

Electroimpedance method for quantitative assessment of respiratory system activity

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- Improve accuracy of tidal volume, peak and mean flows measured by impedance pneumography using several signal processing methods and suitable calibration procedure
- Detect motion artefacts in impedance pneumography signals
- Optimize sport training control by adding respiratory data

Gold standard methods

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Spirometry and pneumotachometry



- Direct measurements
- The most reliable results
- Require mouth piece with nose clip, or face mask
- Cannot be performed in an outpatient setting

Impedance pneumography





Changes of thoracic bioimpedance reflect changes of the amount of air in the lungs

Impedance pneumography



Possible ambulatory applications

Sleep

- Breathing disorders monitoring
- Analysis of the effects of • pharmacological treatment

Physiology

- Observation of hypo-, normo- and hyperventilation in obese and neuromuscular disorders
- Cardiorespiratory coupling and causal paths analyses

Sport medicine

- Home diagnostics
- Training control
- Determining the level of effort







Raw impedance signal





Raw impedance pneumography signal

Could we suppress cardiogenic oscillations (Seppa et al., 2011)? Or even decompose respiratory and cardiac components (Mlynczak et al., 2017)?

Signals after preprocessing

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Flow-related signal





Could we improve flow-related signal dynamics (Mlynczak et al., 2017)?

Fitting improvement

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Calibration and reproducibility





Slopes can change, so we need calibration.

Calibration coefficients are dependent on subject and body position, and not on parameters of breathing (*Mlynczak et al., 2015*)

Calibration coefficients are not permanent in time, they should be recorded just before the measurement (*Mlynczak et al., 2015*)

What is the optimal procedure in terms of volume and flow parameters measurements?

Calibration and parameters





Quantitative parameters determination







Linear relationship maintained for configuration proposed by Seppa et al., 2013, in standing body position. We proved that linearity is still saved in supine and sitting positions (Mlynczak et al., 2014).



Receiving electrodes

Application electrodes

Motion artefacts





Approach with epsilon-tubes based from support vector machine algorithm (Ansari et al., 2016)

Could we detect motion artefacts and remove them without changing the shape of the signal (*Mlynczak et al., 2017*)?

Equipment

Pneumonitor 2 (Mlynczak et al., 2017)

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- Portable Recording on SD card
- Rechargeable battery



 Impedance signal relating to main breathing activity

- 14.2cm x 6.9cm x 2.3cm; 160g
- Sinusoidal application current amplitude adjustable up to 1mA, with a single, adjustable frequency (100kHz by default)
- Impedance range: 0-250 Ohms ٠
- 250Hz sampling frequency, 100Hz pass frequency, 10-bit resolution
- ECG amplifier has a gain of 100V/V, • 10nV/sqrt(Hz) noise
- InvenSense's MPU-6050 (accelerometer and gyroscope unit, available commercially)



 ECG signal to estimate heart rate and tachogram



 Motion signal from 3-axis accelerometer to indicate subject's activity and body position

Equipment

Pneumonitor 3 (Mlynczak et al., 2017)





- Analog, SD and BT outputs
- Improved handling
- 5 electrodes instead of 7



 Impedance signal relating to main breathing activity



• ECG signal to estimate heart rate and tachogram

- 16.7cm x 10.1cm x 3.5cm; 330g
- Wireless pulse oximetry module -Contec CMS50EW (commercially available)
- 900mAh capacity of rechargeable battery



 Motion signal from 3-axis accelerometer to indicate subject's activity and body position



Wireless **pulse oximeter** to acquire saturation and pulse wave

Equipment

Electrode configurations (Seppa et al., 2013; Mlynczak et al., 2017)







The relation between childhood asthma risk and tidal volume (Seppa et al., 2016; Malmberg et al., 2016)

Does adding respiratory signal to commonly used set of cardiac parameters allows to obtain a fuller picture of the physiological condition and optimize sport training control?



