# Estimation of Respiratory Signal from Thoracic Impedance Cardiography in Low Electrical Current

Jeffry Bonar Fernando, Koji Morikawa, and Jun Ozawa

*Abstract*— A new method to estimate respiratory signal from thoracic impedance is proposed. To realize battery powered, wearable respiratory monitoring devices, low current impedance measurement techniques are desired. However, under low current conditions, conventional methods to separate cardiac and respiratory signals do not work well as the cardiac signal is much larger than the respiratory signal. In the proposed method, respiratory signal is estimated by calculating an envelope curve from the detected T waves of cardiac component. The results of the experiments show that the accuracy of proposed method is greater than conventional method.

### I. INTRODUCTION

Respiratory information is useful for fitness and medical areas and its estimation using a small, simple, and non-invasive measurement device has been an active area of research. For example, respiratory information obtained during sleep monitoring is very useful for identifying sleep-related breathing disorders, such as sleep apnea syndrome (SAS), who suffers from abnormal pauses in breathing or instances of low breathing during his/her sleep [1]. For daily respiratory monitoring at home, a sensor module should be smaller and wearable.

Various devices have been proposed to measure the user's respiration, such as thermistors which measure nasal airflow or pulse oximeters which measure the  $O_2$  saturation of the user's hemoglobin at fingertip.

Electrocardiogram (ECG) measurement or thoracic impedance cardiography has also been an active research, since these methods can estimate cardiac activity (heartbeat) and respiration simultaneously. O'Brien and Heneghan [2], Sobron *et al.* [3] estimated respiratory signals from the R wave of the measured ECG in time sequence. Ruangsuwana *et al.* [4] reported that estimation using R wave gave the best result among other parts of ECG. Barros *et al.* [5], Vaz and Thakor [6], Laguna *et al.* [7] developed an adaptive filter, Scaled Fourier Linear Combiner (SFLC), which can select the components synchronous with the R–R interval of the ECG.

Yasuda *et al.* [8] used SFLC to first estimate the cardiac component of the thoracic impedance and then subtracted the estimated cardiac component from thoracic impedance to identify the respiratory signal. The subtracted signal is furthermore low-pass-filtered. The remainder is the estimated respiratory signal. High current ( $\pm 350 \mu$ A) is used for impedance measurement and the respiratory component is larger than the cardiac component. However, under power

Jeffry Bonar Fernando, Koji Morikawa, and Jun Ozawa are with the Advanced Technology Research Laboratories, Panasonic Corporation, Kyoto, 619-0237, Japan (phone: +81-774-98-2410; fax: +81-774-98-2533; e-mail: {fernando.jeffry, morikawa.koji, ozawa.jun}@jp.panasonic.com) restricted conditions in compact or wearable devices, it is desired that the current for impedance measurement is minimised, such as  $10 \text{ nA-}10 \mu\text{A}$ .

Thoracic impedance measured in low current situations shows a different characteristic, where the cardiac component is much larger than the respiratory component. In this case, implementation of the conventional SLFC method is difficult, as respiratory component is so small that enough accuracy is not achieved with subtraction of large cardiac component.

In this research, we propose a novel method to estimate respiratory signal from thoracic impedance. We have found that the changes of T-wave amplitude of cardiac component show good correlation with respiratory changes. Experiments are conducted to compare the accuracy of respiratory estimation using wireless biopotential sensor module developed by our group. The results show the effectiveness of the proposed method.

## II. METHODS

Our approach is focussed on the shape of cardiac components, which are cyclic signals, derived from cardiac activity. One cycle of cardiac component consists of P wave, Q wave, R wave, S wave, and T wave, as shown in Fig.1. P wave, R wave, and T wave are local minimal values. Q wave and S wave are local maximal values. Each value fluctuates in time sequence.

# A. Algorithm

The method consists of the following three steps.

1. Detect R wave of cardiac component

As shown in Fig.1, the R wave in each cycle is detected as a local minimum point whose impedance value is below threshold th1, and the time interval t from local minimum point back to baseline is below threshold th2.

2. Detect the T wave of cardiac component

After the R wave is detected, a range to search for the T wave is set relatively to the detected R wave. The center of the T wave search range is set to be k\*R-*Rint* from the detected R wave. The width of the range is set to be  $\Delta TI$ . k and  $\Delta TI$  are predetermined parameters and *R*-*Rint* is the last R-R interval. The minimum point in the search range is detected as T wave.

3. Calculate envelope curve between T waves

After T wave is detected, the envelope curve between T waves in each cycle is calculated. Figure 2 shows an example of the envelope curve between T waves. Envelope curve is



Fig.2. Envelope curve between T waves



Fig.3. Sensor module

created using spline wave interpolation [9]. This envelope curve is defined as the estimated respiratory signal.

#### B. Experiment Procedure

An experiment was conducted to compare the performance of the three methods below in estimating thoracic impedance in low current.

