Comparison of A Priori Calibration Models for Respiratory Inductance Plethysmography During Running

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***Abstract*— Respiratory inductive plethysmography (RIP) has been introduced as an alternative for measuring ventilation by means of body surface displacement (diameter changes in rib cage and abdomen). Using a posteriori calibration, it has been shown that RIP may provide accurate measurements for ventilatory tidal volume under exercise conditions. Methods for a priori calibration would facilitate the application of RIP. Currently, to the best knowledge of the authors, none of the existing ambulant procedures for RIP calibration can be used a priori for valid subsequent measurements of ventilatory volume under exercise conditions. The purpose of this study is to develop and validate a priori calibration algorithms for ambulant application of RIP data recorded in running exercise. We calculated Volume Motion Coefficients (VMCs) using seven different models on resting data and compared the root mean squared error (RMSE) of each model applied on running data. Least squares approximation (LSQ) without offset of a two-degree-of-freedom model achieved the lowest RMSE value. In this work, we showed that a priori calibration of RIP exercise data is possible using VMCs calculated from 5 min resting phase where RIP and flowmeter measurements were performed simultaneously. The results demonstrate that RIP has the potential for usage in ambulant applications.**

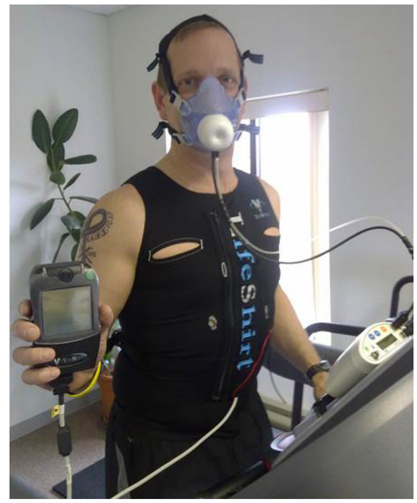

Fig. 1. Subject wearing the LifeShirt garment (VivoMetrics, Ventura, CA, USA) and the face mask of a flowmeter (Oxycon Pro Care Fusion, San Diega, CA, USA)

I. INTRODUCTION

Respiratory inductance plethysmography (RIP) has been introduced as an alternative method for measuring ventilation by means of body surface displacement [1]. The methodological advantage of RIP is obvious as influences of the natural breathing pattern induced by mouth pieces, nose clips or face masks itself [2], [3] are avoided.

Breathing causes changes in the anterior posterior diameters of the rib cage (RC) and abdomen (AB) [4], which can be measured using RIP. The actual RIP device is most often composed of two separate bands (RC and AB) either non-embedded (Respitrace, Ambulatory Monitoring, Inc., White Plains, N.Y., USA) [5] or embedded in a garment like the LifeShirt (VivoMetrics, Ventura, CA, USA) (Fig. 1) [1].

RIP is commonly used in clinical settings but there is some potential for ambulant applications as well. It has already been shown that RIP may provide accurate measurements for ventilatory timing and tidal volume under exercise conditions [6]–[8]. Methods of metabolic performance assessment partially utilize ventilation to quantify inter- and intra-individual variations of the aerobic working capacity [9]. These methods still require the use of restrictive laboratory equipment that could be simplified by a well calibrated RIP device.

As soon as valid and accurate Volume Motion Coefficients (VMCs) were applied to the uncalibrated RIP data, ventilatory volume was estimated reliable within $\pm$ 20% equivalence after a posteriori calibration [6]. Analytical statistical computations are claimed to be the most accurate calibration [1], where VMCs are calculated a posteriori via least squares regression [6], [10], [11].

Compared to a posteriori calibration, there are several restrictions if RIP needs to be calibrated a priori for subsequent measurements in an ambulatory setting. First, either a spirometer or pneumotachograph is required to perform quantitative gain scaling. Second, valid calibration of the relation between VMCs is necessary [10], [12], as compartmental contribution between RC and AB changes as soon as measured tidal volumes cannot be controlled.

