

DeepVentilation: Learning to Predict Physical Effort from Breathing*



Sagar Sen, SINTEF Digital, Norway sagar.sen@sintef.no



Pierre Bernabé, Simula Research Laboratory, Norway pierbernabe@simula.no



Erik Johannes Husom, Department of Physics, University of Oslo, Norway ejhusom@uio.no

Background

Activity tracking has become ubiquitous through smartphones and wearables, as a popular tool for motivating and measuring physical activity. Traditional ways of effort tracking often rely on heart rate, which react slowly to change in intensity, and also exhibits cardiovas cular drift [1]. Our breathing, on the other, responds more quickly to intensity change during physical activity. This research project aims to explore how deep learning can be used to estimate physical effort from breathing. Specifically, we estimate the airflow (minute ventilation) from movement of the chest, also called respiratory inductive plethysmography (RIP). One challenge with using RIP is that the input data can be noisy, as a result of muscular artifacts from movement other than breathing, variation in sensor position and strap tightness. This is why we use deep learning as a method for estimating the airflow, because it can handle this uncertainty.

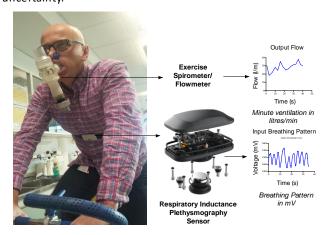


Figure 1: Experimental setup, where the airflow and chest movements of a cyclist is measured during a workout.

Data was collected from five male subjects of age 26±1 years, who performed two different workout protocols: Submaximal effort and incremental effort.

Approach and tool: DeepVentilation

DeepVentilation is a tool using a neural network to estimate the airflow of a person based on respiratory inductance plethys mography. Figure 2 shows the pipeline of the tool, and an outline of the network architecture. Figure 3 shows our results on the test data, with a Pearson correlation coefficient of 0.75.

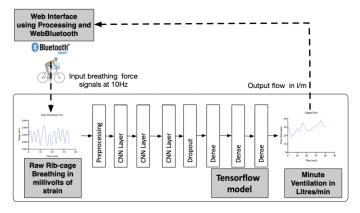


Figure 2: The input data is collected using WebBluetooth, which is then passed to preprocessing. A pretrained model is then used to estimate the current airflow, which are then displayed in the web interface.



Figure 3: This plot shows the ground truth (blue) together with the estimated airflow (red) on the tests et.

Demonstration

Figure 4 shows a demonstration setup of our tool, where a person wearing an RIP sensor on his chest is cycling on an ergometer bike. The raw RIP data is displayed in the top graph, and the estimated airflow is shown in the middle graph. The bike is also connected to the web app, in order to display the effort measured in watt in the bottom graph. The real-time prediction tool can be found at: https://github.com/simula-vias/DeepVentilation

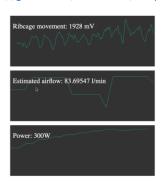




Figure 4: Demonstration of DeepVentilation. Screendump of the web application (left) and a cyclist wearing the RIP sensor (right).

Conclusion

Breathing can reactively estimate effort through the use of deep leaming. Improvements can be made by collecting data from more subjects, with greater diversity in age, gender and fitness level. Improvement may also be achieved by adjusting the network architecture. Possible future works include estimation of aerobic thresholds, and applying these methods to other activity forms than cycling.

References

[1] Edward F Coyle and J Gonzalez-Alonso. Cardiovas cular drift during prolonged exercise: new perspectives. Exercise and sport sciences reviews, 29(2):88–92, 2001