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Improved regression models for ventilation estimation based on chest and abdomen movements

Shaopeng Liu¹, Robert Gao^{1,*}, Qingbo He², John Staudenmayer³, and Patty Freedson⁴

¹Department of Mechanical Engineering, University of Connecticut, Storrs, CT, USA

²Department of Precision Machinery and Precision Instrumentation, University of Science and Technology of China, Hefei, Anhui, China

³Department of Mathematics and Statistics, University of Massachusetts, Amherst, MA, USA

⁴Department of Kinesiology, University of Massachusetts, Amherst, MA, USA

Abstract

Non-invasive estimation of minute ventilation is important for quantifying the intensity of physical activity of individuals. In this paper, several improved regression models are presented, based on the measurement of chest and abdomen movements from sensor belts worn by subjects ($n = 50$) engaged in 14 types of physical activities. Five linear models involving a combination of 11 features were developed, and the effects of different model training approaches and window sizes for computing the features were investigated. The performance of the models was evaluated using experimental data collected during the physical activity protocol. The predicted minute ventilation was compared to the criterion ventilation measured using a bidirectional digital volume transducer housed in a respiratory gas exchange system. The results indicate that the inclusion of breathing frequency and the use of percentile points instead of interdecile ranges over a 60-second window size reduced error by about 43%, when applied to the classical two degrees-of-freedom model. The mean percentage error of the minute ventilation estimated for all the activities was below 7.5%, verifying reasonably good performance of the models and the applicability of the wearable sensing system for minute ventilation estimation during physical activity.

Keywords

minute ventilation estimation; multiple linear regression; piezoelectric sensor

1. Introduction

Unobtrusive determination of respiratory parameters is important for studies on respiratory disorders and airway obstruction. Since ventilation is a measure of a physiological response that is known to increase with exercise, continuous monitoring of ventilation is critical to quantifying both the intensity of physical activity and human exposure to pollutant particles. Compared to indirect calorimetry devices where a mouthpiece or mask is required, non-invasive ventilation measurement using wearable sensors allows for ventilation estimation in a free-living environment, and has been extensively investigated over the past several decades. Generally, these techniques used elastic belts that are placed around the rib cage and abdomen of the test subjects to measure dimensional changes during breathing. From the magnitude of the sensor outputs, the amount of ventilation can be determined. Examples

*rgao@engr.uconn.edu.

using such sensor belts for ventilation estimation include respiratory inductive plethysmography (RIP) (Witt *et al* 2006, Clarenbach *et al* 2005, Cohen *et al* 1994), respiratory magnetometer (Banzett *et al* 1995), and piezoelectric displacement sensors (Pennock 1990, Liu *et al* 2009). Other types of sensors, such as optical encoder embedded belts that measure the motion of code strips (Weinberg and Webster 1998), the Hall sensor that outputs a current when the chest moves relative to a magnet placed next to the sensor (Russell and Helms 1994), and the pneumobelt that detects the pressure changes in rubber tubes (Binks *et al* 2007) carried by the subject, have also been investigated.

The correlation between ventilation and belt dimensional change was first established by modeling the respiratory system as a two degrees-of-freedom (DOF) system (Konno and Mead 1967). The volumetric change of the respiratory system was approximated as the weighted sum of the dimensional changes of the rib cage and abdominal compartments, respectively, measured by the two-belt assembly. Based on such a model, various computational methods, e.g. multiple linear regression (Loveridge *et al* 1983, Stromberg *et al* 1993, Bar-Yishay *et al* 2003), qualitative diagnostic calibration (Sackner *et al* 1989, Groote *et al* 2001), and standard ratio method (Banzett *et al* 1995, Binks *et al* 2007), have been investigated to evaluate the relationship between ventilation and trunk dimensional changes. To improve the accuracy of ventilation estimation, efforts to modify the original 2-DOF model using the difference of two temporally consecutive dimensional changes of the rib cage and abdominal belts as the parameters in the 2-DOF linear model (Stromberg *et al* 1993), adding the interaction between the rib cage and abdominal compartments (Revow *et al* 1987), or applying power (Stromberg *et al* 1993), logarithmic, and exponential transformations for fitting the belt dimensional changes with the ventilation (Loveridge *et al* 1983) have been used. It was found through these studies that the modifications did not (Stromberg *et al* 1993, Revow *et al* 1987) or “only marginally” (Loveridge *et al* 1983) improved the ventilation estimation accuracy. It should be noted that in these studies, the model parameters used were primarily the displacements of the two sensor belts (the dimensional changes of rib cage and abdominal compartments). Considering that human respiration is associated with multiple parameters, it is hypothesized that extending the 2-DOF model by including additional features, such as breathing frequency, height, and body mass, may further improve the accuracy in ventilation estimation.

