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Wearable Impedance Pneumography

Abstract: Respiratory diseases are a leading cause of death worldwide. The prevalence of sleep apnea, its cardiovascular consequences, postoperative respiratory instability and severe respiratory syndromes further highlight the importance of respiratory monitoring. Typical methods, however, rely on obtrusive nasal cannulas and belts. Impedance pneumography (IP) is a promising bioimpedance application which aims to estimate respiratory parameters from the thorax impedance. Currently, IP configurations require large inter-electrode distances, diminishing its applicability in a wearable context. We propose an IP configuration with 55 mm spacing using our recently presented sensor patch. In a study including 10 healthy subjects, respiratory rate (RR) and flow are estimated in the supine, lateral and prone position. Using time-delay neural network regression, RR errors below 1 bpm, flow correlations of 0.81 and relative flow errors of 38 % with respect to a pneumotachometer reference were achieved. We conclude that high accuracy RR estimation is possible in a 55 mm IP configuration. Respiratory flow can be roughly estimated. Further research combining several biosignals for a more robust, wearable flow estimation is recommended.

Keywords: impedance pneumography, wearable respiratory monitoring, respiratory rate, respiratory flow, sensor patch, neural network, bioimpedance

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1 Introduction

Respiratory diseases are the third leading cause of death amongst the noncommunicable diseases worldwide [1]. The high prevalence of obstructive sleep apnea with an estimated 936 million people affected worldwide [2] and its association with increased risk of cardiovascular diseases [3] further

Figure 1: Sensor positions for wearable and half-thorax IP.

underline the importance of respiratory monitoring. Clinically, respiratory instability is known to increase mortality [4] and the recent COVID-19 outbreak highlights the need for early diagnostics [5]. Respiratory monitoring usually relies on nasal cannula pressure sensors, masks or belts. A less obtrusive approach is impedance pneumography (IP), a bioimpedance method employing the thoracic impedance [6]. Electrodes from the electrocardiogram (ECG) are commonly used to measure IP. Most ECG configurations span a large section of the thorax and therefore, a significant portion of the injected current will be influenced by the lung. Large electrode distances, however, are suboptimal for wearable monitors, while minimizing electrode distances reduces the current density in proximity to the lungs. While there has been work on optimizing IP electrode configurations [7], its focus mainly was on preserving a linear relationship between the IP signal and respiratory volume [8]. Most studies on wearable IP setups rely on electrode positions close to known linearly behaving sets [9] and therefore, only very few use nonlinear regression approaches [10]. Jeyhani et al. presented an IP configuration covering half the thorax [11]. Further minimizing size requirements, we presented 8 cm short distance IP [12].

In this work, we evaluate a 55 mm patch-scale, wearable IP concept based on our recently presented multimodal, wearable digital patch stethoscope [13]. In a study including 10 healthy subjects, we estimate the respiratory rate and flow using polynomial and neural network regression. We compare the performance of the wearable IP with a half-thorax configuration in the supine, lateral and prone position.

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2 Materials and Methods

2.1 Data Acquisition

We conducted a study including 10 healthy subjects (26±2 years, 2 female) which were asked to follow an 11-minute long breathing sequence given by a custom developed Android application. The sequences contained combinations of three different breathing frequencies (8, 16 and 24 breaths per minute (bpm)) and two different breathing depths (shallow and normal). We conducted the experiment in the supine, lateral and prone position individually, yielding a total of 33 minutes of data per subject.

Using our multimodal, digital stethoscope patch, we recorded a 55 mm IP signal (1 kHz, 24 bit) between the first and second intercostal spaces (ICS) at the right midclavicular line at an angle of 45°. Simultaneously, the half-thorax IP (200 Hz, 16 bit) was acquired using the Osypka Medical GmbH ICON-Core™ monitor. The electrodes were located at the 1st and 2nd ICS on the sternum as well as at the 5th and 6th ICS on the left midaxillary line. The electrode distances of the half-thorax IP configuration differed due to individual physiology, but can be roughly estimated as 300 mm. Using the SOMNOmedics GmbH SOMNO HD™ system, a respiratory reference (512 Hz, 16 bit) was acquired using a pneumotachometer and facial mask. The patch- and sensor positions are shown in Figure 1.

