# Detection of Respiratory Phases to Estimate Breathing Pattern Parameters using Wearable Bioimpendace

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*Abstract*— Many studies have focused on novel noninvasive techniques to monitor respiratory rate such as bioimpedance. We propose an algorithm to detect respiratory phases using wearable bioimpedance to compute time parameters like respiratory rate, inspiratory and expiratory times, and duty cycle. The proposed algorithm was compared with two other algorithms from literature designed to estimate the respiratory rate using physiological signals like bioimpedance. We acquired bioimpedance and airflow from 50 chronic obstructive pulmonary disease (COPD) patients during an inspiratory loading protocol. We compared performance of the algorithms by computing accuracy and mean average percentage error (MAPE) between the bioimpedance parameters and the reference parameters from airflow. We found similar performance for the three algorithms in terms of accuracy ($>0.96$) and respiratory time and rate errors ($<3.42$ %). However, the proposed algorithm showed lower MAPE in duty cycle (10.18 %), inspiratory time (10.65 %) and expiratory time (8.61 %). Furthermore, only the proposed algorithm kept the statistical differences in duty cycle between COPD severity levels that were observed using airflow. Accordingly, we suggest bioimpedance to monitor breathing pattern parameters in home situations.

*Clinical relevance*— This study exhibits the suitability of wearable thoracic bioimpedance to detect respiratory phases and to compute accurate breathing pattern parameters.

## I. INTRODUCTION

Respiratory measurement has an important role in the assessment of physiological conditions, like in respiratory disease diagnosis and monitoring. In particular, spirometry is the gold standard in the diagnosis of several respiratory diseases like chronic obstructive pulmonary disease (COPD). Spirometry requires the patients to wear facemasks or mouthpieces that could modify their breathing [1]. Accordingly,

many novel techniques are currently investigated to obtain respiratory information and monitor the patients' condition more comfortably [2]–[4] using noninvasive physiological signals like thoracic bioimpedance, electrocardiogram, or photoplethysmogram. Most of these previous studies have focused on estimating respiratory rate [3]–[5] since it is used as an indicator of clinical events.

Respiratory rate is the most commonly used parameter, but breathing can be characterized by other parameters as well. Breathing pattern is affected by age, physical condition, or diseases [6]. Therefore, obtaining other breathing parameters can provide relevant information to monitor respiration in healthy and respiratory patients. The present study proposes an algorithm to detect respiratory phases using wearable thoracic bioimpedance to compute respiratory rate and other time parameters such as duty cycle, inspiratory and expiratory time.

This study assessed the performance of the respiratory cycle detection using bioimpedance and applying different preprocessing. For that, we evaluated the performance of the proposed algorithm and two literature algorithms [7], [8] using detections from respiratory airflow as reference. The novelty of this study is the inclusion of inspiratory time, expiratory time, and duty cycle in the analysis of a respiratory cycle detection providing a more complete breathing characterization. The final objective of the proposed algorithm is its applicability in wearable respiratory monitoring.

## II. MATERIALS AND METHODS

### A. Respiratory protocol and data acquisition

The study population included fifty COPD patients who were recruited at Ziekenhuis Oost-Limburg (Genk, Belgium). The study followed the Declaration of Helsinki and was approved by the local institutional medical ethics committee from Ziekenhuis Oost-Limburg with reference 18/0047U.

The study consisted of measuring physiological signals while the COPD patients performed an inspiratory threshold loading protocol. During the loading protocol, we imposed inspiratory loads proportional to the maximal inspiratory pressure of the patients. The details of the protocol have been explained previously in [9].

