# Correlation Between Respiratory Action and Diaphragm Surface EMG Signal

Giorgio Biagetti[1], Paolo Crippa*[1], Laura Falaschetti[1], and Claudio Turchetti[1]

*Abstract*— **This paper investigates the possibility to effectively monitor and control the respiratory action using a very simple and non invasive technique based on a single lightweight reduced-size wireless surface electromyography (sEMG) sensor placed below the sternum. The captured sEMG signal, due to the critical sensor position, is characterized by a low energy level and it is affected by motion artifacts and cardiac noise. In this work we present a preliminary study performed on adults for assessing the correlation of the spirometry signal and the sEMG signal after the removal of the superimposed heart signal. This study and the related findings could be useful in respiratory monitoring of preterm infants.**

## I. Introduction

Electrical signals captured from muscles' activity are very helpful in recognizing human movements or sports exercises, as well as in monitoring a person's body posture, physical performance, and fitness level, as it has recently been investigated [1]–[9]. This is due to the fact that sEMG signals can be easily acquired using noninvasive sensor devices. Indeed, these signals are related to the electrical potentials generated by muscle contractions, thus they can be collected by simply contacting small and inexpensive electrodes to the skin surface [10]–[12].

Among the body activities, the respiratory activity is the result of the interaction between the respiratory muscles, lung and rib cage compliance, and the airflow in the airways.

The diaphragm is the main muscle involved in inspiration. However several additional muscles participate to this activity such as the external and parasternal intercostal, scalene, upper trapezius, large dorsal, sternocleidomastoid, and the pectoralis major muscles. As a result, the contractions of these muscles can be monitored placing in correspondence of them surface electromyography (sEMG) sensors across the surface of skin [13]–[17].

Unfortunately, these signals are affected by cardiac noise and movement artifacts. In this context several works were devoted to the study of the activity of inspiratory muscles in adults and elderly people and to implement procedures to record surface electromyography (sEMG) signals acquired from them [18]–[22]. However, in preterm infants using noninvasive sEMG signals is an excellent technique alternative to expensive complex endoesophageal probes for the identification and monitoring of apnea, by detecting the contractility of the diaphragm and triggering a mechanical ventilator.

Usually, sEMG signal based techniques for breathing detection use several surface electrodes, in a variable number comprised between 3 and 12, which are placed anteriorly and posteriorly on the skin above the diaphragm to detect its contractility. These electrodes are small in size (i.e. 20 mm), easy to find and do not require specific positioning skills. The correlation between surface respiratory electromyography and esophageal diaphragm electromyography has been investigated [23]. However, the sEMG techniques are inherently more easy to implement than the endoesophageal probe that requires a considerable experience of the operator for its correct localization. Moreover, besides being more expensive than the surface electrodes, the probe is at risk for displacement (especially in non-collaborative subjects such as the infants).

Nonetheless, sEMG is prone to the interference of various factors (artifacts) such as cardiac activity, skeletal muscle contraction during movement; also, the relatively small skin surface available in newborn patients limits the size and number of applied sEMG electrodes. Therefore, the use of the sEMG breathing detectors is not yet widespread in neonatal clinical practice.

Some studies have shown the usefulness of sEMG for monitoring heart rate and respiration, for weaning from noninvasive ventilation. Furthermore, other works have shown a good correlation between respiratory function indices and diaphragm electromyography [24], [25].

The creation of a specific wireless sEMG system specifically designed for neonatal use and equipped with one or more miniaturized electrodes could be a great advantage either for the identification and monitoring of apnea, and for future use as a measuring system for triggering mechanical ventilators instead of expensive complex endoesophageal probes.

In this work we present a preliminary study performed on adults for assessing the correlation of the sEMG signal, obtained from a single lightweight wireless sensor placed in a sternal position and hence affected by cardiac and movement artifacts, to the breathing activity detected by simultaneous recording of the signal from a spirometer worn by the subject over their nose and mouth.

This study and the related findings could be useful in the optimal design of a respiratory monitoring systems for preterm infants.

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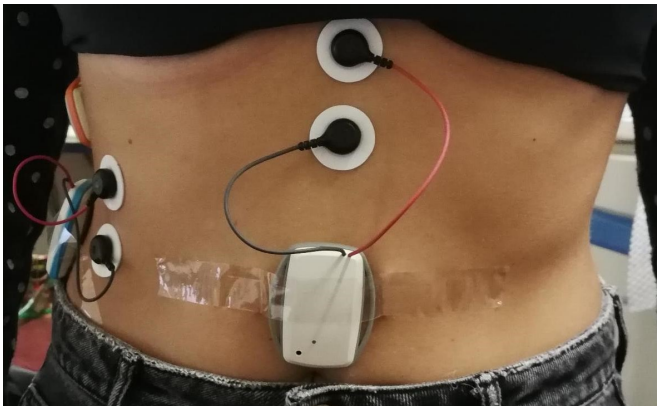

Fig. 1. Electrode placement.

