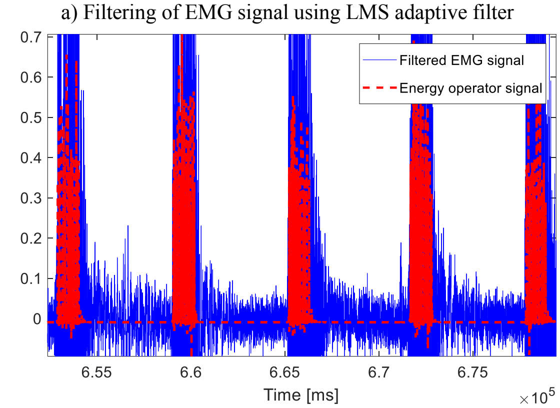
The next goal was to divide the energy signal into segments, where each segment contained one EMG section (representing one breath) and included a part of the surrounding flat signal. The segmentation procedure steps are the following:

1) Calculation of signal envelope from Energy Operator signal.

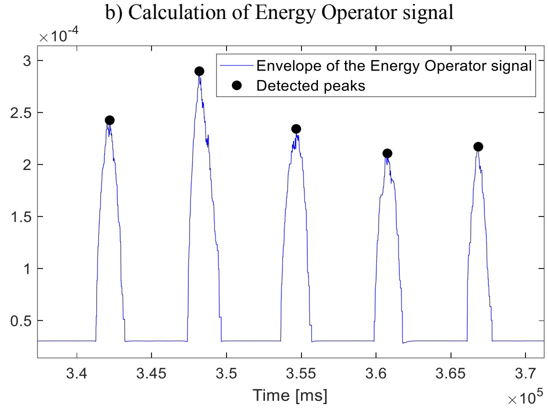
2) Detection of peaks (maximum value points) in a signal envelope (Figure 2c). In this step, parameter representing a distance between peaks needed to be set and it varied across signals. Smaller parameter values resulted in the detection of more peak values for one peak of the signal, while higher parameter values led to skipping the detection of some peaks. Consequently, this parameter needs to be chosen to target the detection of one peak value for each signal peak (Figure 2c).



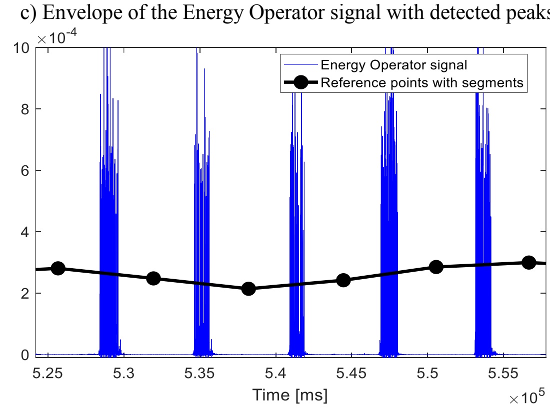
a) Filtering of EMG signal using LMS adaptive filter



b) Calculation of Energy Operator signal



c) Envelope of the Energy Operator signal with detected peaks



d) Calculation of the reference points for segmentation

Figure 2. Detection algorithm steps

3) Calculation of the reference points halfway in-between the peaks, so segments of the signal between reference points include one EMG section (Figure 2d).

Finally, the detection algorithm would check segments one by one and when it detects the first signal point inside a segment higher than a set threshold, that point would be chosen as the onset point in that segment. The same approach is used for offset point detection. The only difference is that the search starts from the end of segments and finishes at beginning of segments (opposite direction from the search for onset points).

We have defined a threshold as a percentage of the peak value of the envelope signal in the segment. A threshold of 5% of peak value works well for most signals, however, for some signals, 6% or 7% works better. A general recommendation is to choose the threshold between 5% and 10% of the peak value of the envelope signal.

The detection algorithm processes one EMG signal in less than a minute, whereas the manual method requires a few hours to analyze one EMG signal.

B. Manual Method

For the manual method, the processed signal after removing ECG artifacts using the LMS algorithm was utilized. A researcher performed the manual analysis of EMG signal by visually identifying time point (in milliseconds) at which a significant increase in EMG signal from baseline (onset) was apparent, and the time point when EMG signal returned to baseline values (offset). EMG onset and offset times were determined for all breaths of each participant.