2.2 Signal Processing and Regression

Both IP and the reference respiration flow signals were low-pass filtered at 1 Hz, baseline removed at 0.05 Hz and down-sampled to 20 Hz. The first derivative of the IP signals has been used as a flow surrogate. The respiratory rate was estimated in 30 s windows with a 50 % overlap as the maximum of the FFT between 4 and 40 bpm.

We employed polynomials up to the order of 3, multi-layer perceptrons (MLP) with two to three hidden layers, 5 to 15 neurons each and time-delay neural networks (TDNN) with the same layer configurations and input delay vectors from 1 to 30 taps as regressors. Models were selected using the Bayesian information criterion (BIC) in a forward wrapper framework. We evaluated the mean error (ME), mean absolute error (MAE) and Pearson correlation (r) for both the respiratory flow and rate estimation and provide two relative measures between the reference *Ref* and the estimate *Est* in percent based on the type of data analysed. For strictly non-zero data, in this case the respiratory rate, we employed the mean absolute percentage error (MAPE) calculated as

$$MAPE = \frac{1}{N} \sum_{i=1}^N \left| \frac{Est(i) - Ref(i)}{Ref(i)} \right| * 100 \%. \quad (1)$$

For data including or closely approaching zero, such as the respiratory flow, the MAPE leads to singularity effects. Therefore, we used the normalized mean squared error (NMSE) calculated as

$$NMSE = \frac{\sum_{i=1}^N (Est(i) - Ref(i))^2}{\sum_{i=1}^N Ref(i)^2} * 100 \%. \quad (2)$$

All performances were calculated individually for the supine, lateral and prone position. Nested cross-validation and a forward chaining data splitting scheme for training, validation and and test data separation were employed.

3 Results

For estimating the respiratory signal, TDNNs with two hidden layers, 5 neurons each and delay input vectors of 0 to 19 taps were selected consistently based on the BIC. The corresponding flow estimation performances in the three subject positions as well as averaged over all positions for both the half-thorax and 55 mm wearable IP configurations are given in Table 1.

Table 1: Performance of respiratory flow estimations per subject position using the optimal TDNN models.

Pose	Config	ME _{ml/s}	MAE _{ml/s}	r	NMSE _%
Supine	Half-Thorax	-3.4±7.9	62.4±13.6	0.97±0.02	14±9
	Wearable	7.7±5.4	103.9±27.9	0.82±0.17	37±26
Lateral	Half-Thorax	-1.3±7.6	60.8±18.6	0.92±0.13	18±21
	Wearable	-0.2±7.9	105.2±32.7	0.82±0.09	36±12
Prone	Half-Thorax	-3.7±8.4	61.0±29.0	0.95±0.02	13±3
	Wearable	-4.2±10.1	101.3±49.3	0.78±0.09	41±14
All	Half-Thorax	-2.6±7.4	61.3±18.9	0.94±0.08	16±14
	Wearable	1.3±8.7	103.8±33.6	0.81±0.11	38±17

As IP regression is oftentimes performed using first order polynomials, Table 2 gives the performance of respiratory flow estimations using linear models as an average over all subject positions. Compared to the found optimal TDNN models, their relative error is 6 % higher in the half-thorax configuration and 9 % in the wearable setup.

Table 2: Linear regression model performances for respiratory flow estimates as average over all subject positions.

Config	ME _{ml/s}	MAE _{ml/s}	r	NMSE _%
Half-Thorax	2.3±6.4	79.3±21.9	0.93±0.00	22±10
Wearable	2.3±6.4	119±36.5	0.74±0.02	47±22

In Figure 2, exemplary signals of the pneumotachometer reference as well as estimated respiratory flows from both the wearable and half-thorax IP configurations are given. The half-thorax configuration shows better tracking of the respiratory curve while the patch estimation over- and underestimates by about 100 ml/s, which is in accordance with the average MAE reported. Between five and ten seconds, transient behaviour of the flow and the response of the different models can be exemplarily observed. Both the half-thorax and patch IP estimates follow its shape, while the half-thorax IP stays closer to the reference waveform.

Figure 2: Exemplary reference and estimated respiratory signals.

The results of the respiratory rate estimations are given in Table 3. Even though the error distribution is quite narrow, it is widened by about 10 % far outliers. Removing points more than three scaled median absolute deviations away from the median, a correlation of 0.9998 ± 0.0001 , a ME of -0.004 ± 0.14 bpm, a MAE of 0.1 ± 0.1 bpm and a MAPE of 0.84 ± 0.83 % was achieved for the wearable IP configuration.