This study comparatively investigates the performance of modified regression models for estimating minute ventilation from data measured by piezoelectric sensor belts. Specifically, a total of eleven features that are directly or indirectly related to ventilation were selected, and five modified models were developed, based on different combinations of the features. The performance of each model was subsequently compared with each other using experimental data, and the effects of different model training approaches and window sizes for computing the features were investigated. The root mean square error (RMSE) between the predicted ventilation from the modified models and a reference base established by a bidirectional digital volume transducer housed in a respiratory gas exchange system was then calculated and served as the criterion measure.

The paper is organized as follows. Section 2 describes improvement of the estimation accuracy of minute ventilation, based on the classic regression model. In Section 3, experimental setup is presented. Section 4 shows the experimental results and discussion, respectively. Conclusions are presented in Section 5.

2. Modeling of ventilation

2.1 Theoretical model

The relationship between the ventilation V and the dimensional changes of the rib cage and abdomen as a result of breathing has been modeled as a 2-DOF system (Konno and Mead 1967), represented by:

$$V = a \cdot RC + b \cdot AB \quad (1)$$

where a and b are coefficients, and RC and AB represent the dimensional changes of the rib cage and abdomen, respectively. Using the notation of regression, Eqn. (1) can be represented as:

$$y = f(\underline{X}, \underline{\beta}) \quad (2)$$

where y is the predicted response (output) in the one-dimensional Euclidean real vector space R^1 , $y \in R^1$, $\underline{X} = [x_1, x_2, \dots, x_p]^T$ is a vector of independent variables (inputs) extracted from the belt sensor signals in the p -dimensional space R^p , $\underline{X} \in R^p$, p is the number of independent variables, $\underline{\beta}$ are regression coefficients, $\underline{\beta} = \{\beta_0, \beta_1, \beta_2, \dots, \beta_p\}$, and f represents the regression function or model, which defines the relationship between $\underline{X}$ and y . In the particular case of a 2-DOF respiratory system, $p = 2$, $\underline{X} = \{x_1, x_2\}^T$, where $x_1 = RC$, $x_2 = AB$, $\underline{\beta} = \{\beta_1, \beta_2\}$, where $\beta_1 = a$, $\beta_2 = b$, $y = V_T$.

A linear form of Eqn. (2) is expressed as:

$$y_i = f(\underline{X}_i, \underline{\beta}) = \beta_0 + \sum_{j=1}^p \beta_j x_{ij} \quad (3)$$

where y_i is i th predicted ventilation, $\underline{X}_i$ is i th vector of covariates (or features), and n is the number of data points. Note that Eqn. (3) can be expressed in the matrix form as:

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}_{n \times 1} = \begin{bmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1p} \\ 1 & x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1} & x_{n2} & \cdots & x_{np} \end{bmatrix}_{n \times (p+1)} \cdot \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_p \end{bmatrix}_{(p+1) \times 1} \quad (4)$$

Equations (3) and (4) provide the analytical model for predicting the ventilation of a test subject. To improve the prediction accuracy, enhancement to the model has been investigated by including additional features that relate to the ventilation.