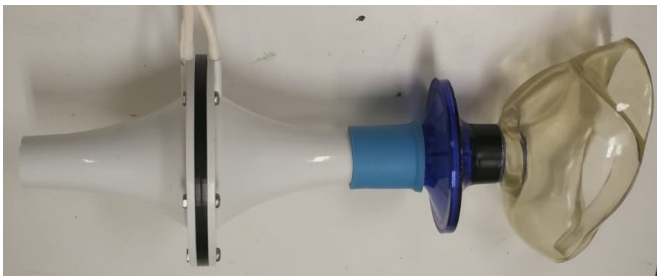

Fig. 2. Spirometer.

## II. Methods

The sEMG signals were acquired using the setup shown in Fig. 1. Of the three electrodes placed to investigate the best position to sense the diaphragm muscle, the one on the side was selected as giving the strongest signal level. A picture of the used spirometer can be seen in Fig.2.

Eight adult volunteers participated in the study. Full details on the recording conditions and apparatus can be found in [26], together with the full dataset used for this investigation.

In order to investigate the possible correlation between the acquired sEMG signals and the respiratory activity, a suitably simple and descriptive feature must be extracted from the signal. We chose to analyze the mean absolute value (MAV) of the sEMG signal, as it is a feature well known to be related to muscle activation level [6], [11]. Still, computing MAV in this particular case is not straightforward because of the strong contamination of the sEMG signal by the heart pulses. This contamination must first be removed.

To this end, the average pulse subtraction technique [27] was employed. To apply it, the positions of the cardiac QRS complexes must be found in the signal, a window around every R peak is then extracted from the signal. The average of all the extracted windows is finally computed. This approach is based on the assumption that the shape of the contaminant QRS wave does not change in the short period of time of analysis. Thus, the averaging process does not distort much their shape, having the waveforms been aligned. The main sEMG signal, on the other hand, has a zero mean value, and so its average vanishes.

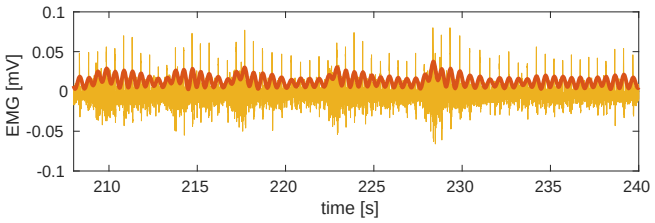


Fig. 3. Raw EMG signal recorded from the lowest intercostal space, with superimposed amplitude envelope in thick red line.

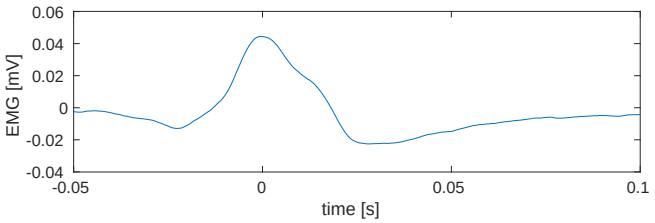


Fig. 4. Average ECG contamination in a window around the QRS complex.

Many techniques exist to locate the QRS complex in an ECG signal. In our case, a simple peak detector suffices. It works as follows.

First, the sEMG signal is resampled so that it has a uniform 2 kHz sample rate. Let us call $s_{\mathrm{M}}(t)$ the result of the resampling. Then, its absolute value is computed and low-pass filtered with a 2.5 Hz cut-off frequency, to obtain its amplitude envelope given by

$$e_{\mathrm{M}}(t) = |s_{\mathrm{M}}(t)| * h_{\mathrm{LPF:2.5}}(t) \tag{1}$$

where $h_{\mathrm{LPF:2.5}}(t)$ is the filter impulse response and "$*$" denotes the convolution operator. For reference, the signal $\pi/2 \cdot e_{\mathrm{M}}(t)$ is shown in Fig. 3 as a thick red line superimposed to the original sEMG signal (scaling by $\pi/2$ was done for visual purposes only, to approximately compensate the crest factor so that the curve appears near the envelope of the original signal).

