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Conference Abstract

Estimation of LT with Dynamic Transfer Function Models with Commercial HR and Power Sensor Data

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Abstract: The anaerobic threshold (LT) serves as a pivotal marker in cycling training but its regular monitoring is hindered by cost and invasiveness. This study explores a modelling approach for LT estimation using heart rate (HR) and power data collected from wearable technology. Twenty-four cyclists underwent incremental tests while wearing various commercial sensors. A discrete-time transfer function method was employed for modelling, with time-variant parameter (TVP) models showing promising accuracy (average error: 4%) in LT estimation. The adaptability of TVP models to capture HR dynamics contributed to their efficacy. This modelling technique offers a potential alternative for routine LT monitoring, leveraging widely used wearable sensors in cycling. Further validation and adaptation to field data are warranted.

Keywords: Lactate Threshold, Performance, Modelling, Estimation, Wearables, Machine Learning, Transfer Function Models.

1. Introduction

The anaerobic threshold is an important marker commonly used in cycling to identify training zones and monitor training progress. However, monitoring of the anaerobic threshold is not performed on a regular basis due to the high costs, invasive blood sampling and time-intensive test protocols. Mathematical modelling might form a suitable alternative for regular monitoring of performance, especially in combination with wearable technology. In cycling, the heart rate (HR), power and cadence are already continuously measured and monitored during training and competition, making them particularly suitable for integration in a modelling technique. This study explores the validity of several different types of low- and high-end commercial HR and power sensors. In future research, we attempt to estimate the anaerobic threshold with linear time-varying parameter (TVP) models based on the HR and power.

2. Methods

24 amateur, trained cyclists (12 male, 12 female) participated in this study. They performed an incremental cycling test on a racebike mounted on a Cyclus 2 ergometer to determine the second lactate threshold (LT). The workload increased with 40 watts every 5 minutes. Lactate samples were taken from the ear lobe at the end of each step and analyzed with the Lactate Pro 2 sensor. Four different smart watches were used to measure HR through photoplethysmography (PPG), Fitbit Inspire 2 and Garmin Forerunner 45 for the low-end price point, and Apple Watch Series 8 and Polar Vantage 2 for the high-end price point. Additionally, two chest straps were used to measure HR through electrocardiogram (ECG), namely the Polar H10 and Zephyr Bioharness 3. Two different power sensors were used. The Favero Assioma Duo pedals measures the power applied bilaterally on the pedals while the SRAM Rival AXS crank measures the power unilaterally on the crank

and extrapolates to two sides. The participants wore two watches (one on each wrist), leading to six different combinations of watches. Because of the 24 participants, each combination of wrist watches was repeated four times. All participants wore both chest straps at the same time. Additionally, both power meters were mounted on the bike. Two Garmin Edge 530 were used to connect the chest straps and power meters.

Table 1.

					HR		Power	
Combination	Apple Watch Series 8	Polar Vantage 2	Fitbit Inspire 2	Garmin Forerunner 45	Polar H10	Zephyr	Favero Assioma	SRAM Rival AXS
1	X	X			X	X	X	X
2	X		X		X	X	X	X
3	X			X	X	X	X	X
4		X	X		X	X	X	X
5		X		X	X	X	X	X
6			X	X	X	X	X	X

Modelling and analysis was performed with the CAPTAIN toolbox in Matlab R2021b. The anaerobic threshold was estimated with a discrete-time transfer function (TF) approach. This method was selected because it is computationally efficient, robust and allows for capturing the system dynamics. The results were compared with the actual LT identified from the incremental step test. ingle-input single-output TF models with time-variant parameters and characteristics were tested. The TF models have the following general form[32],

$$y(k) = \frac{B(z^{-1})}{A(z^{-1})}u(k-\delta) + \xi(k)$$

where $y(k)$ is the output (HR), and $u(k)$ the input (power [W]) of the model; $\xi(k)$ represents uncertainty in the relationship arising from a combination of measurement noise, the effects of other unmeasured inputs and modelling error; δ is the time delay between a change in the input and a corresponding response of the output, expressed in number of time intervals; $A(z^{-1})$ and $B(z^{-1})$ are two series denoted as:

$$A(z^{-1}) = 1 + a_1 z^{-1} + a_2 z^{-1} + \cdots + a_{n_a} z^{-n_a} \quad (2)$$

$$B(z^{-1}) = b_0 + b_1 z^{-1} + b_2 z^{-1} + \cdots + a_{n_b} z^{-n_b} \quad (3)$$

where a_i and b_i are the model parameters to be estimated; z^{-1} is the backward shift operator, i.e., $z^{-1}y(k) = y(k-1)$, with y and k defined as in Eq. 1; n_a and n_b are the orders of the respective A and B polynomials. Consequently, the model structure is defined by the triad $[n_a \; n_b \; \delta]$.