The physiological signals acquired during the protocol were thoracic bioimpedance (bioZ) and respiratory airflow. The signals were acquired using two systems, a wearable research prototype device [10], and a standard wired acquisition system, respectively. The signals were acquired using the same setup presented in [9].
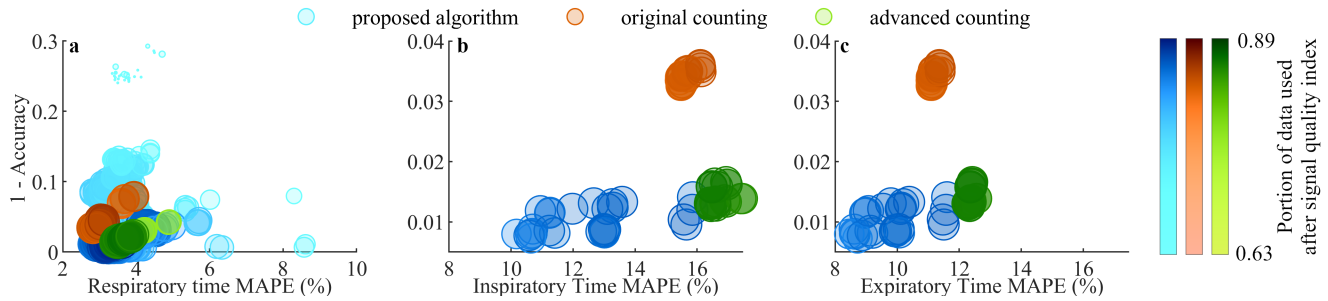
Fig. 1. Performance of the three algorithms under study, the proposed algorithm, original counting [7], and advanced counting [8] algorithms. Each point corresponds to a parameter-based outcome of the preprocessing sweep, the color and size of the marker are related to the portion of data used.

TABLE I

PERFORMANCE OF THE RESPIRATORY CYCLE DETECTION ALGORITHMS

| | Accuracy | Data used (%) | Mean Average Percentage Errors of Respiratory Parameters (%) | | | | | Mean Execution Time (ms) |
| | | | $t_{TOT}$ | $t_I$ | $t_E$ | $t_I/t_{TOT}$ | RR | |
|---|---|---|---|---|---|---|---|---|
| proposed algorithm | 0.9909 | 85.30 | 2.90 | 10.64 | 8.61 | 10.18 | 2.86 | 1.88 |
| original counting [7] | 0.9672 | 83.90 | 2.84 | 15.48 | 11.10 | 14.93 | 2.82 | 45.95 |
| advanced counting [8] | 0.9868 | 86.12 | 3.42 | 16.89 | 12.39 | 16.14 | 3.10 | 49.60 |

$t_{TOT}$: respiratory time; $t_I$: inspiratory time; $t_E$: expiratory time; $t_I/t_{TOT}$: duty cycle; RR: respiratory rate.

## B. Respiratory phase detection algorithms

We propose an algorithm for respiratory cycle segmentation using thoracic bioimpedance. We compared it with two time-domain algorithms from previous studies, the original counting [7] and advanced counting [8].

*Preprocessing:* The respiratory airflow was low-pass filtered to avoid aliasing before the decimation from 10 kHz to 100 Hz. Afterwards, the resulting airflow signal was low-pass filtered (zero-phase $4^{th}$ order Butterworth, $f_c$ = 1 Hz). Finally, airflow signal was smoothed with a moving average filter of 0.25 s. This preprocessing was selected to reduce the high-frequency content without affecting the DC, that it is important to get respiratory cycles accurately. Respiratory cycles obtained after thresholding and visual correction of miss-detections were used as the reference.

The bioimpedance signals were upsampled from 16 Hz to 100 Hz by cubic interpolation. Preprocessing has an effect on the accuracy of the cycle detection. The parameter sweep described below was used to analyze this effect. Accordingly, the following parameters are not specified as numerical values and were swept between common values for breathing analysis. The preprocessing steps were similar to [11] and included: 1) a band-pass filtering ($f_{lower}$ and $f_{upper}$), 2) a moving average filter of $w_1$ s, 3) a Savitzky-Golay differentiation of 250 ms and finally, 4) another moving average filter of $w_2$ s. The filtered bioZ signals were obtained after step 2) step, whereas the derivative bioZ signals were the result of the final step. The sweep comprised the following parameter values: $f_{lower}$: 0.01, 0.05, 0.1 Hz, $f_{upper}$: 1, 2.5, 5, 10 Hz, $w_1$ and $w_2$: No-filter, 0.25, 0.5, 0.75, 1, 1.25, 2 s.