Accurate determination of individual VMCs can either be performed by inapplicable respiratory maneuver [3], [4] or analytical statistical computation [6], [10], [11]. Currently, to the best knowledge of the authors, none of the existing ambulant procedures for RIP calibration can be used for valid subsequent measurements of ventilatory volume under exercise conditions.

The purpose of this study is to develop and validate a priori

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calibration algorithms for ambulant application of RIP data recorded in running exercise. The calibration algorithms are build on resting phases in upright standing posture (5 min) and are applied to exercise data.

II. METHODS

A. Hardware Equipment

RIP was measured with the LifeShirt garment (VivoMetrics, Ventura, CA, USA) (Fig. 1). Embedded in the LifeShirt garment are two parallel elastic bands with insulated sinusoidal wires. One elastic band surrounds the rib cage (RC) and one the abdomen (AB). We used the VivoSense software (Vivonoetics, San Diego, CA, USA) for decryption and processing of the recorded data. A flowmeter (FM) (Oxycon Pro Care Fusion, San Diego, CA, USA) was used as ground truth measurement device for ventilatory timing and volume.

B. Subjects

186 healthy subjects (88 female and 98 male, age 27.1 $\pm$ 8.3 years, height 175.6 $\pm$ 9.0 cm, weight 68.9 $\pm$ 11.1 kg, mean $\pm$ standard deviation (SD)) participated in the study. All subjects gave written informed consent and the study was approved by the Ethics Committee of the University of Freiburg, Re.-No. 208/11.

The experiments were performed on a treadmill (Quasar, H/P/Cosmos Sports and Medical GmbH, Nussdorf-Traunstein, Germany). The experiments started with a resting phase in upright standing posture for 5 min on the treadmill. Afterwards, the subjects had to perform an incremental running test on the treadmill. The starting speed was set to 6 km/h and was increased in steps of 2 km/h every 3 min until voluntary exhaustion. Afterwards, the subjects performed a recovery phase of 10 min in upright standing posture. In between two different speeds, a resting phase of 30 s occurred to collect blood lactate samples.

In this study, we only used the resting phase and the running phase without pauses (referred to exercise phase in the following). For the comparison of the different models including calculation of our gold standard, we only used the inspiratory tidal volume V_T. Table I gives the ventilatory characteristics of the resting and exercise phase used in the creation and evaluation of the different calibration models.

C. Preprocessing

The synchronization of FM and RIP data was done using a VBA routine in Microsoft Excel (Microsoft Office 2010, Microsoft Corporation, Redmond, WA, USA). Further analysis was performed using the Matlab package (Mathworks Inc., Natick, MA, USA).

D. Calibration Algorithms and Gold Standard

We used the two-degree-of-freedom model of Konno and Mead [4] where it is assumed that the chest wall has two moving parts (RC and AB). The inspiratory tidal volume V_T is then calculated as

$$V_T = gain_{RC} \cdot uV_{T_{RC}} + gain_{AB} \cdot uV_{T_{AB}} \qquad (1)$$

where $gain_{RC,AB}$ represents the volume motion coefficients (VMCs) for the RC and AB band. $uV_{T_{RC,AB}}$ are the corresponding uncalibrated values of partial tidal volume in each band.

In the regression model, data from the resting phase ($uV_{T_{RC}}$ and $uV_{T_{AB}}$ of RIP and $V_{T_{FM}}$ of the flowmeter data) were used to determine individual gain factors $gain_{RC/AB}$ for each subject. These individual gain factors were further utilized for the a priori calibration of inspiratory tidal volume from the exercise phase.

We used the following seven different models for determining the accurate gain factors from the resting phase:

1) Calculation of $gain_{RC,AB}$ of the two-degree-of-freedom model (Eq. 1) using least-squares-approximation (LSQ)
2) Calculation of $gain_{RC,AB}$ of the modified two-degree-of-freedom model (Eq.2) using LSQ

$$V_T = gain_{RC} \cdot uV_{T_{RC}} + gain_{AB} \cdot uV_{T_{AB}} + c_{offset} \qquad (2)$$

with c_{offset} as a constant in LSQ.

