Workshop Modelling in Endurance Sports

11.-13. September 2016
University of Konstanz, Germany

PROCEEDINGS

Foreword

This book contains the proceedings of the Workshop Modelling in Endurance Sports, which has taken place in Konstanz (Germany) from 11 to 13 September 2016. The workshop was supported by the German Research Foundation (DFG) and the University of Konstanz and co-organized by the University of Konstanz and the German Society of Sport Science (dvs).

In 15 oral presentations, current research topics with focus on modelling in endurance sports like cycling, running and speed skating were discussed. They were organized in four sessions: “Performance Modelling”, “Physiology: VO2, HR, and Lactate”, “Parameter Estimation”, and “Training: Monitoring and Modelling”. Additionally four invited speakers presented their topics of research and in a practical demo session, the workgroup Multimedia Signal Processing of the University of Konstanz presented their Powerbike simulator.

All authors submitted an extended abstract of up to six pages. Each abstract was reviewed by three members of the program committee. The extended abstracts as well as the four short abstracts of the keynote speakers are included in this book. A special issue of the International Journal of Computer Science in Sport (IJCSS) with the topic “Modelling in Endurance Sports” will follow this workshop.

We thank all the participants for making the workshop an inspiring and productive event. Especially, we thank the authors and the invited speakers for their interesting contributions as well as the program committee for helping us with their expertise. Last but not least we also thank our secretaries for their excellent work.

Workshop:
https://www.informatik.uni-konstanz.de/saupe/workshop2016/

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Content

Keynote Speakers

Performance Modelling

Physiology: VO2, HR, and Lactate

Parameter Estimation

Training: Monitoring and Modelling

Modelling of Fatigue, Function and Performance During Endurance Cycling

Chris Abbiss, Edith Cowan University, Australia.

Many methods and techniques have been developed in order to model endurance performance. Such modelling provides valuable information regarding the quantification of load during both training and competition. This quantification is of importance to understanding fitness and fatigue and thus hopefully assist in the prediction of both optimal (i.e. competition) and suboptimal (i.e. overreaching) performances. However, the modelling of performance in endurance sports is often complicated by difficulties in the quantification of input and output variables to these models. This presentation will discuss some of these issues in the quantification of load during prolonged exercise.

Modeling Sprint Finishes of Endurance Cycling Competitions

Jim Martin, Associate Professor, University of Utah, USA.

Endurance cycling events are often won or lost in a maximal finishing sprint. Supply and demand modeling may provide useful insight regarding optimal sprinting strategies. However, modeling energy supply during such a sprint is complicated by the initial conditions for that sprint, including fatigue and pedaling rate, and by the progression of fatigue during the sprint itself. Energy demand is highly dependent on aerodynamic drag which, in turn, depends on velocity and proximity to other riders. In this presentation, validation of a recently-developed model for supply power during maximal cycling will be presented. An established demand model will be modified to include recently published data on rider-rider aerodynamic interactions. These supply and demand models will be coupled to predict performance using forward integration and to explore a variety of sprint finish strategies including starting point, gear selection, following distance, and lateral clearance during passing.

Performance Index for Cycling

Daniel Green, Trek-Segafredo Cycling Team.

In order to evaluate if an athlete is adapting and improving to a training stimulus it is essential to have a method to assess performance. Due to the highly stochastic nature of road cycling, the attributes essential to achieving results requires athletes to produce high power outputs for durations as short as 3 seconds, or for more than 40 minutes. Therefore a new methodology has been devised which calculates a Performance Index for Cycling (PIC). The PIC is single metric which is representative of the performance capabilities of a cyclist across a range of time durations and racing circumstances. The PIC can then be used to monitor changes within a single cyclists or to compare cyclists with different attributes in order to assess their potential for success in road cycling.

Practical Applications of Simulation & Optimisation in Road Cycling

Rob Kitching, www.cyclingpowerlab.com, London, UK.

The domain of road cycling benefits from several established models which can be used to account for the interplay between physical power demands and physiological limitations on power supply. Computational approaches which leverage these models can often provide further insights in the quest for high performance and this presentation will review some practical applications of holistic performance modelling with simulation and optimisation. It will consider some crossover from the domain of computational finance where simulation is used heavily and lessons learned from applied work assisting coaches and elite athletes.

Predicting Performance from Outdoor Cycling Training with the Fitness-Fatigue Model

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Introduction

The Fitness-Fatigue model (Calvert et al. 1976) is widely used for performance analysis. This antagonistic model is based on a fitness-term, a fatigue-term, and an initial basic level of performance. Instead of generic parameter values, individualizing the model needs a fitting of parameters. With fitted parameters, the model adapts to account for individual responses to strain.

Even though in most cases fitting of recorded training data shows useful results, without modification the model cannot be simply used for prediction.

Previous work

According to the Fitness-Fatigue model, performance can be defined by

$$\widehat{p_n} = p^* + k_1 \cdot \sum_{t=1}^{n-1} w_t \cdot e^{-(n-t)/\tau_1} - k_2 \cdot \sum_{t=1}^{n-1} w_t \cdot e^{-(n-t)/\tau_2}$$

where $\widehat{p_n}$ describes modeled performance at day n and p^* is an initial basic level of performance (Busso et al. 1994). The input w (e.g., velocity, wattage, or other forms of strain) is considered for the past $n-1$ days of training. Here, τ_1 and τ_2 are time constants while k_1 and k_2 are multiplicative enhancement factors. It is recommended to constrain $k_1 < k_2$ and $\tau_1 < \tau_2$.

While performance models are widely used for simulating performance, they might also be used for performance prediction for future training sessions, similar to heart rate prediction of single training sessions as described in (Ludwig et al. 2015). Therefore, the model parameters (e.g., of any heart rate model or of the Fitness-Fatigue model) are fitted to a subject such that the model is individualized, and reproduces the subjects past training data. The same parameters are used for performance prediction as well.

Recently, (Schäfer et al. 2015) presented a method for generating individual training plans based on the Fitness-Fatigue model, where performance prediction is needed beforehand.

Methods

Usually, the Fitness-Fatigue model is used to simulate performance during laboratory studies and not useful to simulate outdoor training performance on a daily basis due to huge fluctuations. To use the Fitness-Fatigue model in outdoor training, data has to be cleaned and prepared. Since individual performance limit is not reached in each and every cycling ride, it is necessary and useful to group performance data according to a time interval in which it holds that the subject's individual performance limit is reached regularly (e.g., weekly or monthly). Performance then is set to the maximum performance value of each group (Ludwig et al. 2016).

Outdoor cycling data was collected of 20 male subjects aged 31-63 years without any training control and without any laboratory performance tests. Information about the time interval in which each cyclist approximately reaches his performance limit was provided by the cyclist himself. Performance is given as 60 Minute Peak Power (PP60) (Balmer et al. 2000; Tan und Aziz 2005) and strain is given as Training Stress Score (TSS) (Allen und Coggan 2012).

When trying to predict performance with the Fitness-Fatigue model, the main problem is that the prediction process has to start again with the initial performance parameter p^* despite the performed training before. Any information about possible performance progress is missing since this level parameter only states a very basic initial performance level which cannot be undershot.

In order to perform a reliable prediction, we supplemented these missing progress information as a *preload* added to the model after fitting process. Since training effect fades away over time, the preload is convolved with an exponential function over time, too:

$$\widehat{p_n} = p^* + k_1 \cdot (\mathrm{pr}_1 \cdot e^{-n/\tau_1} + \sum_{t=1}^{n-1} w_t \cdot e^{-(n-t)/\tau_1}) - k_2 \cdot (\mathrm{pr}_2 \cdot e^{-n/\tau_2} + \sum_{t=1}^{n-1} w_t \cdot e^{-(n-t)/\tau_2})$$

The preload pr_1 consists of the fitness-part (i.e., the first sum), and pr_2 is defined by the fatigue-part respectively from the entire training data used for parameter fitting. The preload therefore is meant to lift the simulated performance level to an actual performance level besides the initial performance level given by p^*.

Results and Discussion

The root-mean-square error (RMSE) of PP60 is shown in Table 1 as average, median and standard deviation (std.) value comparing the simulation of raw data to preprocessed data with grouped performance values.

Table 1: RMSE of simulating raw data and preprocessed data (Range of PP60 here: 0-340)

RMSE	Raw Data	Preprocessed Data
Mean	35.77	14.13
Median	40.59	12.07
Std.	18.27	6.43

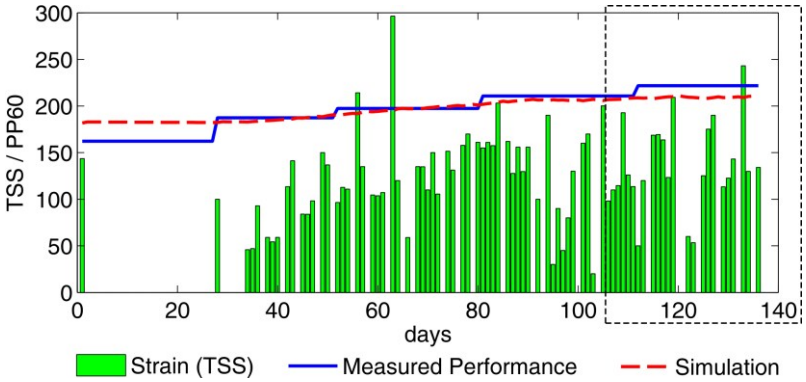

Figure 1: Fitting process of the whole performance curve from one subject; RMSE: 4.04. Last month excluded and used for prediction framed with a dotted line.

In (Ludwig et al. 2016), we showed that around 50% of simulation results with preprocessed data from outdoor cycling training sessions are comparable to simulation results from published laboratory performance studies.

As stated before, especially for creating suitable training plans it is very helpful to predict performance according to given strain. Using individualized parameters for the Fitness-Fatigue model, the gap between the measured performance and the predicted performance differs strongly, even if compared to the fitting process before. Figure 1 shows an example of a fitted performance curve, where the whole performance progress for one subject is illustrated and the last month used for prediction is highlighted. Figure 2 shows three different curves: the relevant part of the fitting process; the corresponding prediction using the parameters computed during the fitting process without any changes; the corresponding prediction using the same parameters but with the additional preload. Here, the gap between simulation and measuring is comparatively high for prediction while the prediction with preload can achieve identical results as the original simulation from fitting process.

The mean, median, and standard deviation values over all 20 subjects for the unchanged prediction and the adjusted prediction with a preload are shown in Table 2. Comparing a usual prediction with the fitting, the RMSE doubles, while the prediction process with preload can improve results by around 33% compared to the usual prediction.

