Motion artifact detection in respiratory signals based on Teager energy operator and accelerometer signals

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Abstract— **Growing number of applications in which respiratory activity could be measured during natural functioning of patients amplifies the need for replacement of spirometric or pneumotachometric testing with other, indirect methods. One of them, impedance pneumography, thanks to the use of electrodes mounted on the chest, can produce signals distorted by motion artifacts. Since the subject of detection and removal of artifacts from impedance pneumography signals had not been properly studied yet, we proposed a real-time method based on the Kaiser-Teager energy operator and 3-axis accelerometer signals. 24 participants were asked to follow a breathing protocol involving imitating sleep-time changes in body position and sleeping normally. Compared to manual marking, we obtained** 81.3% **accuracy** (80.9% **sensitivity and** 81.6% **specificity) for the optimal combination of coefficients used to estimate the threshold level based on the operator and accelerometer signals.**

Keywords— **Impedance Pneumography, Long-term monitoring, Motion artifacts, Physiology, Teager energy operator**

I. INTRODUCTION

Impedance pneumography (IP) technique is increasingly widely used as indirect replacement for spirometry testing to measure and monitor respiratory activity in different contexts outside medical environments [1, 2]. *Seppa et al.* and *Malmberg et al.*, for instance, have demonstrated the possibility of associating sleep-time impedance pneumography (IP) signals analysis with asthma risk in young children [3, 4].

However, this method suffers from some drawbacks. Indirect measurement can limit registration of volume- or flow-related parameters, increasing noise. Apart from that, electrical bioimpedance measurements may be distorted by artifacts, decreasing signal quality and negatively affecting automatic algorithms. Finally, the baseline of the impedance signal is usually independent of instantaneous respiratory function, e.g., due to "permanent" change in body position.

Ambulatory IP recordings are mainly disrupted by motion artifacts, which have specific features. First, the frequency range of an artifact signal partly overlaps that of breathing. Second, artifacts are not strictly related to the cardiac components visible in raw impedance pneumography signals [5, 6]. Both should be extracted and/or ignored. Further, artifacts amplitude is usually uncorrelated with motion intensity and characteristics. Moreover, artifact shape may be repeatable, but not in the same way in each subject [7].

The issue of finding motion artifacts in physiological signals has already been examined. Algorithms based on, e.g., spectral or wavelet features, signal decomposition [8], and Kalman filtering [9] (depending on the number of signals available for processing and the kind of registration) are well known in the literature. *Ansari et al.* proposed an adaptive method for impedance pneumography based on ε-Tube, derived from the support vector regression algorithm [10].

However, to our knowledge, the problem had not been studied in depth as it applied to estimation of quantitative respiratory parameters. Therefore, we proposed a novel method (relatively computationally simple and adapted to IP signal characteristics) to detect motion artifacts using the Teager energy operator and exploiting additional accelerometer signals. The aim of this paper is to assess the accuracy of our artifact classifier relative to manual marking.

II. MATERIALS AND METHODS

A. Participants and devices

The study group comprised of 24 generally healthy students (12 females and 12 males, without any reported respiratory diseases). 23 of them (11 females) underwent laboratory testing. The remaining subject - sleep examination. All were informed about the aim of the study and gave written consent. Table 1 summarizes the participants' basic characteristics.

Sleep signals were registered using our impedance pneumography prototype, the Pneumonitor 3, which also records motion signals from a 3-axis accelerometer module. Other acquisitions were made using the simpler Pneumonitor 2 [11].

We used the electrode configuration proposed be *Seppa et al.*, in which voltage electrodes are positioned on the midaxillary line at about 5th-rib level and application electrodes on

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Table 1: Information about the study participants.

	Female		Male	
	Avg	Std	Avg	Std
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

the arms at the same level [12]. Movements were recorded at the belt. A sampling frequency of $f_s = 250Hz$ was used.

B. Motion artifact detection

A schematic of the proposed motion artifact detection method is presented in Figure 1. The proposed system is based on the continuous Teager–Kaiser energy operator. It was originally introduced by *Kaiser et al.* as a nonlinear operator to measure instantaneous energy changes of signals consisting of a single time-varying frequency [13, 14]. More general applications to detect sudden changes, particularly onsets, were later proposed [15, 16].

The continuous Teager-Kaiser energy operator for a signal x in time t is calculated as follows:

$$TKE\left(x\right) = \left(\frac{dx}{dt}\right)^2 + x\frac{d^2x}{dt^2} \quad (1)$$

It was found that the calculated energy is derived from both amplitude and frequency. Therefore, this operator emphasizes both instantaneous properties [14].