2.1. LT estimation with time-variant parameter (TVP) models

A first-order model was created for each individual, with varying parameters. A first-order model has two parameters able to vary over time: $a_1(k)$ and $b_0(k)$. The modelling equation can be written as follows:

$$y(k) = -a_1(k) \times y(k-1) + b_0(k) \times u(k-\delta) + \xi(k)$$

The dynamics of the time-varying parameter signals change considerably at a certain point, which we hypothesize is the estimated LT. This is visually represented by the red circles shown in figure 1.

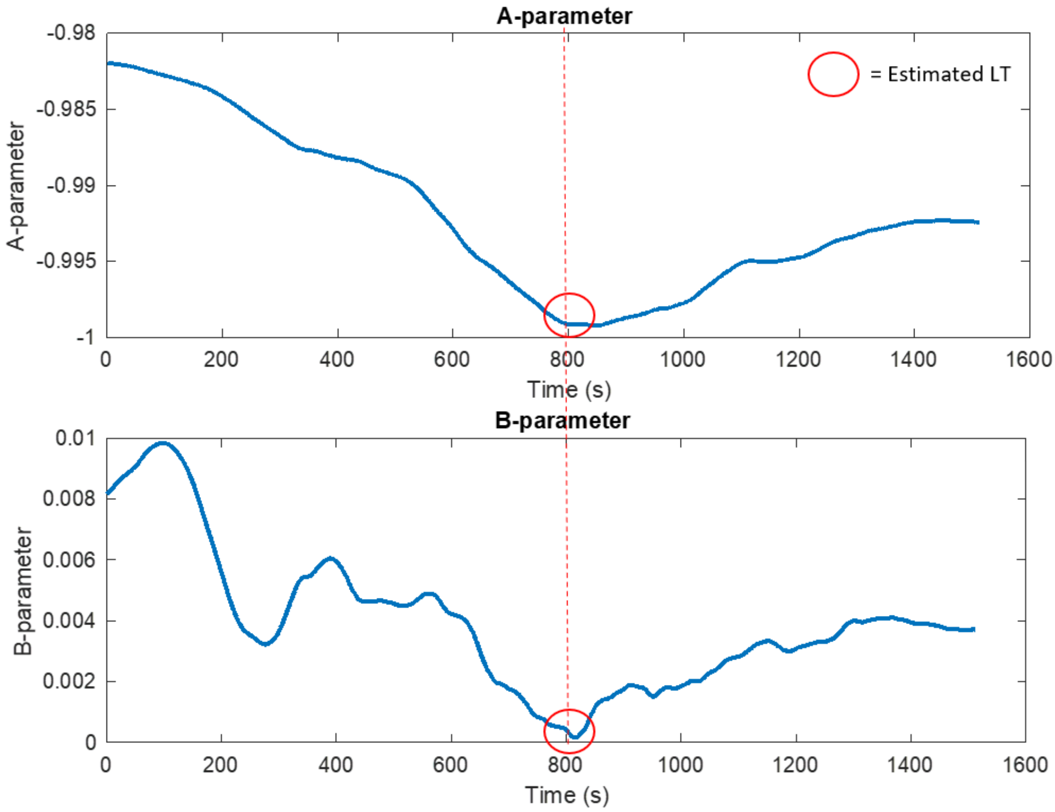

Figure 1. Visual representation of LT estimation out of A and B parameters

3. Results

Preliminary research showed that the time-variant parameter (TVP) models performed with an average error of 4%. For 9 out of 11 participants, the LT was estimated with an error smaller than 10 watts. This study showed that the Fitbit Inspire 2 proved to be completely unsuitable, due to maximal sampling rate of 1 sample per minute obtained from the extracted data. From all the watches, the Apple Watch series 8 provided the most accurate HR measure when compared to the Zephyr Bioharness. Finally, there was no significant difference between the HR signals measured with the Polar H10 and the Zephyr Bioharness. Similarly, the Favero Assioma and SRAM Rival AXS performed with similar accuracies when compared to the Cyclus 2 ergometer. The Favero Assioma pedals measure the power dual-sided while the SRAM Rival AXS only measures single-sided, and duplicated the measure to obtain the total power. It is not possible to measure power differences between the left and right leg, which could be useful information for some athletes. For further estimation of LT, we recommend only using chest strap HR monitors such as the Polar H10, and any (calibrated) power meter.

4. Conclusions

Modelling techniques based on the HR and power output approximate the LT with a decent accuracy with time-varying parameter models. Our results are interesting to the Science & Cycling community since they propose an alternative to the current gold-standard of testing that might enable at regular monitoring of the anaerobic threshold. Given the widespread popularity of HR, power and cadence sensors in the cycling population, this modelling approach could relatively easy and low-cost be integrated in the workout routine. The modelling approach based on wearable-captured HR, power and cadence data might even be applied in the field. Future work needs to focus on verifying the technique in a bigger population and adapting it to field-captured data.