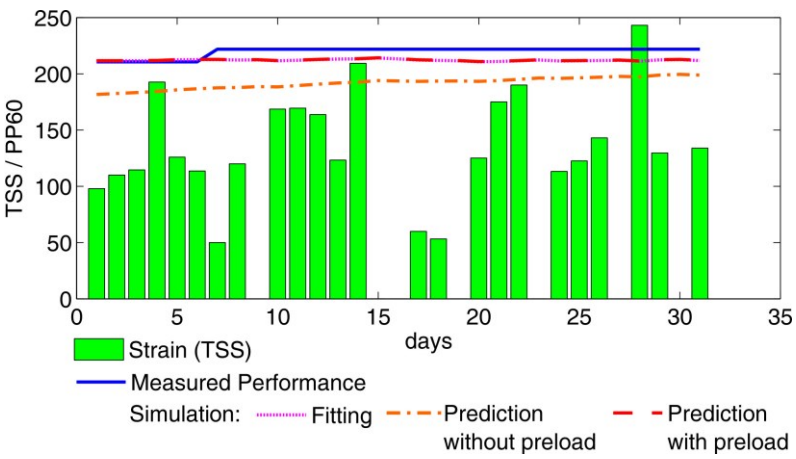

Figure 2: Fitting, and Prediction without and with preload; RMSE: 6.59, 27.52, 6.59.

Table 2: RMSE of prediction process without and with preload over all subjects.

RMSE	Prediction normal	Prediction preload
Mean	30.47	20.45
Median	28.55	20.17
Std.	28.55	10.73

Conclusion and Future Work

Predicting performance is helpful for training planning, but not very accurate even if using individualized model parameters. Individualization can be based on outdoor training data if data is cleaned and aggregated beforehand. Using the Fitness-Fatigue model, performance prediction can be improved by around 33% using a preload calculated from former training.

However, the concept of the additional preload should be further evaluated with indoor cycling training sessions gathered under controlled conditions. Additionally, the possibility of estimating and including the preload into the whole fitting process should be investigated.

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A 4-Parameter Critical Power Model for Optimal Pacing Strategies in Road Cycling

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Introduction

Minimum-time pacing strategies in road cycling may be computed as solutions of optimal control problems. Both a mechanical model for road cycling power and speed and a physiological endurance model, that quantifies the energy resources and power limits of an athlete, are involved.

This contribution introduces a 4-parameter critical power model that arises from a combination of the 3-parameter critical power model (3PCPM), [4], and an exertion model developed by Gordon [2]. It has the form of a constrained dynamical system and is designed for the computation of minimum-time pacing strategies.

Previous work

In [1], we computed minimum-time pacing strategies using the 3PCPM, [4], and an exertion model, [2], for synthetic continuously varying slope profiles.

The 3PCPM extends the classical critical power model, that involves critical power P_c and anaerobic work capacity E_a by a parameter for maximum power at rest P_max. It can be illustrated as an hydraulic system as depicted in Figure 1a. For a pedalling power demand $P > P_\mathsf{c}$, the mechanical work beyond critical power is discounted from the remaining anaerobic resources

$$\dot{e}_\mathsf{a} = P_\mathsf{c} - P \ , \tag{1}$$

which are initially filled with E_a when the athlete is at rest.

The maximum power P_m is defined by a function decreasing linearly from P_max at rest to critical power in the exhausted state when the anaerobic resources are is empty ($e_\mathsf{a} = 0$) :

$$P\left(t\right) \leq P_\mathsf{m}(e_\mathsf{a}) = P_\mathsf{c} + \frac{P_\mathsf{max} - P_\mathsf{c}}{E_\mathsf{a}} e_\mathsf{a} \ . \tag{2}$$

Thus, for constant power exercises with $P\left(t\right) = \bar{P}$, exhaustion occurs at time T, when P_m falls below the power demand $\bar{P}$.

In contrast, the exertion model abandons the power constraint (2) and defines an exertion rate that is inversely proportional to time to exhaustion for arbitrarily varying power:

$$\dot{e}_\mathsf{ex}\left(P\right) = -\frac{E_\mathsf{a}}{T} = \frac{(P_\mathsf{max} - P_\mathsf{c})(P_\mathsf{c} - P)}{P_\mathsf{max} - P} \ , \tag{3}$$

thus implicitly limiting power by the infinitely growing exertion rate for P approaching P_max.

Methods

We develop our 4-parameter exertion model by combining the advantageous properties of both models.

From a physiological viewpoint maximum power is constrained depending on the duration of an exercise because either ATP utilization itself or its replenishment of secondary energy resources is rate limited [3]. It is impossible to model these complex details quantitatively but a single separate energy rate limit such as the power constraint (2) of the 3PCPM can be handled and is clearly favourable compared to the further simplification in Gordon's exertion model.

Moreover, using the principle of optimality, it can be shown that with the constraint (2) a minimum-time pacing strategies will always feature a final spurt at the end. In contrast, when using Gordon's exertion model, the athlete is necessarily exhausted on the last section where his power is limited to critical power.

However, we prefer the non-linear dependence of the exertion rate in (3) to the linear dependence in the 3PCPM (1). With high intensity power, glycolysis is increasingly impeded for example by the accumulation of lactic acid. For a load beyond the anaerobic threshold, the lactate concentration grows disproportionately high and leads to a reduced efficiency of power production that our heavily simplifying model may account for by an exertion rate that grows non-linearly. It is not realistic that for an athlete a constant power represents the same load as any time variant power with the same average. Furthermore, concerning pacing strategies, the linearity leads to a singular control problem that can cause numerical difficulties.

This is not the case for minimum-time strategies that rely on Gordon's exertion model. However, due to the pole at $P = P_{\text{max}}$ high intensity power is heavily punished, leading to very little variations in the optimal pedalling power.

Therefore, we seek a modification of (3) that takes a finite value at $P = P_{\text{max}}$ while roughly preserving the characteristics for lower power. We may imagine the pole in the graph at a very high hypothetical pedalling power, that in practice can never be achieved due to the maximum power constraint that we adopted from the 3PCPM. The definition of an exertion rate

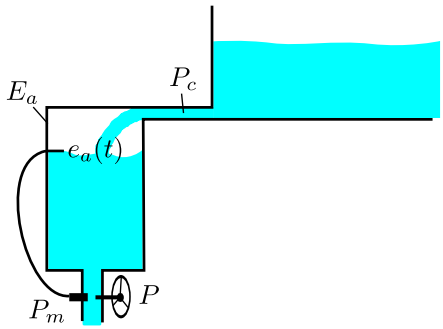
$$\dot{r} = \alpha \frac{(P_{\text{max}} - P_{\text{c}})(P_{\text{c}} - P)}{\alpha P_{\text{max}} - P} \tag{4}$$

with $\alpha \geq 1$ achieves these requirements and adds a fourth steering parameter α to the model. The graph of (4) is plotted in Figure 3.

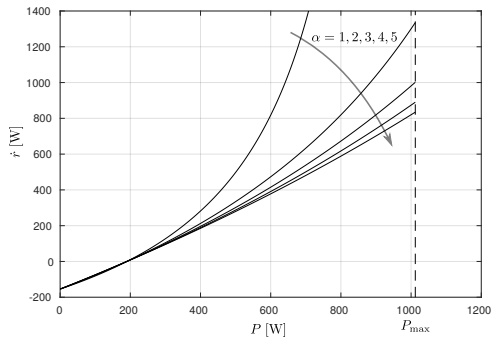
Results

Figure 2 illustrates a minimum-time pacing strategy for a typical setup on a track near Pfyn in Switzerland. It was computed with the MATLAB optimal control package GPOPS-II, [5].

Initially, high power is indicated to accelerate from rest. Thereafter, both power and speed vary according to the slope profile $\frac{\mathrm{d}h}{\mathrm{d}x}$ that contains many details. Differential gps was used to measured the height in order to ensure the required accuracy. At the end of the steepest section around 4000 m, the athete uses his maximum power to reach the top as soon as possible, where he is completely exhausted. On the following descent he recovers partially before he enters the final spurt on the last 480 m.



(a) The 3PCPM depicted as a hydraulic system. The black line connects a sensor for the level of anaerobic resources e_a to the size of the outlet according to the power constraint (2).



(b) Graph of the exertion rate (4) of the 4-parameter exertion model. For $\alpha = 1$ the rate is identical to Gordon's exertion rate defined in (3).

Figure 1: Characteristics of the physiological models.

Conclusions

The components of the 3PCPM and Gordon's exertion model may be combined to a 4-parameter exertion model. The exertion rate grows non-linearly with power load but not excessively for high intensity power. A separate power constraint limits the maximum available power. Solutions to minimum-time pacing strategies are numerically stable for complex realistic slope profiles, reveal a balanced variability in power and speed, and guarantee a final spurt.

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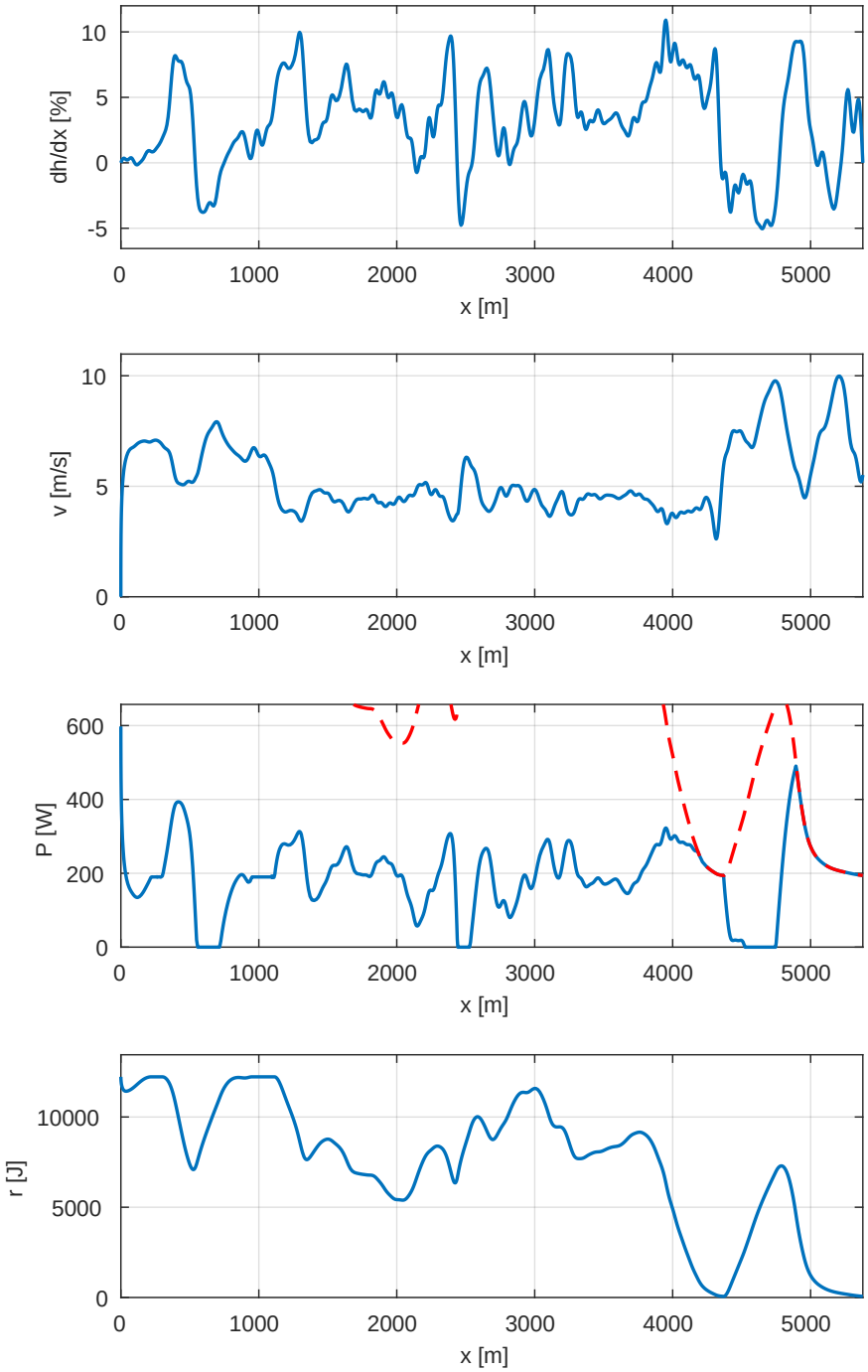