2.2 Model enhancement

Respiration is reflected by multiple parameters (or covariates or features). As an example, the breathing frequency is closely related to respiration, and body size is directly related to lung size, which in turn will affect the ventilation (Stahl 1967). It is thus hypothesized that the accuracy of minute ventilation ($\dot{V}_E$) prediction may be improved by incorporating additional *features* into the original 2-DOF regression model. In this study, a total of 11 features, grouped into three categories, have been extracted from the recorded dimensional changes of the rib cage and abdomen during breathing, measured by two elastic belts. The three categories of features include:

1. *Volume features*: statistical distribution information of the respiratory signals;

2. *Frequency features*: frequency information of the respiratory signals;
3. *Body size features*: physical characteristics of the testing subjects.

2.2.1 Volume features (VF)—Dimensional changes of the rib cage and abdomen directly relate to the changes of ventilation. They were traditionally represented by the peak-to-peak amplitudes of the two respiratory signals, which were the features used in the respiration model (Konno and Mead 1967, Banzett *et al* 1995). It is observed from experiments that respiratory signals measured by these sensors generally contain high-frequency artifacts caused by muscles or tissues in the regions where the belts were applied, thereby introducing errors to the ventilation estimation. This shortcoming is addressed in this study by 1) a pre-processing to the measured respiratory signals to remove tissue artifact, and 2) the selection of 10th and 90th percentiles of the respiratory signals from the two sensor belts as the model features.

The Empirical Mode Decomposition (EMD) (Huang *et al* 1998) method was investigated for removing tissue artifacts from the respiratory signals before extraction of the respiratory and frequency features. With this method, the respiratory signal measured from the piezoelectric sensor belt is decomposed into a number of intrinsic mode functions (IMF's), each of which corresponds to a specific range of frequency components contained within the respiratory signal. Analysis has shown that, depending on the intensity of the physical activity performed by subjects, the first few IMF's, corresponding to relatively higher frequency range (e.g. 1~3 Hz), are typically associated with the artifacts, whereas IMF's corresponding to lower frequencies related more closely to respiratory components. The peak frequencies of the IMFs and the original respiratory signal were compared to determine the most representative IMF for removing tissue artifacts from the signal (Liu *et al* 2008). If the peak frequency of an IMF is less than the peak frequency of the original signal, the IMF was considered part of the respiratory component. Otherwise, it was treated as a tissue artifact. Through this process, a denoised respiratory signal was reconstructed, as shown in (a) and (b) of figure 1.

In this study, a total of six groups of features extracted from the denoised respiratory signals were selected as described below:

1. 10th and 90th percentiles of abdominal respiratory signal (labeled as features F_1 and F_2),
2. 10th and 90th percentiles of rib cage signal (as F_3 and F_4),
3. difference between 90th and 10th percentiles (as F_5 and F_6),
 - interdecile range of the abdominal signal (as $F_5 = F_2 - F_1$), and
 - interdecile range of the rib cage signal (as $F_6 = F_4 - F_3$).

These features were computed from a range of small time segments or windows of the signal, e.g. 20, 30, 40, 50 and 60 seconds. The percentiles were computed for the positive portions of the respiratory signals as illustrated in figure 1(c), which corresponded to the volume inhaled by subjects. The reason for choosing the above features is that they incorporated the distribution variability when outliers (e.g., artifacts) are present (Sheskin 1997).

