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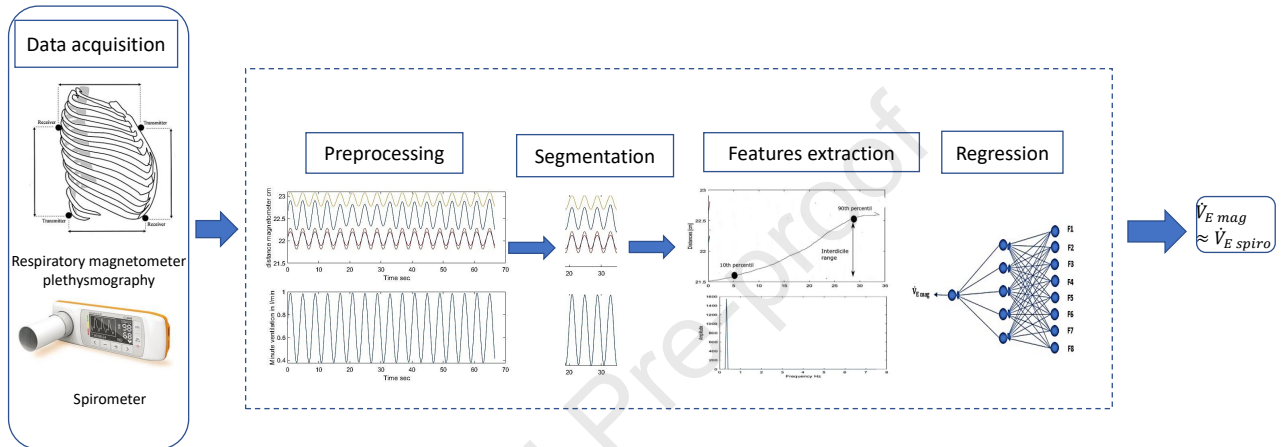
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## Graphical Abstract

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## Highlights

### **A novel algorithm for minute ventilation estimation in remote health monitoring with magnetometer plethysmography**

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- A portable device to accurately estimate minute ventilation using thoracoabdominal distances
- A non-linear model integrated to outperform linear regression models
- A subject-specific approach to further enhance estimation results

Journal Pre-proof

# A novel algorithm for minute ventilation estimation in remote health monitoring with magnetometer plethysmography

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## Abstract

**Purpose** The purpose of this study was to evaluate the accuracy of minute ventilation ( $\dot{V}_E$ ) estimation using a novel method based on a non-linear algorithm coupled with cycle-based features. The experiment protocol was well adapted for remote health monitoring applications by exploiting data streams from respiratory magnetometer plethysmography (RMP) during different physical activity (PA) types. **Methods** Thirteen subjects with an age distribution of  $24.1 \pm 3.4$  years performed thirteen PA ranging from sedentary to moderate intensity (walking at 4 and 6 km/h, running at 9 and 12 km/h, biking at 90 W and 110 W). In total, 3359 temporal segments of 10s were acquired using the Nomics RMP device while the iWorx spirometer was used for reference  $\dot{V}_E$  measurements. An artificial neural network (ANN) model based on respiration features was used to estimate  $\dot{V}_E$  and compared to the multiple linear regression (MLR) model. We also compared the subject-specific approach with the subject-independent approach. **Results** The ANN model using subject-specific approach achieved better accuracy for the  $\dot{V}_E$  estimation. The bias was between  $0.20 \pm 0.87$  and  $0.78 \pm 3$  l/min with the ANN model as compared to  $0.73 \pm 3.19$  and  $4.17 \pm 2.61$  l/min with the MLR model. **Conclusion** Our results demonstrated the pertinence of processing data streams from wearable RMP device to estimate the  $\dot{V}_E$  with sufficient accuracy for various PA types. Due to its low-complexity and real-time algorithm design, the current approach can be easily integrated into most remote health monitoring applications coupled with wearable sensors.

## 1. Introduction

Respiratory failure affects millions of people (Schindhelm and Farrugia 2013) whose lungs are unable to inspire sufficient oxygen or expire sufficient carbon dioxide to ensure the homeostasis of the body. Continuous monitoring of respiratory functions is essential to detect respiratory pathologies such as asthma, obstructive sleep apnea, and chronic obstructive pulmonary disease. It also allows the monitoring of both hospitalized and home care patients to predict high-risk situations, and it is thus considered a vital tool for health care providers (Folke et al. 2003, Sierra et al. 2014). Numerous studies have shown that minute ventilation ( $\dot{V}_E$ ) provides accurate markers for acute respiratory dysfunctions (Schlesinger 2015, Voscopoulos et al. 2013, Voscopoulos et al. 2014). It is defined as the volume of air inhaled or exhaled per minute, or equivalently as the product of the tidal volume ( $V_T$ ) and the breathing frequency (Fr),  $\dot{V}_E = V_T * Fr$ . Due to its importance in respiratory medicine, the precise measurement of  $\dot{V}_E$  over time remains a subject of research interest (Chhabra 2015).