Objective 1

Improve accuracy of tidal volume, peak and mean flows measured by impedance pneumography using several signal processing methods and suitable calibration procedure



	Minimum	Mean	Maximum
Weight [kg]	65.0	77.4	100.0
Height [cm]	171.0	179.3	187.0
BMI	20.75	24.14	33.41
Age	19	23	27

Test procedure

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6 breaths with different **depths**:

- normal (approx. 0.5 2.0 L)
- deep (approx. 2.0 5.0 L)

for 3 respiratory rates:

- ➡ 6 BPM
- → 10 BPM
- ➡ 15 BPM

and for 3 **body positions**:

- supine
- sitting
- standing

<u>Reference</u>: **Flow Measurement System M909** (Medikro Oy, Finland)

> Optimization criteria: absolute and relative error in comparison to reference

Calibration procedures



Determining optimal in terms of tidal volume and flow parameters

- The shortest one
 - ➡ Free breathing for 30 seconds
- To check the impact of longer measurement
 - Free breathing for 2 minutes
- To verify that adding frequency and depth variation can significantly improve accuracy
 - Fixed breathing

Each procedure was repeated for all considered body positions:

- supine
- sitting
- standing

Calibration procedures



Determining optimal in terms of tidal volume and flow parameters

- The shortest one
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 - Fixed breathing

The best for tidal volume measurements

The best for flow parameters measurements

Each procedure was repeated for all considered body positions:

- supine
- sitting
- standing

Decomposition

Separating respiratory and cardiac components

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Raw signal





Decomposition



- Moving average smoothing, with windows:
 - ➡ 0.5 s (mild)
 - 1.0 s (as proposed by Koivumaki et al., 2012)
 - ➡ 1.5 s (strong)
- Savitzky-Golay filter
 - ➡ 2nd-order, with a 25 probes window
 - → 7th-order, with a 25 probes window
- Least mean square adaptive filtration
 - subtraction of raw IP signal and the noise component, then smoothed with **200 ms** window
 - subtraction of raw IP signal and the noise component, then smoothed with 400 ms window



Decomposition



Impulse response filtration

- 25-fold decimation (performed twice using 5-fold coefficient), then applying 10th order least-square
 FIR filter with 1 Hz pass and 2.5 Hz stop frequencies, at the end the spline interpolation to return to original sampling frequency
- the same process as above, but with use of
 10th order stable Chebyshev IIR filter with 1 Hz pass frequency

Wavelet denoising

- soft heuristic SURE thresholding and scaled noise option,
 on coefficients obtained at level 5 by sym8 wavelet
- minimax thresholding at level 5 by db5 wavelet
- Smoothing Splines









Best results obtained for moving average smoothing (with 1s window)

Impedance pneumography seemed to **underestimate tidal volumes** with **206 ml** on average; **average accuracy - 86.5%**; calibrated with 30-second-lasting free breathing



Dynamics correction



Non-linear model for flow-related signals

- Simple linear modeling based on flow-related signals (as a reference)
- Neural network approach, trained individually:
 - ➡ single hidden layer with 10 or 20 neurons
 - two hidden layers of 5 or 10 neurons
- Simple linear modeling and neural network correction, trained individually:
 - ➡ single hidden layer with 10 or 20 neurons
 - two hidden layers of 5 or 10 neurons
- Simple linear modeling and neural network correction, trained globally:
 - single hidden layer with 10 or 20 neurons
 - two hidden layers of 5 or 10 neurons



Dynamics correction



Non-linear model for flow-related signals

Best results obtained for individually trained perceptron with 2 hidden layers (with 10 neurons)

Average error level of flow parameters estimation - **20%** (in comparison to **27.5%** for linear modeling); using fixed breathing calibration





Objective 2

Detect motion artefacts in impedance pneumography signals



	Females		Male	Males	
	Average	SD	Average	SD	
Weight [kg]	58.6	5.6	76.2	9.5	
Height [cm]	168.2	6.2	178.8	5.6	
BMI	20.7	1.6	23.9	3.3	
Age	22.3	5.3	22.9	3.2	

Proposed algorithm





$$TKE(x) = \left(\frac{dx}{dt}\right)^2 + x\frac{d^2x}{dt^2}$$

(Kaiser 1990)

$$TKE[n] = x^{2}[n] + x[n-1] \cdot x[n+1]$$

Abbreviations:

- TKE the sum of all Teager-Kaiser Energy operators
- TKEspec the signal being a processed TKE spectrogram
- TKEenv the envelope of the original TKE signal
- MRD motion-related signal
- THR adaptive threshold, established from TKE, TKEspec and MRD