To account for the impact of different artifacts as much as possible, operators (with numerical approximations of differentiations) were estimated after application of various moving-average smoothing filters to the raw IP signal. We chose 120 window lengths, from $40ms$ to $1s$. At the end, all operators were aggregated to produce a single "output" signal (**TKE**). We also estimated two auxiliary IP-related signals:

- **TKEspec** was derived by estimating **TKE**'s spectrogram (with a "Hann" window with 32 probes), adding all spectral components for a given point in time, interpolating the result to fit the original amount of data (using splines), and finally saving as a normalized natural logarithm.
- **TKEenv** was the smoothed envelope of the absolute values of **TKE**, estimated using the Hilbert transform.

A "motion-related" auxiliary signal (**MRD**) was calculated by adding the absolute values of the single-axis accelerometer signal derivatives, then normalizing.

The final decision reached by comparing **TKEenv** with the threshold (**THR**) estimated based on the level of **TKE** in a $20s$ windows with 50% overlap and on the levels of **MRD** and **TKEspec**.

A heuristics was added to remove very short, densely spaced detections. We considered 4 ways of determining thresholds:

- **Low** - **5** times the third quartile of **TKE**, **15%** of **MRD** and **TKEspec** levels,
- **Med1** - **4** times the third quartile of **TKE**, **25%** of **MRD** and **TKEspec** levels,
- **Med2** - **4** times the third quartile of **TKE**, **25%** of **MRD** and **TKEspec** levels with **TKEenv** smoothing **half** as strong and
- **High** - **3** times the third quartile of **TKE**, **35%** of **MRD** and **TKEspec** levels.

C. Protocol and analysis

Laboratory testing consisted of mimicking changes in body position occurring before and during sleep, in the order: supine, lying on side, prone, side, supine, sitting, standing, sitting, supine. In each position, subjects were asked to take 4 unconstrained breaths. The recordings lasted approximately 2-3 minutes.

Motion artifacts were marked manually based on visual inspection of IP signal (with simultaneous accelerometer signal display). For each participant, we also marked 9 correct signal segments (one per position) to estimate specificity. The algorithm indications and the reference were compared, and accuracies, Cohen's kappas, sensitivities, and specificities were estimated.

Sleep signals (approx. 9h) were analyzed qualitatively, by assessing the output of the motion artifact detector. The processing time of the algorithm for various selected 4 hours recordings was measured by averaging the lengths of three repetitions by a computer with an Intel i5-class processor. All analyses were performed using MATLAB 2016b.

III. RESULTS

Sample signals obtained from changing body position are presented in Figure 2. The accuracies for the thresholds applied in the algorithm are summarized in Table 2.

The algorithm seemed to operate well for the sleep-related signal. The 4h recordings were analyzed in $87.2s$ on average.

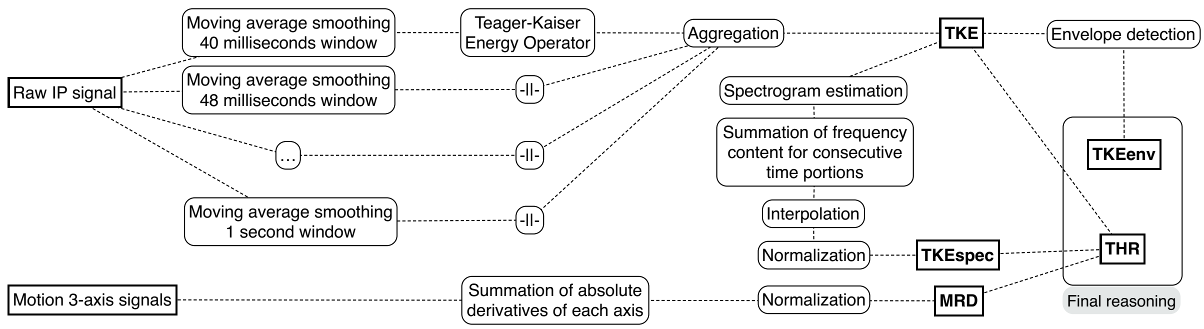

Fig. 1: Method of motion artifact detection.