As can be seen, the cardiac contamination continues to affect the signal envelope. To remove it, a simple peak detector was implemented. The sEMG signal $s_{\mathrm{M}}(t)$ is low-pass filtered at 75 Hz to remove some noise while retaining the fundamental shape of the QRS complex, obtaining the signal $s_{\mathrm{H}}(t)$

$$s_{\mathrm{H}}(t) = s_{\mathrm{M}}(t) * h_{\mathrm{LPF:75}}(t) \tag{2}$$

then the positions $t_i$ of the peaks that are above a prescribed threshold $k$ of the envelope are sought

$$t_i \;:\; s_{\mathrm{H}}(t_i) > k\, e_{\mathrm{M}}(t_i) \quad i = 1, \ldots, N \tag{3}$$

where the optimal value of $k$ was experimentally found to be $k = 1.6\,\pi/2$, and $N$ is the number of peaks found. To remove spurious peaks due to noise, the $t_i$'s that do not fall within a 100 ms interval from local maxima of $e_{\mathrm{M}}(t)$ are discarded.

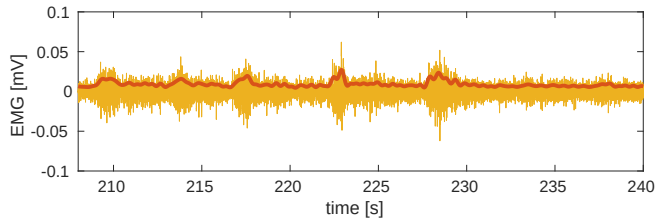


Fig. 5. EMG signal cleaned of the ECG contamination, with superimposed amplitude envelope.

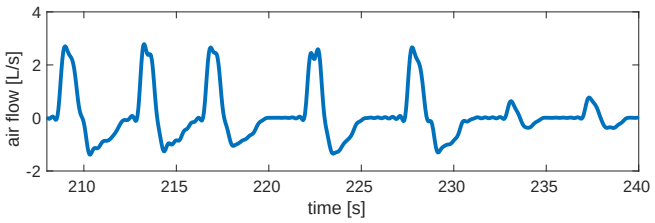


Fig. 6. Filtered air flow with compensated offset.

Once the positions of the QRS complexes are known, the waveforms are averaged as

$$s_{\mathrm{QRS}}(t) = \frac{1}{N}\sum_{i=1}^{N} s_{\mathrm{M}}(t+t_i) \quad t \in [-50, 100]\ \mathrm{ms} \tag{4}$$

and the result is shown in Fig. 4.

Since $s_{\mathrm{QRS}}(t)$ is an average signal, before subtracting it from the original sEMG signal it is necessary to scale and offset it so that it best matches the specific contamination to be removed. The baseline of the sEMG signal is indeed not perfectly stable due to cable movements and other factors, and the exact amplitude of each pulse can be slightly different as well.

So, for each $i$ in $1, \ldots, N$, the coefficients $a_i^0$, $a_i^1$, $a_i^{\sim}$ are computed as the least-square solution of

$$a_i^0 + a_i^1\, t + a_i^{\sim}\, s_{\mathrm{QRS}}(t) \simeq s_{\mathrm{M}}(t+t_i) \tag{5}$$

and then the cleaned sEMG signal $s_{\mathrm{C}}(t)$ can be computed as

$$s_{\mathrm{C}}(t) = s_{\mathrm{M}}(t) - \sum_{i=1}^{N} s_i(t) \tag{6}$$

where

$$s_i(t) = \begin{cases} a_i^0 + a_i^1\, t + a_i^{\sim}\, s_{\mathrm{QRS}}(t) & t \in [-50, 100]\ \mathrm{ms} \\ 0 & \text{elsewhere}\ . \end{cases} \tag{7}$$

As a final step, the possible baseline wander is removed by high-pass filtering the previous result, yielding the signal

$$s_{\mathrm{F}}(t) = s_{\mathrm{C}}(t) * h_{\mathrm{HPF:5.0}} \tag{8}$$

where $h_{\mathrm{HPF:5.0}}$ is a 5.0 Hz high-pass filter impulse response, and then computing its amplitude envelope, re-applying again the procedure (1)

$$e_{\mathrm{F}}(t) = |s_{\mathrm{F}}(t)| * h_{\mathrm{LPF:2.5}}(t)\ . \tag{9}$$

The result is shown in Fig. 5, which reports $\pi/2 \cdot e_{\mathrm{F}}(t)$ as a thick red line together with the cleaned signal $s_{\mathrm{F}}(t)$. As can be seen, the cardiac contamination was nearly completely removed.

As a reference, Fig. 6 reports the air flow, filtered with the same 2.5 Hz low-pass filter to reduce some noise, for the same time interval.

A correlation between the extracted signal $e_{\mathrm{F}}(t)$ and the air flow is apparent, as will be investigated next.

