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Article

On the marginal gains of computed optimal pacing strategies

Ramona Burger [1,*], Alexander Artiga Gonzalez [1] and Dietmar Saupe [1]

[1] Department of Computer and Information Science, University of Konstanz, Germany.

* Correspondence: (Ramona Burger) ramona.burger@uni-konstanz.de.

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Abstract: There are numerous sources of computed pacing strategies that optimize the power output over a cycling activity using mathematical models. In this work, we analyze and compare three computed optimal pacing strategies with each other and compare them to the recorded pacings of approximately 12,000 empirical rides on a popular uphill road segment in Adelaide, Australia. We found that the computed strategies differ significantly, and that the majority of the riders could have benefited from adapting to a computed strategy.

Keywords: data analysis; pacing strategy; marginal gains; road cycling

1. Introduction

In road cycling and generally in endurance sports, the way an athlete distributes the available energy resources over the course of an activity is known as the pacing strategy. The right pacing strategy can be the crucial factor to win a race. There have been numerous studies to investigate pacing strategies. Swain (1997) and Atkinson et al. (2007) examined in a simulation how an athlete's power output needs to be varied to cope with wind and hilly roads to achieve a better result with the same average power output. Cangley et al. (2010) confirmed these simulated results in a field experiment. In all three studies the power was selected using a trial-and-error approach but they agreed that varying power output can be beneficial in changing environmental conditions.

Subsequently, there were several studies that tried to solve the problem of finding the optimal pacing strategy more systematically. The first mathematical approach for optimizing the power distribution was done by Gordon (2005) applying a model based on air, rolling, and grade resistance. An extension of Gordons work was done by Dahmen (2012) and Dahmen et al. (2012). They replaced the physical model with the model developed by Martin et al. (1998) and used an extension of the critical power model by Morton (1996). Furthermore, they improved the computation of these mathematical optimal strategies by defining an optimal control problem. The goal was to find a power distribution that minimizes the time needed for an activity with respect to the physiological model used. Similar approaches were investigated by Fayazi et al. (2013), Sundström et al. (2014), Dahmen (2016), Sundström and Bäckström (2017) and Wolf et al. (2019).

Another source of pacing strategies are online platforms where athletes can share and compare their rides. These platforms were emerging over the last years and offer the possibility to compute, download and use optimal solutions for pacing on the road, e.g., using a Garmin cycling computer. Ryan Cooper, the founder of the platform

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BestBikeSplit[i], also developed mathematical models to compute pacing strategies starting out during the Tour de France in 2013 when he predicted the time trial times for some athletes (Sexty 2017).

In practice, road cyclists and other endurance athletes apply different types of pacing strategies. Abbiss and Laursen (2008) presented six common pacing profiles in their literature review paper, namely positive, negative, even, all-out, parabolic shaped, and variable pacing. These pacing profiles have been observed in numerous field and laboratory studies. In 2019, we collected records of 12,202 maximum effort rides from Norton Summit (Adelaide, Australia), which is a popular 5.54 km long uphill road segment with a climb of 270.3 m (Saupe et al. 2019). It was confirmed that the pacing strategies observed in the literature also showed up in the rides on the Norton Summit segment, except for the all-out strategy.

A question that remained open is to what extent optimal pacing strategies would be able to reduce the total riding time of experienced cyclists at different personal performance levels. In the following, we compare optimal, computed strategies from our Powerbike project as described by Wolf (2019) and from the online platforms BestBikeSplit and Strava with the empirical ride data. This approach differs from other similar analyses since we compare the computed strategies to a huge amount of empirical data unlike other studies that encompass few participants or just simulations. Such a comparison presents several major challenges: (1) Only a small number of cyclists have power meters installed on their bikes, and, moreover, the power measurements produced by these devices are not comparable because of differences in accuracy in the wide range of devices used. (2) Thus, one has to resort the mathematical models to estimate power. However, this requires many rider specific parameters, in particular the system mass besides friction coefficients, all of which are unknown. (3) For a fair comparison when applying a mathematical model, we have to make use of a unique, single height profile of the course, but the recorded height profiles in the data records differ by large amounts. (4) Last, but not least, the data records contain sequences of location, distance, and speed, however, contaminated by noise and sampled nonuniformly at different places. Therefore, the data must be denoised and uniformly resampled.

2. Materials and Methods

We considered computed optimal strategies for the Norton Summit segment from BestBikeSplit, Powerbike, and Strava. The pacing strategies were obtained for goal times of 11, 12, …, 23, 24 minutes, corresponding to finish times achieved by best efforts of hobby riders up to professional athletes on the Tour Down Under. We compared the empirical and computed strategies for fixed average speed and average power.