V. Results

Participants were (mean ± standard deviation) 24 ± 0.4 years old with a BMI of 23 ± 2 kg/m^2, and maximum inspiratory pressure of 112 ± 21 cmH_2O. The inspiratory threshold loading lasted for 1329 ± 569 seconds.

Detection algorithm results (Figure 3) show the Energy Operator signal with the detected onset and offset points. Visual inspection of the results suggest a high accuracy of the algorithm. However, further quantitative analysis to validate the algorithm against the manual method is necessary. The comparison analysis was based on the data from 5 participants, 2 EMG signals, and both, onset and offset points (3050 onset and offset points in total). The mean difference between the algorithm and manual method was 0.0407 seconds, while the root mean square difference was 0.3834 seconds, which indicate a strong agreement between these methods.

In total, 91.54% points were detected correctly, 5.13% onset and offset points were not detected and 3.33% of detected points were not the actual onset or offset points. One reason for omitting the detection of some points may come from non-detected envelope signal peaks in one of the algorithm steps and thus skipping the corresponding segment of the signal in further processing. Hence, it is crucial to choose the parameter representing the distance between the envelope signal peaks in this algorithm step correctly. Detected points that are not the actual onset or offset points may be a result of backlog noise in-between the EMG signal parts with amplitudes higher than the defined threshold.

The Bland-Altman plot is commonly used in the analysis of the agreement between two measurements [23].

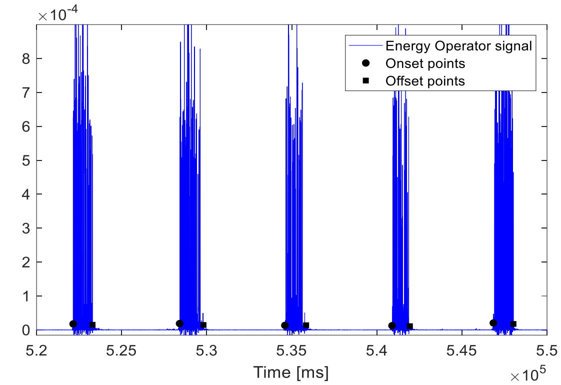


Figure 3. Energy Operator signal with detected onset and offset points

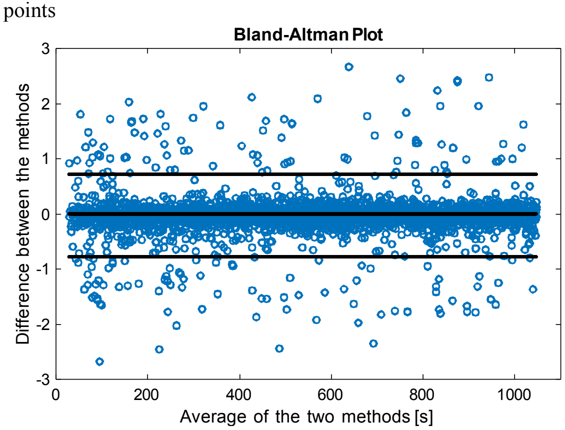


Figure 4. Bland-Altman plot of differences between the proposed algorithm and manual method

Figure 4 shows the Bland-Altman plot of measurement differences between the algorithm and manual method with limits of agreement of ±1.96 standard deviation. Most points lie around the mean difference and inside limits of agreement. Points outside the limits of agreement on the Bland-Altman plot indicate that in some cases, there is a higher difference between the methods. The presence of sporadic noise can influence the correct detection of some points by the algorithm. Alternatively, the manual method may have errors due to incorrect readings by a rater.

VI. CONCLUSION

We presented an efficient algorithm for onset and offset detection of respiratory muscle EMG data using the Energy Operator signal. Our results, based on data from 5 participants, showed a high percentage of correctly detected points and strong agreement with the manual method.

The detection algorithm has two potential limitations. The first one is tuning the parameter representing the distance between envelope signal peaks for every signal. The choice of this parameter is crucial for further algorithm steps and can significantly impact results. The second limitation is the threshold in the last algorithm step. The threshold of 5% of envelope signal peak value works in most cases. However, in the case of extremely noisy signals, other threshold values may improve detection.

We plan to improve this algorithm by finding better ways to tune parameters and testing the algorithm on extended data set, including participants with respiratory diseases. We also plan to build models for the prediction of healthy vs. unhealthy participants using machine learning techniques.