2.2.2 Frequency features (FF)—Breathing frequency is closely associated with minute ventilation ($\dot{V}_E$), thus it is meaningful to have it included in the estimation. It is known that $\dot{V}_E$ has a sigmoidal response with breathing frequency that: a) before $\dot{V}_E$ increases to moderate levels, there is little increase in breathing frequency; and b) breathing frequency

begins to increase rapidly once $\dot{V}_E$ exceeds a moderate intensity where lactate accumulation leads to a greater minute ventilation (Wilmore, Costill and Kenney, 2008). Observed from the collected subject data, the breathing frequency has shown a correlation coefficient of 0.70 with the minute ventilation. For simplicity, breathing frequency is therefore approximated as linearly related with $\dot{V}_E$ and employed by the multiple linear regression as in Eqn. (3). Based on preliminary spectrum analysis, three breathing frequency-related features were extracted from the respiratory signals:

1. average of the dominant frequencies from the rib cage and abdominal measurement (as F_7), as illustrated in figure 1(d),
2. product of breathing frequency F_7 and volume feature F_5 (as $F_8 = F_7 \times F_5$), and
3. product of F_7 and volume feature F_6 (as $F_9 = F_7 \times F_6$).

2.2.3 Body size features (BF)—Two parameters describing the physical characteristics of the test subjects, including the body height (F_{10}) and body mass (F_{11}), were included in the study. These features were directly measured in the subjects, and their influence on the estimation of minute ventilation was investigated.

The above described eleven features are listed in table 1, with the corresponding average values during physical activity testing presented in table 2.

2.3 Regression models

In the present study, five regression models listed in table 3 were examined to determine accuracy in predicting minute ventilation. Model M_1 is based on Konno and Mead's model (Konno and Mead 1967), and serves as the baseline for comparing with the other four models. Breathing frequency, F_7 , was included in all the other four models, considering its relationship with the minute ventilation ($r = 0.70$ between minute ventilation and breathing frequency). Model M_2 , M_3 and M_4 are extended version of the classical model M_1 , and enable a comparison of the estimation performances with an emphasis on the percentile points (M_2), the interdecile range (M_3), and the interactions of frequency and interdecile range (M_4), respectively. Model M_5 consisted of body size features and breathing frequency, and was employed to examine how subject body size affected ventilation estimation.

These five models were trained using a multiple linear regression model, as shown in Eqn. (3). The quality of the estimated models is evaluated by their respective RMSE, which is the square root of the average squared difference between the estimated ($\dot{V}_{E-PE}$) and measured ($\dot{V}_{E-SP}$) minute ventilation. The Bland-Altman analysis (Bland and Altman 1986) was employed to assess the agreement between $\dot{V}_{E-PE}$ and $\dot{V}_{E-SP}$. By plotting the means against the differences of the predicted and measured minute ventilation, the agreement between the two measures, as well as how this agreement relates to the magnitude of the measurement, was examined. Limits of agreement were computed as the mean differences (bias) plus and minus $1.96 \times$ standard deviation, representing the range where 95% of the differences will lie.

The five models were trained using two approaches: 1) a subject-specific approach, where each model was trained for each subject separately, using only that subject's data, and 2) a subject-independent approach, where each model was trained using all the data. In each approach, the estimation performance is assessed using the *leave-one-out* cross validation. Cross-validation estimates of the RMSE provide valid estimates of how the models would perform if they were applied to different data under similar conditions. When using the

subject-specific approach, the models were trained using all but one of the data points for a specific subject, and the RMSE was calculated for the left-out datum point. This procedure was repeated for all the data points and all the subjects, and the average RMSE is reported for purpose of analysis. In the case of subject-independent approach, the models were trained using all but one subject's data, and the RMSE was calculated for the left out subject. Each subject was left out in turn, and the average RMSE was reported.

3. Experiments

3.1. Subjects

Fifty healthy test subjects consisting of 19 male and 31 females were recruited. Subject characteristics are shown in table 4.

3.2. Experimental protocol

Each subject completed activities in one of the two following routines in a random order:

1. *Routine 1*: computer work (*CW*), moving boxes (*MB*), cycling at 300 kpm/min, 1 kp resistance, 50 rpm (*CT*), treadmill walking at 3.0 mph with 0% grade (*T3-0*), treadmill walking at 3.0 mph with 5% grade (*T3-5*), treadmill walking at 4.0 mph with 5% grade (*T4-5*), and tennis (*TE*);
2. *Routine 2*: filing papers (*FP*), vacuuming (*VA*), self-paced walk (*SW*), cycling at 600 kpm/min, 2 kp resistance, 50 rpm (*C2*), treadmill walking at 4.0 mph with 0% grade (*T4-0*), treadmill jogging at 6.0 mph and 0% grade (*T6-0*), and basketball (*BA*).