Figure 2: Minimum-time pacing strategy for the 4-parameter exertion model with $\alpha = 3$ and the real slope profile of the cycling track in Pfyn. The minimum time is $t_{\mathrm{f}}^{\star} = 18$ min 17.8 s. The red dashed line represents the maximum power P_{m}.

A Practical Investigation of Optimal Strategies on the Flüela Pass

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Introduction

During recent years, the optimization of pacing strategies in the field of endurance sports based on mathematical models has become more and more popular. Strategies have been developed for running [1] as well as for cycling [2],[3]. But most of these studies are of theoretical nature and lack of practical relevance.

In this work we want to present an experiment where the optimal strategy has been applied on a simulated real world track by providing feedback to the athlete on-the-fly. We will present the underlying mathematical models, the parameter estimation, the experiment setting and first results.

Methods

All tests are performed on a bike simulator based on a Cyclus2 brake and our own software [4]. In cases where a strategy is simulated, the riders get a constant visual feedback of the difference in the travelled distance and are advised to keep that gap as small as possible.

The experiment consists of five tests: At first, the subject performs an incremental step test to obtain an estimate of his anaerobic lactate threshold (AT). The other tests are rides on a real track, namely the eastern climb of the Flüela Pass in Switzerland. The first ride (I) is for familiarization purposes. In order to obtain a decent benchmark, subjects were advised to ride as close to their AT as possible but were free in the selection of their power output. In the second ride (II) subjects rode with their own predefined pacing strategy. In ride I and II subjects were instructed to perform with maximal effort.

The third ride (III) is performed with an optimal strategy feedback and the fourth ride (IV) with a validation strategy feedback.

The optimal strategy is calculated based on a physical model describing the equilibrium of the rider's pedal force and the forces induced by aerodynamic drag, friction, gravitation and inertia (see [2]). The physiological capabilities of the athlete are modelled by a dynamic version of Morton's critical power model [5]. The resulting optimal control problem is solved by the state-of-the-art solver GPOPS II [6].

The validation strategy is determined by adding a constant power offset to the rider's own strategy of ride II in order to achieve the same time than with the optimal strategy. This trial was performed to give information on whether only the optimal strategy or if also the modified own strategy with supportive visual feedback can lead to an improved performance. Obviously the energy demand of this strategy is higher than in ride II.

The parameters of the physiological model are determined with the step test and rides I and II by assuming that the athlete is fully exhausted at the end of each test. Therefore parameters are chosen in a way that the anaerobic work capacity level is zero at the end of the race by minimizing its squared error.

Results

All subjects were able to perform the optimal strategy ride as proposed and the total race time improved by around 1.9% compared to the self-paced ride II (Table 1). Three out of six subjects were able to follow the validation strategy IV. One reason for this could be that they were not fully exhausted in ride II and therefore could maintain the more energy consuming validation task until the end. Also day to day variations in performance could lead to such a result. Nevertheless, the three subjects that could not follow the validation strategy show that the optimal strategy offers a benefit over the self-paced strategy.

Table 2 shows the root mean square error between proposed power output and power output during the experiment. The error is significantly higher in the validation ride as in the ride with optimal strategy feedback.

rider	II	III		IV	
	(hh:mm:ss)	(hh:mm:ss)	(%)	(hh:mm:ss)	(%)
1	00:43:03	00:42:43	-0.77	00:42:43	-0.77
2	01:00:12	00:59:26	-1.27	00:59:26	-1.27
3	00:44:28	00:43:55	-1.24	00:44:44	+0.59
4	01:19:01	01:16:51	-2.74	01:18:42	-0.40
5	00:58:17	00:57:00	-2.20	00:57:49	-0.80
6	00:53:55	00:52:10	-3.24	00:52:10	-3.24

Table 1: Total race-times for rides II, III and IV. Additionally for rides III and IV the improvement compared to test II is provided in relative values.

Conclusions

Our experiment showed that the calculated strategy is feasible, which means that all athletes were able to follow it until the end. Furthermore, it provides an advantage over the strategy the athletes chose on their own. However, it should be noted that three riders could improve their performance with a different pacing strategy. This leaves the question whether the strategy or the external feedback given to the subjects allows for an improvement in performance.

rider	III		IV	
	RMS	Mean P	RMS	Mean P
1	13 W	391 W	18 W	391 W
2	13 W	266 W	16 W	266 W
3	22 W	337 W	25 W	331 W
4	4 W	175 W	12 W	170 W
5	9 W	264 W	19 W	260 W
6	16 W	293 W	20 W	294 W

Table 2: Root mean square error in power output between proposed strategy and experiment for rides III and IV and mean power output during the ride in Watt.

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Two Body Dynamic Model for Speed Skating Driven by the Skaters Leg Extension

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Introduction

In speed skating forces are generated by pushing in a sideward direction against an environment, which moves relative to the skater. De Koning et al. (1987) showed that there is a distinct difference in the coordination pattern between (elite) speed skaters. Models can help to give insight in this peculiar technique and ideally find an optimal motion pattern for each individual speed skater. Currently there are three models describing and optimizing the behaviour and performance of skaters, of which only two are relevant in terms of coordination patterns (Allinger & Bogert, 1997; Otten, 2003). However, none of them have been shown to accurately predict the observed coordination pattern via verification with empirical kinetic and kinematic data. Therefore, the objectives of this study are to present a verified three dimensional inverse skater model with minimal complexity, based on the idea of (Cabrera, Ruina, & Kleshnev, 2006), modelling the speed skating motion on the straights. The model is driven by the changing distance between the torso and the skate (further referred to as the leg extension), which is also the true input of the skater to generate a global motion. This input, which is indirectly also a measure of the knee extension of the skater, is a variable familiar to the speed skaters and coaches. In this extended abstract we verify this novel model for two strokes (left and right) of one skater through correlation with observed kinematics and forces.

METHODS

2.1 Model Description

The model presented in this section simulates the upper body transverse translation of the skater together with the forces exerted by the skates on the ice. The model input is the measured leg extension (coordination pattern). Based on empirical data from previous studies using elite skaters, the double stance phase, the time in which both skates are in contact with the ice, is rather short. For the sake of simplicity, we assume that there is only one skate at a time in contact with the ice, alternating left and right. The point of alternation is defined as the moment in time where the forces exerted on both skates are equal.

Furthermore the arm movements and the rotations of the upper body are assumed to be of marginal effect on the overall power and are therefore neglected. Based on these assumptions, the skater can be considered as a combination of two point masses, which are situated at the upper body (mass B) and at each (active) skate (mass S). The body mass of the skater is distributed over the two active masses by a constant mass distribution coefficient (η) to compensate for the shift in the center of mass position during the speed skating movement. Each mass has three degrees of freedom. The set of parameters is restricted to the position coordinates of mass B (x_b, y_b, z_b), two translations in the transverse plane of mass S with the position coordinates (x_s, y_s) (because the skate is assumed to be on the ice, making $z_s=0$ at all times) and one rotation in the same plane, the steer angle (ϕ_S). The orientation of the skate is of importance for the constraint forces acting on the skate. All other rotations of the skates are ignored.

Since we want to obtain a model which is driven by generalized (local) coordinates, we introduce a set of generalized coordinates q_i (Figure 1), so the global coordinates can be expressed in terms of leg extension via the kinematic relation $x_i = f(q_i)$. These generalized coordinates consist of the leg extension (w_s, u_s, v_s, θ_s)(Figure 1), that is actively controlled by the skater and therefore serves as the input coordinates to the model and the generalized coordinates of the upper body (u_b, v_b), which will be a result of the system dynamics (equal to x_b, y_b)

The equations of motion are expressed in generalized coordinates, so that the constraints are inherently fulfilled. Since we assume no lateral slip, a non-holonomic constraint acting in the lateral direction of the skate was added, causing the undetermined external force λ perpendicular to the skate blade in the transverse plane. This leaves a model with two degrees of freedom in position and only one in velocity. The known external forces acting on the model are the air frictional forces and the ice frictional forces.

2.2 Solving the Model

The model is solved in two steps. First, since the parameters (w_s, u_s, v_s, θ_s) are considered inputs and the air frictional forces acting on the upper body are assumed to be known, the constraint force λ and the transverse position of the upper body (u_b, v_b) can be determined by means of integration (Runge Kutta method), starting from the initial condition $\left(x_{b,0}, y_{b,0}, \dot{x}_{b,0}, \dot{y}_{b,0}\right)$. The constraint is fulfilled for each integration step by a projection method. Hereby a minimization problem was formulated, concerning the distance from the predicted solution to the solution which is on the constraint surface. The global coordinates x_i, which are the global positions of the upper body and the skate, can then be found analytically via the kinematic relation. Finally, with the found upper body position and λ,

the local forces acting on the skate can be solved analytically such that a complete two-body dynamic model of the skater has been established.

