Body position classification for cardiorespiratory measurement

Marcel Młyńczak[1], Martin Berka[2], Wiktor Niewiadomski[3], and Gerard Cybulski[1,3]

***Abstract*— Heart activity, or at least heart rate variability, is associated with body position. Our previous studies have confirmed that impedance pneumography may be used to record respiratory function, but the calibration coefficients for this method depend on position. Data were collected from 24 students (12 male, 12 female), who alternated positions between lying (on front, back, and right side), sitting and standing. Signals from an attached iPhone's internal sensors (accelerometer, gyroscope, magnetometer) were recorded and attitude relative to gravity was calculated. The signals were subsequently segmented and marked. Five algorithms were trained and cross-validated for different sensor combinations. Without differentiation of sitting and standing, 100% accuracy was achieved using all algorithms. The classifier best differentiating these two states was based on random forests, with overall accuracy of 90%. Simple methods based on a proposed hybrid classifier were tested for online measurement without the need for signal segmentation, with 99% accuracy. The prospect of the algorithms' use in long-term studies (particularly cardiorespiratory monitoring) was assessed.**

I. INTRODUCTION

The effect of body position on respiratory [1], [2] and cardiac function [3] is well established, but is rarely fully accounted for in ambulatory monitoring (which implies concurrent, automatic body position detection). Heart activity, *e.g.*, heart rate variability, tracked alongside body position, could improve the physiological inference.

Besides affecting unconscious respiratory activity, body position is also needed to provide accurate ventilation parameters for impedance pneumography (IP) in both laboratory [4] and ambulatory [5] settings.

Substantial position-detection research is available. A number of wearable sensors can be used to deduce the orientations of the torso and limbs relative to each other and to the ground surface. Inertial sensors consist of accelerometers, which can provide orientation information when the direction gravity is known and other accelerations are minimal, and gyroscopes, which provide angular data more directly, but are subject to drift [6]. Each of them may be employed for a separate purpose [7], or they may be used jointly to calculate attitude relative to the gravitation [6], [8].

Laboratory studies with restricted body position may need only one- or two-axis sensors, but tri-axial information is needed for classification of a broader range of positions [7], [9]. The static body positions normally identified (sitting, standing, various lying ones) mostly involve the body's extension and a unique, perpendicular orientation of the torso (sitting being the exception). A single sensor's data on the torso's orientation is mostly sufficient. Sitting differs primarily by the relative orientation of the thigh and can be detected with a second sensor [10].

Once a three-dimensional vector has been obtained, positions can be identified from the vector's orientation relative to a classification model or with heuristic algorithms. Apart from static positions, identification may focus on transitions between positions or on patterns of non-transition movements [11].

Studies have historically developed unique sensor setups for this purpose, but a consumers increasingly possess an alternative solution: smartphones. Recent generations of phones contain an array of instruments including tri-axial accelerometers, gyroscopes and magnetometers. Phone accelerometers, in particular, have been verified in recognition of simple activities [12] such as ambulation [13]. The broader use and comparison of the aforementioned sensors is an area of current development [14].

We employed a smartphone in choosing optimal sets of sensors and classification methods for algorithms used in long-term ambulatory and clinic-based monitoring for determination of body position. Our aim was to assess the accuracy of automatic position classification performed without segmentation. Furthermore, we sought to consider intermediate torso positions, which may have an indirect effect on respiratory function as measured using impedance pneumography.

This paper is organized as follows. Equipment, protocol, and analysis process are described in *Methods*. The experimental and analysis *Results* are followed by their *Discussion* and resulting *Conclusions*.

II. METHODS

A. Subjects and Measurements

We studied 24 healthy students, 12 female and 12 male, both groups aged 19-23. All were informed of the aim and protocol of the study and gave written informed consent. We complied with the Declaration of Helsinki on research on humans.