In practice, conventional spirometric techniques have frequently been used to accurately measure the  $\dot{V}_E$  (Miller et al. 2005). However, these techniques require the use of a mouthpiece or a mask inconvenient to wear during various physical activities (PA) and thus unfitted for long-term monitoring, particularly with ambulatory settings. Furthermore, these devices add dead space and resistance to normal breathing (Askanazi et al. 1980, Perez and Tobin 1985, Rameckers et al. 2007). Additionally, the measurements are usually performed in laboratories, and do not necessarily reflect  $\dot{V}_E$  during daily life PA of patients at their home or workplace. To overcome these difficulties, indirect  $\dot{V}_E$

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measurements have been developed by inferring from the rib cage and abdomen movements since the lung volume is a function of these two variables (Konno and Mead 1967). A number of systems and devices have been investigated, including the magnetometers (McCool et al. 2002) and the respiratory inductive plethysmography (RIP) belts (Leino et al. 2001, Hollier et al. 2014). Gastinger et al. (2010) have developed a portable respiratory magnetometer plethysmography (RMP) system, based on the studies of McCool et al. (1986) and Paek and McCool (1992). It is composed of two pairs of electromagnetic coils, each composed of a transmitter and a receiver attached to the rib cage and abdomen to measure the anterior and posterior distances of the rib cage and abdomen. Gastinger et al. (2010) have proposed an accurate method to estimate the  $\dot{V}_E$  using RMP during resting and walking activities.

The calibration procedure is key to the estimation accuracy of  $\dot{V}_E$ . Multiple linear regression (MLR) model is the most commonly used calibration technique based on statistical linear regression. It was adopted by McCool et al. (2002) and Gastinger et al. (2010). Other authors have demonstrated that non-linear machine learning models and especially the artificial neural network (ANN) are more suited to the variability of breathing, as movements of the respiratory system are often associated with non-linear and compound thoracoabdominal interactions during variable breathing (Raoufy et al. 2013; Lin et al. 2012). Dumond et al. (2017) also demonstrated that the ANN is better than the MLR model for predicting other respiratory variables from RMP, such as  $V_T$ .

To investigate the potential of non-linear models on the accuracy of  $\dot{V}_E$  estimation using RMP, we compared the ANN model with the MLR model in Gastinger et al. (2010). To our knowledge, only Gastinger et al. (2010) and Dumond et al. (2017) evaluated RMP to estimate respiratory variables. While Dumond et al. (2017) demonstrated the feasibility of the ANN model,  $\dot{V}_E$  estimation was not included. Gastinger et al. (2010), on the other hand, evaluated the  $\dot{V}_E$  estimation accuracy with resting and walking activities only. Another major contribution of our study is the use of cycle-based respiration features to take into account the phase differences from the raw distance signals instead of the sample-wise regression methods proposed by Dumond et al. (2017) and Gastinger et al. (2010). We hypothesized that measurements of distance changes from the rib cage and abdomen during light to moderate PA contain information about  $V_T$  and  $Fr$ , and that a non-linear ANN model would improve the estimation results with respect to the reference spirometer measurements of  $\dot{V}_E$ .

## 2. Materials and Methods

This study is part of the Sherpam (Sensors for Health Recording and Physical Activity Monitoring) project (<https://project.inria.fr/sherpam/>) that aims to develop a new generation monitoring system to allow health monitoring at home, during indoor and outdoor activities (at work, shopping, sports practicing, etc). Concretely, the project has the ambition to improve the recognition of PA (Rahman et al. 2017) and the estimation of associated energy expenditure in healthy subjects (Khreis et al. 2020; Houssein et al. 2019). A modular Android application aggregates data from various types of sensors and transmits these data to a remote aggregation server for storage and analysis. A web application provides access to the data maintained on the aggregation server, and it can also send alerts to the user's smartphone (see Figure 1). Details on data collection, experimental protocol, instrumentation, and pre-processing data are presented in this section.

### 2.1. Subjects

Thirteen subjects, nine men and four women, aged  $24.1 \pm 3.4$  years voluntarily took part in this study (height  $174.5 \pm 9.4$  cm, weight  $67.5 \pm 9.2$  kg, body mass index  $22.21 \pm 2.32$   $\text{kg}\cdot\text{m}^{-2}$ ). All procedures involving human subjects were approved by the University of Rennes 2 Research Ethics Committee. A written assent has been signed by each subject who had been informed about the development of the study. The subjects were healthy and did not present any pathological disorder.

### 2.2. Experimental protocol

The experiment protocol was composed of a variety of activities of various intensities. During data acquisition, each subject performed three successive postures activities with intervals of 3 minutes of rest: sitting, standing, and lying laterally, for a duration of 3 minutes. These postures were performed in two modes of breathing, natural and paced breathing. In paced breathing mode, subjects control their breathing by following a metronome, with the rhythm fixed at 50 breaths per minute (bpm). After a period of rest, each subject performed a set of PA in a random order: working on a computer, walking at 4 km/h (slope 2%) and 6 km/h, running at 9 km/h (slope 2%) and 12 km/h, cycling at 90 and 110 W. Walking and running activities were performed on a treadmill, and cycling on a cycle ergometer. Each activity



Figure 1: Different stages for health monitoring using Sherpam system.

was performed for 6 min, separated by a 5-minutes rest. In total, 54 min of data were recorded and analyzed for each subject. The tests were conducted under controlled laboratory conditions.

