Improvement of Body Posture Changes Detection during Ambulatory Respiratory Measurements Using Impedance Pneumography Signals

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Abstract—**Impedance pneumography could be used for measuring respiratory parameters quantitatively in ambulatory conditions. It was noted that body posture affects the calibration coefficient connecting the measured impedance values and their first derivatives with volume and flow reference signals. Standard techniques for automatic detection of body posture and activity usually require additional motion sensors. However, in terms of the measurement comfort, less number of sensors is needed. Single sensor mounted on the chest provides good results, however its accuracy decreases during frequent changes of body posture. The aim of this study was to assess the possibility to detect body posture changes using the impedance signal itself, without any other devices or the active cooperation of the person being studied and prospectively improving the body posture change detection method using single motion sensor (e.g. 3D accelerometer). Fifteen healthy students (11 males) performed two body posture changes - get-ups and stand-ups. Six classification techniques were checked for prediction accuracy. It was found that artificial neural networks provided the best overall accuracy (90%).**

Keywords—**Impedance pneumography, Ambulatory respiratory monitoring, Motion tracking, Machine learning.**

I. Introduction

Development of wearable technologies and the ease of large data sets processing seem to increasingly affect the number of surveys performed at home, during normal life, over long periods, ”in the background” [1-2].

Respiratory monitoring appears to gain more interest for long-term measurements protocols in the future, due to the increasing number of respiratory-related problems existing both during the day and at night (e.g. apneas or asthma).

Impedance pneumography (IP) could be used as a non-invasive method to measure quantitative respiratory parameters [3-5]. It measures changes in transthoracic electrical impedance with four electrodes fastened to the patient’s thorax. It uses the tetrapolar technique, in which there are two application electrodes (injecting high-frequency, 10kHz−100kHz, sinusoidal, rectangular or other current with a constant amplitude, 100μA−1mA, regardless of the output load) and two receiving ones. The current signal is injected into the body and, as a result of the breathing action, it is amplitude-modulated. Demodulation extracts the breathing component.

However, it was noted that the calibration coefficient connecting the measured impedance values and their derivatives with the volume and flow reference signals are strongly dependent on changes of subject’s body posture [4,6]. Therefore, long-term impedance pneumography systems would require an automatic body posture detection part.

Signals describing natural patient activity were used in home-care applications for elderly persons [7-8], in evaluation of the activity of small children during the day and at night [9], for indirect measurements of energy expenditure (particularly in athletes) [10-12] or for fall detection systems [13-14].

There are several methods to determine a given subject’s posture or body activity. Among them, the most popular are methods employing accelerometers and gyroscopes [15], as well as contact-free, 4D optical systems [16].

The optical systems calculate a map of the depth of the scene, using a combination of cameras for visible and infrared light. On the basis of raster deformation and triangulation analysis, they determine the shape of the surface of the body [17]. However, it seems that the currently used systems cannot be adapted for use in Holter-type tests.

Regardless of the type of motion sensor [15, 18], signals associated with change of body posture are largely avoidable and dependent on the person being studied and sensors’ setting [7, 19]. Thus, the issue of projecting solution for detecting body posture should be divided into two aspects: 1) equipment (applied technology, number of sensors, configuration of their placement) and 2) signal analysis (initial processing, classification algorithms – types of differentiable activity, types of parameters constituting input data for the algorithm).

A greater number of sensors allow more detailed analysis, at the cost of greater complexity of the signal processing procedure, greater power consumption, increased discomfort for users, and also difficulties in online mode running. Alternatively, using one sensor allows the data analysis to be simplified, what is important in the contexts of performing detection in online mode and optimization of power consumption. It minimally distorts normal activity, provides

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good results in the context of physiological measurements, but its accuracy decreases during frequent changes of body postures, and the number of states that can be differentiated is limited. However, this solution seems to be the best compromise and is usually used with the setting in which the front side of the chest is the place to fix the sensor [20-21].

For the reasons described above it is needed to improve the detection of body posture changes. The idea is to detect body posture changes using the impedance signal itself and use it as a supplement to the data generated by systems for automatic body activity detection.