An iPhone 4 was used to measure motion signals using the following embedded sensors:

[1]M. Młyńczak, Student Member, IEEE, and G. Cybulski are with Institute of Metrology and Biomedical Engineering, Faculty of Mechatronics, Warsaw University of Technology, Boboli 8, 02-525, Poland
mlynczak at mchtr.pw.edu.pl

[2]M. Berka, Student Member, IEEE, is with the Department of Electrical and Computer Engineering, University of Calgary, 2500 University Dr NW, Calgary, AB T2N 5A6, Canada

[3]W. Niewiadomski and G. Cybulski are with the Department of Applied Physiology, Mossakowski Medical Research Centre, Polish Academy of Sciences, Pawinskiego 5, 02-106 Warsaw, Poland

- 3-axis accelerometer (STM LIS331DLH $\pm 2g$ range, $1mg/digit$ sensitivity),
- 3-axis gyroscope (STM L3G4200D $\pm 250dps$ range, $8.75mdps/digit$ sensitivity),
- 3-axis magnetometer (AKM AK8975 $\pm 1200\mu T$ range, $0.3\mu T/digit$ sensitivity).

We used a mobile application to record signals from the three sensors and calculate attitude (expressed as pitch around the x-axis, roll around the y, and yaw around the z) [15]. The sampling frequency was set to $200Hz$. Time jitter was observed, even with the phone in airplane mode. Piecewise Cubic Hermite interpolation was performed to obtain correctly sampled data for further analysis. The phone was affixed with a belt around the torso, as shown in Fig. 1.

Fig. 1. The method of smartphone arrangement during measurement.

B. Protocol and Analysis

Each subject assumed a series of positions in the following order: supine (lying on back) $\rightarrow$ lying on right side $\rightarrow$ prone (lying on front) $\rightarrow$ on right $\rightarrow$ supine $\rightarrow$ sitting $\rightarrow$ standing $\rightarrow$ sitting $\rightarrow$ supine $\rightarrow$ on right $\rightarrow$ prone $\rightarrow$ on right $\rightarrow$ supine $\rightarrow$ sitting $\rightarrow$ standing $\rightarrow$ sitting $\rightarrow$ supine. There was a pause of a few seconds between transitions. Subjects were asked to establish and change body positions as naturally as possible.

The main purpose of the analysis was to provide a method for classification of body position during collection of data associated with respiratory and cardiac activity. We performed a preparation consisting of:

- manual review of segmentation of the body positions (supine, lying on right side, prone, sitting, standing),
- calculation of parameters (particularly the mean) for each segment for all signal axes (yielding 12 means),
- preparation of a matrix of parameters, ultimately divided into training (70

We then evaluated 5 classification techniques for accuracy and the viability of limiting the number of sensors used:

- Manual decision tree, based on hierarchically set thresholds for input parameters, manually established through exploratory data analysis. In practice, it consisted of deriving mean vectors for each position from training data and selecting the position that yielded the largest vector product for a given set of sensor values.
- Automatic decision tree, including hierarchical thresholds for input parameters, however determined automatically, based on all provided dataset, using the *rpart* R package [16].
- Tree boosting - an initially weak classifier is repeatedly re-weighted with training data, allowing voting for the best classifier. On each iteration, the weights in the decision tree change. This was performed with the train function in the *caret* R package [17].
- Random forests, which output the mode of classes resulting in a large number of individually and randomly set (differently seeded) trees. They correct overfitting which may occur in the simple decision tree algorithm. All calculations employed the *randomForest* R package [18].
- Multilayer perceptron with input, hidden, and output layers, with sigmoid activation functions and bias or weights of the connections established during a supervised back-propagation procedure (algorithm delivered by Matlab's Neural Network Toolbox) [19]. In a smartphone application, the learned model might be implemented as a set of weight matrices related to the perceptron configuration.

All algorithms had tuned settings, which are described in the Results section.

Sitting and standing are difficult to differentiate based only on the mean value of current signals from the torso. We proposed a more sophisticated method using correlation analysis and pattern-finding, based on the observation that getting up and sitting down have similar shapes for various axes, various sensors, and for all tested subjects.

The hybrid classifier consisted of two parts. The first worked with the signals' mean values for consecutive overlapping time windows (we tested windows from $20ms$ to $1s$ with overlap from 0% to 50%), applying the first algorithm (ignoring the distinction between sitting and standing). The second employed pattern recognition. The algorithm calculated the vector of the 3-axis signals, compared it with the stand-up sample, and sought the specific shapes (from which the beginnings of stand-up and sit-down could be found) during the sitting/standing phase.