3) - 6) Calculation of $gain_{RC,AB}$ using Support Vector Regression (SVR) [13], [14] with four different kernels (linear, radial basis, sigmoid kernel, and polynomial). The cost parameter c and ϵ in the loss function of the SVR were determined in a grid search using only the data of the resting phase with five-fold-cross-validation with regard to minimizing the root mean squared error ($RMSE$) (see definition below). The parameters for c were {0.1, 1, 10, 100, 1000} and for ϵ were {0.001, 0.01, 0.1, 1}.

7) Calculation of K (Eq. 3) and M (Eq. 4) using the qualitative diagnosis calibration (QDC) model of Sackner et al. [12]. After calculating K with only resting data that lay within ± 1.0 SD around $[uV_{T_{RC}} + uV_{T_{AB}}]$, M is calculated using LSQ.

$$K = -\frac{SD(uV_{T_{AB}})}{SD(uV_{T_{RC}})} \qquad (3)$$

with SD as standard deviation.

$$V_T = M[K \cdot uV_{T_{RC}} + uV_{T_{AB}}] \qquad (4)$$

As gold standard model, we calculated the two gain factors directly from the exercise data using LSQ without offset [6], [10]. This gold standard requires the simultaneous measurement of FM and RIP.

E. Performance Measure

We calculated the root mean squared error (RMSE) for multiple linear regression [15]

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (V_{T,i} - V_{T_{FM},i})^2}{N - n}} \qquad (5)$$

with $V_{T_{FM}}$ as the reference volume of the FM, N as the total number of breaths, and n as the number of coefficients in the model ($n = 2$ for model 1, $n = 3$ for models 2 - 6,

TABLE I

VENILATORY CHARACTERISTICS USED IN THE CREATION (RESTING PHASE) AND EVALUATION (EXERCISE PHASE) OF THE CALIBRATION MODELS.

	Resting phase					**Exercise phase**				
	Mean	±	SD	Min	Max	Mean	±	SD	Min	Max
Number of breaths	93	±	22	34	149	545	±	147	189	931
Total time* [min]	5.9	±	0.2	4.3	6.2	16.5	±	3.2	7.4	25.3
Inspiratory time [min]	2.6	±	0.3	1.6	3.7	7.9	±	1.6	3.6	12.1

SD: standard deviation, *The total time consisted of the inspiratory and the expiratory time.

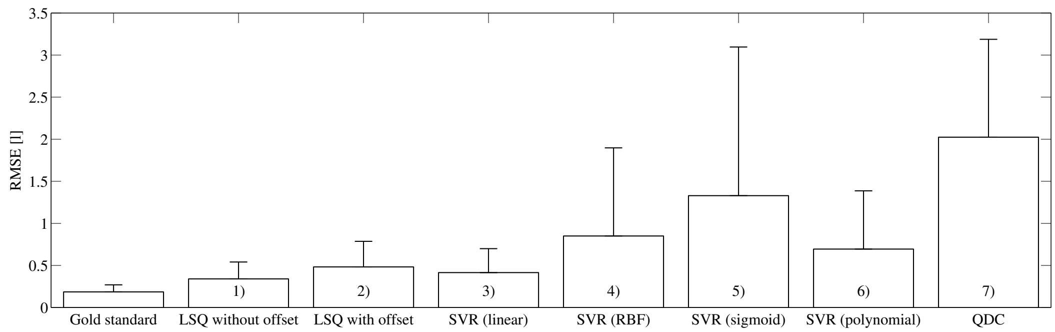

Fig. 2. RMSE of the seven models (1 - 7) and the gold standard. LSQ: least squares approximation; SVR: support vector regression; RBF: radial basis function; QDC: qualitative diagnostic calibration.

and $n = 1$ for model 7). In regression, we seek for a perfect fit (small residuals $V_T - V_{T_{FM}}$).

F. Statistics

We used a multivariate Analysis of Variance (ANOVA) with repeated measures [16] followed by post-hoc t-tests with Bonferroni correction to test if the means of the seven models were different from the mean of the gold standard. An α level of 0.05 was used throughout the study.