Subjects were not required to complete all activities and were allowed to skip the high-intensity activities that they did not feel comfortable to complete, e.g., treadmill at 6.0 mph, basketball or tennis. Each activity, when performed, lasted for 7 minutes long, followed by a 2-minute rest period. Prior to the start of each test, subjects were asked to lie down on a bed to rest for 10 minutes, in order to achieve a baseline metabolic rate. All the tests were performed during the day, and the subjects were asked to eat four hours before the test, after which no food or drink other than water is allowed to be taken. For the cycling and treadmill testing, the Monark Ergonomic 818E cycle ergometer, and the Burdick TM55 treadmill were used.

3.3. Measurement system

Figure 2 illustrates the configuration of a data acquisition system worn by the human subjects. It includes a belt assembly (Piezo Respiratory Effort, Ambu Sleepmate, Glen Burnie, MD) for ventilation measurement, and a respiratory gas exchange system (Oxycon Mobile, Cardinal Health, Yorba Linda, CA), which included the criterion volume transducer that assessed minute ventilation and breathing frequency.

Two piezoelectric sensors attaching two Velcro belts encircled subject's rib cage and abdomen snugly. Based on the piezoelectric effect, the sensors output zero-amplitude signals when subjects are at rest, and once subjects start activities, the piezoelectric sensors output signals with a sensitivity of 30 $\mu\text{V}/\text{mm}$. The rib cage and abdominal sensor belts were located at the level of nipples and umbilicus for male subjects. While for female subjects, the rib cage sensor belt was placed at the bottom of breast, and the abdominal sensor belt was placed at the level of umbilicus. The two sensors were directly connected to an integrated measurement system (IMS) which was developed elsewhere (Liu *et al* 2010), and data was then stored into a secure digital (SD) card.

The respiratory gas exchange system utilizes a turbine-like fan as the volume transducer, which is attached to the face mask. The ventilation is determined from the rotational speed of the fan. The respiratory gas exchange system is secured to the subject using an adjustable vest. Breath-by-breath ventilation data are collected and then transmitted to a laptop computer wirelessly. The system has demonstrated consistent estimation of minute ventilation with a validated respiratory gas exchange system – Oxycon Pro (Díaz *et al* 2008). Pre-calibration of the system (including a separate calibration of the volume transducer with a certified calibrated volume syringe) was performed before the experiments. The clocks of both the piezoelectric sensor belt system and the respiratory gas exchange system were synchronized by recording the time of each system at the beginning of each activity.

4. Results and discussions

4.1 Experimental results

Figure 3 shows the performance comparison of the five types of models, for both the subject-specific and subject-independent approaches. The models that include the breathing frequency (F_7), such as M_2 , M_3 , and M_4 , perform better than the traditional model M_1 . This indicates that the breathing frequency is important to consider when estimating minute ventilation. Model M_5 , which includes the breathing frequency (F_7) and the body size features (F_{10} , F_{11}), yielded a larger error than the other four models under subject-specific approach. Specifically, the error is about 6% larger than M_1 , 86% larger than M_2 , 40% larger than M_3 , and 19% larger than M_4 , when the regression models were trained using the subject-specific approach and a 60-second window size. This indicates that combining the breathing frequency with body size characteristics of the subjects does not improve accuracy in ventilation estimation under subject-specific approach. This is expectable since the body size characteristics don't vary for an individual subject. While under subject-independent approach, the inclusion of body size characteristics has shown improved estimation performance of minute ventilation compared with the traditional model M_1 , reducing the RMSE by about 11%.