*Respiratory cycles detection:* The proposed algorithm uses the derivative bioZ signal to detect the zero crossings corresponding to the local extrema of the bioZ signal. Firstly, from all the detected extrema, only the pairs separated more than 0.2 s in time are selected. The inspiratory phases are the segments between the consecutive minimum and maximum

extrema, on the contrary, the expiratory phases are the segments between maxima and minima. Therefore, this time restriction is connected to the minimum respiratory phase duration used in previous studies. Secondly, the algorithm aims to reject false detections by constraining the respiratory phases to include at least one zero-crossing. If a segment does not meet this condition, it will be integrated into an adjacent phase or rejected depending on the slope between its start and the end of the next segment. The slope sign gives the increasing or decreasing trend of the segment, thus, the segment will be combined with the adjacent segment with the same trend.

1) If a segment without zero-crossings has a positive slope, it will be combined with the adjacent inspiration since bioimpedance is regularly increasing during inspiration.
2) Alternatively, a segment with a negative slope will be integrated into an expiratory phase.
3) Finally, a segment will be rejected only if it is an inspiratory segment (i.e., between a minimum and a maximum) and the angle generated by its slope is mostly flat, between -10 and 10 degrees.

This constraint is justified by the conventional waveform of bioimpedance after the DC filtering.

We wanted to compare this new detection algorithm with state-of-the-art options. The selected algorithms are based on counting and have been previously used to detect respiratory rate in several physiological signals such as bioimpedance [5]. These algorithms detect local extrema and reject the wrong ones based on the amplitude statistics of the detected extrema. The constraints of Original and Advance Counting algorithms are different and can be consulted in [7], [8]. These algorithms were designed to estimate the respiratory rate by the time difference between the selected adjacent peaks. Therefore, we adapted the algorithms and we also kept the troughs to get the start of a respiratory cycle/inspiration. If a segment had more than one troughs, we selected the one

with the highest absolute magnitude.

*Signal quality index:* We used the signal quality index [12] to identify high-quality signal segments and get more robust estimations from bioimpedance signal. We computed the index on 32s segments with 75 % overlap. Only the segments marked as low-quality in all the corresponding overlapping segments were rejected.

*Performance comparison:* We calculated common time parameters related to the breathing pattern, such as inspiratory time ($t_I$), expiratory time ($t_E$), respiratory time ($t_{TOT}$), duty cycle ($t_I/t_{TOT}$) and respiratory rate (RR). These parameters were computed for all detections from each algorithm, and also for the airflow detections considered as the reference values. The performance of the three algorithms was assessed by calculating the accuracy of the detections compared to the airflow ones and the mean absolute percentage error (MAPE) between the parameters computed from bioimpedance and the ones from airflow. Additionally, we included in the analysis the amount of rejected data after we applied the signal quality index and the mean execution time. The cycle detections were executed for each subject load signal on an Intel Core i7-7700 CPU @ 3.60 GHz RAM 16 GB.

We performed the Kruskal-Wallis statistical test to evaluate the differences in the respiratory parameters between two COPD groups. The grouping was on the COPD severity level using the spirometry parameter $FEV_1$. We computed two representative values for each patient, the values were the median of the parameters for quiet breathing and loaded breathing (i.e., 12 % to 60 % of MIP).

## III. RESULTS

Fifty COPD patients were recruited in the study. 7 patients were excluded from the analysis because of an allergic reaction (1), technical device problems (4) and, low signal-to-noise ratio of the bioZ (2). The resulting population included 9 females and 34 males, their age was $64.63 \pm 6.60$ *years*, and their body mass index was $25.71 \pm 4.48$ $kg/m^2$.