Therefore, the aim of this paper was to assess the accuracy of body posture changes classification using impedance pneumography signals and classifiers - artificial neural networks (ANN) [22], support vector machines (SVM) [23], decision trees (DT) [24], boosting with trees algorithms (BTA) [25], random forests (RF) [26] and generalized linear models (GLM) [27]. We did not consider combining the classifiers into hybrid one.

This work is a preliminary pilot study to test the novel consideration. The analyzed data come from measurements, which had to exhibit agreement between impedance pneumography and pneumotachometry signals. Therefore, there are only two kinds of body posture changes - get-ups (from supine to sitting) and stand-ups (from sitting to standing). It was assumed that if the results were promising, these analyses and deliberations would next be applied to sleep studies and for other body posture changes, separately.

II. Method

We measured volume-related impedance signals using our own prototype, impedance pneumograph, with a sinusoidal application current of 250μA amplitude and 100kHz frequency [28]. The signals were gained to confirm the linear relationship between respiratory parameters measured by reference pneumotachometry (PNT) and impedance pneumography. The WinAcq ADC recorder stored the signal at a 200Hz sampling frequency. Then, the IP signal was smoothed, filtered and 8-fold decimated. No other signal processing methods necessary to determine respiratory parameters, such as detrending, were used.

The measurements were carried out on 15 healthy students: 11 males aged 19-25 (M: 22.1; SD: 1.8) and 4 females aged 21-26 (M: 23.0; SD: 2.4), for whom body mass indexes were in range 19.3-34.2.

We have complied with the World Medical Association Declaration of Helsinki regarding ethical conduct of research involving human subjects. We obtained informed consent from all participants and the approval from Ethical Committee of Warsaw Medical University.

Four electrodes (tetrapolar method) were positioned as proposed by Seppa et al. [29]. The receiving electrodes were placed on the midaxillary line at about 5th-rib level and the application ones on the proximal side of the arm, on the receiving electrodes' level. We utilized standard, spot, disposable ECG electrodes.

The procedure consisted of taking 8-10 breaths each in supine, sitting and standing postures (with different breathing rates and depths) in immediate succession. The participants changed body postures after each sub-session of breathing, without any break. They were not informed that the get-ups and stand-ups were being registered; therefore these body posture changes were possibly the most natural.

Signal segmentation was performed through determining episodes, which are defined as signal parts between consecutive beginnings of inspiration periods. They were automatically marked using the measure of correlation with breathing pattern and some heuristics techniques (to improve detection, e.g. the correlation threshold was provided in order to exclude the non-breathing episodes). In that way, we had 6 repetitions of about 24-30 breaths, get-up and stand-up for each subject. Fig. 1 presents the sample IP signal stored for the seventh subject (deep breathing at a rate of 10x/min) with the automatically detected episodes starts. We did not calibrate the values into volumes, due to the linear transition function between IP and PNT [4].

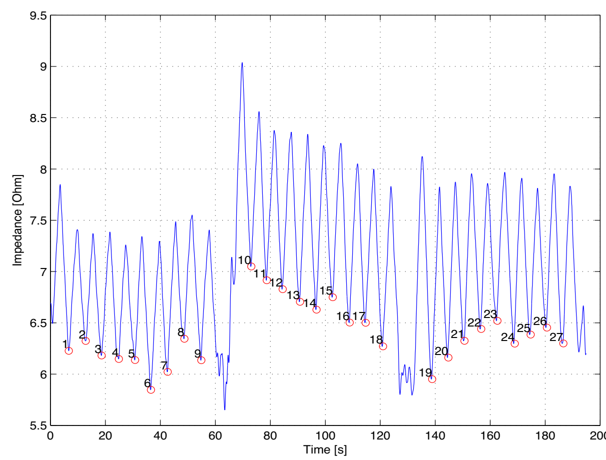

Fig. 1 An example of the impedance pneumography signal stored for the seventh subject (deep breathing at a 10x/min rate) with the automatically detected episodes' starts; there was a "get-up" between the 9th and 10th marks and a "stand-up" between 18th and 19th