TABLE I

CANONICAL CORRELATION BETWEEN EXTRACTED FEATURE AND AIR FLOW, AFTER AUTOMATED SIGNAL ALIGNMENT.

| subject | correlation | lag [s] |
|---|---|---|
| 1 | 0.7760 | 0.488 |
| 2 | 0.3290 | 1.984 |
| 3 | 0.1061 | 1.056 |
| 4 | 0.4900 | 0.528 |
| 5 | 0.4706 | −0.120 |
| 6 | 0.3757 | −1.704 |
| 7 | 0.3564 | 1.712 |
| 8 | 0.5808 | 0.504 |

## III. RESULTS

To investigate the correlation between the extracted feature and the actual air flow, a dataset consisting in recordings from 8 adult volunteers was used. Each recording consists in two manually synchronised traces, one from the sEMG sensor and one from the spirometer. Since the spirometer signal manifested a significant offset, its mean value was removed before any further processing. Let us call $s_{\mathrm{A}}(t)$ this signal, with the convention that inhaled air corresponds to $s_{\mathrm{A}}(t) > 0$, and exhaling to $s_{\mathrm{A}}(t) < 0$. Since the diaphragmatic muscles are in principle only involved while inhaling, only the positive part of the signal $s_{\mathrm{A}}(t)$ should be correlated to the sEMG envelope. Hence, the negative portion was removed, by posing $e_{\mathrm{A}}(t) = \max(0, s_{\mathrm{A}}(t))$.

The canonical correlation between $e_{\mathrm{F}}(t)$ and $e_{\mathrm{A}}(t-\tau)$ was then computed for different time lags $\tau$, to compensate for small misalignments between the two traces, and the maximum value recorded.

The results are shown in Table I, and a few significant examples are reported in Fig. 7, which reports the $e_{\mathrm{A}}(t-\tau)$ signal and the $k_0 + k_1\, e_{\mathrm{F}}(t)$ signal, with $k_0$ and $k_1$ estimated for best least-square fitting of the two curves.

As can be seen, the sEMG envelope provides a good estimation of the positive portion of the airflow. Sometimes, especially for subject 4, diaphragmatic muscle activation was also detected during the exhaling phase.

## IV. CONCLUSIONS

In this work we presented a simple feature extraction technique that can be applied to a sEMG signal recorded from the diaphragmatic muscle to obtain a first rough estimate of the breathing activity. After cardiac and cable motion artifacts are removed, the sEMG signal envelope shows a significant correlation to the ground true airflow

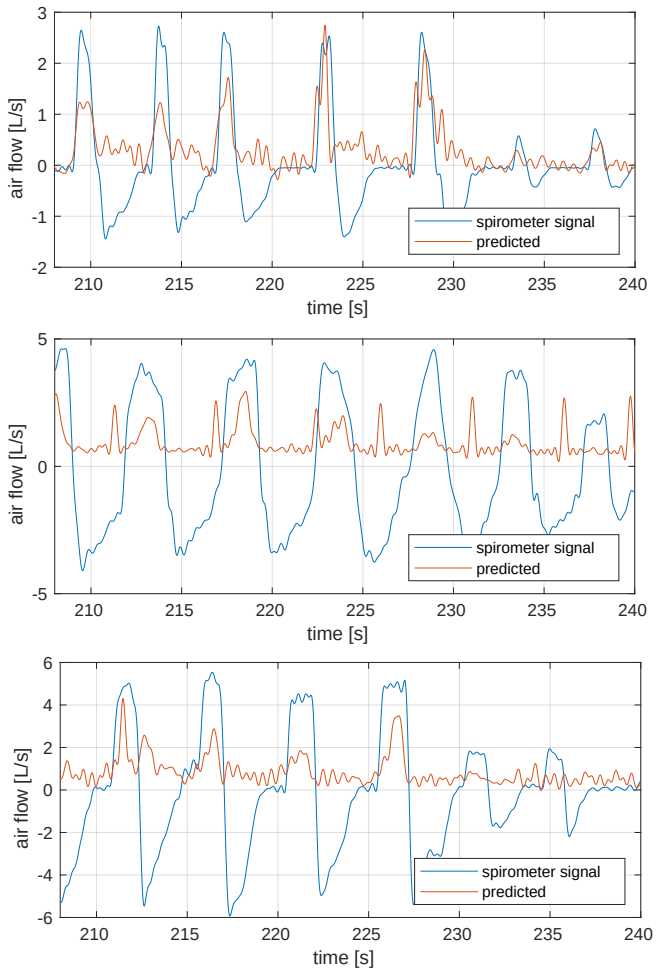


Fig. 7. Predicted inhaled air flow vs. spirometer signal for subjects (from top to bottom) 1, 4, and 8.

obtained by simultaneous recording with a spirometer. Least-square fitting of the sEMG-derived feature to the positive (inhaling) portion of the air flow shows that it could be possible to estimate this signal from electrical measures of diaphragmatic activity.

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