We also proposed methods for smoothing outputs using median filters to remove brief, erroneous indications not coinciding with body position changes.

The quality of hybrid classification was assessed by comparing it with the manual labeling of all raw data segments, for windows which fit entirely within a segment. Assessment was carried out for the most effective sensor combination identified for the first algorithm.

Signal processing and calculations employed MATLAB. All statistical analyses were carried out with R and corresponding R packages [20].

III. RESULTS

The overall accuracies of classifiers applied to the entire set of sensors (excepting Attitude for Manual Decision Trees) are presented in Table I.

The automatic methods achieved superior accuracy, above 90% and varying by only 0.6% among themselves. The best of these, random forests, was applied for checking single sensors' classification accuracy. The results are provided in Table II.

The best result was obtained for the gyroscope. Fig. 2 shows the sample gyroscope-related signal obtained for one subject.

The results of the classification are presented in Table III in the form of a confusion matrix where rows correspond to the algorithm's prediction and columns to the reference classes.

TABLE I

OVERALL ACCURACIES FOR THE CLASSIFIERS

Classifier	Accuracy
Manual Decision Tree	82.5%
Automatic Decision Tree	90.8%
Boosting with Trees	90.7%
Random Forests	91.3%
Multilayer perceptron	91.1%

TABLE II

CLASSIFICATION ACCURACIES FOR RANDOM FOREST CLASSIFIER WITH SINGLE-SENSOR INPUTS

Signal source	Accuracy
Accelerometer	30.0%
Gyroscope	84.2%
Magnetometer	82.5%
Attitude calculation	73.3%

TABLE III

CONFUSION MATRIX FOR GYROSCOPE RANDOM FOREST CLASSIFICATION

	Reference				
Prediction	*Supine*	*Side*	*Prone*	*Sitting*	*Standing*
Supine	**36**	0	0	0	0
Side	0	**28**	0	0	0
Prone	0	0	**14**	0	0
Sitting	0	0	0	**16**	12
Standing	0	0	0	7	**7**

Using a simple vector-product condition algorithm, 4 states (sitting and standing combined into one) were differentiated with 100% accuracy based only on gyroscope data. Nearly equal accuracy was achieved with the magnetometer, but the gyroscope is more reliable as measured magnetic field vectors are affected by other factors besides subject orientation. An accelerometer outputting proper acceleration might match these outcomes.

We provided a method for distinguishing sitting and standing based on cross-correlation with the Euclidean norm of all gyroscope axes and the pattern signals. The curves taken into account are presented in Fig. 3.

Based on its accuracy in whole-segment classification, the gyroscope axes' data were used for the time-window portion of the hybrid classifier. This combination was found to be effective for distinguishing the basic positions. Little variation in accuracy was found for different window lengths; one subject's accuracy remained only 92.7%, while all others remained over 95%, and a majority over 99%. Longer

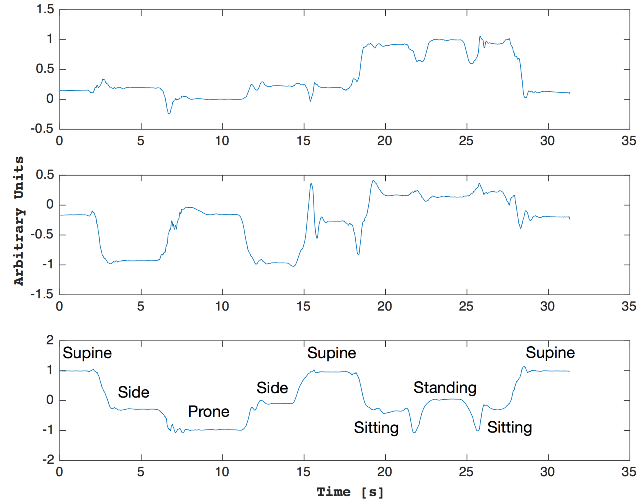

Fig. 2. Sample 3-axis gyroscope signal for half of the session performed by one subject, with annotations; X axis on top, Y in the middle.