2.3 Model Verification

The purpose of the model verification is to quantify the error between the simulated data and the measured forces and positions. The forces were measured by a set of instrumented klapskates (van der Kruk, den Braver, Schwab, van der Helm, & Veeger, 2016). The position of the masses was measured by a motion capture system on 50 meter of the straight part of the rink, with a passive marker on the Lateral Malleolus (representing mass S) and on the back near the Sacrum (representing mass B). A parametric function was fitted to the recorded data, consisting of a linear and a geometric function, which could be differentiated twice in order to obtain velocity and acceleration data. The air and ice friction were estimated based on previous papers (J. J. De Koning, De Groot, & Van Ingen Schenau, 1992; van Ingen Schenau, 1982). The body mass was assumed to be distributed equally over mass S and mass B. In this abstract the data of one Dutch elite female speed skater are presented (65kg, 1.75m).

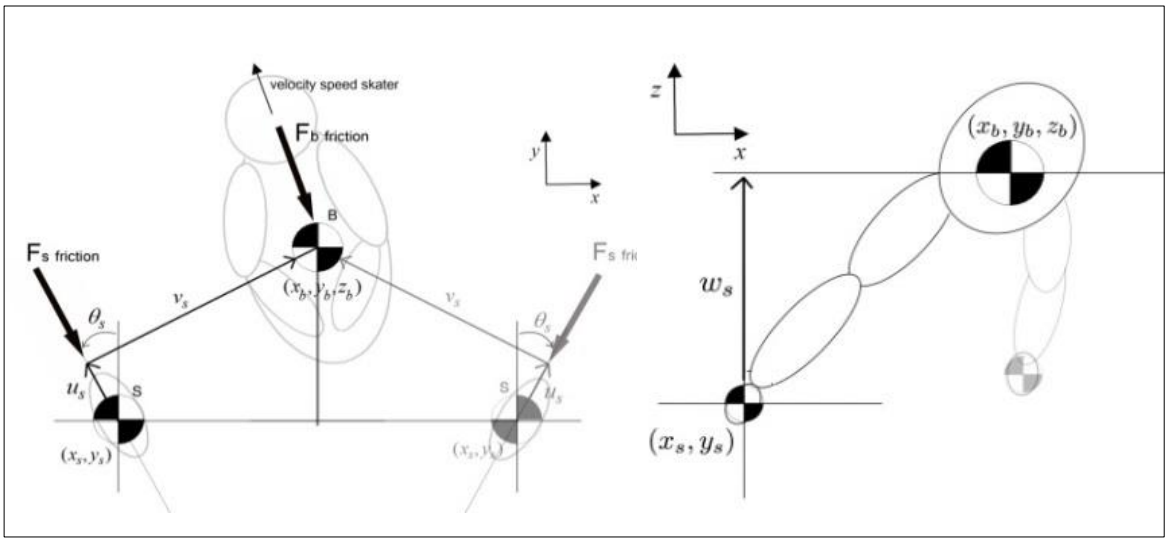

Figure 1: The global and generalized coordinates of the two-mass skater model. Leg extension consists of vertical distance (ws) and horizontal distance between the mass S and mass B in heading direction (us) and perpendicular to heading direction (vs) and the heading of the skate (θs) (orientation).

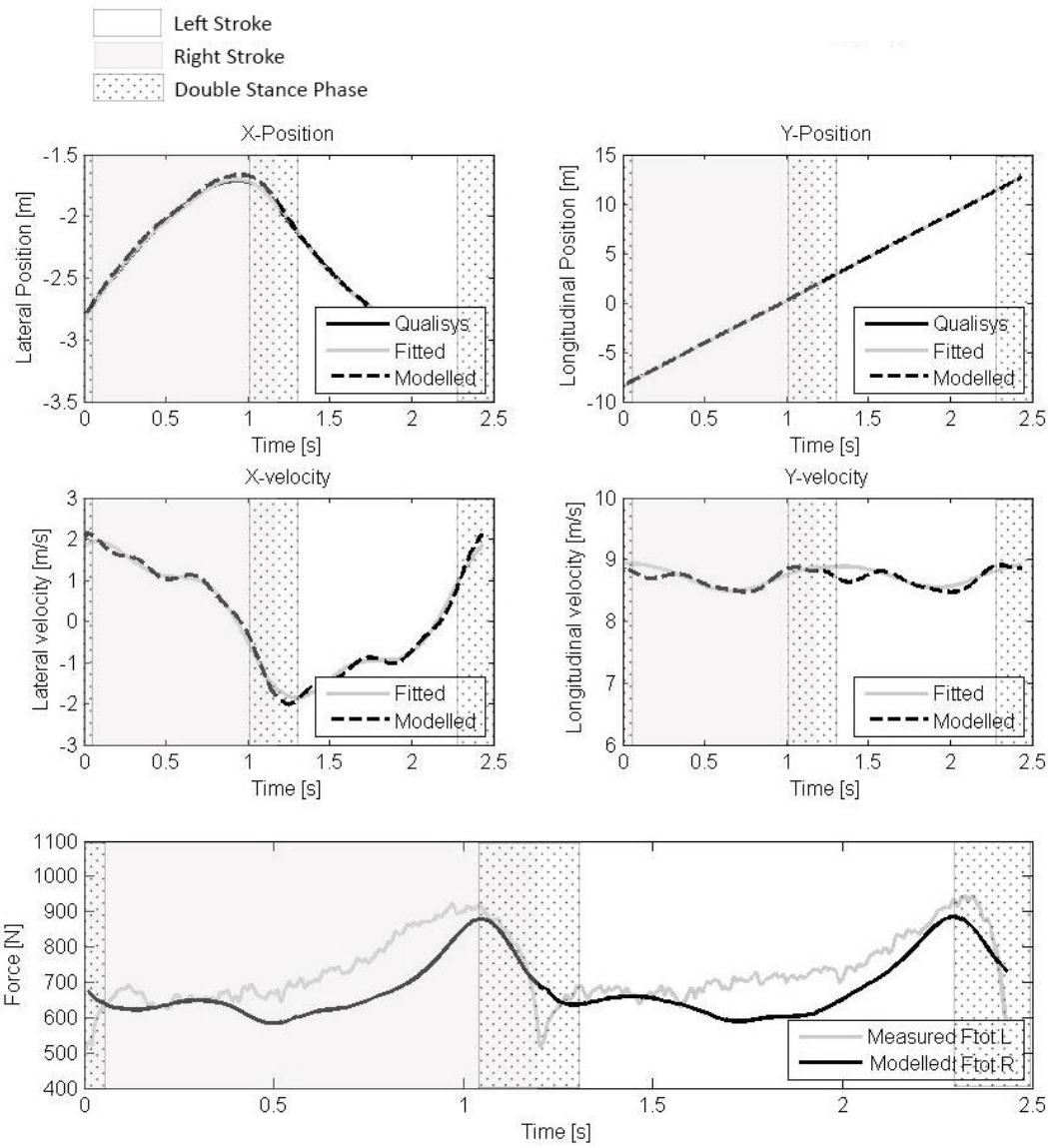

Figure 2 The measured (Qualisys), fitted and modelled data of two consecutive strokes for position and velocity of mass B and the total force. The grey area indicates a left stroke, the white area a right stroke, the pattern indicates the double stance phase as measured.. Y is in line with the skate lane, X is perpendicular to the skate lane.

RESULTS

The results show that the model estimated the forward position and velocity of mass B the best (*Jmin* (based on (Cabrera et al., 2006))), followed by the lateral position and velocity, which were all within 1% accuracy. The model was least accurate for the force determination (Table 1). The forces were consistently estimated too low (Figure 2, bottom graph).

Table 1: Error between the simulated data and the measured data.

	RMSE	Mean Error	SD Error	Jmin
x-position	0.025 [m]	0.019 [m]	0.016 [m]	0.000310
y-position	0.045 [m]	0.033 [m]	0.031 [m]	0.000004
x-velocity	0.116 [m/s]	0.002 [m/s]	0.117 [m/s]	0.0028
y-velocity	0.096 [m/s]	-0.048 [m/s]	0.084 [m/s]	0.000123
F	82 [N]	-54.0 [N]	61.8 [N]	0.0305

DISCUSSION

4.1 Kinematic Complexity

Preliminary results presented in this abstract showed that the model, despite the simplicity, was able to simulate the upper body movement accurately. The forces on the skate were underestimated, which can be explained by the simplicity of the model. The skater was considered as a combination of two point masses, which moreover were situated at fixed positions on the body parts, with each a mass half of the total body weight. In reality there might however be a different mass distribution and the CoM of these bodies move throughout the movement. Additionally, the changing distance between the two masses (leg extension), was modelled piston-like without any damping. Optimization of the mass distribution and determination of the true CoM (with a full body marker set) will improve the model estimation. The model would also benefit from improved acceleration measurements by adding IMU's.

Although the double stance phase was neglected based on previous papers, the collected data showed that the double stance phase is apparent in about 13% of the stroke. However the force on the inactive skate is low during this phase and the results do not seem influenced by this assumption.

4.2 Frictional Forces

The estimation of air and ice friction based on previous papers, probably caused an inaccuracy in the model outcome. Moreover, the air friction was assumed to be only dependent on velocity, while the friction coefficient might differ within a stroke, due to change of frontal area and drag. It would be interesting to determine the magnitude and repeatability of this change, in order to relate this to the model error, and to perhaps improve the estimation of the fluctuating character in the forward velocity within one stroke.

4.3 Application

When the model is verified with more data, it will be possible to determine the sensitivity of the model for each parameter, and with that determine the performance-dependent variables in speed skating. This insight will help to provide more valuable feedback on

technique to skaters and coaches and via optimization propose individual optimal coordination patterns.

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Predicting maximum speed in a 4x1000 m Field Test based on estimated VO_2max values from Shuttle Run Test and Queens College Step Test

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Introduction

The maximal oxygen uptake (VO_2max) measures the maximum amount of oxygen that an individual can use per unit of time during strenuous physical exertion. It is one of the most distinguished measures in endurance sports and serves as an index of cardiorespiratory function, general health, and aerobic fitness [1]. Besides its physiological meaning, VO_2max is also relevant in exercise prescription. The intensity of cardiorespiratory exercise [2] and endurance training is commonly quantified as a percentage of VO_2max. Due to that, assessing the maximal oxygen uptake plays an important role in endurance sport. It provides a basis for diagnosing aerobic capacity or designing programs to improve cardiovascular fitness. Since VO_2max is also one of the predominant limiting factors in endurance exercises and training, it may also serve as a predictor for performance in endurance sports

This study aims to (a) estimate the VO_2max in healthy adults by two common endurance tests and (b) construct and evaluate a statistical model that predicts the performance in a 4x1000 m Field Test based on these estimated VO_2max values.