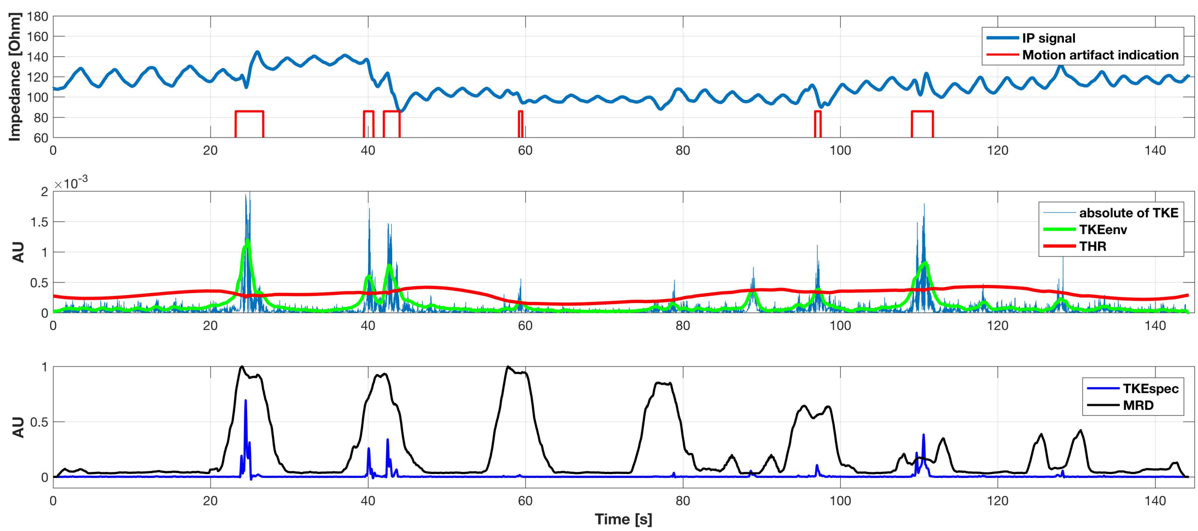

Fig. 2: Sample signal obtained for body position changing of first subject, using the algorithm with the highest threshold level and lowest impact of motion signal; single motion artifact instance, around 80*s*, was not properly marked.

Table 2: Summary of accuracies of the proposed motion artifact detection method; abbreviations: **Low** - algorithm with highest threshold level and lowest influence of motion signal; **Med1** - algorithm with medium threshold level and motion impact effect; **Med2** - algorithm with medium threshold level and motion impact effect, with weaker smoothing of signal envelope; **High** - algorithm with lowest threshold level and highest influence of motion signal.

	Low	**Med1**	**Med2**	**High**
Accuracy [%]	75.6	79.6	81.3	81.0
Sensitivity [%]	62.6	71.7	80.9	83.1
Specificity [%]	89.4	87.9	81.6	78.7
Cohen's kappa	0.52	0.59	0.63	0.62

IV. Discussion

This work presents our preliminary approach to motion artifact detection in impedance pneumography signals. Our interest is driven by the presence of such artifacts in respiratory data gathered under dynamic conditions and during sleep.

In our opinion, the characteristics of respiratory activity allow one to focus on finding and removing segments with motion artifacts, without the need to ”smooth” those parts of signal (even due to non-obvious levels of impedance recorded before and after artifacts).

To our knowledge, state-of-the-art methods, which remove motion artifacts in other physiological signals (e.g., regular cardiac function), are poorly suited for respiratory data, because they usually assume some regularity in the signals. In the next step, we would like to compare our method with other ones on all-night data, gathered in wider, more representative cohort (older people's movements may have a different effect on the signals).

We assumed that the best operator to emphasize various types of motion artifacts should be related to instantaneous changes in amplitude and frequency. Therefore, we assessed the Kaiser-Teager energy operator for motion artifact detection. It has previously been used for environmental physiology signal analyses, and even related to motion artifact detection [17, 18, 19]. We would like to extend the analysis by evaluating the spectral features of the operator and adding the accelerometer signals, which are certainly not necessary, but could be used to adapt the threshold, intended to determine whether some part of a signal is more likely to have motion artifacts.

In our opinion, this method could be improved by:

- changing the thresholding approach into continuous analysis using time series methods, machine learning heuristics, and/or Kalman filtering fusion method;
- verifying the accuracy improvement by making the whole analysis fully independent on the respiratory-related impedance amplitude; and
- adding wavelet-based parameters to the analysis, with wavelet shapes closely resembling those most often observed as motion artifacts.

V. Conclusions

As impedance pneumography signals contain motion artifacts, we proposed a method for automatic detection. It is based on the Kaiser-Teager energy operator and 3-axis accelerometer signals, and could be applied in real time during signal acquisition.

We tested 24 participants in different conditions, simulating sleep-related changes in body position and recording sleep at home. We obtained 81.6% accuracy (81.3% sensitivity and 80.9% specificity) versus manual marking for the optimal combination of threshold level estimation and assumptions made to utilize motion signals.

The proposed method seems promising for ambulatory respiratory registrations.

Conflict of Interest

The authors declare that they have no conflict of interest.