### 2.3. Measurement systems

During all activities, subjects are equipped with a Nomics RMP device (Nomics s.a, Liège Science Park, Belgium), and an iWorx spirometer (BIO-SP304). RMP includes two pairs of electromagnetic coils connected to a device, and each pair is composed of a transmitter and a receiver to measure the temporal variations of the four distances, namely the anteroposterior displacement of the rib cage and abdomen, and the axial displacement of the chest wall and spine (Figure 2). These data are recorded at a frequency of 15 Hz. The spirometer is used as a reference with a sampling frequency of 100 Hz. All data from the electromagnetic coils and the spirometer were exported under Matlab for processing.

### 2.4. Data processing

#### 2.4.1. Preprocessing data

Data collected from spirometer and RMP contains noise and artefacts, especially for those collected during PA (cf upper panel of Figure 3). To reduce noise and artefacts, a low-pass filter was applied with a cut-off frequency of 1.5 Hz, retaining only breathing-related frequency components for human activities between 0.1 and 0.5 Hz. Note that the filtered results in the lower panel of Figure 3 have variable phase delays: peaks and troughs are not synchronized and temporal delays are unfixed among the four channels. Thus, any sample-by-sample regression method would be biased due to the desynchronization effects between channels, and that is why we propose here a cycle-wise estimation method by applying regression on features of each cycle instead of each sample.

#### 2.4.2. Segmentation

Cycle-by-cycle breathing pattern parameters ( $V_T$ ,  $Fr$ ,  $\dot{V}_E$ ) were calculated from the spirometer data. Then, all respiratory signals measured by RMP and spirometer were divided into non-overlapping segments of 10 seconds. A total of 3359 temporal segments was obtained for all subjects.

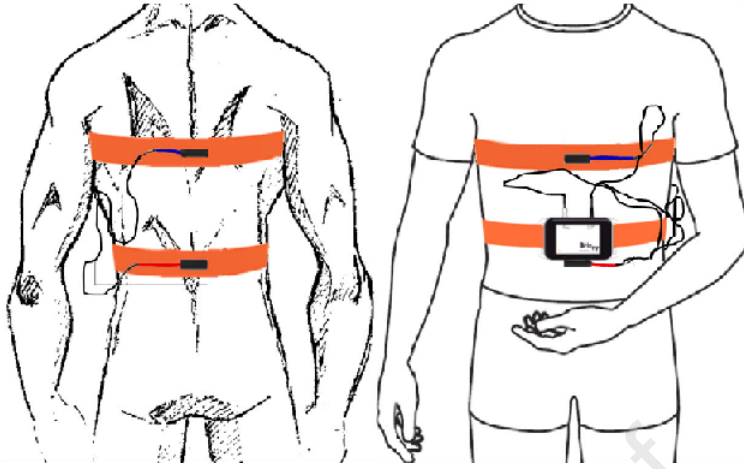


Figure 2: Illustration of the positions of RMP device.

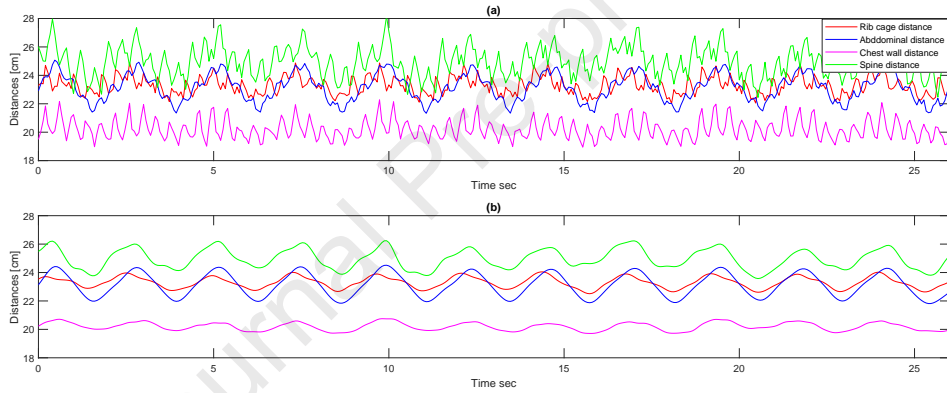


Figure 3: Example of respiratory signals obtained by RMP for a subject during running at 12 km/h a) before processing and b) after processing.