- 1. SFLC (subtraction of cardiac component) [8]
- 2. Envelope curve of T waves (proposed method)
- 3. Envelope curve of R waves[2-4]

The proposed method is first compared to SFLC method, then to the envelope curve of R waves.

Six subjects (six healthy males, age from 26-35) participated in the experiment. Preceding the experiment, informed consent was obtained from all subjects.

For the measurement, a compact wireless biopotential sensor module which is developed by our group [10, 11] was used, shown in Fig.3. The sensor module can measure variety of biopotentials including electroencephalogram (EEG) and ECG. The size is  $38 \times 38 \times 16$  mm, it weighs 23.5 g including battery, and it is low power (26 mW@3.6 V). It also has active electrodes, which makes the module robust to environmental noise. Each active electrode of the sensor module has a built-in current generator for electrode-tissue impedance. It can generate low electrical current ( $10 \text{ nA-2 } \mu\text{A}$ ), which is used for body impedance measurement. During measurement, the sensor module transmits the data wirelessly to a base station which is connected to a PC. In the experiment, the base-station was located within 1 m from the sensor module.

Four-terminal sensing is used in order to ignore the effect of contact impedance with skin. Two electrodes to measure potential difference were located in the upper and lower end of the sternum (NASA lead) [12]. Two electrodes to apply current were located approximately 3 cm above and below the aforementioned two electrodes.

An external signal generator (SIGGI II, FMS) was used to supply calibrated current during the experiment. The current applied was  $\pm 10$  nA sine wave. The developed sensor module was used to measure the potentials under current injection.

The experiment was aimed to verify whether each method can detect no breathing period and estimate respiration change correctly. Each subject was asked to sit on a chair and breathe continuous four phases of respirations for two minutes during thoracic impedance measurement.

Phase 1: normal breath (15 times with 2-second cycle)

Phase 2: deep breath (8 times with 4-second cycle)

Phase 3: stop breathing for 28 seconds

Phase 4: normal breath (15 times with 2-second cycle)

Each subject was asked to follow the above procedure for two trials. A metronome was used during the experiment so that subject can synchronize their breath in each phase.

To implement SFLC, the number of harmonics H, the rate of convergence  $\mu$ , and low pass filter (LPF) are set to 15, 0.05, and 1 Hz respectively.

To implement proposed algorithms, th1 is set to be the standard deviation of the last 500 samples, and th2 is set to be 0.04 s for R wave detection. To detect T wave, k and  $\Delta T1$  are set to be 0.33 and 0.18 s.

In order to evaluate the performance of respiratory estimation only, falsely detected R waves were removed manually before going to the next steps in all three methods. Some falsely detected T waves were also corrected manually. The number of falsely detected R waves and T waves across all subjects and trials was 11 and 15 respectively.

### C. Evaluation

The proposed method was compared to other two methods in the following three areas:

- 1. Synchronicity between estimated respiratory signal wave and actual respiration cycles.
- 2. Amplitude between estimated respiratory signal and depth of breathing (normal and deep).
- 3. Accuracy rate between estimated number of respiration and actual number of respirations

Each set of thoracic impedance data was analyzed using three methods: the proposed method and two other conventional methods.

In the evaluation of area 2, the magnitude relation between the four phases was used. Due to the subject's normal breath (phase 1, 4), deep breath (phase 2), and no breathing (phase 3), the correct relation of the four phases in terms of breathing



Fig.4. Respiratory estimation result (1<sup>st</sup> trial of subject 1)

quantity will be phase 2>phase1, 4>phase3, where phase 3 is equal to 0. When the respiratory signal is estimated accurately, the order of amplitudes will follow the aforementioned relation. Moreover, the subject breathed in the same manner in each phase, and thus one phase will ideally have small standard deviation in amplitude. The amplitude is calculated as the difference between consecutive local minimum and local maximum in the estimated signal.

As to the evaluation point 3, accuracy rate was used to evaluate the performance in estimating respiratory rate. For phase 1, 2 and 4, the estimation is "true" when there is only one peak in the estimated respiratory signal during one cycle of breath. For phase 3, the estimation is "true" when the fluctuations are within the predetermined threshold. Otherwise, the estimation is "false". Accuracy rate was calculated as the ratio of how many "true" cycles are detected.

#### III. RESULTS

Figure 4 shows an example of the estimated signal wave to the same measured data (1<sup>st</sup> trial of subject 1). The vertical grey lines are the beginning of each breath cycle. The results of SFLC did not synchronize with the actual signal, as there were numerous peaks in each cycle. Synchronicity in T waves and R waves result were better than SFLC. T waves performed better than R waves since there were more cycles with only one peak.