Methods

29 subjects participated in this study (8 male: age 28.8 ± 8.4 years, height 186.4 ± 5.7 cm, mass 81.4 ± 8.7 kg, and 21 female: age 22.8 ± 2.6 years, height 169.0 ± 6.9 cm, mass 59.8 ± 6.6 kg). Each subject gave written consent to participate in the following three tests:

(1) The Shuttle Run Test (SRT)(e.g. [3], [4]): Subjects ran shuttles between two marked lines placed 20 m apart at increasing fast speeds. Running speed was increased each minute from one level to another. Accordingly, each level consisted of a different number of shuttles within that minute (from 7 runs in level 1 up to 16 runs in level 21). Subjects were verbally

encouraged to give maximum effort in this test. VO_2max of subjects were determined based on their successfully completed levels and runs (see [4]).

(2) The Queens College Step Test (QCST)[5]: The test started with a 3 min rest when the subjects sat on a bench step (height: 41 cm). For women, a metronome was set at 88 beats per minute (bpm) leading to 22 steps per minute, for men it was set at 96 bpm leading to 24 steps per minute. Subjects made contact with a foot on each beep of the metronome in an up-up-down-down manner. After exactly 3 min of stepping, the subjects stopped and palpated for the radial pulse at exactly 3:05 to 3:20. Recovery heart rate (HR) was derived for a full minute (bpm) and used to calculate VO_2max based on the following formulas from [5]:

Men: $VO_2max\ [ml \cdot kg^{-1} \cdot min^{-1}] = 111.33 - (0.42 \times HR)$,

Women: $VO_2max\ [ml \cdot kg^{-1} \cdot min^{-1}] = 65.81 - (0.1847 \times HR))$

(3) The 4x1000 m Field Test (FT)[6]: In this test, the subjects individually chose their running speed based on written instructions. The first three runs requested incremental running speeds corresponding to common training intensities (slow, medium and fast). The last run corresponded to the maximum speed that the subjects can run for a 1000 m. Therefore, the term *maximum speed* refers to the average speed achieved and maintained in the last maximal effort trial of the 4x1000-m-Field-Test. Between each run a two-minute rest was allowed. Instructions for runs defined the different intensities according to (a) the usual durations of such runs, (b) a rating of perceived exertion after these runs, and (c) information about the breathing during the runs (e.g. “slow” refers to an intensity of a 1 h jog which is a bit tiring but not exhausting, where breathing and talking is easy). Participants were also instructed to run a preferably constant pace in each trial [cf. 7].

The SRT (1) and QCST (2) were chosen, because they estimated the subjects’ VO_2max from different points of view. Test (1) is a maximal effort test that aims at an athlete’s ability to continue an incremental endurance activity and primarily resist to fatigue. In contrast, test (2) is a submaximal effort test which measures the recovery heart rate of an athlete, because it returns to resting values more quickly in fitter people than it does in those who are less fit.

The VO_2max estimates from test (1) and (2) were used in a multiple regression model as predictor variables (*SRTVO2max* from Shuttle Run Test and *QCSTVO2max* from Queens College Step Test). In that regression model, maximum speed in a 1000 m run (in FT) served as the criterion variable (i.e. the outcome).

Results

Estimated VO_2max values for males were 49.3 ± 5.3 [$ml \cdot kg^{-1} \cdot min^{-1}$] in SRT and 55.3 ± 9.8 [$ml \cdot kg^{-1} \cdot min^{-1}$] in QCST. For female they were 41.9 ± 5.5 [$ml \cdot kg^{-1} \cdot min^{-1}$] in SRT and 40.3 ± 3.6 [$ml \cdot kg^{-1} \cdot min^{-1}$] in QCST. Figure 1 shows a grouped boxplot of the results according to the two tests.

The VO_2max values from SRT and QCST were significantly correlated ($r = 0.72$, $p < 0.01$). An ANOVA (*factor group with two levels: male and female; factor test with two levels: SRT and QCST*) revealed a significant main effect of group ($F(1, 27) = 28.46$, $p < 0.01$, $\eta^2 = 0.45$), i.e. men had higher VO_2max values than women, but no main effect between the both tests ($F(1,27) = 0.22$, $p = 0.64$). Thus, the two tests did not differ systematically, i.e. they did not

show significant differences in estimating the subjects' oxygen uptake. However, we found a significant interaction effect ($F(1,27) = 12.09$, $p < 0.01$, $\eta^2 = 0.09$), i.e. men tended to achieve higher scores in QCST compared to SRT, while the scores for women were not influenced. However, effect size of this interaction was quite small.

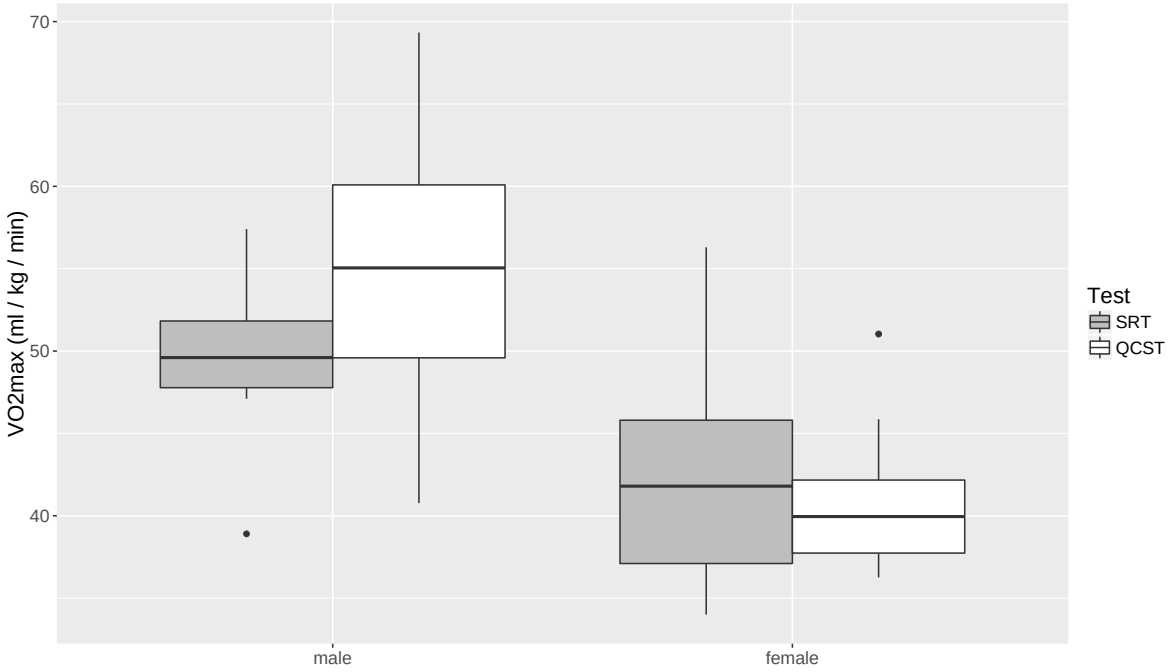

Figure 1. Boxplot of estimated VO2max for male and female participants based on Shuttle-Run-Test (SRT) and Queens-College-Step-Test (QCST)

Multiple regression analysis was used to test if the estimated VO_2max from SRT and QCST significantly predicted participants' maximum speed. The mean across participants of the maximum speeds in the 1000 m runs was 15.1 ± 1.5 km/h for men and 13.2 ± 1.4 km/h for women. The results of the regression model indicated the two predictors explained 65% of the variance ($R^2_{ad} = 0.65$, $F(2,26) = 26.46$, $p < 0.01$). Furthermore, the prediction of the model was evaluated by a 10-fold-cross-validation approach. An overall root mean square error (RMSE) of 1.03 km/h was obtained.

Conclusions

The estimated VO_2max from both the Shuttle Run Test and the Queens College Step Test are, taken all together, able to predict a remarkable amount (65%) of variance in maximum speed in a 1000 m run. This is in line with the concept that VO_2max has an important influence on endurance performance.

A mean prediction error of approximately 1 km/h of the real maximum speed seems to be small, but may still be too big to allow detailed recommendations for training based on

running velocities. Additionally, there is still 35% variance left that could not be explained by this statistical model. Many aspects may have contributed to this unexplained variance. For instance, the motivation of the subjects in maximal effort tests (such as the SRT and the last trial in FT) and environmental factors could have influenced the results profoundly. With respect to environmental factors, the tests were performed on varying floor types and different days and therefore with varying weather conditions. Other aspects may be related to the different facets of endurance. The 4x1000 m Field Test requires resistance to fatigue (in each run) as well as a quick recovery (in between to runs). Thus, a specific combination of these two aspects is important for this test and affects the maximum speed in the last 1000 m run. The SRT and the QCST, however, focus mainly on one of these aspects rather than the combination of both. Last but not least, the athletes' anaerobic energetics might have an impact, too. In a short duration 1000 m run, anaerobic metabolism contributes substantially to the total energy expenditure. Therefore, variations in the anaerobic energetics between runners might also contribute to the observed variance in running speed. Taken together, these aspects may limit the prediction and amount of explained variance based on their estimated VO_2max values.

Furthermore, even though the estimated VO_2max values from SRT and QCST were highly correlated, both tests did not measure oxygen uptake directly with a spirometer. Although the SRT was validated with respect to estimating VO_2max, we still have to consider an estimation error. For instance [8] found a standard error of estimate of 5.4 [$ml \cdot kg^{-1} \cdot min^{-1}$] in an early version of the SRT. This applies analogously to the inaccuracy of the QCST results. While formulas from [5] appear to be very accurate, [9] found a standard error of prediction of 2.9 [$ml \cdot kg^{-1} \cdot min^{-1}$] in their test persons. Hence, the two predictor variables in our linear model may be inaccurate to a certain amount, which also affects the accuracy in predicting the speed as outcome variable.

To finalize, the multiple regression approach in this study also neglects other potential predictors like age, sex, as well as further experiences with endurance sports, and – from a methodological point of view – the regression is statistically based on linear models. This, however, may be a severe limitation, because in real world settings many influencing factors and non-linear processes occur in contexts of sports.

A next step should be to improve the prediction model by adding further variables that might influence and explain performance in a 1000 m run. Besides that, different non-linear alternatives for modeling also seem to be promising to improve the accuracy of the prediction. Artificial neural networks, particularly multilayer perceptrons, may provide more sophisticated non-linear approaches for prediction. However, a major amount of variance in maximum speed can already be explained from the linear model approach chosen in this study.

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Determination of Critical Speed and the Running Distance above Critical Speed under Laboratory and Field Conditions using Equal Exhaustive Durations – a Pilot Study

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Introduction

The power-duration concept of Critical Power (CP) [1] and its related 'anaerobic' parameter (*W´*) was adapted to treadmill running in the early 1980ies by Hughson et al. [2] and consequently termed Critical Speed (CS) and its 'anaerobic' parameter Running Distance Above CS (*D´*). This finite distance can be maximally run, when performing at values above CS.