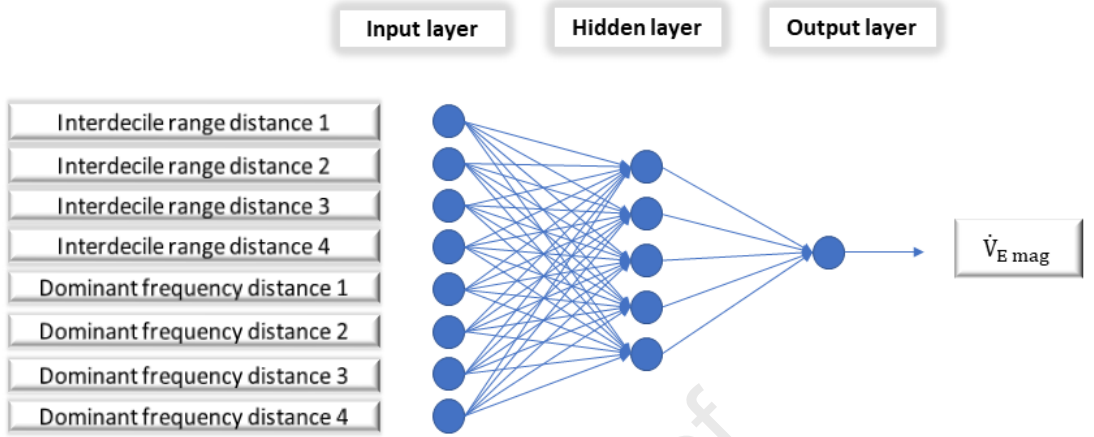
### 2.4.3. Features extraction

Gastinger et al. (2010) and Dumond et al. (2017), have assumed that the respiratory volume can be estimated as a weighted sum of the anteroposterior displacement of the rib cage and abdomen, and the axial displacement of the chest wall and spine on a sample-wise basis:

$$V = \alpha.L_1 + \beta.L_2 + \gamma.L_3 + \delta.L_4 + \epsilon \quad (1)$$

where  $\alpha$ ,  $\beta$ ,  $\gamma$  and  $\delta$  are the regression coefficients to be identified, and  $\epsilon$  is the error of the model. We, however, argue that the sample-wise regression method proposed in Gastinger et al. (2010) and Dumond et al. (2017) does not take into account the phase differences from RMP sensors (cf Figure.3b) whereas features extracted from a segment are indifferent to these phase shifts.

Liu et al. (2012), on the other hand, have shown that by including features such as the 10th and 90th percentiles of the abdominal and rib cage signal, the dominant frequency of the rib cage and abdominal variations, the estimation accuracy of  $\dot{V}_E$  can be further improved. In the current study, we propose to include two features closely related to  $\dot{V}_E$ . One is the interdecile range of the RMP signals to reflect the volume changes in the thoracoabdominal distances in each segment. It is defined by the difference between the 90th and 10th percentiles of the signal in each temporal segment, typically containing several breathing cycles. Another one is the dominant frequency of the respiratory



model.png

**Figure 4:** Artificial neural network architecture for  $\dot{V}_E$  estimation.  
 $\dot{V}_{E \text{ mag}}$ : output of ANN model (minute ventilation estimated).

signals, calculated from its periodogram. The product of the volume change and  $Fr$  is indeed  $\dot{V}_E$  as discussed in the introduction. In the following, regression models are calculated using these two features per channel to estimate  $\dot{V}_E$  for each temporal segment.

#### 2.4.4. Regression and statistical methods

An ANN model was designed and implemented to introduce the non-linear relationships 1) between the variations of thoracoabdominal distances represented by features and the volume change per segment, 2) the measured  $\dot{V}_E$  as the product of volume change and  $Fr$ . An ANN consists of neurons organized into a series of layers of nodes interconnected by weighted arcs. The ANN model learning procedure is based on a feedforward/backward approach. In our study, we used a three-layer architecture as shown in Figure 4 containing an 8-node input layer, each corresponding to a feature, followed by a hidden layer, and then a single-node output layer to output the target value  $\dot{V}_E$ . The hyperbolic tangent sigmoid transfer function `transig` was used for the hidden layers, and the linear transfer function `purelin` for the output layer.

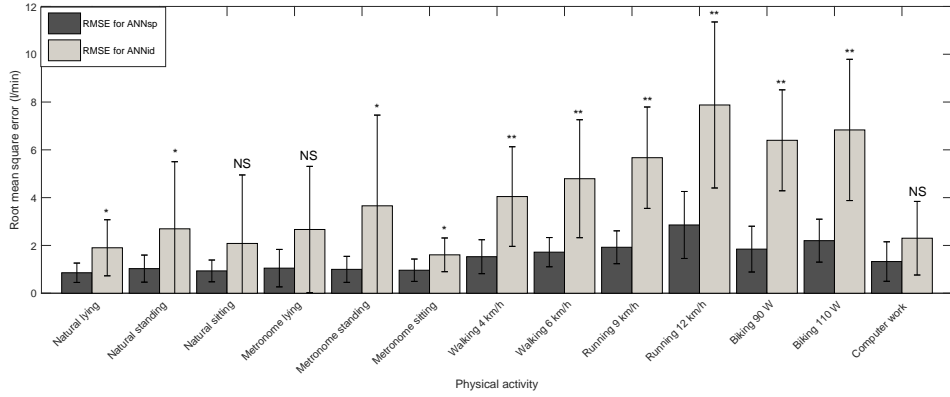
The ANN model was trained using two approaches: a subject-specific approach (ANN<sub>sp</sub>) in which ANN model was trained for each subject separately. The estimation performance was assessed using 5 fold cross-validation. The second ANN approach was a subject-independent approach (ANN<sub>id</sub>) in which ANN model was trained using all but one subject's data. The performance was calculated for the left-out subject, each subject was left out in turn. We compared also ANN<sub>sp</sub> to a linear model (MLR) trained using a subject-specific approach as used by Gastinger et al. (2010). The performance of models was evaluated by their root mean square error (RMSE):