TABLE I. MILAN AMILITUDES (I TRIAL OF SUBJECT I	TABLE I.	MEAN AMPLITUDES	(1 <sup>st</sup> trial of subject 1	)
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	Phase 1	Phase 2	Phase 3	Phase 4
SFLC	7.37	4.05	2.29	2.19
	±2.59	±1.90	±0.81	±0.84
Curve of	4.75	11.85	2.64	5.05
T waves	±2.38	±5.36	±1.18	±3.10
Curve of	6.46	9.82	5.17	8.61
R waves	±2.75	±5.76	±1.46	±4.31

TABLE II.	MEAN AMPLITUDES	(ALL SUBJECTS)
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	Phase 1	Phase 2	Phase 3	Phase 4
SFLC	15.82	9.49	6.85	8.60
	±8.22	±5.89	±4.11	±7.38
Curve of	16.46	21.70	6.12	19.26
T waves	±14.40	±22.71	±8.73	±17.42
Curve of	30.41	28.35	7.29	28.64
R waves	±33.04	±31.97	±9.53	±32.29

TABLE III. TOTAL ACCURACY RATE

SFLC Curve of		Curve of	
T waves		R waves	
0.04	0.71	0.64	

TABLE IV. ACCURACY R.	ATE FOR EACH SUBJECT
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	SFLC	Curve of T waves	Curve of R waves
Subject 1	0.00	0.79	0.58
Subject 2	0.13	0.74	0.54
Subject 3	0.04	0.69	0.64
Subject 4	0.05	0.68	0.77
Subject 5	0.04	0.76	0.72
Subject 6	0.01	0.59	0.62

Table I shows the mean amplitudes in each phase for the result shown in Fig.4. The results of SFLC method did not satisfy the correct order of amplitude, since amplitude in phase 3 is larger than that of phase 4. T waves and R waves successfully estimated the signal in terms of the magnitude order between phases. However, the difference between phase 1 and 2 in results of T waves is larger than that of R waves. Moreover, the standard deviation of T waves is smaller than that of R waves. This shows that the proposed method is more accurate and there is a good relation to breathing quantity.

The mean amplitudes in each phase for all subjects are shown in Table II. The results of proposed method are the only one which satisfies the ideal magnitude order. The results of R waves failed, since phase 1 is larger than phase 2. Based on this result, proposed method is the only one which showed a positive correlation between amplitude and breathing quantity.

In the results of proposed method result, phase 3 showed the smallest average with 6.12  $\mu$ V. If the threshold of the amplitude is set between phase 3 and phase 1, no breathing period can be detected by using the amplitude threshold.

Table III shows total accuracy rate for all subjects. SFLC gives a very low result (4%) as multiple peaks exist in most cycles. Accuracy rate in T waves (71%) is better than in R waves (64%). This shows that the proposed method is the most accurate among the three methods.

Table IV shows the accuracy rate for each subject. The accuracy of SFLC is very low for all subjects with 13% at most. Four of six subjects (subject 1, 2, 3, 5) give better performance in T waves than in R waves, while in the other two (subject 4, 6), the performance of R waves is better.

#### IV. DISCUSSION

The failure to estimate respiratory signal in SFLC method is due to the large cardiac component and small respiratory component. Even after subtraction, the cardiac component remains with magnitude which is still larger than respiratory component. In contrast, the estimation's performance in the proposed method is not affected by the larger cardiac component. However, it may have some difficulties in finding T wave when cardiac component is smaller than respiratory component.

In the case of subject 4 and subject 6, the accuracy rates of T waves were less than that of R waves. Figure 5 shows the typical respiratory signal estimated by T waves which has false peaks in 1<sup>st</sup> trial of subject 4. Some cycles have small false peaks which decrease the accuracy rate. Thus, false detection of small peaks can be removed by improving the peak detection algorithms.

In the experiment, the current was applied by external signal generator. However, the sensor module has 8 channels, and thus measurement with four-terminal sensing is possible when current for each electrode can be controlled separately. This enables us to compact sensor module for both ECG and respiration.

#### V. CONCLUSION

We proposed a new method to estimate respiratory signal from thoracic impedance measured in low electrical current. Respiratory signal is estimated by first detecting the T wave of the cardiac component and calculating envelope curve of all the T waves in each cycle. The results of experimental tests using our proposed technique show that it can identify the respiratory signal under low current measurement conditions, where conventional SFLC technique failed. The T wave envelope was 7% more accurate than the method using envelope of R waves. A positive correlation between the amplitude and the breathing quantity was also observed. The results also show that a no-breathing instance can be detected, which also implies that the proposed method has potential for



Fig.5. False detected peaks in estimated respiratory signal (1<sup>st</sup> trial of subject 4)

use in sleep monitoring. Further validation is necessary by increasing the number of subjects.

In the future, we plan to improve the proposed method by adding false detected peaks removal process. R wave and T wave detection algorithm needs to be improved. A model which can combine the estimated amplitude with the actual breathing quantity is necessary. The effect of subject's motion artifact on the estimation needs further examination. We also plan to implement our proposed method in a real-time respiratory estimation system.

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