III. RESULTS

Table II shows the final cost parameters c and ϵ found in the grid search for each kernel. We excluded all parameter combinations where no SVR-model was found. We had to exclude 13 subjects, as at maximum only 19.3% of breaths of these subjects of the resting phase lay in the area of ± 1 SD around the mean and appropriate calibration was not satisfactory. We further did not include the QDC method in the multivariate ANOVA and in the post-hoc procedure.

Fig. 2 displays the RMSE of the seven different calibration models applied on the exercise data including the gold standard approach. The multivariate ANOVA revealed significant differences between the six calibration models (without QDC method) compared to the gold standard ($F(6, 180) = 54.67, p > 0.001$). Every t-test revealed significant differences.

TABLE II

SUPPORT VECTOR REGRESSION (SVR) PARAMETERS c AND ϵ OBTAINED USING A GRID SEARCH.

Kernel type	c	ϵ
Linear	10	0.01
Radial basis	0.1	0.01
Sigmoid	0.1	0.001
Polynomial	0.1	0.01

IV. DISCUSSION

In this work, we aimed for an a priori calibration of exercise RIP data. We used the resting data of each subject to calculate individual gain factors using seven different models. These models were compared with the gold standard calibration using multivariate ANOVA with repeated measures and a post-hoc procedure. The gold standard calibration demonstrated the best possible outcome of the LSQ-calibration, but required the simultaneous measurement of FM and RIP data, which is not available in an ambulant setting.

The multivariate ANOVA and the post-hoc procedure of multiple dependent t-tests revealed that all means differ significantly. This implies that the performance of the six models are different and one calibration model performed best. The best calibration model was LSQ without offset, followed by SVR with linear kernel and LSQ with offset (Fig. 2). The LSQ without offset model is widely used in literature, also known as MLR (multiple linear regression), and accurate results have been achieved [6], [10]. Consequently, we used the LSQ without offset calibration model for determining the gold standard values. This model might possibly be improved by solving Eq. 1 using least absolute deviations or L^p-norms with $p > 2$ instead of least squares approximation (LSQ).

Liu et al. [11] modified the standard LSQ approach from Eq. 1 with volume, frequency, and body size features calculated over 20 s to 60 s-windows. They concluded that their approach using four volume and one frequency feature with 60 s-window performed best, but they did not compare their model with the general LSQ approach. Calculating features in a $60\,$s-window is not appropriate in breath-by-breath comparisons, whereas we did not include this modified model in our analysis.

The QDC model was first introduced by Sackner et al. [12] and is widely used by different research groups [17], [18]. In this study, this model performed worst. The limitations of the QDC model concerning changing of breathing pattern are known in literature [19], [20], and our findings confirm these.

To the best knowledge of the authors, SVR has never been used for the calibration of exercise RIP data. SVR with linear kernel achieved the second lowest RMSE value, whereas the other three kernels (RBF, sigmoid, and polynomial) achieved rather high RMSE values with a large SD. For obtaining the best c and ϵ values, we had to exclude all parameter combinations where no SVR-model was found. The training of the SVR-model was based on only 93 ± 22 breaths (Table I) from the complete resting phase (individually for each subject). The number of breaths used for the training might be too small for the creation of accurate SVR-models.

All seven calibration models were calculated using only data from the resting phase. The resting phase was between $4.3\,$min to $6.2\,$min long with total number of breaths between 34 and 149. Hence, we measured subjects with low breathing frequencies and calculating gain factor of such few values might be inaccurate. In the future we suggest to not use a resting phase with predefined time, but rather a predefined number of breaths.

In this work, we assumed that the two-degree-of-freedom model of Konno and Mead [4] is valid, as with this model accurate calibration was achieved [6]. Nevertheless, different studies suggested that respiratory motion is complex and might not be described by a two-degree-of-freedom model [19]. In further studies, nonlinear models for the calibration of RIP data should be investigated. Currently, we only compared calibration models that required a preliminary resting phase in upright standing posture of about $5\,$min with simultaneous measurements of RIP and FM. Calibration models without the use of additional equipment like a FM would be desirable.

In this work, we showed that a priori calibration of RIP exercise data is possible using VMCs calculated from $5\,$min resting phase where RIP and FM measurements were performed simultaneously. The results demonstrate that RIP has the potential for usage in ambulant applications.

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