We preprocessed the computed strategies in the same way as the 12,202 empirical data records were treated in Saupe et al. (2019). First, distances were adjusted to a length of 5,545.54 m and secondly, the road gradients were derived from the height profiles based on the altitude measurements of several thousands of empirical rides. Then speed was computed from time and distance pairs using central differences. To smooth the speed, we applied a Gaussian filter with a standard deviation of σ = 10 s. Finally, we ensured that the speed is consistent with total distance and the reported finish time by applying a small offset.

To estimate power for the collected data, we used the physical model introduced by Martin et al. (1998). For this purpose, we configured a virtual standard rider, applying the same parameters as in Dahmen et al. (2011), except for the masses

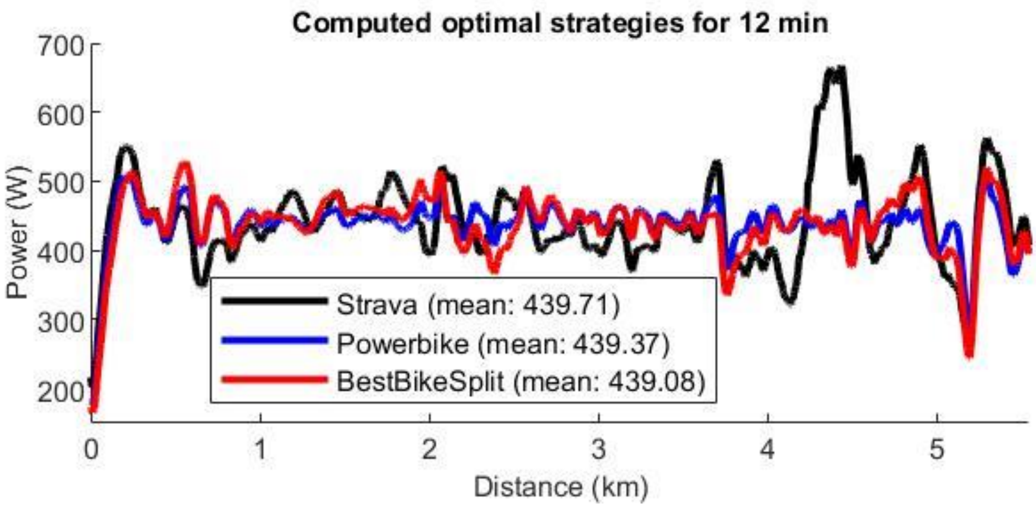

Figure 1. Computed optimal strategies from Strava, Powerbike and BestBikeSplit for a goal time of 12 minutes.

of rider and bike. We determined the sum of the masses of the standard rider and the bike, based on the minimization of the error between the results of the physical model and the power measurements collected in many of the empirical rides. Finally, for each recorded ride we computed the average power and the average speed.

3. Results

Figure 1 shows the optimal pacing strategies from Strava, Powerbike, and BestBikeSplit for a finish time of 12 minutes. Despite having the same finish time and nearly the same average power, the power distribution differs. While the power distribution of Powerbike and BestBikeSplit strategies is similar, Strava follows a different approach with higher maximum power, up to more than 600 W for several hundred meters.

In Table 1, there is an overview of the correlations of pairs of computed strategies, averaged over all goal times. Furthermore, it shows average correlations between the computed strategies and the empirical rides. To compute these values, we selected the 20 empirical rides which were closest to each goal time, computed the average correlation coefficient of these 20 rides with the respective strategy and again computed the average over all goal times. The strategies suggested by BestBikeSplit and Powerbike behave rather similarly for all goal times with an average correlation of 0.88. The correlations with Strava's strategies are noticeably smaller. Also, the correlations of the empirical rides with BestBikeSplit (0.7) and Powerbike (0.71) are higher than with Strava (0.49).

To point out the difference between computed and empirical strategies in terms of average power for different goal times, Figure 2 shows the differences in average power between the power corresponding to the data and the computed strategy with the lowest average power. In Figure 2, this computed strategy with minimal power requirement is given as the baseline at zero offset. Up to an average speed of 26.27 km/h the Powerbike strategy has the lowest power demand. For all higher considered average speeds, the BestBikeSplit strategy has the lowest power demand. Goal times are converted to average speed in Figure 2.