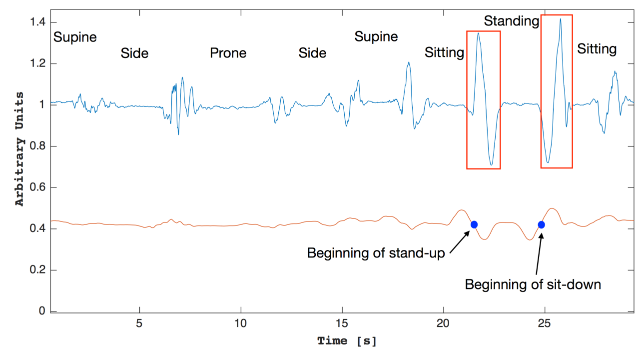

Fig. 3. Cross-correlation between the signal and the pattern representing sitting-to-standing position change, with an indication of the characteristic evolutions; the Euclidean norm of the gyroscope axes is colored in blue, the correlation signal in red.

windows lead to 100%, which may have been due to the number of considered windows decreasing (from thousands to a hundred) and the smoothing of any brief movements that may dominate a short window. We obtained a mean accuracy of 99.1% for a $100ms$ window.

IV. DISCUSSION

A. Smartphone-based measurements

From an ambulatory point of view, the obtained data constitute very good approximations of body position. Regrettably, the default signals returned by the phone accelerometer indicate acceleration relative to normal gravity and cannot alone indicate orientation. It seems that raw accelerometer signal could provide better results than those presented; [12] used raw accelerometer and gyroscope data with a multilayer perceptron to obtain 93% accuracy for a wide range of activities.

The tests conducted using a smartphone allow quick, systematic checking of the feasibilities of motion sensor sets, especially for the rarely used magnetometer. Data from the magnetometer seem less reliable, being subject to noise and somewhat divorced from the body's mechanics. Therefore, it seems that the use of a magnetometer increases system complexity without providing additional value for body position classification.

B. Classification

A single well-adapted sensor is sufficient for differentiation of perpendicular orientations of the phone. This is consistent with works such as [10], where a neural network achieves 93% accuracy with accelerometer data alone. Distinguishing between sitting and standing with only a torso-mounted sensor is difficult, as these have found; confusion stems from similarly-oriented positions and activities.

The automatic methods used all available data from all sensors, yet the best decreased sitting/standing misidentification by less than half. As in [9], the benefits of multiple torso sensor types are limited - better differentiation based on short-term data requires a sensor located in the area most affected by change in position (the thigh). As additional sensor sites increase cost and inconvenience, we did not investigate this approach. Position-characteristic activities (walking, leaning in various directions, prolonged immobility) and transition data (net vertical acceleration, tilting for balance) may be used to infer the dominant position from torso-based data.

Nevertheless, real-time implementations of the presented algorithms could yield high accuracy, at least for healthy people. Sickness and age result in noisier signals and would probably degrade the results. The robustness of the algorithms in this regard will be checked in upcoming investigations.

C. Intermediate body positions

In contrast to automatic methods able to tailor their classification sets to the training data, the manually developed method based on vector alignment could be adapted to return the top matches and their percentage shares of total response. This matters in an ambulatory setting where intermediate body positions may be adopted. While oriented partway between typical positions, the lungs may exhibit intermediate respiratory parameters. An intermediate calibration coefficient for impedance pneumography could be determined via a weighted average of those positions.

We plan to investigate these matters, including dynamic states and conditions imitating natural functioning.

V. CONCLUSIONS

We emphasized the need to synchronize information about subject body positions during cardiorespiratory measurements (especially when using impedance pneumography to record ventilation). A smartphone was used to investigate combinations of accelerometer, gyroscope, magnetometer, and various algorithms for body position classification.

The proposed hybrid classifier based on random forests and pattern-associated cross-correlation analysis allows detection of body positions without prior segmentation. Overall classification accuracy was 99.1% for a $100ms$ gyroscope window with 50% overlap.

A body position detection system should augment each cardiorespiratory system used for ambulatory diagnostics, as position is significant from a physiological perspective.

REFERENCES

[1] E. Blair, J.B. Hickam, The effect of change in body position on lung volume and intrapulmonary gas mixing in normal subjects, J Clin Invest, vol. 34, no. 3, 1955, pp. 383 - 389.