REFERENCES

[1] Reid WD, Dechman G. Considerations when testing and training the respiratory muscles. Phys Ther. 1995;75(11):971-982.
[2] De Troyer A, Estenne M. Coordination between rib cage muscles and diaphragm during quiet breathing in humans. J Appl Physiol Respir Environ Exerc Physiol. 1984;57(3):899-906.
[3] Hudson AL, Gandevia SC, Butler JE. The effect of lung volume on the co-ordinated recruitment of scalene and sternomastoid muscles in humans. J Physiol. 2007;584(Pt 1):261-270.
[4] Ceriana P, Vitacca M, Carlucci A, et al. Changes of Respiratory Mechanics in COPD Patients from Stable State to Acute Exacerbations with Respiratory Failure. COPD. 2017;14(2):150-155.
[5] Vitacca M, Porta R, Bianch et al. Differences in spontaneous breathing pattern and mechanics in patients with severe COPD recovering from acute exacerbation. Eur Respir J. 1999;13(2):365-370.
[6] Parthasarathy S, Jubran A, Tobin MJ. Cycling of inspiratory and expiratory muscle groups with the ventilator in airflow limitation. Am J Respir Crit Care Med. 1998;158(5 Pt 1):1471-1478.
[7] Micera S, Vannozzi G, et al. Improving detection of muscle activation intervals. IEEE Eng Med Biol Mag. 2001;20(6):38-46.
[8] Tenan MS, Tweedell AJ, Haynes CA. Analysis of statistical and standard algorithms for detecting muscle onset with surface electromyography. PLoS One. 2017 May 10;12(5):e0177312.
[9] Li X, Zhou P, Aruin AS. Teager–Kaiser Energy Operation of surface EMG improves muscle activity onset detection. Annals of Biomedical Engineering 2007;35(9):1532–1538. [PubMed: 17473984]
[10] Solnik S, DeVita P, Rider P, et al. Teager–Kaiser Operator improves the accuracy of EMG onset detection independent of signal-to-noise ratio. Acta of bioengineering and biomechanics/Wroclaw University of Technology. 2008;10(2):65.
[11] Zhang X, Zhou P. Sample entropy analysis of surface EMG for improved muscle activity onset detection against spurious background spikes. J Electromyogr Kinesiol. 2012; 22(6):901±7. https://doi.org/10.1016/j.jelekin.2012.06.005 PMID: 22800657
[12] Barry D, Hartigan JA. A Bayesian analysis for change point problems. J Am Statist Assoc. 1993; 88 (421):309±19.
[13] Erdman C, Emerson JW. bcp: an R package for performing a Bayesian analysis of change point problems. J Stat Softw. 2007; 23(3):1±13.
[14] Drapala J, Brzostowski K, Szpala A, et al. Two stage EMG onset detection method. Archives of Control Sciences. 2012;22:427-40.
[15] Staude G, Flachenecker C, Daumer M, Wolf W. Onset detection in surface electromyographic signals: a systematic comparison of methods. EURASIP Journal on Advances in Signal Processing. 2001 Dec 1;2001(2):867853.
[16] Derbakova A, Khu S, Ho K, et al. Neck and Inspiratory Muscle Recruitment during Inspiratory Loading and Neck Flexion. Med Sci Sports Exerc. 2020.
[17] American Thoracic Society/European Respiratory S. ATS/ERS Statement on respiratory muscle testing. Am J Respir Crit Care Med. 2002;166(4):518-624.
[18] Laveneziana P, Albuquerque A, Aliverti A, et al. ERS statement on respiratory muscle testing at rest and during exercise. Eur Respir J. 2019;53(6).
[19] Abbaspour S, Fallah A. Removing ECG artifact from the surface EMG signal using adaptive subtraction technique. Journal of biomedical physics & engineering. 2014 Mar;4(1):33.
[20] Yacoub S, Raoof K. Noise removal from surface respiratory EMG signal. International Journal of Computer, Information, and Systems Science, and Engineering. 2008 Feb 28;2(4):226-33.
[21] Haykin S. Adaptive filter theory. Prentice-Hall, Inc.; 1996 Jan 1.
[22] Hooman Sedghamiz (2020). Teager Keiser Energy Operator Vectorized(https://www.mathworks.com/matlabcentral/fileexchange/45406-teager-keiser-energy-operator-vectorized), MATLAB Central File Exchange. Retrieved August 26, 2020.
[23] Bland JM, Altman D. Statistical methods for assessing agreement between two methods of clinical measurement. The lancet. 1986 Feb 8;327(8476):307-10.