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (\dot{V}_{E \text{ mag}i} - \dot{V}_{E \text{ spi}i})^2}{n}} \quad (2)$$

where  $\dot{V}_{E \text{ mag}i}$  and  $\dot{V}_{E \text{ spi}i}$  represent  $\dot{V}_E$  from estimation and the spirometer measurement respectively.  $n$  is the total number of temporal segments.

We have also evaluated the agreement between  $\dot{V}_{E \text{ mag}}$  and  $\dot{V}_{E \text{ sp}}$  by plotting the values of  $\dot{V}_{E \text{ mag}}$  against the values of  $\dot{V}_{E \text{ sp}}$ , and by calculating the coefficient of determination. The mean differences (bias) were also reported.





**Figure 5:** Performance (RMSE) for the two ANN approaches: Comparison between ANNsp and ANNid. NS: non significant difference:  $p>0.05$ . \*: significant difference:  $p<0.05$ . \*\*: high significant difference:  $p<0.01$ .

### 3. Results

#### 3.1. Comparison between ANNsp and ANNid

RMSE of the two training approaches (ANNsp and ANNid) of the ANN model is reported in the Figure 5. Our results show that ANNid yielded significantly larger errors than ANNsp. The RMSE range is 1.60-7.85 l/min for the ANNid while that of the ANNsp is 0.85-2.85 l/min. In addition, in both ANN models the error increases with the PA intensity. Specifically, the RMSE of postures activities in the ANNsp approach is between 0.85 l/min and 1.05 l/min (for naturally sitting and metronome lying respectively). These RMSE values were much lower than those of walking (4 km/h) and running (12 km/h), between 1.52 l/min and 2.85 l/min respectively.

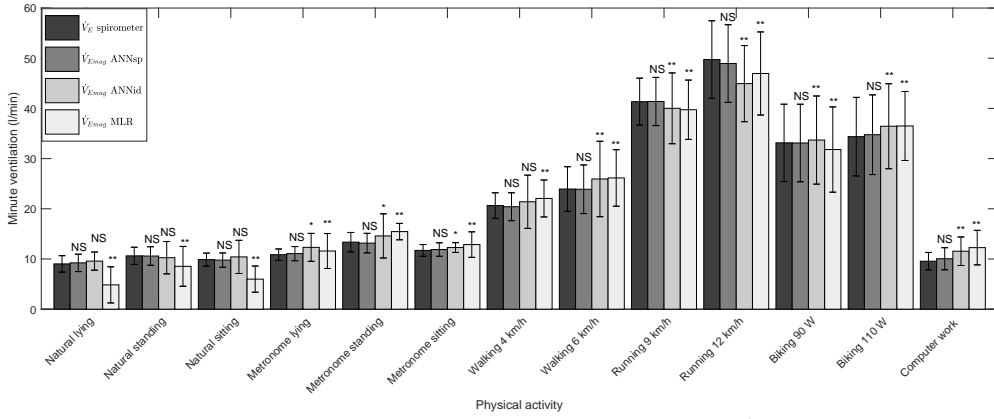
The mean values of  $\dot{V}_E$  measured by the spirometer ( $\dot{V}_{Esp}$ ), and estimated by the magnetometers ( $\dot{V}_{Emag}$ ) are illustrated in Figure 6. Our results show that there are no significant differences between  $\dot{V}_{Emag}$  and  $\dot{V}_{Esp}$  for all activities in the ANNsp ( $p>0.05$ ). Likewise, for ANNid, there are no significant differences between mean  $\dot{V}_{Esp}$  and  $\dot{V}_{Emag}$  for natural postures activities (standing, lying, sitting and computer work) and walking at 4 km/h ( $p>0.05$ ), while a highly significant difference ( $p<0.01$ ) between  $\dot{V}_{Emag}$  and  $\dot{V}_{Esp}$  appears for PA (walking at 6 km/h, running and biking).