[2] K. Kaneko, J. Milic-Emili, M.B. Dolovich, A. Dawson, D.V. Bates, Regional distribution of ventilation and perfusion as a function of body position, J Appl Physiol, vol. 21, no. 3, 1966, pp. 767 - 777.

[3] K.F. Hossack, R. A. Bruce, Maximal cardiac function in sedentary normal men and women: comparison of age-related changes, J Appl Physiol, vol. 53, no. 4, 1982, pp. 799 - 804.

[4] G. Cybulski, W. Niewiadomski, A. Strasz, L. Laskowska, A. Gasiorowska, Relationships Between Systolic Time Intervals and Heart Rate During Initial Response to Orthostatic Manoeuvre in Men of Different Age, J Hum Kinet, vol. 27, 2009, pp. 57 - 64.

[5] M.C. Mlynczak, W. Niewiadomski, M. Zylinski, G.P. Cybulski, Ambulatory impedance pneumography device for quantitative monitoring of volumetric parameters in respiratory and cardiac applications, Computing in Cardiology Conference Proc., 2014, pp. 965 - 968.

[6] H. Rehbinder, X. Hu, Drift-free attitude estimation for accelerated rigid bodies, Automatica, vol. 40, no. 4, 2004, pp. 653 - 659.

[7] M.C. Boonstra, R.M.A. van der Slikke, N.L.W. Keijsers, R.C. van Lummel, M.C. de Waal Malefijt, N. Verdonschot, The accuracy of measuring the kinematics of rising from a chair with accelerometers and gyroscopes, Journal of Biomechanics, vol. 39, no. 2, 2006, pp. 354 - 358.

[8] G. Ligorio, A.M. Sabatini, A novel Kalman filter for human motion tracking with an inertial-based dynamic inclinometer, IEEE Transactions on Biomedical Engineering, vol. 62, no. 8, 2015, pp. 2033 - 2043.

[9] B. Najaf, K. Aminian, A. Paraschiv-Ionescu, C.J. Buela, P. Robet, Ambulatory system for human motion analysis using a kinematic sensor: monitoring of daily physical activity in the elderly, IEEE Transactions on Biomedical Engineering, vol. 50, no. 6, 2003, pp. 711 - 723.

[10] K. Aminian, P. Robert and E.E. Buchser, Physical activity monitoring based on accelerometry: Validation and comparison with video observation, Med Biol Eng Comput, vol. 37, no. 3, 1999, pp. 304 - 308.

[11] J.J. Kavanagh, H. B. Menz, Accelerometry: A technique for quantifying movement, Gait and Posture, vol. 28, no. 1, 2008, pp. 1 - 15.

[12] S. Dernbach, B. Das, N.C. Krishnan, B.L. Thomas, D.J. Cook, Simple and complex activity recognition through smart phones, in Intelligent Environments, Guanajuato, Mexico, 2012.

[13] H.K.Y. Chan, H. Zheng, H. Wang, R. Gawley, M. Yang, R. Sterritt, Feasibility study on iPhone accelerometer for gait detection, in Pervasive Computing Technologies for Healthcare, Dublin, 2011.

[14] M. Shoaib, S. Bosch, O.D. Incel, H. Scholten, P.J.M. Havinga, Fusion of smartphone motion sensors for physical activity recognition, Sensors, vol. 14, no. 6, 2014, pp. 10146 - 10176.

[15] C. Vozny, Data Collection, Mobile App sold at the Apple App Store for iOS system

[16] T. Therneau, B. Atkinson, B. Ripley, rpart: Recursive Partitioning and Regression Trees. R package version 4.1-9. http://CRAN.R-project.org/package=rpart, 2015.

[17] M. Kuhn et al, caret: Classification and Regression Training. R package version 6.0-41. http://CRAN.R-project.org/package=caret, 2015.

[18] A. Liaw, M. Wiener, Classification and Regression by randomForest. R News, vol. 2, no. 3, 2002, pp. 18 - 22.

[19] MATLAB and Neural Network Toolbox Release 2015b, The MathWorks, Inc., Natick, Massachusetts, United States.

[20] R Core Team, R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL http://www.R-project.org/, 2015.