The study consisted of detecting respiratory phases using bioZ signal and varying its preprocessing. Common time respiratory parameters were used to evaluate the performance of the detections by comparing them with the detections from the airflow signal. The reference (median ($1^{st}$ - $3^{rd}$ quartile)) values of the respiratory parameters were: $t_{TOT}$ 3.41 (2.76 - 4.36) s, $t_I$ 1.48 (1.17 - 1.89) s, $t_E$ 1.91 (1.54 - 2.48) s, $t_I/t_{TOT}$ 0.43 (0.39 - 0.48), and RR 17.60 (13.76 - 21.74) breaths/min.

588 parameter-based outcomes were evaluated from the sweeping parameters for the proposed algorithm and 84 for the other two algorithms. Note that the counting algorithms do not need the second moving average filter since they do not use the derivative of bioZ, so they had fewer outcomes. Fig. 1a shows the accuracy and the MAPE of respiratory time calculations of all the sweep steps run in the study. The proposed algorithm and the original counting had similar performance in terms of MAPE but the proposed algorithm slightly improved the accuracy. Fig.1b and c focused on the 30 best outcomes based equally on accuracy and MAPE. These panels exhibit the MAPE of the inspiratory and
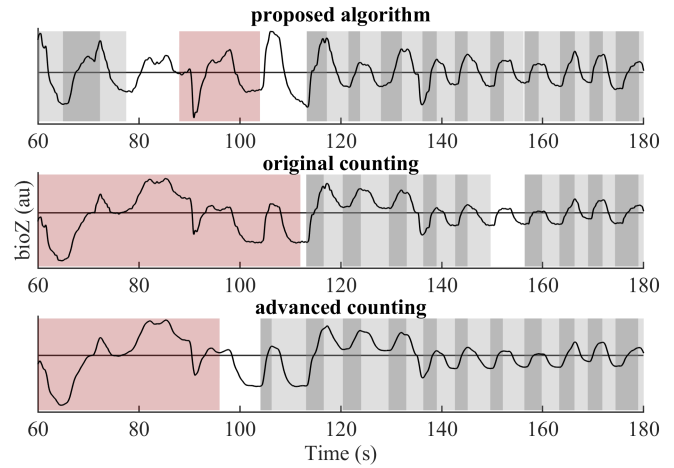


Fig. 2. Example of the respiratory phase detections for the three algorithms. The detections are represented as grey boxes, darker boxes for inspirations and lighter ones for expirations. The segments with red backgrounds were marked as low-quality ones and were not used for the analysis. If no breathing was detected, the background is not colored.

expiratory times. In this case, the MAPE errors from the proposed algorithm substantially improved the ones from the other two algorithms. The portion of data used after applying the signal quality index is represented by the color and size of the markers and went from 0.63 to 0.89.

Henceforth the reported results correspond to the best performance of each algorithm. The proposed algorithm exhibited its best performance with a bandwidth of the bioZ of $f_{lower}$ = 0.05 Hz, $f_{upper}$ = 2.5 Hz, a moving average filter before the differentiation of $w_1$ = 0.25 s, and after the differentiation of $w_2$ 0.75 s. For the original counting, the best performance was when using similar bandwidth of $f_{lower}$ = 0.01 Hz and $f_{upper}$ = 2.5 Hz, but without the moving average filter. The advanced counting best preprocessing included a broader bandwidth, $f_{lower}$ = 0.01 Hz and $f_{upper}$ = 10, but a wider moving average filter, $w_1$ = 0.75 s. To exemplify the differences in preprocessing, Fig. 2 shows the same segment with the detections from the three algorithms under study. Table I shows the detailed performance for each algorithm, confirming what is shown in Fig. 1. Note that the lower errors were for the respiratory time and rate since we selected the best preprocessing parameters based on respiratory time and accuracy. Note also that the mean execution time is higher in the literature algorithms than in the proposed one.

