DeepVentilation: Learning to Predict Physical Effort from Breathing

Sagar Sen[1*] , **Pierre Bernabé**[1] , **Erik Johannes B. L. G. Husom**[2]
[1]Simula Research Laboratory, Pb 135, 1325 Lysaker, Norway
[2]Department of Physics, University of Oslo, Norway
{sagar, pierbernabe}@simula.no, ejhusom@uio.no

Abstract

Tracking physical effort from physiological signals has enabled people to manage required activity levels in our increasingly sedentary and automated world. Breathing is a physiological process that is a reactive and realistic representation of physical effort. In this demo, we present **DeepVentilation**, a deep learning system to predict *minute ventilation* in litres of air a person moves in one minute uniquely from real-time measurement of rib-cage movement due to breathing. DeepVentilation has been trained on input signals of expansion and contraction of the rib-cage obtained using a non-invasive respiratory inductance plethysmography sensor to predict minute ventilation as observed from a face/head mounted exercise spirometer. The system is used to track physical effort closely matching our perception of actual exercise intensity. The source code for the demo is available here: *https://github.com/simula-vias/DeepVentilation*

1 Introduction

Global physical activity levels have declined substantially over the last five decades [Ozemek *et al.*, 2019]. Therefore, a market for consumer wearable devices to track number of steps [Bassett *et al.*, 2017], and heart rate [Thomson *et al.*, 2019] has grown enormously in our so-called *health society* [Adams, 2019]. Step counting is tremendously popular with devices such as the FitBit [Diaz *et al.*, 2015] and the Apple Watch [Veerabhadrappa *et al.*, 2018] where people aim to reach the quintessential 10,000 steps per day [Schneider *et al.*, 2006]. Heart rate monitors have been popular with athletes for several years since their invention in 1977 by Polar Elektro. The integration of *near infrared spectroscopy* (NIRS) on smartwatches has made heart rate measurement ubiquitous. Heart rate measures *intensity of work* and goes beyond step counting to provide a more fine-grained feedback on physical effort. However, the heart rate exhibits *cardiovascular drift* [Coyle and Gonzalez-Alonso, 2001] which refers to the increase in heart rate that occurs during prolonged endurance exercise with little or no change in workload. In addition, heart rate is slow to react to the real physical effort which sometimes varies quickly such as in high-intensity interval training (HIIT). Therefore, we ask, can our breathing help us predict physical effort in a more reactive and representative manner?

DeepVentilation is a deep learning system that has been trained to predict *minute ventilation* in litres per minute directly from the expansion and contraction of the breathing muscles around the ribcage. The output minute ventilation is the amount of air a person moves in one minute which is typically measured using a face/head mounted exercise spirometer. While, the input is the measurement of breathing forces (in *millivolts* across a strain gauge) due to ribcage expansion and contraction. It is measured from a *respiratory inductance plethysmography* (RIP) sensor called Flow [1] [Laugstøl, 2018]. The raw ribcage movement signals contain information about change in lung volume which DeepVentilation leverages to predict minute ventilation. Minute ventilation as predicted by DeepVentilation instantly follows exercise intensity (in comparison to standard heart rate) matching the user's perception of physical effort.

The rest of the article is organized as follows. In Section 2, we describe the data set used to train DeepVentilation. In Section 3, we present the complete architecture of DeepVentilation and it evaluate with respect to ground truth data from a spirometer. We conclude in Section 4.

2 Training Data

Predicting minute ventilation required us to collect ground truth data from an exercise spirometer at the same time as obtaining data from a RIP sensor. The data collection has been performed by exercise physiologists at the Norwegian School of Sports Science[2] as part of a joint project.

We carried out measurements from five subjects (all male, aged 26±1 years), on a cycle ergometer (17980 Lode Excalibur Sport, Lode BV, Groningen, Netherlands) during a sub-maximal exercise test (at three different power levels) as well as an incremental exercise/ramp test. These measurements were repeated for each subject on two separate