Today, coaches and sport scientists use this concept to assess performance, to prescribe training, and to predict performance. Traditionally, these tests were carried out only under laboratory conditions. However, field tests are preferred over laboratory test by many coaches due to their similarity to competitive races and their reflection of real-world training. Field tests carry a higher level of ecological validity, although lack of environmental control is often criticized. To translate relevant laboratory tests into the field arguably presents a challenge for sport scientists.

Previous work

A growing body of literature has assessed the interchangeable use of CS and CP under laboratory and field conditions.

For example, Galbraith et al. [3] postulated that the determination of CS can be translated into field conditions as their work did not find a significant differences between respective CS values. However, these authors demonstrated significant differences in *D´* between conditions. Recently, another study assessing CS and *D´* under both conditions found significant differences for both, CS and *D´* [4].

Similar to running, studies have compared estimates of CP and *W´* between laboratory and field conditions [5-7]. These results demonstrated non-significant differences and a good level of agreement for CP, but not for *W´*.

Aforementioned studies [3-6] used different durations for the prediction trials under laboratory and field conditions and these differences in duration might explain the significant differences in *W´*/*D´*. When comparing time-to-exhaustion runs under laboratory conditions with time-trials or fixed distances under field conditions, it seems obvious that it is nearly impossible to match the exact duration of the corresponding prediction trial.

Therefore, the aim of this study was to evaluate CS and *D´* between treadmill running and over-ground running using equal durations for the corresponding prediction trial. A recent study suggested to use equal duration of the prediction trials to alleviate differences in *D´* [4]. We hypothesized non-significant differences and a good agreement between laboratory and field estimates CS and *D´*.

Methods

Six moderately trained soccer players (mean ± SD: age 25.6 ± 2.5 yrs; stature 179.3 ± 5.4 cm; body mass 73.8 ± 7.0 kg; $\dot{V}O_{2max}$ 53.8 ± 3.1 mL·min^{-1}·kg^{-1}) volunteered to participate in this study. Participants had to give written informed consent after all experimental procedures were explained. The study was conducted in accordance to the declaration of Helsinki and all procedures have been approved by the local ethics committee (Ref. nbr. 00155).

After an initial incremental exercise test to determine respiratory thresholds and maximum aerobic speed (MAS), participants performed three prediction trials leading to exhaustion on a treadmill and on a 400 m athletics track. Speeds for the laboratory test were taken as 75%Δ of the difference between speed at first respiratory threshold and MAS, 98% of MAS (i.e. 0.98 x MAS) and 108% of MAS (i.e. 1.08 x MAS). These intensities have shown to lead to exhaustion between 2.5 and 15 min [4, 5]. Treadmill grade was set to 1% to compensate for air resistance. Under field conditions, participants were asked to cover the greatest distance possible within the time achieved during the respective prediction trial. All prediction trials were interspersed with 30 min passive rest [3-6]. The parameter estimates (CS and *D´*) were resolved using the linear speed/inverse-time model:

$$speed = D' \; x \; 1/t + CS \qquad (1)$$

where speed is in m·s^{-1}, and t represents time (s).

Results

Using the Shapiro-Wilk test all data was normally distributed. A paired sample t-test revealed no significant differences between the conditions (P = 0.548 and P = 0.265 for CS and *D´*, respectively). Results of the tests are presented in Table 1. Moreover, we found significant correlations between the conditions (r = 0.947; P = 0.004 and r = 0.913 and P = 0.011 for CS and *D´*, respectively) (Figure 1). The bias was 0.04 ± 0.13 m·s^{-1} (95% LoA: -0.23 to 0.30 m·s^{-1}) for CS and -17.3 ± 33.8 m (95% LoA -83.5 to 48.9 m) for *D´* (Figure 2).

Conclusions

The main finding of this study was that when using equal exhaustive durations non-significant differences between the conditions were observed for both, CS and *D´*.

Our results for CS are supported by previous findings [3, 5], but results for *D´* are in vast contrast to previous works [3-7]. A significant correlation was shown only for CS between the conditions in previous works [3-7], and only a single study found a significant correlation for *D´* between the conditions [5]. In comparison to previous studies we found higher correlation coefficients for CS and *D´* ($r > 0.913$) and significant correlations ($P < 0.011$) compared to studies using non-equal durations [3-5]. The 95% Limits of Agreement (LoA) revealed a closer agreement between methods compared to other studies assessing CS (0.04 $m \cdot s^{-1}$ vs. 0.25 $m \cdot s^{-1}$ [3] and -0.39 $m \cdot s^{-1}$ [4]) and *D´* (-17.3 m vs. 187 m [3] and 36.7 m [4]).

This is the first study that found a non-significant difference, a close agreement, and a significant correlation between the conditions for CS and for *D´*. Using equal durations under both conditions therefore represent a valid comparison for CS and *D´*. Our results support the use of both test interchangeably. CS and *D´* are considered a valid measure under both conditions.

	Laboratory	Field conditions
CS ($m \cdot s^{-1}$)	3.87 ± 0.39	3.84 ± 0.41
D´ (m)	225.1 ± 80.5	242.5 ± 81.2

Table 1: Results of the CS ($m \cdot s^{-1}$) and *D´*(m) tested under laboratory and field conditions.

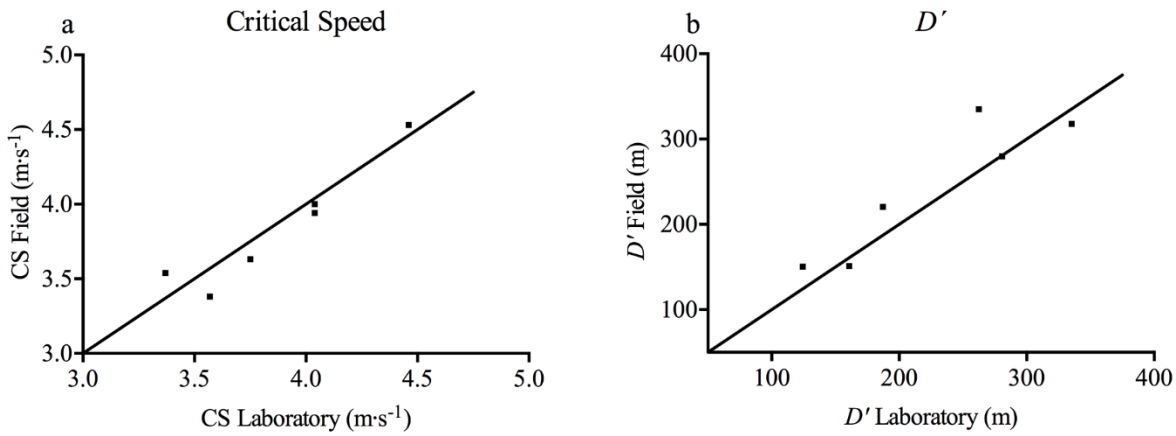

Figure 1: (a) Relationship between CS during laboratory and field test. (b) Relationship between *D´* during laboratory and field test. Solid line represents the line of identity.

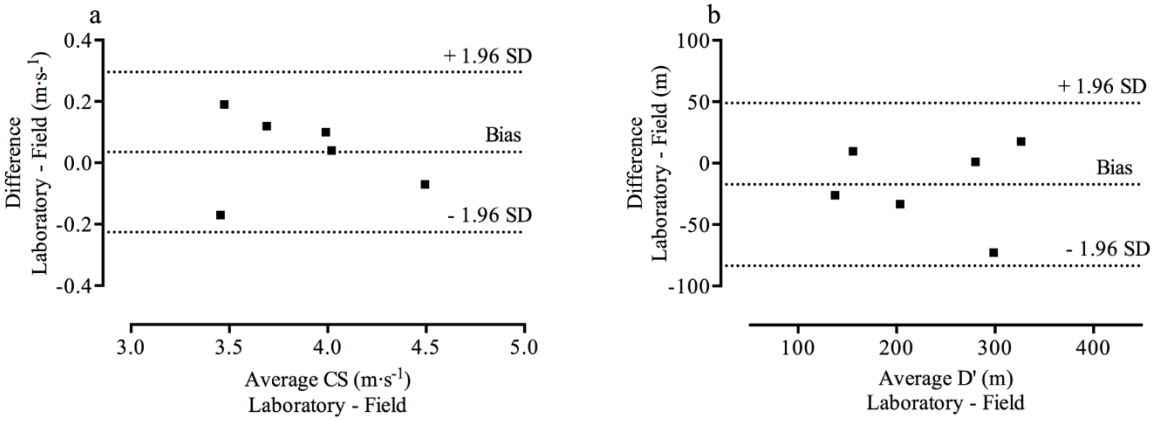

Figure 2: Bland-Altman plot of the difference in (a) CS (b) and *D´* during the laboratory and field test.

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Ball (not) in play: the distortive effect of net playing time on the decline of match running performance in professional football

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Introduction

This study aimed to (1) compare established running performance parameters in respect to the development of fatigue and (2) determine whether the frequently reported declines in physical performance are distorted by an increase of game stoppages towards the end of a football game.

Methods

1134 individual match performances from eighty-one German Bundesliga games were analyzed during the 2012-2013 and 2013-2014 competitive season, using a multi-camera computerized tracking system (TRACAB, Stockholm, Sweden). Parameters selected for analysis included the relativized distances traveled in generally used speed zones, number of accelerations and sprints as well as metabolic power. Performance data were divided into eighteen 5min periods for the analysis of temporal changes over the course of the game. Student's t-test and ANOVA with Bonferroni post hoc tests were used to identify effect sizes of temporal changes considering both absolute and actual playing time (excluding game interruptions).

Players' running performances were divided into the following categories: total distance (TD), walking (0.7-7.2 km • h^{-1}), jogging (7.2-14.4 km • h^{-1}), running (14.4-19.8 km • h^{-1}), high-speed running (HSR) (19.8-25.2 km • h^{-1}), and sprinting (> 25.2 km • h^{-1}). High intensity running (HIR) consisted of running, high-speed running, and sprinting. Very high-intensity running (VHIR) consisted of high-speed running and sprinting. We further subdivided the distances covered at low, moderate and high acceleration ($L_{ACC,}$ 0-2 m • s^{-2}; $M_{ACC,}$ 2-3 m • s^{-2}; $H_{ACC,}$ >3 m • s^{-2}) and deceleration ($L_{DEC,}$ 0 to -2 m • s^{-2}; $M_{DEC,}$ -2 to -3 m • s^{-2}; $H_{DEC,}$ < -3 m • s^{-2}).

Acceleration and deceleration efforts were classified as consecutive samples (0.2 s) exceeding the abovementioned acceleration and deceleration thresholds (#$L_{ACC,}$ #$M_{ACC,}$ #$H_{ACC,}$ #$L_{DEC,}$ #$M_{DEC,}$ #H_{DEC}. A sprint was defined as the attainment of sprint speed (> 25.2 km • h^{-1}) for a minimum of 0.5 s.