Finally, we divided the patients into moderate ($FEV_1 \geqslant 50$ %) and severe ($FEV_1 < 50$ %) resulting in 21 and 22 patients, respectively. Firstly, we performed the statistical test on the reference breathing parameters values (i.e., computed using airflow signal) and only the duty cycle parameter exhibited significant differences in both quiet and loaded breathing. We repeated the same test on the detections from the bioZ signal, and only the proposed algorithm showed significant differences also in the duty cycle values. In this case, the duty cycle values only exhibited the statistical differences during quiet breathing as Fig. 3 shows.
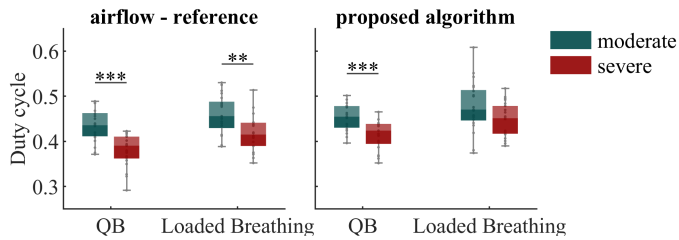
Fig. 3. Duty cycle values of the airflow detections and the detections from the proposed algorithm using bioZ during loaded and quiet breathing (QB). The statistical differences between groups were evaluated by Kruskal-Wallis' test with Bonferroni's correction. **: p-value < 0.01 and ***: p-value < 0.001.

## IV. DISCUSSION

This study aims to propose and evaluate an algorithm to detect respiratory phases depending on different preprocessing. The detection was performed using three different algorithms: the proposed algorithm and two algorithms from literature [7], [8]. The differences in performance between the outcomes of the parameter sweep show the importance of the preprocessing to get accurate detections.

Jeyhami et al. [5], also compared different algorithms using bioimpedance for estimating respiratory rate. Their comparison showed that the advanced counting algorithm was the best algorithm for estimating respiratory rate. However, they used the same method for bioZ and the reference (flow thermography), whereas we employed manually corrected detections from airflow. In addition, we computed the MAPE of all the respiratory times from the correct detections and Jeyhami's study computed an average estimation of the respiratory rate in time windows of 15 s. Having the respiratory rate for each respiratory cycle gives more time resolution to track dynamic changes. Despite the differences, both studies conclude that bioimpedance is promising for noninvasively estimate of respiratory time/rate.

We applied a signal quality index that has been recently presented in [12] which rejects segments based on the plausibility of valid breath durations and similarity of cycle morphologies. Using 32s segments with 75 % overlap, we were able to use like 6 % more of data than without it with slightly lower performance (0.0024 decrease in accuracy and 0.20 % increase in error). We acknowledge that both the segment and preprocessing selections are not static parameters and may be adjusted depending on the application.

Most of the previous studies on novel noninvasive techniques have focused on the estimation of respiratory rate [3], [5], [13], [14]. Respiratory rate is an important marker used to monitor the progression of illness. However, other respiratory parameters can provide relevant information about the breathing pattern of the patients [15]. One novelty of this study is including other time parameters from the detections on bioimpedance signal. We found significant differences in the reference duty cycle values between moderate and severe COPD patients. The differences were maintained only when using the detections of the proposed algorithm in quiet breathing. Tracking these parameters over time could be a useful clinical application to home monitor COPD patients. Therefore, these results are the first step for further

studies to confirm the suitability of these parameters for noninvasive monitoring of respiratory patients. Regarding the results on loaded breathing, we hypothesize that the different contributions of bioimpedance cause delay [16]. Thus, the inspiratory and expiratory phase detections were affected by that and we did not observe the same differences as airflow parameters. But, the total respiratory time was robust showing less error probably because by adding the two phases, the differences were counteracted.

Our results open up the way to use the proposed algorithm to monitor breathing parameters using bioimpedance. However, further studies are needed to validate the algorithm under other conditions like walking and confirm its suitability to provide relevant information about COPD condition.

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