*Contact Author

[1]http://www.sweetzpot.com/flow

[2]http://www.nih.no

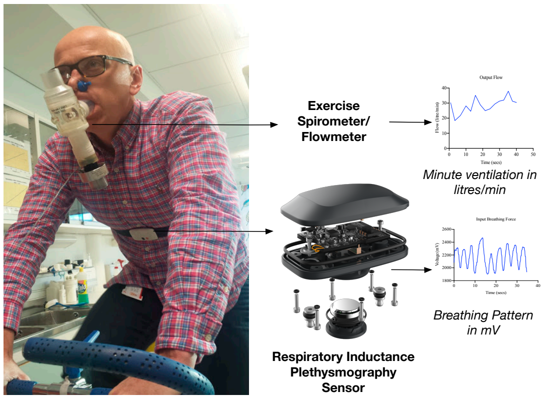

Figure 1: Training Data from a Spirometer and a RIP sensor

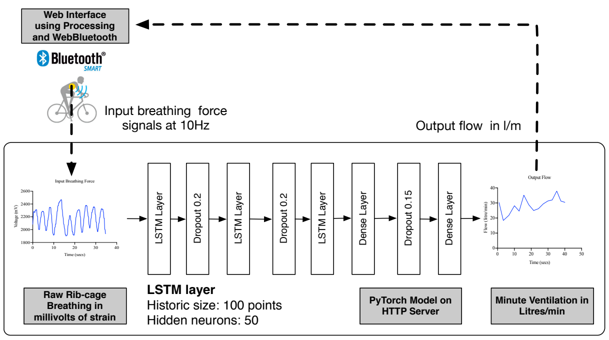

Figure 2: DeepVentilation's Architecture

days. We obtained input rib-cage movement data using the Flow RIP sensor containing a *semi-conductor strain gauge* measuring forces through the click on button attached to a chest strap as shown in Figure 1. The output tidal volume and minute ventilation was measured simultaneously with a Douglas Bag (components from Harvard Apparatus, Kent, UK) also shown in Figure 1. The data was synchronized by means of *three deep breaths*. The measurements were carried out over a period of seven weeks. The data is made available in four columns: *timestamp (s), minute ventilation (l/m), ribcage movement (mV), heart rate (bpm)* to a deep learning model.

3 Architecture

DeepVentilation's architecture is illustrated in Figure 2. Ribcage breathing data (strain in the range 0 to 4096mV) is transmitted via Bluetooth Low Energy protocol [Nikodem and Bawiec, 2020] to a Web Application running on Google Chrome. DeepVentilation transforms a sliding window of received values to one value in litres/min (l/m) using several layers of *long short term memory networks* (LSTMs)[Greff *et al.*, 2016] as shown in Figure 2. The LSTM network model is implemented in PyTorch [Lerer *et al.*, 2019] and is available as a running web service through a RESTful web API [Richardson *et al.*, 2013]. We use an LSTM model because its recurrent neural network architecture is capable of learning long-term dependencies in a sequence of raw breathing data. The dropout layers in the architecture are used to regularize each LSTM layer by dropping neurons with a probability of 0.2. It is an effective method to remove large weights that may cause over-fitting of the data. The last layer in the network is a dense fully connected layer that transforms 10 values from the last LSTM node to a single value in l/m. A sequence of 100 points of raw breathing data sampled at 10Hz is sent in a request to the neural network model. The web application receives a response from the API and renders the predicted minute ventilation in real-time. The real-time feedback is developed using the P5.js [McCarthy, 2015] and sensor connectivity is handled via Web Bluetooth [3].

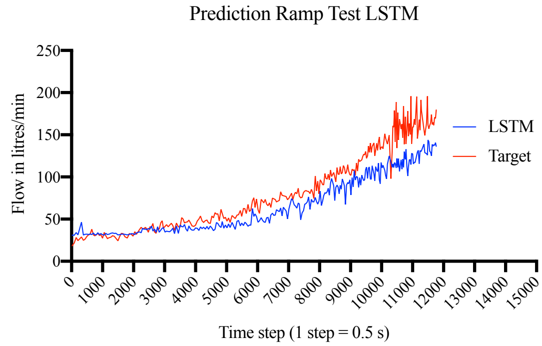

Figure 3: Evaluation of LSTM Model in DeepVentilation

3.1 Evaluation

We compared the output of DeepVentilation's LSTM model to the ground truth data obtained from the exercise spirometer as shown in Figure 3. The evaluation shown in the figure corresponds to a ramp test where a user starts at low power output and gradually increases power output until he in this case could no longer increase power output. In 90 % of the breathing data we observed a maximum deviation of 20 % from the ground truth. The LSTM model exhibits lower fluctuation which gives a perception of stability to a user. We believe that the model will improve in accuracy if a second sensor is used to also measure abdominal breathing. Nevertheless, for an easier user experience our aim is to achieve reasonable accuracy primarily from ribcage breathing.

4 Conclusion

DeepVentilation is a system that predict physical effort based on minute ventilation. It can continually improve with additional data from different endurance sports. DeepVentilation can handle uncertainty due to muscular artifacts from movements other than breathing, sensor position on the body and strap tightness. It can also be trained to distinguish between genders, age, weight, height, and fitness level for diverse user groups. Novel neural network models such as attention-based transformer models[Vaswani *et al.*, 2017] can improve prediction accuracy as it is independent of the sequence of input data.

[3] https://webbluetoothcg.github.io/

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Demo Setup

Material Requirements

- Flow[4] sensors arranged by author (one or two)
- Laptop computer with Bluetooth Low Energy with Google Chrome Browser arranged by author
- Internet access to download Github repo https://github.com/simula-vias/DeepVentilation
- Indoor bike (optional if possible to borrow from organizer)
- Large screen 20" with power supply to be obtained from organizer
- Poster stand to explain DeepVentilation to be obtained from organizer
- A large table for the screen and laptop.
- Floor space of $7 - 10m^2$ for bike, poster, table, screen, and presenter.

Demo Steps

The demo will be organized in the following steps:

Step 1. The user wears a Flow sensor around the ribcage. The sensor will be paired to DeepVentilation and the raw breathing pattern will be visible on the screen. The prediction of minute ventilation will appear shortly after on the interface.

Step 2. The user will generate physical effort by running or indoor cycling. The resulting breathing pattern and minute ventilation will appear immediately on the screen.

Step 3. The user will change exercise intensity to visualize changes in minute ventilation computed by DeepVentilation and compare it to an external heart rate monitor.

Step 4. Feedback from the users at the demo stall will be collected anonymously about the system to help improve the system.

[4]https://www.sweetzpot.com/flow