Improvement in Accuracy of Regression Estimates of Oxygen Consumption (VO_2) From Wireless Sensors by Incorporating Muscle (EMG) Sensor Data

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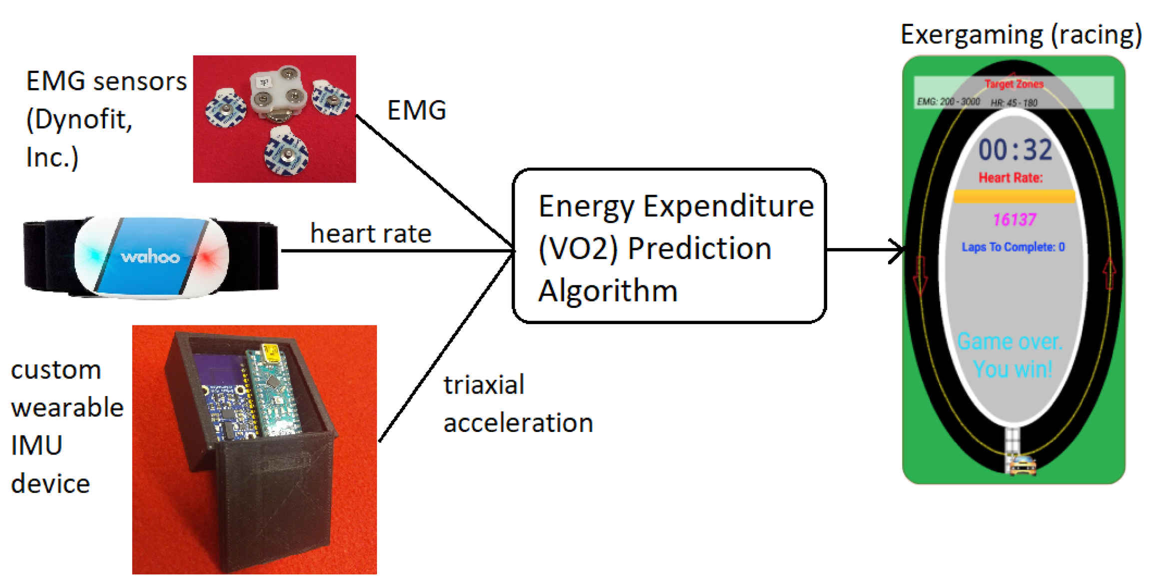
Background

Fitness trackers and activity monitors provide useful information to users regarding their physical activities performed such as the number of calories burnt. Such information presents a source of motivation for the user to adhere to a consistent workout regimen. Therefore, it is important for activity monitors to provide real-time calculations for energy expenditure from wireless sensors. VO2, or oxygen consumption, is the gold standard of measuring energy expenditure. Most current activity monitors rely on heart rate and accelerometry for energy expenditure calculations and detect steps, but these have limitations in accuracy and reliability. None have yet been developed specifically for users who use wheelchairs for physical activity.
We have already developed an app to perform mobile fitness tracking and exergaming. We focus here on improving the accuracy of measuring energy expenditure.



Objectives

Our goal was to determine whether incorporating wireless electromyography (EMG) sensors could yield more accurate estimations of energy expenditure by reliably modelling of VO2.

Prediction methods

Single linear regression using HR vs. VO2

$$\hat{Y}(S) = b_0 + b_1 S$$

Logistic fit using HR vs. VO2

$$\hat{Y}(S) = K / (1+e^{-r(S-120)})$$

Multiple linear regression using EMG and HR vs. VO2

$$\hat{Y}(S) = b_0 + b_1S_1 + b_2S_2 + \dots + b_nS_n$$

Optimal linear filter using EMG and HR vs. VO2

$$\hat{Y}(S) = \Sigma_k h_k * S_k$$

Experimental Protocol

Data was collected from 6 subjects:

- 4 with spinal cord injury and 2 without
- ages ranging from 22-58 years old
- weights ranging from 54-115 kg.

Each subject performed the following three workouts seated in a wheelchair.