The mean differences between  $\dot{V}_{Esp}$  and  $\dot{V}_{Emag}$  (bias) were also calculated from all activities for the two ANN approaches (ANNsp and ANNid) (Table 1). Our results show that the bias is low for all activities in the ANNsp. In addition, the bias for the ANNid (bias range 0.36-4.78 l/min) is significantly greater ( $p<0.01$ ) than the bias for the ANNsp (bias range 0.02-0.78 l/min) except for postures activities and biking at 90 W. Indeed, the bias reaches its maximum in higher intensity exercises such as running at 12 km/h for both ANN approaches: reaching  $0.78 \pm 3.00$  and  $4.78 \pm 7.23$  l/min for ANNsp and ANNid respectively. The pooled data of  $\dot{V}_E$  for all postures and PA are shown in Figure 7. We note that  $\dot{V}_{Emag}$  was highly correlated with  $\dot{V}_{Esp}$  ( $R^2=0.98$ ) in ANNsp (Figure 7a) compared with that of the ANNid ( $R^2=0.84$ ) (Figure 7b).

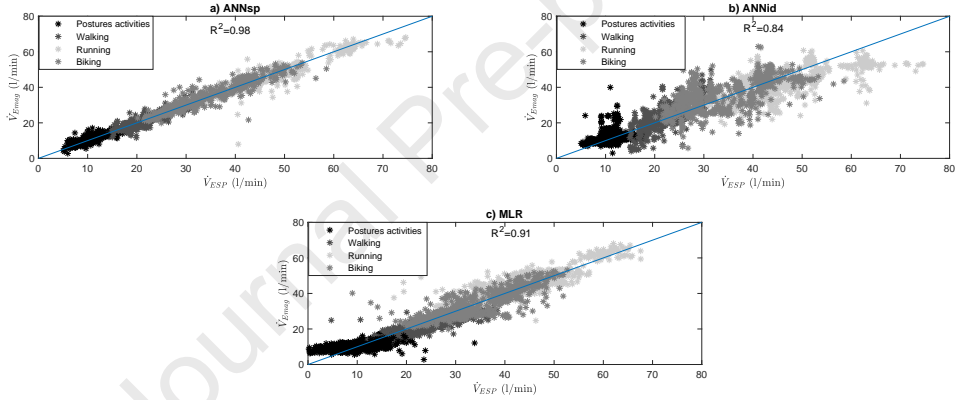
#### 3.2. Comparison between ANNsp and MLR

The RMSE was also used to compare the ANNsp and MLR model (Figure 8). The RMSE range of the ANN model (0.84 – 2.84 l/min) is significantly lower ( $p<0.05$ ) than that of the MLR model ( 2.73 – 5.19 l/min). Moreover, for the MLR model in all activities, there is a highly significant difference ( $p<0.01$ ) between mean values measured by spirometer ( $\dot{V}_{Esp}$ ), and those estimated by magnetometers ( $\dot{V}_{Emag}$ ), as shown in Figure 6. In addition, the bias range of the ANNsp (0.03 – 0.78 l/min) is significantly lower ( $p<0.01$ ) than that of the MLR model (1.15 – 4.17 l/min) for all the activities (Table 1).

Figure 7 (a and c) shows that the ANNsp model is better correlated with the reference ( $R^2 = 0.98$ ) than MLR model ( $R^2 = 0.91$ ) for the estimation of  $\dot{V}_E$ . In addition, the disparity from the line of identity and thus the errors are more important when the intensity of PA is higher.



**Figure 6:** Mean values of minute ventilation in l/min measured by spirometer and estimated by RMP. NS: non significant difference between  $\dot{V}_{Esp}$  and  $\dot{V}_{Emag}$ :  $p > 0.05$ . \*: significant difference between  $\dot{V}_{Esp}$  and  $\dot{V}_{Emag}$ :  $p < 0.05$ . \*\*: high significant difference between  $\dot{V}_{Esp}$  and  $\dot{V}_{Emag}$ :  $p < 0.01$ .



**Figure 7:** Pooled data of  $\dot{V}_E$  measured by spirometer and estimated by magnetometer in postures and physical activities.

### 3.3. ANNsp optimization

Results presented in Figure 9 show that the optimal number of nodes in the hidden layer of the ANN structure was 10 and the optimal number of layers was 1, for all categories of activities. Further, increasing the number of nodes in the hidden layer and the number of layers no longer contributes to lower RMSE. On the contrary, even worse results are observed when more nodes and layers are added resulting in an overfitting configuration.

