Journal of Science & Cycling
Breakthroughs in Cycling & Triathlon Sciences

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Conference Abstract

Estimation of Anaerobic Threshold with dynamic transfer function models based on heart rate and power in cycling

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Received: 10 March 2023; Accepted: 14 March 2023; Published: 23 October 2023

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. Furthermore, modelling allows for identifying the effect of certain influential variables on the performance, resulting in performance prediction. They might enable more practical applications, especially in combination with wearable technology. In cycling, the heart rate, 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 attempts to estimate the anaerobic threshold with linear time-invariant and linear time-varying models based on the heart rate, power.

2. Materials and Methods

11 amateur, trained cyclists (6 male, 5 female) participated in this study. They performed an incremental cycling test on a Lode Excalibur ergometer in laboratory conditions to determine the maximal oxygen consumption (VO2max), ventilatory thresholds (VT) and second lactate threshold (LT). The workload increased with 40 watts every 3 minutes. The heart rate was measured with a 12-lead electrocardiogram (ECG). Lactate samples were taken at the end of each step and analyzed with the EKF Biosen Lactate Analyzer. 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. First, single-input single-output TF models with fixed parameters and characteristics were tested. Secondly, the parameters for the same model structures were estimated in a time-variant way to allow for changes in the parameters over time. The TF models have the following general form:

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

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 $[n_a \; n_b \; \delta]$.

Time-invariant parameter (TIP) models

The heart rate was modelled with a first-order TIP model with the power as the input for the first step only for each individual, shown in Figure 1. This model was subsequently applied to the rest of the data with the same model parameters and characteristics, shown in Figure 2. Since the actual heart rate was also captured, the error could be calculated. The LT was estimated at the point at which the cumulative absolute error increased exponentially.

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: a1 and b0. The LT was estimated at the point at which the dynamics of the parameters changes, shown in Figure 3.

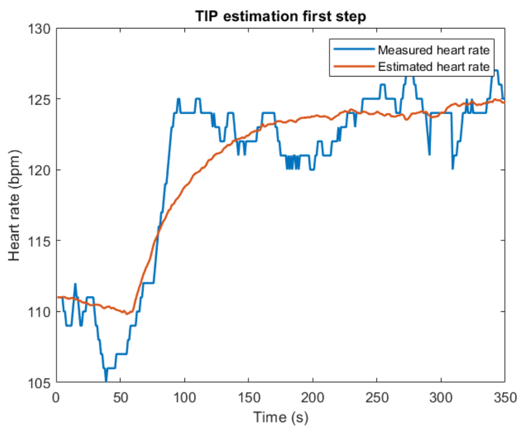

Figure 1. Visualization of the time-invariant parameter modelling technique. A model is constructed for the data of the first step only. The heart rate is modelled in function of the power with dynamic transfer function models.

a)

b)

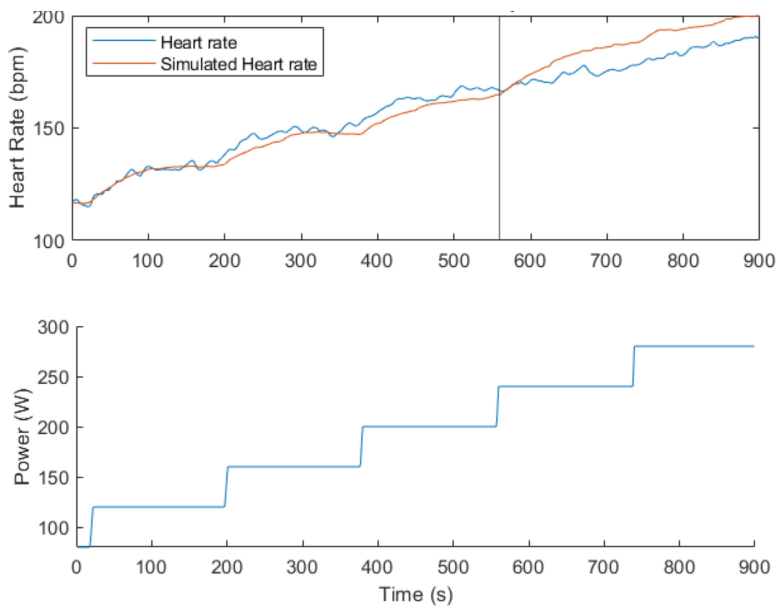

Figure 2. (a) Actual and simulated heart rate data with the TIP estimation method. The black vertical line signifies the start of the step with the LT (b) Power steps throughout the testing protocol. Starting value was 80 W with increments of 40 W

a)

b)

