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Modeling in Road Cycling for Optimal Pacing Strategies: Theory vs. Practice

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Introduction: The right choice of a pacing strategy for a time trial race is important and often difficult to establish. With the increasing popularity of online sports data platforms like Strava (www.strava.com), pacing strategies may become interesting even for recreational cyclists since they can compete against each other virtually on selected segments. Methods are now available to generate pacing strategies that are optimal, however, only in a mathematical sense. Until now, they were tested in practice only under laboratory conditions [1]. Pacing strategies are generally based on two mathematical models: (1) to describe the relation between power output and speed [2], and (2) to describe the fatigue of the rider related to the power output [3]. The quality and validity of these pacing strategies relies on the accuracy of the predictions made by those models.

In this paper, we describe our findings on a pilot study during a two week period of cycling with regard to the prediction quality of the two models while following precalculated optimal pacing strategies in the field rides. This is not meant to be a fully-fledged study applying, e.g., a statistical analysis for a sufficiently large number of participants. This pilot study rather intended to demonstrate that, in principle, the theoretically optimal pacing strategies can in fact be implemented for field rides in practice. Moreover, it was the purpose of the study to identify the problems of the approach occurring in practice, and to outline solutions for these.

Methods: The physiological model is similar to the one used in [1]: an extension of the critical power (CP) concept with reduced recovery. The physical model to predict speed from the rider's power output is taken from [4]. The optimization of the pacing strategy for an uphill time trial proceeded as in [1]. To calibrate the CP model, four tests were performed in the laboratory for a single hobbyist rider, followed by a number of rides on Strava segments with the goal to achieve personal bests by pursuing the given optimal pacing strategies.

The precalculated pacing strategies were communicated during the field rides by means of a custom developed App on a smartphone mounted on the handle bar. Feedback was given numerically, e.g., the current deviation from the optimal speed, and visually by a dash board type gauge. Accumulated deviations from the optimal pacing were attempted to be corrected using a PID control mechanism. These rides were taken to update the parameters of the CP model continually.

Results and Discussion: Four rides with optimal feedback were performed on three different Strava Segments. These segments were mainly climbs with a length of 3.5 to 5 km and an average grade from 5.6 to 7 %. The rider's critical power ranged from 230 to 257 W depending on which tests were used for calibration. The feedback was followed with a root-mean-square error of 0.77 m/s in speed and 48 W in power. Modelling errors and deviations from the optimal strategy lead to time differences at the end of the segment ranging from 15 s quicker to 100 s slower than the optimal strategy predicted.

This discrepancy in time is partly explained by having short downhill parts within the segments and errors in the estimation of the slope profile, which is shown in Figure 1. In the downhill parts, the optimal strategy suggested speeds higher than those during the field ride in which additionally braking was necessary. This error could be reduced by adding a more realistic speed constraint to the optimization and consider braking in the pacing strategy.

While the physiological model first was calibrated using tests with a length of about 30 min, the model prediction for the first ride on a shorter segment showed quite poor performance. Adding this segment to the parameter estimation changed the parameters in a way that critical power was reduced and anaerobic capacity increased. With this new parameter set, short as well as mid-range segments were predicted quite well. This shows how important it is to use a range of test durations that covers the future applications.

Conclusions: The results showed, that the models work quite well in general and they can be applied to uncontrolled conditions when considering some limitations. Downhill parts are difficult to model and time differences between prediction and ride must be expected in these scenarios. The physiological model needs to be calibrated using segments similar in length and load to the ones that are predicted. With proper model parameter selection and visual feedback with respect to an optimal pacing strategy, significant performance gains for uphill time-trials of hobbyist, amateur, and perhaps also professional athletes can be expected.

References:

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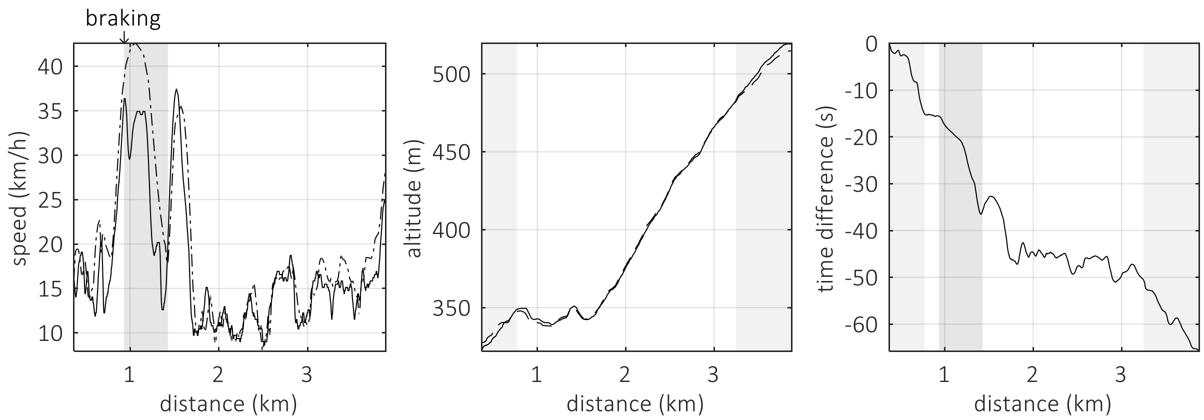

Figure 1: Difference between ride and model prediction. The left figure shows the measured (solid) speed and the speed modeled from the measured power output (dash-dot). The figure in the center shows the measured (solid) and estimated (dash) slope. The right figure shows the time difference between ride and model prediction.