Furthermore, model M_2 performed better than M_3 and M_4 , indicating that the inclusion of percentile points (as is the case for M_2) is better than the inclusion of interdecile ranges (as is the case in M_3) and the interactions between breathing frequencies and interdecile range (as in M_4), respectively. Overall, model M_2 performed consistently better than other models, and the error was reduced by nearly 43% when compared with the traditional model M_1 .

The effect of different window sizes on the accuracy of ventilation estimation is shown in figure 4. Generally, longer time intervals led to more accurate estimation. Compared with the 20-second window, the error associated with the 60-second window was reduced by about 21% for the subject-specific approach, and reduced by about 6% for the subject-independent approach. This indicates that in order to achieve accurate estimation, a longer window size should be selected for computing the features.

A summary of the RMSE and mean absolute bias of the two training approaches is given in table 5. The results obtained from the subject-specific approach consistently outperformed those from the subject-independent approach, for all models $M_1 \sim M_5$. These results suggest that a subject-specific approach should be adopted for the estimation of minute ventilation to maximize the estimation accuracy.

Figure 5 shows a comparison between the estimated and measured minute ventilation of different activities. The estimated ventilations are from model M_2 , with the subject-specific training approach under 60-second window size. The black circles are mean values, while the width of the box indicates the variability (standard deviation) of each activity, in both the

measured and predicted minute ventilation. The mean percentage error for each activity is shown in table 6. Ventilation estimation RMSE is 5.8 liters/min with an overall mean percentage error of 7.5%. While the estimation deviated from the line of identity, the fitting equation of the data points follows a high coefficient of determination, reflected in the R^2 value of 0.964. This indicates that a systematic error correction mechanism can be included into data analysis such that under-estimation and over-estimation relative to the intersection point may be corrected.

To further assess the agreement between the estimated and measurement minute ventilation, figure 6 shows the Bland-Altman plot of ventilation estimation for all activity types, using model M_2 trained by the subject-specific approach under a 60-second window. Model M_2 produced a smaller bias of 0.4 liters/min (95% confidence interval: $-0.5 \sim 1.2$ liters/min) than those obtained in previous studies (Witt *et al* 2006), with comparable limits of agreement. The differences between the estimated and measured minute ventilation ranged from -14.3 liters/min to 15.0 liters/min for all the 14 activities, 10.4% less than that from a previous study (Witt *et al* 2006) (-17.1 liters/min to 15.7 liters/min), indicating a good agreement between the estimated and measured minute ventilation (Bland and Altman 1986).

4.2 Generic regression model

The results presented above demonstrate superior estimation of minute ventilation when the regression models were trained for each specific subject. However, when subject specific models are adopted, they need to be first calibrated for each subject before they can be used to predict minute ventilation. This raises a question as to how to calibrate devices that only collect the sensor belt displacements without a calibration reference (e.g., the respiratory gas exchange system). Due to the significant variability of human testing subjects, some commercial products, e.g., the LifeShirt from VivoMetrics, utilizes a fixed volume calibration bag through which the model is trained for a specific subject at the beginning of testing. However, this process greatly increases the subject burden and system cost and is not practical for large scale investigations.

An alternative is to develop a generic model for the population. It is hypothesized that when data from more subjects are included in the training data set, the corresponding trained model will be more generalizable and provide improved estimation accuracy and lower RMSE than the models trained with data from only a few subjects. A test was performed on model M_2 under 60-second window size, with the objective to confirm that improvement in ventilation estimation accuracy comes solely from the regression model being more “generalized”. The model was trained on a subset of the 50-subject data with N subjects, where N varied from 1 to 12, and tested on data from the rest ($50-N$) subjects. The results shown in figure 7 confirm the hypothesis that, the more subjects were included in the training data set, the more accurate estimation of minute ventilation the regression model will be, as reflected in the continually decreasing error of the ventilation estimation. The specific number of the individuals to be included in the training set should be determined through experiments on a larger scale.