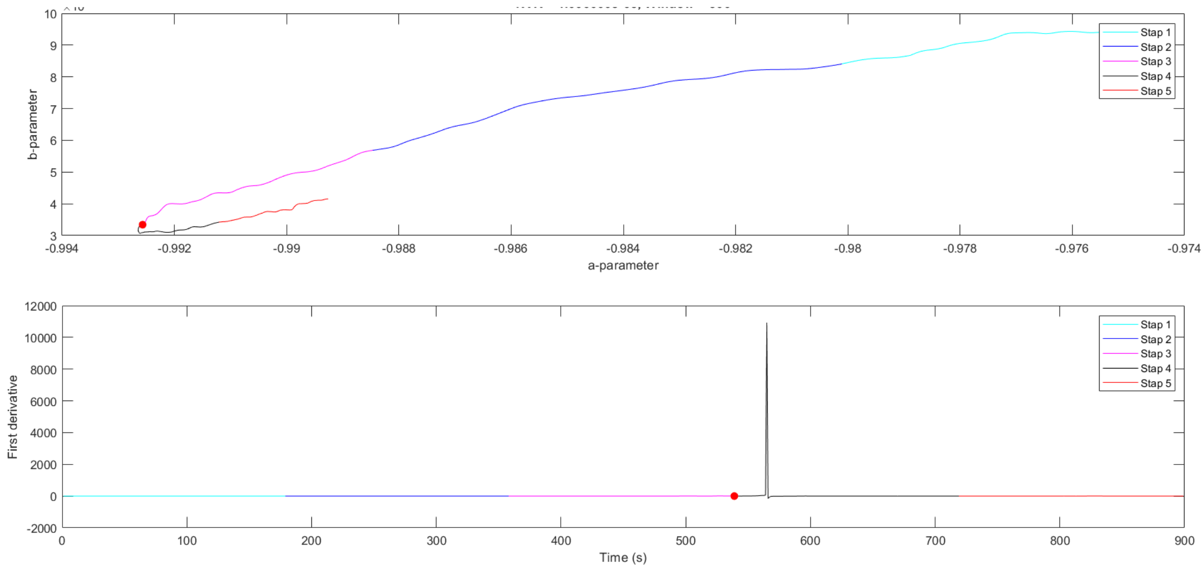

Figure 3. (a) b_0 parameter plotted in function of a_1 parameter with different colors for the different steps. The red dot signifies the start of the step with the LT (b) First derivative/slope of (a) with different colors for the different steps. The red dot signifies the start of the step with the LT.

3. Results

Calculation of the LT with time-invariant parameter (TIP) models was performed with an average error of 11%. For 5 out of 11 participants, the estimated LT was approximated with an error smaller than 10 watts. 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. The better performance of the time-variant parameters was attributed to their adaptability and their ability to capture a highly varying signal such as the heart rate better.

4. Conclusions

Modelling techniques based on the heart rate and power output approximate the LT with a decent accuracy, with time-varying parameter models performing better than time-invariant 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 in cycling. Given the widespread popularity of heart rate, power and cadence sensors in both elite and recreational cyclists, this modelling approach could relatively easy and low-cost be integrated in the training routine of cyclists. The modelling approach based on wearable-captured heart rate, power and cadence data might even be applied in the field. However, the accuracy of the technique is lower when compared to the gold-standard. Incorporating the cadence into the models might improve the accuracy. Future work also needs to focus on verifying the technique in a bigger, more varied population and finding a way to adapt it to field-captured data.