## 4. Discussion

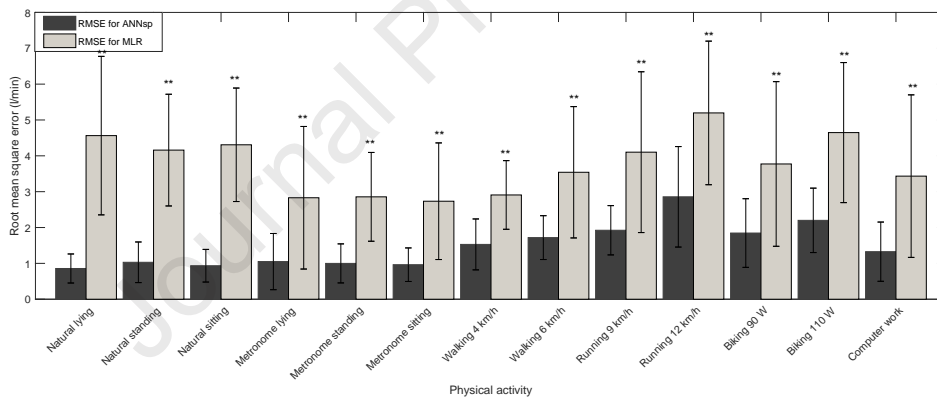
The purpose of this study was to evaluate the accuracy of RMP for  $\dot{V}_E$  estimation using a novel method based on cycle-based features during different types of PA based on the studies of Liu et al. (2012) and Dumond et al. (2017). Gastinger et al. (2010) have previously validated RMP for resting and walking activities using a sample-wise linear regression method. In our study, RMP was also validated for  $\dot{V}_E$  estimation during different postures and PA of daily life: sitting, standing, lying, running, walking, biking, working on PC. Its small size and light-weight are the key advantages as an alternative to spirometers that limit the free movement of the subject during ambulatory conditions.

Our ANNsp method showed no significant difference compared with the reference measurements from spirometer ( $\dot{V}_{Esp}$ ), in terms of both RMSE and bias. This result is found for all activities: sitting, standing, lying, walking, running, and biking. We have thus proven the validity of RMP during light to moderate PA. On the other hand, significant

**Table 1**  
Mean differences between  $\dot{V}_{Esp}$  and  $\dot{V}_{Emag}$ .

Activity	ANNsp (l/min)	ANNid (l/min)	MLR (l/min)
Natural lying	-0.20 ± 0.87	-0.55 ± 2.13 <i>NS</i>	4.17 ± 2.61 ##
Natural standing	0.03 ± 1.13	0.36 ± 3.82 <i>NS</i>	2.08 ± 3.99 ##
Natural sitting	0.10 ± 0.99	-0.53 ± 3.69 <i>NS</i>	3.89 ± 2.13 ##
Metronome lying	-0.21 ± 1.10	-1.46 ± 3.11 **	-0.73 ± 3.19 ##
Metronome standing	-0.19 ± 0.98	-1.23 ± 5.28 **	-2.09 ± 2.05 ##
Metronome sitting	-0.17 ± 1.00	-0.57 ± 1.68 **	-1.15 ± 2.79 ##
Working computer	-0.49 ± 1.34	-1.98 ± 2.07 **	-2.70 ± 2.92 ##
Walking 4 km/h	0.22 ± 1.61	-0.76 ± 4.41 **	-1.42 ± 2.76 ##
Walking 6 km/h	0.04 ± 1.76	-2.00 ± 4.98 **	-2.21 ± 3.32 ##
Running 9 km/h	-0.03 ± 2.03	1.32 ± 5.63 **	1.60 ± 4.23 ##
Running 12 km/h	0.78 ± 3.00	4.78 ± 7.23 **	2.77 ± 4.89 ##
Biking 90 W	0.02 ± 2.23	-0.55 ± 6.75 <i>NS</i>	1.33 ± 4.51 ##
Biking 110 W	-0.38 ± 2.47	-2.07 ± 7.21 **	-2.12 ± 4.84 ##

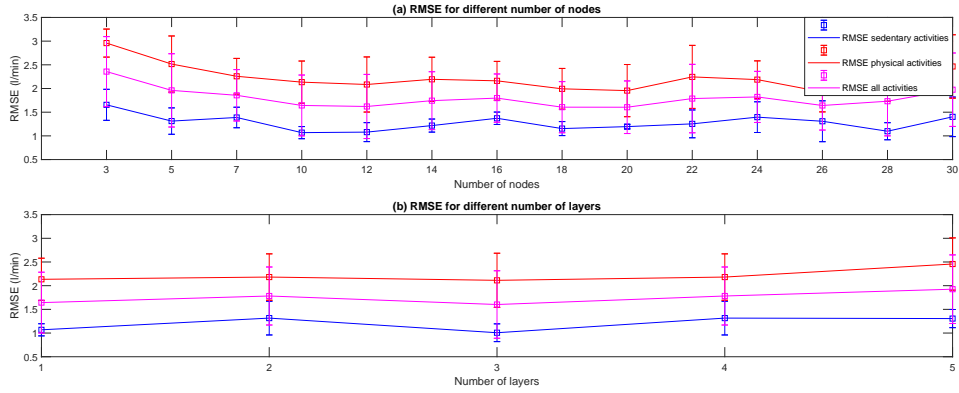
NS: non significant difference between bias of the ANNsp and ANNid ( $p > 0.05$ ).  
 \*\*: high significant difference between bias of the ANNsp and ANNid ( $p < 0.01$ ).  
 ##: highly significant difference between ANNsp and MLR.