Table 3: Performance of the respiratory rate estimation per subject position using the optimal TDNN models.

Pose	Config	ME _{bpm}	MAE _{bpm}	r	MAPE _%
Supine	Half-Thorax	0.1±1.3	0.2±1.3	0.98±0.04	2±17
	Wearable	-0.2±1.6	0.3±1.6	0.98±0.04	2±7
Lateral	Half-Thorax	-0.3±1.9	0.3±1.9	0.97±0.05	2±8
	Wearable	0.6±4.0	1.3±3.9	0.85±0.13	14±44
Prone	Half-Thorax	-0.2±1.7	0.3±1.7	0.97±0.05	1±7
	Wearable	-0.5±2.9	0.8±2.8	0.91±0.05	4±13
All	Half-Thorax	-0.1±1.7	0.3±1.7	0.97±0.04	2±11
	Wearable	0.1±3.2	0.9±3.1	0.90±0.10	8±31

Using linear models without outlier removal, a correlation of 0.88 ± 0.1 , a ME of -0.14 ± 1.0 bpm, a MAE of 0.96 ± 0.72 bpm and an MAPE of 15 ± 24 % were found. In Figure 3, the RR estimation performance is visualized using a Bland-Altman plot. The three distinct respiratory frequencies of the study become clearly visible as clusters. The previous statement on the narrow error distribution, contaminated by a few large outliers can be observed. No rate-dependent error distribution or bias were found.

Figure 3: Bland-Altman plot of the wearable IP respiratory rate estimation performance including all subject positions.

4 Discussion

Time-delay neural networks consistently outperformed polynomials and multi-layer perceptrons. The performance increase using TDNNs over linear models was higher in the wearable IP (9 %) compared to the half-thorax configuration (6 %). This finding further supports the assumption that the linearity of the relationship between the breathing volume and thorax impedance is sensitive to electrode placement and distance [8]. The average performances for both respiratory flow and rate estimations in the half-thorax IP configuration are consistent with those previously reported [12].

The wearable IP has lower estimation performance with a flow correlation of 0.81 (NMSE: 38%), compared to the 8 cm setting with 0.88 (NMSE: 19%) [12] and the half-thorax approach with 0.94 (NMSE: 16%). We found position-dependent performances, with the prone position being the least optimal. We assume that the body weight reduces the expandability of the thorax in the prone position and favours a different air distribution in the lungs compared to the supine and lateral positions. The volume in the middle and inferior lobes are less optimally captured by the wearable IP in the chosen acquisition location. Transients in the respiratory signal, however, were still tracked, even though with less accuracy, which is also represented by the lower correlation coefficient.

The average respiratory rate estimation performance of the wearable IP (ME: 0.1 bpm, MAE: 0.9 bpm) was slightly lower than that of the 8 cm IP (ME: -0.03 bpm, MAE: 0.13) [12] and half-thorax configuration (ME: -0.1 bpm, MAE: 0.3 bpm). Differences between subject's positions are minimal. High standard deviations of the error distributions and the large relative errors are predominantly caused by a limited number of outliers. When removed, an MAPE of below 1 % and correlations close to 1 were achieved.

The most important limitation of the study is the relatively small size of the subject pool consisting of young, healthy, mostly male individuals. However, the position-dependent analysis allowed for a more use-case oriented interpretation of the data which highlighted possible constraints in an ambulatory scenario. The consistency with previous results using different data consolidates both the currently and previously reported findings. The current breathing protocol covers a wider variety of breathing rates and depths across the physiologically plausible range.

5 Summary and Conclusion

We presented a 55 mm electrode distance, wearable impedance pneumography configuration using a multimodal, digital patch stethoscope. Employing time-delay neural network regression, we estimated the respiratory flow with a correlation of 0.81 and a relative error of 38 % with respect to a pneumotachometer reference in the supine, lateral and prone position. Respiratory rate estimation errors stayed below 1 bpm in almost all cases. Performances vary with the position of the subject, however, in the case of respiratory rate estimation, the errors remain acceptably small.

We conclude that respiratory rate estimation is possible with a 55 mm impedance pneumography approach using both linear and nonlinear models. For estimating the respiratory flow, nonlinear, time-lagged models are recommended. The resulting signals should be usable for rough estimates. However, further research should focus on reducing the estimation error and increasing the tracking capability, possibly by including different biosignals in the regression.

Author Statement

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