Finally, the metabolic power equations were also included in the analysis in order to estimate the average metabolic power (P_{MET}, W • kg^{-1}) at any given moment.

All categories were relativized to a minute by minute value.

Results

Initially we found a significant decline in effective playing time (E_t, $p < .01$) over the course of a match, accounting for a decrease from 69% of the total play time in the 1-5min period to 56% in the 85-90min period. In consideration of the total playing time (T_t), performance parameters decreased by 26.2% on average ($\eta^2 = 0.29$, corresponding to large effect sizes). Considering the effective playing time (E_t), performance parameters decreased by only 12.1% on average ($\eta^2 = 0.12$, corresponding to medium effect sizes) (Figure 1).

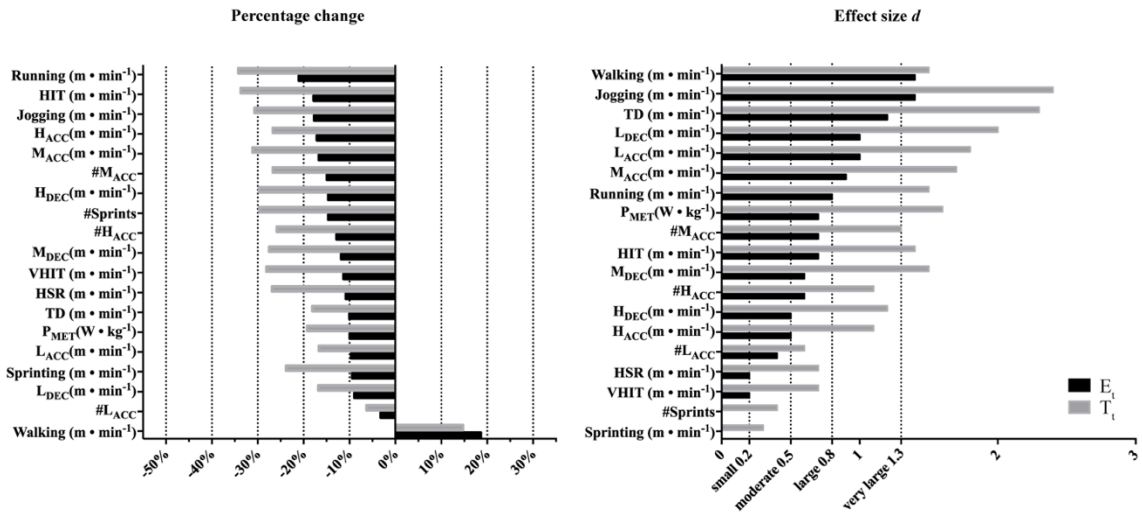

Figure 1: Changes in match running performance between the first (0-5min) and last (85-90min) match period; left figure shows the average percentage change of the different movement categories; right figure shows the resulting effect sizes *d* of the observed differences; comparison between effective playing time (E_t) and total playing time (T_t)

Conclusions

In conclusion, this study showed that the decrease in physical performance during a football match is strongly enhanced by an increase of game interruptions over the course of the game. This indicates that the occurring fatigue in professional football should be examined in consideration of the actual playing time.

Prediction of individual short term heart rate responses

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Introduction

In the physical training process, optimal training adaptations require individually optimal strain on the human body. Especially in endurance training, the individual heart rate (HR in beats per minute) response has become a very important indicator to measure and determine the individual strain. As the same load can lead to complete different responses in different individuals the prediction of this individual HR response is very challenging and one of the key problems in the physical training process. This paper is analyzing two different procedures to predict individual HR responses for cycling on a bike ergometer.

Methods

HR data of sixteen healthy and physically active participants were recorded and processed while the participants were playing the Exergame "LetterBird" [1]. This game was developed by the communication laboratory in Darmstadt and aimed at realizing playful endurance training.

All tests were performed on a Daum Cycle Ergometer (8008 TRS 3) with a flywheel. HR was constantly monitored by a chest belt (POLAR, T31), processed by the ergometer and logged together with the corresponding time stamp (in milliseconds), with the Power in W (measured by the ergometer) and the pedal rate (PR) in revolutions or rates per minute (rpm; measured at the flywheel). The PR controlling the game was expected to have no influence on the HR [2]. The individual optimal training range was set to 70 – 80% of the maximal HR (HRmax) depending on age (in years) calculated with the formula:

$$HRmax = 220 - age \text{ [3]}$$

The first procedure was developed basing on literature research [4] and aimed at calculating the individual HR response using a calibration phase prior to the actual training phase. Therefore, the individual HR responses to two defined load levels set at the ergometer were measured. Depending on the body weight and the BMI of the participants these successive load levels were set at the ergometer for 2 minutes each. Expecting a linear relationship of load and HR response in submaximal range an algorithm calculating load that is expecting to evoke a defined HR was developed. Using the HR data obtained the algorithm calculated the load that was expected to evoke an individually optimal training HR of 75 % HRmax. After a break the calibration phase was replicated to validate the results, successively followed by one minute of the calculated target load and another five minutes of an automatic

load control (ALC). In the ALC the load automatically adapts the load if the HR exceeds or falls below the training range.

The second procedure aimed at predicting the individual HR response to the change of load bouts while training or cycling. Therefore, the HR data obtained with procedure 1 were approximated using the formula

$$HR = HRend - (HRend - HRstart) * e^{-c*t} \text{ [5]}$$

with value c representing the slope of the HR course. First, reliability of the approximated data was calculated. In a second step, the c values representing the slope of the course of the two load levels of the calibration phase were analyzed. As the changes of load bouts were similar in both load levels we tested the hypotheses that the c values were also similar using the Wilcoxon-Test. In the third test, HR data at discrete time points (10 sec (t1), 20 sec (t2), 30 sec (t3), 40 sec (t4), 50 sec (t5), 60 sec (t6) and 90 sec (t7)) and parameter c of the first load level was used to predict the final HR of the second load using the formula

$$HR_{end-calc} = \frac{HR - HR_{start} * e^{-c*t}}{1 - e^{-c*t}}$$

The deviation of the calculated HR end and the measured HR end was calculated and analyzed using Wilcoxon. Cronbach´s Alpha was calculated for reliability over all time points.

Results

Using procedure 1, fifteen of sixteen participants reached the final HR zone in the exercise phase within 10 min (deviation of measured and expected HR between 9:30 – 10:00 after onset of exercise; *M* = 3.98 bpm; *SD* = 3.12; *Range* = 11.61 bpm). One participant exceeded the training range with 80.6% HRmax. In the ALC, the load was adapted downwards in 13 of 16 participants.

The regression analysis using procedure 2 revealed a regression coefficient R^2 of 0.864 (*SD* = 0.126, *Range* = 0.210)

Parameter c of load level 1 is not significantly different to parameter c of load level 2 (Δ c1 – c2: *M* = 0.02, *SD* = 0.37, *Range* = 1.22, Wilcoxon: z = -0.664, p = 0.507).

The deviation of the calculated and the measured HR differs significantly in time points t1, t2 and t3. There is no significant deviation in time points t4 – t7. The lowest deviation can be found in time point t6. All deviations for the corresponding time points are displayed in table 1.

	t1	*t2*	*t3*	*t4*	*t5*	*t6*	*t7*
M [S/min]	-24.1	-12.5	-7.7	-2.2	0.6	1.4	1.7
SD	18.47	17.20	11.36	11.09	9.21	8.37	6.03
Range [S/min]	76	67	42	49	38	31	27
Wilcoxon	-3.310; p<.01	-2.467; p<.05	- 2.510; p<.05	-1.591 not sign.	-0.31 not sign.	-0.199 not sign.	-1.008 not sign.

Table 1: deviation of calculated HR end and measured HR end at discrete time points (Δ HRend_calc – HRend _real

Cronbach α over all time points was 0.921).

Conclusions

The results confirm that it is possible to evoke the expected submaximal HR within 10 minutes. However, the frequently occurring downward adaptations of load caused by an overpassing HR revealed weaknesses. The calculated load occasionally evokes HR responses that exceed the target range. This miscalculation of the target load can be caused by the delayed HR response to load changes. In that case, the load levels of 2 min were not sufficient for the HR to adapt to the load properly.

The second procedure reveals a possible prediction of the individual HR course already while training within the tested sample. However, a sample time of at least 40 sec is required to obtain sufficient results.

In future research, not only discrete time points but the whole course and slope of the HR response should be integrated in the calculations.

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A Comparison of Models for Oxygen Consumption

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Introduction

Measurements of oxygen uptake are central to methods for assessment of physical fitness and endurance capabilities in athletes. Though respiratory gas exchange can easily be measured in a lab, these kind of measurements aren't practicable in the field and even less during competitions. Thus, we are looking for a model, which provides the means for fitting and prediction of oxygen uptake response.
Oxygen uptake kinetics are well researched for constant workrate exercises [4] and specific load profiles like ramps [3] or constant work rate, but hardly generalized for variable load profiles which occur often in the field. Thus, we compare six dynamic models with power as independent variable and evaluate their fitting and prediction abilities.

Data

Five healthy, recreationally to well trained subjects completed four different cycle ergometer (Cylus2, RBM elektronik-automation GmbH, Leipzig, Germany) tests with continuous breath-by-breath gas exchange and ventilation measurements at the mouth (Ergostik, Geratherm Respiratory GmbH, Bad Kissingen, Germany). The tests were designed to determine a set of useful physiological parameters of aerobic capacity ($\dot{V}O_{2\text{max}}$, ventilatory threshold 1 (VT_1), and maximal lactate steady state (MLSS)). Furthermore the tests featured a variety of load profiles in order to comprehensively evaluate the model prediction quality [1] (Figure 1 and Figure 2). A more detailed describtion of the testing procedures and test design can be found in Artiga Gonzalez et al. [1].