**Figure 8:** RMSE for the ANN and MLR model: Comparison between ANNsp and MLR model.  
 NS: non significant difference:  $p > 0.05$ . \*: significant difference:  $p < 0.05$ . \*\*: high significant difference:  $p < 0.01$ .

differences exist between  $\dot{V}_{Esp}$  and  $\dot{V}_{Emag}$  using either the ANNid or the MLR model. The ANNsp method achieved better results ( $R^2 = 0.98$ ) compared to those using the MLR model ( $R^2 = 0.91$ ) and ANNid ( $R^2 = 0.84$ ). These results validate our hypothesis and the proof of concept to estimate  $\dot{V}_E$  for both resting and PA.

Our results corroborate several previous studies in similar contexts in the literature. The accuracy of the ANN model to estimate  $\dot{V}_E$  was evaluated by Lin et al. (2012) and Nyhan et al. (2014) during exercises performed by healthy subjects. Both studies reported that the ANN model achieved better performances compared to a partial least squares (PLS) model. Lin et al. (2012) reported a mean difference of 0.9% between the reference  $\dot{V}_E$  from differential pressure pneumotachograph and the ANN estimations versus 7.1% with the PLS model. Similarly, Nyhan et al. (2014) found a smaller mean percentage error for  $\dot{V}_E$  with the ANN model (2.4%) as compared to the PLS model (5%). Raoufy et al. (2013) compared two non-linear models for the estimation of respiratory volume based on thoracoabdominal distance variations: the ANN and the adaptive neuro-fuzzy inference system vs the MLR model. They showed that both non-linear models estimated  $\dot{V}_E$  variations that fitted the spirometer volume curves significantly ( $p < 0.05$ ) better than those with the linear methods. Recently, Dumond et al. (2017) compared a linear MLR model and a non-linear



**Figure 9:** RMSE as a function of the number of nodes in the hidden layer and the number of layers.

ANN model to estimate respiratory volume. They found that the ANN model performed significantly better than the MLR model to estimate respiratory volume. The difference (bias) between respiratory volume measured by spirometer and estimated using RMP was higher for the MLR model ( $0.0019 \pm 0.14$  L) than for the ANN model ( $0.0015 \pm 0.15$  L). Indeed, physiological time series obtained from the cardiopulmonary system are non-stationary (Suki et al. 2003, Zhang and Bruce 2000) and are often associated with complex thoracoabdominal interactions, especially when respiratory movements are irregular (Poole et al. 2000, Smith and Mead 1986, Dumond et al. 2017). Therefore, a model that may be adapted to this type of non-linearity would be useful.

Additionally, the comparison of the RMSE and bias between the two ANN approaches (ANNsp and ANNid) showed that the subject-specific approach (ANNsp) outperforms that of the subject-independent approach (ANNid). This is mainly due to the inter-subject variability: the non-linear relationship between deformations and minute volume changes from one subject to another. The ventilation response also differs between subjects due to the differences in elastic properties of the respiratory system, depending on the size and morphology of the subjects (Chowdhuri and Badr 2017, Pinna et al. 2006). Thus, a subject-specific approach should be advised in the estimation of  $\dot{V}_E$  to maximize estimation accuracy. Our results were closely related to other studies, such as Liu et al. (2012). Gastinger et al. (2010) also suggested that mathematical equations must be developed for each subject to estimate  $\dot{V}_E$  from the RMP measurements.

Finally, whatever the model used, it seems that estimation errors always increase with physical intensities. These results are expected because of the greater range of  $\dot{V}_E$  during exercises of higher intensities. Furthermore, during intense PA, more movements occur that are not necessarily related to respiration (Saunders et al. 2004, Dumond et al. 2017), but could lead to increasing estimation errors.

Note that our study only covers the activities under laboratory conditions and restricted to structures of fixed durations. Future research efforts should include free-living PA of randomized orders and durations. Indeed, future RMP developments are expected to cater for remote monitoring under free-living conditions for patients with cardiovascular or pulmonary diseases. Such applications should include functions such as continuous assessment of respiratory functional status, and early-stage diagnosis of severe respiratory dysfunctions. These would require the use of simple, reliable, and reproducible methods across a variety of daily PA without specific subject cooperation by integrating more complex machine learning methods to deal with intra- and inter-subject variabilities.

## 5. Conclusion

We have proposed a novel method for  $\dot{V}_E$  estimation based on cycle-based features extracted from wearable RMP device under light-to-moderate PA. The combination of the non-linear ANN model with a subject-specific approach is shown to be more effective than the linear regression approach (MLR). Results also demonstrated the feasibility of individualized  $\dot{V}_E$  monitoring during different postures and PA conditions, paving the way for the more sophisticated energy expenditure estimation in various health monitoring applications for all PA types.

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## Highlights

### **A novel algorithm for minute ventilation estimation in remote health monitoring with magnetometer plethysmography**

Aya Houssein, Di Ge, Steven Gastinger, Remy Dumond, Jacques Prioux

- A portable device to accurately estimate minute ventilation using thoracoabdominal distances.
- A non-linear model integrated to outperform linear regression models.
- A subject-specific approach to further enhance estimation results.

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**Conflict of Interest**

There are no conflicts of interest regarding this research.

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