- Spinning – Subjects spun wheelchairs forwards and backwards on stationary rollers.
- Resistance – Subjects used resistance arm bands to perform 5 isometric contractions for each of 6 different muscle groups.
- Exchange – Fast-paced exercise in which subjects threw a 20.7 cm diameter ball against a wall and caught it.

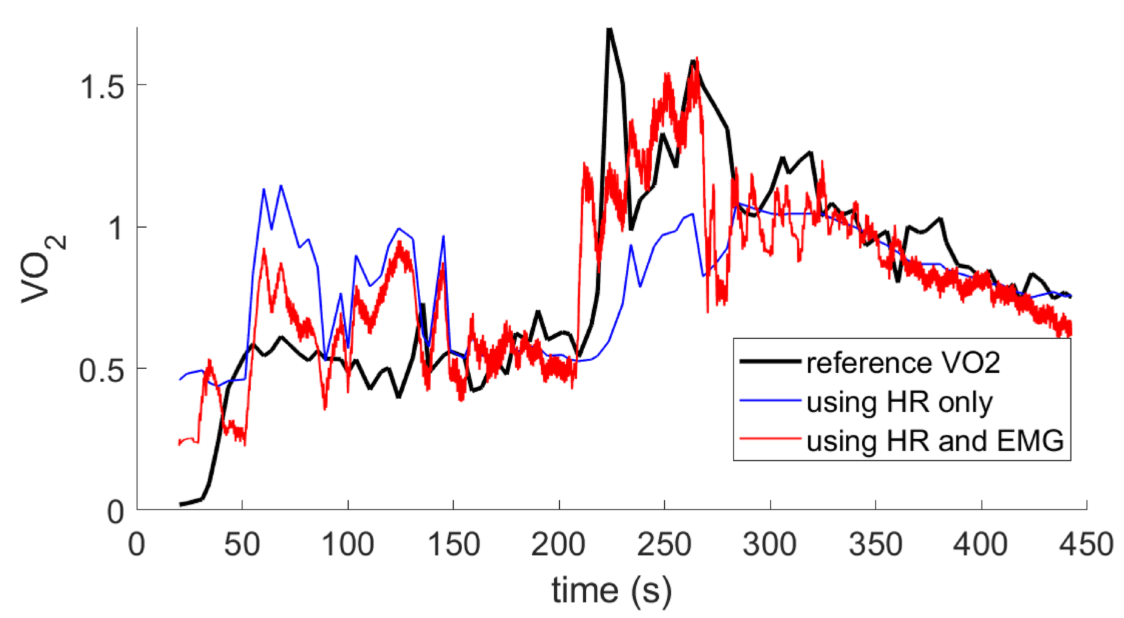
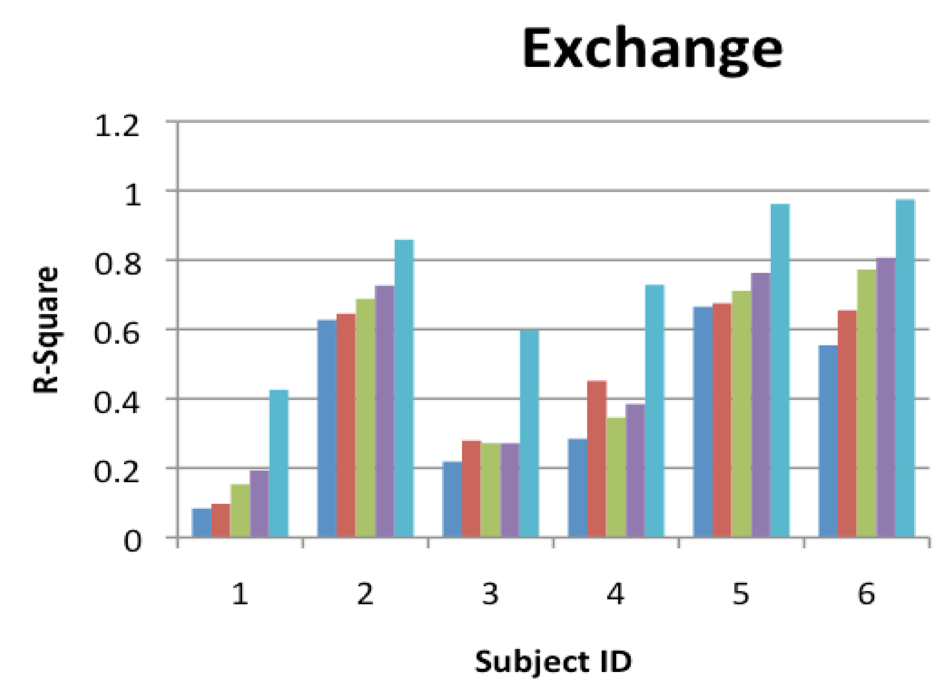
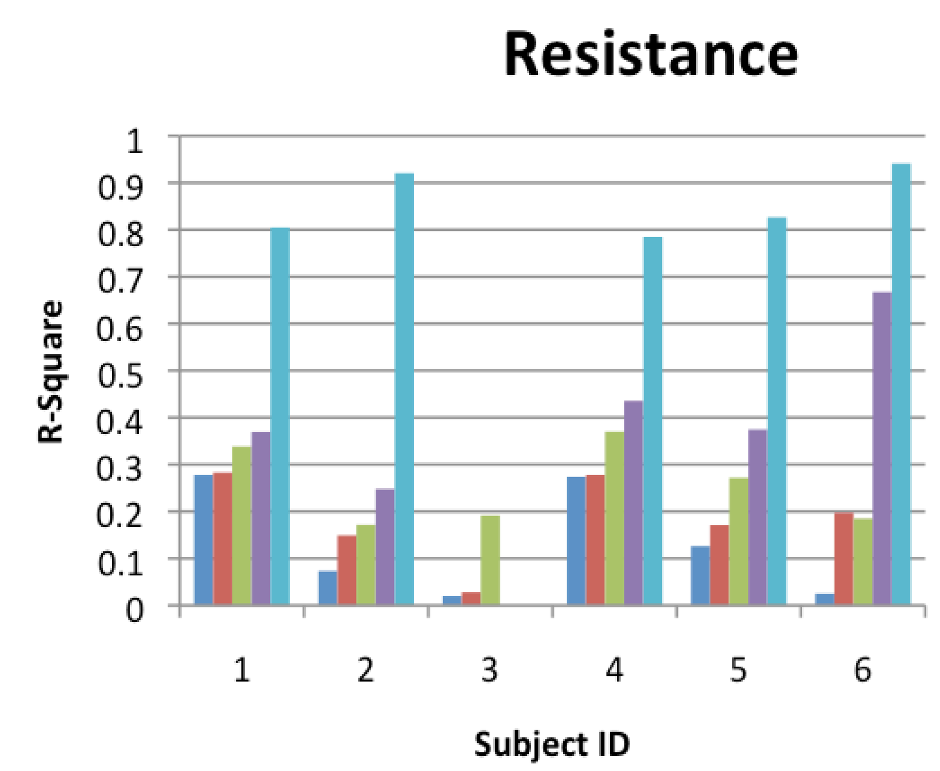
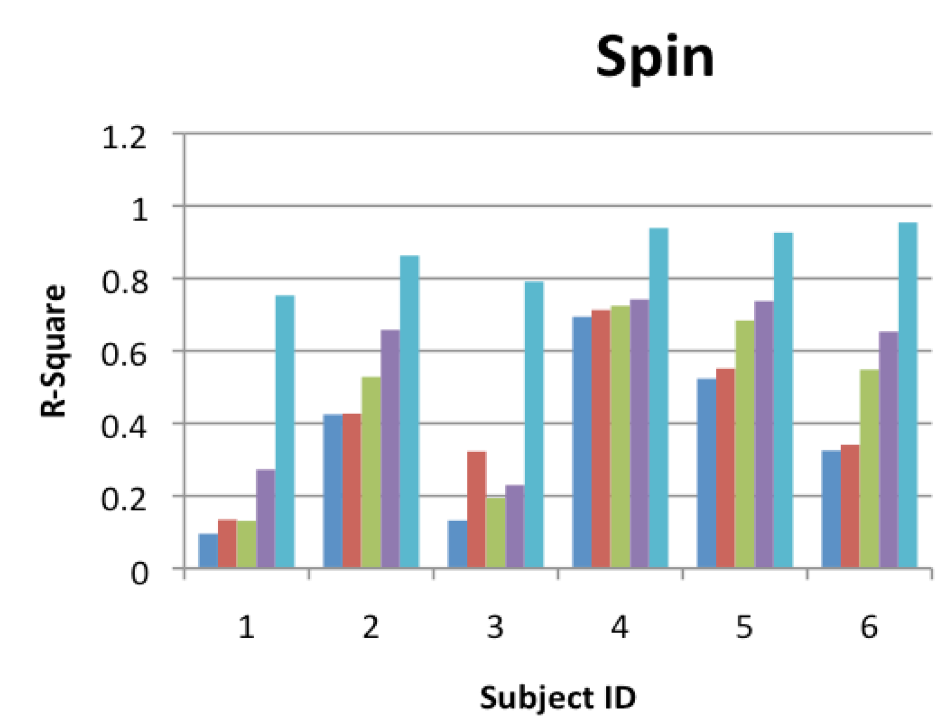