4.3 Effect of number of sensors on estimation accuracy

Results obtained in the previous section are based on the data from both the rib cage (RC) and abdominal (AB) sensor belts. Considering that using one belt would reduce subject burden and make the measurement more realistic to perform under free living conditions, the effect of number of sensors on the estimation accuracy of minute ventilation was investigated. For this purpose, four single-sensor regression models were investigated, for which only one sensor belt (AB or RC) was used in each test. The input features used in the one belt models are shown in table 7.

Figure 8 shows the results of the four 1-belt models compared with the five models developed in Section 2. The model M_7 yields the third best estimation accuracy (RMSE = 7.9 liters/min) in the group, underperforming only by about 3.4% as compared to the second best performing 2-belt model M_3 (RMSE = 7.6 liters/min). The RMSE of model M_9 is 8.3 liters/min, which is comparable with (about 5.2% more than) the model M_7 . Furthermore, the data points of the ventilation estimation continued to return high R^2 values for model M_7 (0.962) and M_9 (0.965). These results show that the model using single piezoelectric sensor belt has provided a reasonably good estimate of minute ventilation, and especially, the chest-wall mobility measured in the abdominal region (model M_7) appears to better correlated with respiratory function (Malaguti *et al* 2009). Such finding motivates further studies under free living condition using one belt, as it reduces the subject burden.

5. Conclusions

Improvement in regression models for the estimation of minute ventilation was investigated through the design of five regression models that involved a combination of eleven features. Experimental results obtained revealed that model M_2 , consisting of both the breathing frequency and the 10th and 90th percentiles from both the rib cage and abdominal respiratory signals, is accurate in estimating the minute ventilation. Using M_2 , the RMSE was less than 5.8 liters/min, and the mean percentage error of the minute ventilation estimation for all the activities was less than 7.5%, under free living conditions. This indicates that for improved estimation accuracy, both breathing frequency and 10th and 90th percentiles should be included in the regression model. Furthermore, these features should be computed over a window size of 60 seconds for reducing estimation error.

In addition, the regression model using a single (abdominal) piezoelectric sensor belt has shown good estimation accuracy. This opens up new opportunities for monitoring physical activities under free living conditions with significantly less subject burden.

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Figure 1.

An example of the respiratory signal measured by piezoelectric sensor belts. (a) A 60-second respiratory signal from jogging; (b) zoom-in view of the first 20 seconds of the signal; (c) illustration of the 10th and 90th signal percentiles; (d) illustration of breathing frequency estimation.

Figure 2.
Schematic of the data acquisition system.

Figure 3. Performance comparison on feature models.

Figure 4.
Performance comparison on window sizes.

Figure 5.
Comparison of measured and estimated minute ventilation for each activity.

Figure 6.

Bland-Altman analysis of minute ventilation estimation for all activities. Dotted lines represent limits of agreement and solid line represents the mean bias.

Figure 7.
RMSE comparison of different number of subjects in the training set.

Figure 8. Performance comparison of regression models using one and two sensor belts (All models were trained for each subject with 60-second window size).

Table 1

Feature categories for ventilation estimation.

Feature Type	Feature No.	Description
VF	F_1	10 th percentile of abdominal signal
	F_2	90 th percentile of abdominal signal
	F_3	10 th percentile of rib cage signal
	F_4	90 th percentile of rib cage signal
	F_5	F_2 minus F_1
	F_6	F_4 minus F_3
FF	F_7	Breathing frequency
	F_8	F_7 multiplied by F_5
	F_9	F_7 multiplied by F_6
BF	F_{10}	Body height
	F_{11}	Body mass

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Table 2

Average characteristics of features for each type of activity.