Next, the set of parameters describing the episodes was provided for each one. We considered time-domain and spectral-related parameters and chose 18 input parameters describing each episode. They were determined using the Minimum Redundancy and Maximum Relevance (MRMR) feature selection method [30] and the visual observation of the box-plots for consecutive parameters values. The final set consists of:

- The mean and the standard deviation of the short-time energy (STE) of the episode signal.
- The mean and the standard deviation of the zero-crossing rate (ZCR) for the first derivative of the episode signal.
- Some of the linear prediction 8th-order filter coefficients (LPC).
- The first two frequency formants of the episode signal (according to the LPC calculation).
- The number of the smoothed episode signal extremes.
- The number of extremes of the smoothed first derivative of the episode signal.
- The sum of the contribution of the frequency quartiles to the overall spectrogram.
- The standard deviation of the normal distribution fitting to the histogram of the episode signal samples.
- The standard deviation of the normal distribution fitting to the histogram of the first derivative of the episode signal samples.

Parameters from Burg autoregressive estimation, LPC and FFT spectral analysis, STE calculations of the first derivative and ZCR of the episode signal were removed from the consideration due to the very small variation.

All of the input parameters were normalized in order to improve classification performance. The outputs were divided into four possible states:

- ”1”: normal breath (2080 times)
- ”2”: get-up (88 times)
- ”3”: stand-up (73 times)
- ”4”: other artifact (4 times)

The difference in the number of get-ups and stand-ups episodes results from the fact that several stand-ups were so quick that they did not result in specific changes in the signal. As the breathing episodes were significantly more numerous than the others, we used for classification only 2.5 times the number of get-ups, randomly selected. The data was divided into randomly selected training and testing sets with the proportions 0.6/0.4, respectively. For all classifiers, the division was the same and prepared before training.

Due to the high variability of the episode signal shapes corresponding to body posture changes, various classification techniques were examined:

- Artificial Neural Network (ANN) - three-layer perceptron with 36 neurons in the first and second hidden layers (twice the number of input parameters, chosen for the best performance). Levenberg-Marquardt back-propagation learning algorithm was used.
- Support Vector Machines (SVM) – classic binary classifier, tuned for the best performance (3th degree of polynomial kernel with 0.001 gamma). It must be noted, that for multiclass-classification the ‘one-against-one’-approach is used, for 4 states (distinguished in the protocol) 6 binary classifiers are trained and the appropriate output is found using a voting scheme [23].
- Decision Tree Algorithm (DTA) - automatically set using *rpart* package for R.
- Boosting with Trees Algorithm (BTA) – classification by taking lots of possibly weak decision tree predictors and getting the stronger one by weighting and adding classifiers.
- Random Forests (RF) – the improvement of decision tree algorithm adding tree bagging and random selection of feature vectors; after pre-tuning 150 trees were chosen for the best performance, however each calculation provides different results, due to randomness.
- Generalized Linear Models (GLM) fitting with Principal Component Analysis (PCA) as a pre-processing tool to get the parameters, which gain 99% of variance, in order to decrease the dimensionality of the problem, with 10-time cross-validation.

For each classifier, we determined overall accuracies (not for each subject alone, due to the small number of data) and balanced accuracies (the arithmetic average of sensitivity and specificity) [27].

Signal processing, parameter calculations, dimensionality reduction of the input vector and neural network classification were performed using the MATLAB with corresponding toolboxes. R program carried out other classification techniques, with the *caret* package [27].

III. Results

Overall accuracies and balanced accuracies for normal breathing, get-ups, stand-ups and other artifacts are collected in the Table I.

In order to assess the predictor’s ability to distinguish between get-up and stand-up, confusion matrices, presented in the Table II, were calculated for all classifiers.