Sample signals and results





Abbreviations:

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Classification results

For the best strategy of threshold level establishing

Accuracy [%]	81.3
Cohen's Kappa coefficient	0.63
Sensitivity [%]	80.9
Specificity [%]	81.6

Objective 3

Optimize sport training control by adding respiratory data

Study group - Polish elite athletes

Study before Olympic Games in Rio de Janeiro 2016: 32 females and 68 males

	Minimum	Average	Maximum
Weight [kg]	49.1	78.6	151.0
Height[cm]	158.0	183.3	208.0
BMI	17.4	23.2	42.7
Age	16.0	24.6	40.0

5 minutes

Free breathing

Supine, then standing

Input and output data

Parameters based on input data

- Only tidal volume signal
- Only tachogram signal
- ➡ Both, linked

• Due to the domain

- ➡ time
- ➡ frequency
- ➡ information

Output labels

- I moderate dynamic component during performance (wrestling)
- II high dynamic component during performance (triathlon)

- Recursive Partitioning (CART)
- Random Forests
- Support Vector Machines (SVM)
- adaBoost
- Generalized Boosted Regression Models (GBM)

The best set of parameters

Established by dimensionality reduction algorithms

- 1. Absolute spectral content in the high-frequency band (0.15 0.4 Hz), extracted from the respiration signal
- 2. Average heart rate
- 3. Mutual information between signals aligned to mean sample entropy
- 4. Difference between the slope of the long axis of the fitted ellipse and the slope of the line of equivalence in a standard Poincare Plot
- 5. Distance from the center of the fitted ellipse to the line of equivalence in the standard Poincare Plot
- 6. Sample entropy of the cardiac signal
- Absolute spectral content in the high-frequency band (0.15 0.4 Hz), extracted from the cardiac signal
- 8. Absolute spectral content in the very-low-frequency band (0 0.04 Hz), extracted from the respiration signal
- 9. Absolute cross-spectrum phase between breathing signal and HRV curve in the high-frequency band (0.15 0.4 Hz)
- 10. Relative spectral content in the high-frequency band (0.15 0.4 Hz), extracted from the cardiac signal

	Accuracy	Cohen's Kappa
Recursive partitioning	0.666	0.333
Random forest	0.817	0.631
SVM	0.733	0.447
adaBoost	0.767	0.533
GBM	0.833	0.669

Comparison of cardiac and cardiorespiratory set using GBM

Standard cardiac parameters utilized in sport medicine applications are:

- root-mean-square difference of successive normal R-R intervals (RMSSD);
- standard deviation of instantaneous R-R interval variability from Poincare plots,
- absolute cardiac spectral content in the high frequency (0.15 0.4 Hz)

(Plews et al., 2013; Bellenger et al., 2016)

	Accuracy	Cohen's Kappa
Cardiac set	0.633	0.267
Novel cardiac + respiratory set	0.833	0.669

Discussion

Method verification

- Only 10 and 24 healthy and young participants in two studies
- Conducted in static conditions, without taking into account possible artefacts during natural functioning
- ECG analysis based only from single-lead configuration

Sport medicine application

- No athletes from group of low dynamic component during performance
- No reproducibility and trend analysis
- Lack of taking into account other parameters and psychological questionnaires collected before and after the Olympic Games

- Development of new ambulatory devices for measuring impedance pneumography, ECG, movement, blood saturation and pulse wave data
- Quantitative assessment of the effects of various factors (inter-individual variability, body position, depth and frequency of respiration) on the accuracy of the method
- Evaluation of reproducibility of calibration coefficients
- Checking the configuration of electrodes proposed by Seppa et al. (2013) in static conditions in three body positions

- Evaluation of various methods of IP signal decomposition for the estimation of tidal volume and cardiac function
- Development of non-linear correction technique using neural networks to improve the dynamics of flow-related signals
- Development of algorithm for detecting motion artefacts based on Teager-Kaiser energy operator and motion signal
- Evaluation of the ambulatory testing of respiratory activity in sport medicine application
- Proposing a set of known and new cardiorespiratory parameters to assess the athlete's profiling

Selected references

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