References

1. Koivumaki T, Vauhkonen M, Kuikka J T, Hakulinen M a. Bioimpedance-based measurement method for simultaneous acquisition of respiratory and cardiac gating signals *Physiol Meas.* 2012;33:1323–1334.
2. Roebuck A, Monasterio V, Gederi E, et al. A review of signals used in sleep analysis *Physiol Meas.* 2013;35:R1-R57.
3. Seppa Ville-Pekka, Pelkonen Anna S, Kotaniemi-Syrjanen Anne, Viik Jari, Makela Mika J, Malmberg L Pekka. Tidal flow variability measured by impedance pneumography relates to childhood asthma risk. *Eur Respir J.* 2016:1–10.
4. Malmberg Leo Pekka, Seppa Ville-Pekka, Kotaniemi-Syrjanen Anne, et al. Measurement of tidal breathing flows in infants using impedance pneumography *Eur Respir J.* 2016:1600926.
5. Młyńczak Marcel, Cybulski Gerard. Decomposition of the Cardiac and Respiratory Components from Impedance Pneumography Signals in *Proc 10th Int Joint Conf Biomed Eng Systems and Technol (BIOSTEC 2017) - Vol 4: BIOSIGNALS*:26–33SCITEPRESS 2017.
6. Seppa Ville-Pekka, Hyttinen Jari, Viik Jari. A method for suppressing cardiogenic oscillations in impedance pneumography. *Physiol Meas.* 2011;32:337–345.
7. Młyńczak Marcel, Cybulski Gerard. Improvement of Body Posture Changes Detection During Ambulatory Respiratory Measurements Using Impedance Pneumography Signals in *XIV Mediterranean Conf on Med and Biol Eng and Comput MEDICON*:167–171Springer International Publishing 2016.
8. Reddy K Ashoka, Kumar V Jagadeesh. Motion artifact reduction in photoplethysmographic signals using singular value decomposition in *Proc Instrumentation and Measurement Technology*:1–4IEEE 2007.
9. Lee Boreom, Han Jonghee, Baek Hyun Jae, Shin Jae Hyuk, Park Kwang Suk, Yi Won Jin. Improved elimination of motion artifacts from a photoplethysmographic signal using a Kalman smoother with simultaneous accelerometry *Physiol Meas.* 2010;31:1585.
10. Ansari Sardar, Ward Kevin, Najarian Kayvan. Motion Artifact Suppression in Impedance Pneumography Signal for Portable Monitoring of Respiration: an Adaptive Approach *IEEE J Biomed Health.* 2016;11:1–1.
11. Młyńczak Marcel, Niewiadomski Wiktor, Żyliński Marek, Cybulski Gerard. Ambulatory Devices Measuring Cardiorespiratory Activity with Motion in *Proc 10th Int Joint Conf Biomed Eng Systems and Technol (BIOSTEC 2017) - Vol 1: BIODEVICES*:91–76SCITEPRESS 2017.
12. Seppa Ville Pekka, Hyttinen Jari, Uitto Marko, Chrapek Wojciech, Viik Jari. Novel electrode configuration for highly linear impedance pneumography *Biomed Eng-Biomed Tech.* 2013;58:35–38.
13. Kaiser James F. Some useful properties of Teager's energy operators in *Int Conf Acoustics, Speech, and Signal Processing*;3:149–152IEEE 1993.
14. Solnik Stanislaw, Rider Patrick, Steinweg Ken, DeVita Paul, Hortobágyi Tibor. Teager–Kaiser energy operator signal conditioning improves EMG onset detection *Eur J Appl Physiol.* 2010;110:489–498.
15. Atit M, Hagan J, Bansal S, et al. EEG burst detection: Performance evaluation in *21st Annual Conf BMES/EMBS*;1:441IEEE 1999.
16. Li Xiaoyan, Zhou Ping, Aruin Alexander S. Teager–Kaiser energy operation of surface EMG improves muscle activity onset detection *Ann Biomed Eng.* 2007;35:1532–1538.
17. Kvedalen Eivind. Signal processing using the Teager energy operator and other nonlinear operators *Master Thesis, University of Oslo Department of Informatics.* 2003;21.
18. Sabir Mohannad K. PCG signal analysis using teager energy operator & autocorrelation function in *Int Conf Computer Med Appl (ICCMA)*:1–7IEEE 2013.
19. Wen Xiaotong, Kang Mingxuan, Yao Li, Zhao Xiaojie. Real-time ballistocardiographic artifact reduction using the k-teager energy operator detector and multi-channel referenced adaptive noise cancelling *Int J Imag Syst Tech.* 2016;26:209–215.

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