Table 1 Overall accuracies and balanced accuracies of the considered predictors: ”1” denotes breath, ”2” – get-up, ”3” – stand-up ”4” - other artifact during breathing

Predictor	Overall	“1”	“2”	“3”	“4”
ANN	**90.2%**	97.2%	**90.3%**	**87.3%**	**100%**
SVM	79.7%	**98.1%**	83.2%	57.3%	50%
DT	83.7%	94.2%	78.4%	80.5%	50%
BTA	83.0%	96.4%	88.6%	67.4%	50%
RF	81.7%	96.6%	84.4%	69.4%	50%
GLM	75.2%	93.4%	80.0%	58.7%	50%

Table 2. The summary of confusion tables for all classifiers; accuracies are presented in percent

Artificial Neural Network

	Reference			
Prediction	"1"	"2"	"3"	"4"
"1"	**94.4**	0.0	0.0	0.0
"2"	3.4	**88.2**	21.4	0.0
"3"	2.2	11.8	**78.6**	0.0
"4"	0.0	0.0	0.0	**100.0**

Support Vector Machines

	Reference			
Prediction	"1"	"2"	"3"	"4"
"1"	**97.8**	0.0	0.0	50.0
"2"	2.2	**88.2**	82.1	50.0
"3"	0.0	11.8	**17.9**	0.0
"4"	0.0	0.0	0.0	**0.0**

Decision Tree

	Reference			
Prediction	"1"	"2"	"3"	"4"
"1"	**97.8**	0.0	17.9	50.0
"2"	2.2	**61.8**	10.7	50.0
"3"	0.0	38.2	**71.4**	0.0
"4"	0.0	0.0	0.0	**0.0**

Boosting with Trees

	Reference			
Prediction	"1"	"2"	"3"	"4"
"1"	**94.4**	0.0	3.6	0.0
"2"	5.6	**97.1**	60.7	100.0
"3"	0.0	2.9	**35.7**	0.0
"4"	0.0	0.0	0.0	**0.0**

Random Forests

	Reference			
Prediction	"1"	"2"	"3"	"4"
"1"	**93.3**	0.0	0.0	0.0
"2"	6.7	**88.2**	57.1	50.0
"3"	0.0	11.8	**42.9**	50.0
"4"	0.0	0.0	0.0	**0.0**

Generalized Linear Regression Model

	Reference			
Prediction	"1"	"2"	"3"	"4"
"1"	**89.9**	0.0	3.6	50.0
"2"	10.1	**85.3**	75.0	0.0
"3"	0.0	11.8	**21.4**	50.0
"4"	0.0	2.9	0.0	**0.0**

IV. Discussion

We proposed a set of 18 parameters to classify the impedance signal episodes into normal breathing, get-up, stand-up and other artifact. The number of parameters might be even reduced, but this was not the subject of the work. The currently selected ones allow calculations without any computational problems.

The chosen parameters are strongly redundant as regards the distinction between breathing and another state. However, the most important aspect of the study was to distinguish between body posture changes in the best possible way, and the greater number of parameters seems to be necessary for this purpose.

We did not perform inter-individual analysis due to small amount of data, which should be further divided into training and test sets.

As the results appear promising, it seems that further measurements should take into account 'natural' activities and the body posture changes characteristic during sleep, e.g. the change from lying on side to supine.

Due to author's consideration, the usage of Deep Learning methods for raw episodes signals, without parameterization is promising technique for distinguishing between larger numbers of possible body posture changes. For current issue, the usage of deep architectures of classifiers is not needed, because of the lack of high dimensionality of the problem.

Presented paper is not intended to provide the method replacing usage of 3D accelerometers as a motion sensor. The possible issue of joining accelerometer/gyroscope-based body posture detection algorithms with the results come from IP (perhaps by using some heuristics or fusion methods, like Kalman filter) seems to be considered in order to check whether the additional information could improve the analysis significantly.

V. Conclusions

The aim of this paper was to assess body posture change detection during respiratory measurements using only impedance pneumography signals for improving the classification made by additional motion sensing equipment. We found that a set of 18 parameters describing episodes with an artificial neural network (three-layer perceptron topology with 36 neurons in first and second hidden layers, with a Levenberg-Marquardt back-propagation training algorithm) as a classifier provided the best overall accuracy (90%). This method also distinguished each body posture change in the best way.

However, further studies with greater number of body posture changes for greater numbers of subjects should improve the assessment and could provide conclusions for the Holter-type quantitative respiratory measurement system based on impedance pneumography.

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CONFLICT OF INTEREST

The authors declare no financial or otherwise conflicts of interest.

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