Activities (measured METs: mean ± standard deviation)	Features						
	$F_1(V)$	$F_2(V)$	$F_3(V)$	$F_4(V)$	$F_7(\text{min}^{-1})$		
Computer work (1.4±0.5)	0.01	0.17	0.08	0.41		19.85	
Filing papers (1.8±0.3)	0.01	0.25	0.07	0.42		21.57	
Vacuuming (3.6±0.7)	0.01	0.41	0.04	0.50		29.42	
Self-paced walk (3.9±0.8)	0.03	0.26	0.11	0.30		25.18	
Treadmill at 3.0 mph 0% grade (4.4±0.9)	0.01	0.36	0.04	0.65		26.01	
Cycling at 300 kpm/min, 1 kp resistance, 50 rpm (4.8±1.0)	0.06	0.36	0.11	0.43		27.83	
Moving the box (5.5±1.1)	0.01	0.58	0.01	0.88		28.77	
Treadmill at 4.0 mph 0% grade (5.9±1.1)	0.06	0.30	0.11	0.41		27.64	
Treadmill at 3.0 mph 5% grade (6.4±1.2)	0.01	0.30	0.03	0.61		26.17	
Cycling at 600 kpm/min, 2 kp resistance, 50 rpm (6.8±1.0)	0.04	0.33	0.15	0.33		29.40	
Treadmill at 4.0 mph 5% grade (8.9±1.7)	0.06	0.32	0.10	0.45		29.66	
Treadmill at 6.0 mph 0% grade (10.0±1.6)	0.06	0.37	0.16	0.41		33.89	
Tennis (10.2±3.3)	0.01	0.35	0.02	0.33		36.18	
Basketball (10.5±2.1)	0.01	0.34	0.04	0.40		37.23	

Not all the averages of features are includes, as some of them are combinations of others.
kpm: kilopond; *rpm*: revolutions per minute; *kpm*: kilopond-meters per minute.

Table 3

Regression models

Model	Feature Combination
M_1	F_5, F_6
M_2	F_1, F_2, F_3, F_4, F_7
M_3	F_5, F_6, F_7
M_4	F_7, F_8, F_9
M_5	F_7, F_{10}, F_{11}

Table 4

Subject characteristics

Characteristics	Men	Women	All
n	19	31	50
Age (years)	32.4(21–50)	32.8(21–57)	32.6(21–57)
Height (cm)	175.0(166.5–187.0)	164.7(155–186.8)	168.6(155.0–187.0)
Body mass (kg)	74.8 (54.4–95.8)	66.9(47.0–117.5)	69.9(47.0–117.5)
BMI (kg/m ²)	24.3 (19.6–29.8)	24.5(18.1–39.7)	24.4(18.1–39.7)

Values are means with range in parentheses, n: no. of subjects; BMI: body mass index.

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Table 5

Summary of overall results of the two training approaches

Training approach	M ₁		M ₂		M ₃		M ₄		M ₅	
	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias
Subject-specific	10.2	-1.4	5.8	-0.5	7.6	-1.0	9.0	-1.0	10.7	-1.5
Subject-independent	15.2	-2.1	12.9	-1.7	13.0	-1.7	13.0	-1.8	13.0	-2.1

RMSE and bias values are in liters/min, under a 60-second window.

Table 6

Mean percentage error for different activities

Activity	Mean Percentage Error (%)	Activity	Mean Percentage Error (%)
<i>CW</i>	37.5	<i>T3-0</i>	17.1
<i>FP</i>	48.9	<i>T3-5</i>	-4.5
<i>VA</i>	47.8	<i>T4-0</i>	-2.3
<i>MB</i>	9.1	<i>T4-5</i>	-12.3
<i>SW</i>	13.2	<i>T6-0</i>	-15.7
<i>C1</i>	5.7	<i>TE</i>	-14.8
<i>C2</i>	-6.1	<i>BA</i>	-18.0

Table 7

Regression models

Model	Feature Combination
M_6	F_1, F_2
M_7	F_1, F_2 , breathing frequency estimated from abdominal belt
M_8	F_3, F_4
M_9	F_3, F_4 , breathing frequency estimated from rib cage belt