The average differences in power between the three computed strategies are small, approximately 0.36 W. To analyze how close the riders paced to the optimal strategies, we divided them in two groups: riders with an average speed less or equal to 29 km/h (99.78%) and riders with an average speed greater than 29 km/h. A large fraction of the riders of the first group (71%) yielded

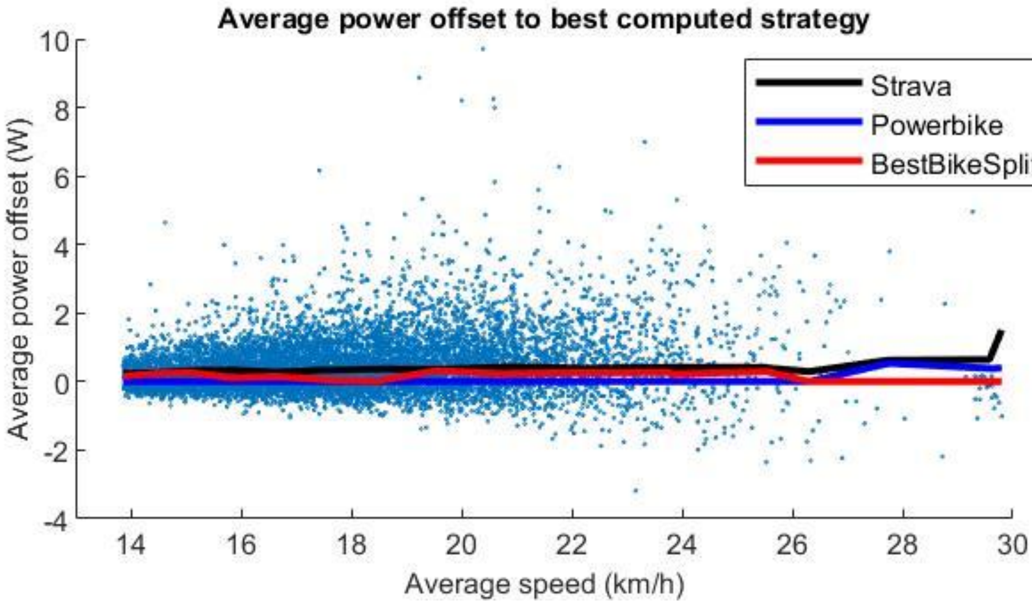

Figure 2. Scatter plot of the differences in average power to the computed strategy with the lowest average power of the empirical rides.

a higher average power (0.70 W ± 0.72 W) than the optimal strategies. The remaining portion of this group (29%) yielded an average power below the baseline (-0.27 W ± 0.27 W). While this holds for the majority of the riders, the fastest riders paced closer to the computed strategies. Their power only deviated by 0.52 W ± 0.93 W from the computed strategy with the lowest power demand.

Table 1. Average correlations and standard deviations of the computed strategies and empirical rides over all goal times.

	BestBikeSplit	Powerbike	Strava
empirical rides	0.70 ± 0.03	0.71 ± 0.03	0.40 ± 0.05
Strava	0.59 ± 0.05	0.60 ± 0.05	
Powerbike	0.88 ± 0.02		

4. Discussion

While the average power demand for the three optimal pacing strategies differ by only little, the power distributions of Strava's strategies propose much higher variations in power than can be considered realistic. Also, the local power peaks are not aligned with the local maxima of the road gradients, as should be expected. Both of these artifacts may be due to an incorrect height profile that Strava might have used. The Norton Summit segment continuously climbs in altitude, but the publicly available height profile provided by Strava (Strava 2020) for the segment incorrectly shows several stretches of the road with negative gradients.

The Powerbike strategies were investigated in a laboratory study (Wolf et al. 2016) and a field experiment (Artiga Gonzalez et al. 2019) confirming validity and feasibility. Because of the analogy between Powerbike and BestBikeSplit strategies, one can expect similar performance for the BestBikeSplit strategies.

The major part of the riders on the Norton Summit segment yielded a higher average power than the computed strategies suggest and could therefore benefit from the computed strategies. These riders can improve their performance by following an optimal strategy. While the fastest and most experienced riders already adapted strategies that are close to optimal, it is possible for riders who are already performing well to further improve their efficiency by adopting optimal strategies.

Even though there is also a considerable number of riders who climbed the Norton Summit segment at a lower average power than the computed strategies suggest, this is not a contradiction to the optimality. Since the Powerbike strategies ensure the feasibility by incorporating a physiological model, it is possible that a rider with diverging physiological capabilities finds a strategy with lower average power requirements.

Still, riders of both groups can profit by having a digital pacemaker as this can be highly motivational and challenge the riders to new best performances.

5. Conclusions

We showed that the majority of the 12,202 riders of our empirical dataset could have slightly benefited from adapting to a computed pacing strategy on the 5.54 km hill climbing segment. Therefore, optimal pacing strategies may well serve as one of the components integrated into the concept of marginal gains that became popular in road cycling over the last years.

Supplementary Materials: The data of the 12,202 maximum effort rides is available online at https://www.mmsp.uni-konstanz.de/research/projects/powerbike/.

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Conflicts of Interest: The authors declare no conflict of interest.

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