Figure 2) Predictions of VO2 (black) obtained from single linear regression (SLR, blue trace) and multiple linear regression (MLR, blue trace) . While heart rate alone captures the average VO2 quite well, it does not tend to follow dynamic temporal changes on a faster time scale than on the order of 10s. The incorporation of EMG in the linear regression model allows the estimate to much better follow the shorter time scale peaks in oxygen demand. This kind of fidelity in an activity monitor is important for motivating users to push themselves for more intense, but short periods of time, and to follow their prescribed exercise regimen.







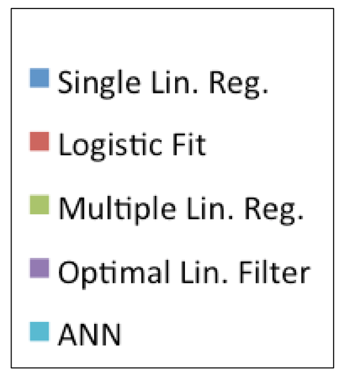
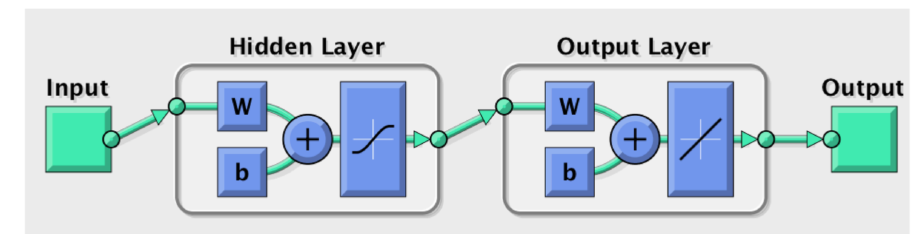


Figure 3) Goodness of fit, as measured by R^2, compared across different models for each subject, as well as across exercise types. Adding EMG (via Logistic, MLR, OLF, or ANN) consistently increased R^2.

Incorporating EMG in an Artificial Neural Network (ANN)



Another estimation method for VO2 involved constructing an artificial neural network (ANN) with 10 hidden layers. VO2 estimations produced by the ANN contained R2 values ranging from 0.74 – 0.97, superseding all other previous methods tested.

	Single Lin. Reg	Logistic	Multiple Lin. Reg	OLF	ANN
Average R2	0.302	0.359	0.414	0.502	0.826
Average Relative Improvement to SLR	N/A	+19.06%	+37.10%	+66.14%	+173.55%

Discussion and Conclusions

Ultimately, any method which VO2 estimations from the yielded the highest R^2 values than the other methods, particularly in the resistance exercises. These results indicate that EMG contains non-redundant information not present in heart rate alone. Thus, a more accurate fitness tracker can be achieved by incorporating wireless EMG sensors in addition to heart rate monitors. Furthermore, methods which incorporate multiple interactions between the different muscles (i.e., the ANN) outperforms the other methods.

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