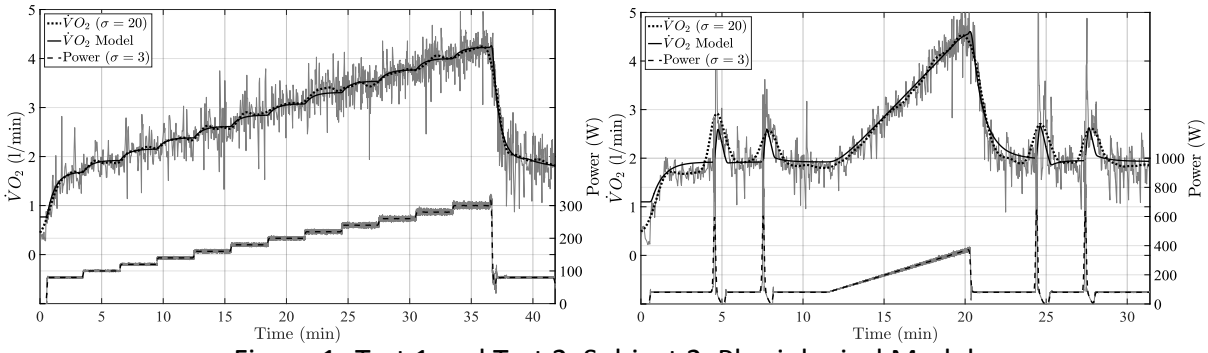

Figure 1: Test 1 and Test 2, Subject 2, Physiological Model

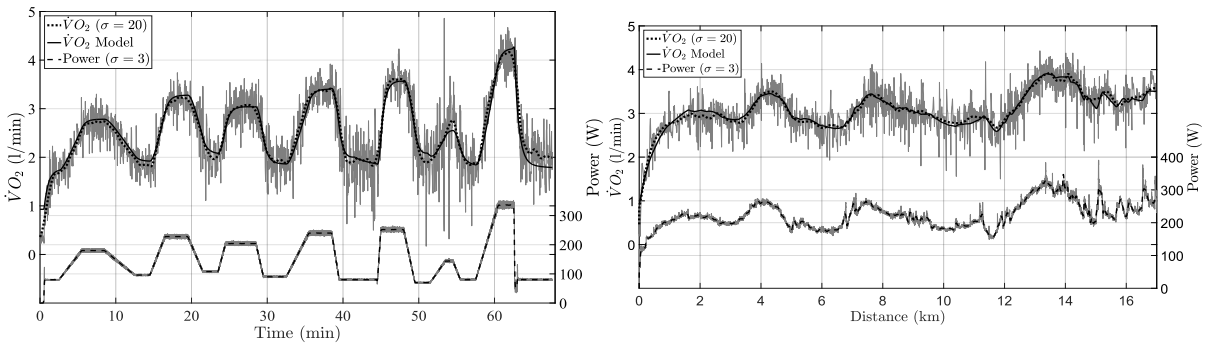

Figure 2: Test 3 and Test 4, Subject 2, Physiological Model

Models

3.1 Physiological Model

The first model from Artiga Gonzalez et al. [1] is based directly on a commonly accepted model for constant workrate [4] and takes most physiological evidence into account. We extended it by another two parameters to the following:

$$\dot{V}O_2 = \dot{V}O_{2\text{base}} + x_1(t) + x_2(t)$$

where $x_1(t)$, $x_2(t)$ are solutions of

$$\dot{x}_k(t) = \tau_k^{-1}\left(A_k(P(t)) - x_k(t)\right), x_k(T_k) = 0, k = 1, 2$$

with

$$A_1(P) = \text{min}\left(s \cdot P, \dot{V}O_{2\text{max}} - \dot{V}O_{2\text{base}}\right)$$
$$A_2(P) = \begin{cases} V_\Delta \cdot \text{exp}\left(-\left(P_c - P\right)/\Delta\right) & P \leq P_C \\ \dot{V}O_{2\text{max}} - \dot{V}O_{2\text{base}} - A_1(P) & P > P_C \end{cases}$$

and parameters $\dot{V}O_{2\text{base}}$, $\dot{V}O_{2\text{max}}$, P_C, s, V_Δ, Δ,τ_1, τ_2, T_1, T_2.
The physiological model consists of two important parts. The steady-state function described by A_1 and A_2 and the differential equations describing the exponential behavior. Instead of changing the whole model, we can just exchange the steady-state function and also omit the second component. This leads to the following variations:

3.1.1 Smooth Steady-State

A smooth alternative avoiding the discontinuity at P_C:

$$A_1(P) = V_{1\text{max}} \cdot \left(1 - \text{exp}\left(-s_1 \cdot P\right)\right)$$
$$A_2(P) = \begin{cases} 0 & P = 0 \\ V_{2\text{max}} \cdot \frac{\left(1 + \text{tanh}\left(\frac{P^2 - P_C^2}{P} \cdot s_2\right)\right)}{2} & P > 0 \end{cases}$$

3.1.2 Simple Linear Model

Only one linear component: $A_1(P) = \min\left(s \cdot P, \dot{V}O_{2\text{max}} - \dot{V}O_{2\text{base}}\right)$

3.1.3 Simple Exponential Model

Only one exponential component: $A_1(P) = V_{1\text{max}} \cdot (1 - \exp(-s_1 \cdot P))$

3.2 Stirling

The second model was introduced by Stirling et al. [5] and originally designed for running:

$$\ddot{V}O_2(t) = A \cdot \left(\dot{V}O_2(t) - \dot{V}O_{2\text{min}}\right)^B \cdot \left(\dot{V}O_{2\text{max}} - \dot{V}O_2(t)\right)^C \cdot \left(D(v,t) - \dot{V}O_2(t)\right)^E$$

We adapt it for cycling by replacing the speed based demand function $D(v,t)$ with a simple linear demand function

$$A(P) = \min\left(s \cdot P, \dot{V}O_{2\text{max}} - \dot{V}O_{2\text{base}}\right)$$

. With $E = 1$ the following parameters are estimated: $\dot{V}O_{2\text{base}}$, $\dot{V}O_{2\text{max}}$, s, A, B, C.

3.3 Cheng

The third model by Cheng et al. [2] was used for heart rate modeling on a treadmill. As heart rate behaves similar to $\dot{V}O_2$ (Figure 3), we modified the model for power as input instead of treadmill speed:

$$\dot{x}_1(t) = -a_1 \cdot x_1(t) + a_2 x_2(t) + a_6 \cdot P(t)$$
$$\dot{x}_2(t) = -a_3 \cdot x_2(t) + \frac{a_4 \cdot x_1(t)}{1 + \exp(-(x_1(t) - a_5))}$$

with $x(0) = [x_1(0)\ x_2(0)]' = [0\ 0]'$.

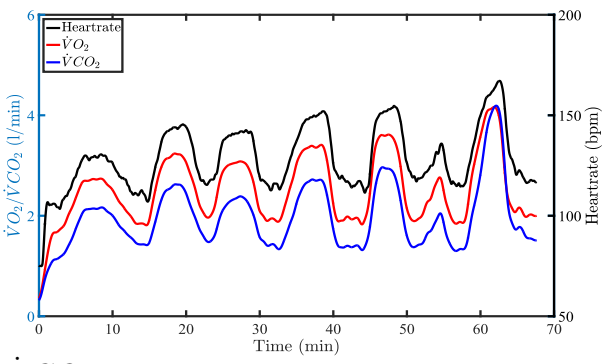

Figure 3: $\dot{V}O_2$, $\dot{V}CO_2$and Heart rate measured for one subject during Test 3.

Model	3.1 l/min	3.1.1 l/min	3.1.2 l/min	3.1.3 l/min	3.2 l/min	3.3 l/min	3.4 l/min	3.5 l/min
Subject 1	0.13	0.29	0.20	0.33	0.40	0.38	0.07	0.14
Subject 2	0.09	0.12	0.11	0.18	0.24	0.26	0.05	0.10
Subject 3	0.06	0.15	0.13	0.21	0.33	0.30	0.07	0.12
Subject 4	0.10	0.10	0.07	0.17	0.23	0.21	0.04	0.09
Subject 5	0.09	0.11	0.11	0.15	0.26	0.27	0.06	0.08
Average	0.09	0.15	0.12	0.21	0.29	0.29	0.06	0.10

Table 1: Average root-mean-square modeling error for all four tests.

3.4 System Identification: Wiener-Model

Going towards black box models in the field of system identification, the wiener model has proven well. The wiener model consists of a linear transfer function followed by a nonlinear function. For these output nonlinearity a piecewise linear function is selected. This model type coincides with the observation, that there is a linear and a smaller nonlinear relationship between power and $\dot{V}O_2$. This can also be seen in Figure 2 and Figure 3.

3.5 Feedforward Neural Networks

An even more recent approach in black box modeling are neural networks. Here a feedforward neural network is taken. The neural networks got trained with randomly resampled data from Test 3. Different network settings from one up to three hidden layers with between 10 and 400 neurons were tested.

Results

All models were implemented and evaluated in MATLAB®. For parameter estimation the Genetic Algorithm *ga* from the Global Optimization Toolbox™ was used. *nlhw* and *feedforwardnet* from the System Identification Toolbox™ were used for the Wiener model and the neural networks.

Table 1 shows the root-mean-square modeling error for all five subjects and all four tests. For prediction, the models were trained on Test 3 and applied on Test 4 (Table 2).

Model	3.1 l/min	3.1.1 l/min	3.1.2 l/min	3.1.3 l/min	3.2 l/min	3.3 l/min	3.4 l/min	3.5 l/min
Subject 1	0.38	0.38	0.39	0.46	0.49	0.51	0.40	1.51
Subject 2	0.31	0.16	0.18	0.21	0.27	0.29	0.21	0.93
Subject 3	0.21	0.20	0.23	0.25	0.35	0.52	0.25	1.15
Subject 4	0.23	0.18	0.16	0.30	0.29	0.26	0.19	0.86
Subject 5	0.38	0.28	0.23	0.23	0.33	0.35	0.29	0.87
Average	0.30	0.24	0.23	0.29	0.34	0.39	0.27	1.07

Table 2: Average root-mean-square prediction error for all four tests.

The models by Stirling and Cheng show weak performance for both, modeling and prediction. The model by Cheng even turned out unstable for some predictions.

Surprisingly, the smooth variations of the physiological model (3.1.1, 3.1.3) performed worse than their counterparts for modeling.

Despite its simplicity, Model 3.1.2 performed well for modeling and prediction. The Physiological Model 3.1 reached a good modeling result but only average for prediction.

Better modeling results are obtained with Wiener models which also show some weakness on prediction.

The results of the neural networks are hard to evaluate. If they are trained only once on the time series from Test 3 than the fitting error is near zero. We trained them more often on differently sampled data series from Test 3 to avoid overfitting. Prediction results show, that this attempt was not successful. The networks trained once on Test 3 with fitting errors of 0.00 l/min performed similar for prediction.

Conclusions

Modeling results below 0.09 l/min are better than the natural variability in $\dot{V}O_2$ (unpublished work) and they can be regarded as very satisfactory results. The physiological Model, the Wiener models and neural networks are able to perform better than that threshold.

The best prediction was made by model 3.1.3 that also still fits well with 0.12 l/min. Overall, the models perform worse than expected for prediction. A reason for that may be, that the data set is too small and too specific. Most likely, prediction results can be improved by larger training and validation data sets.

Also off- and on-transient differences have to be taken into account [6].

Another improvement can be obtained by adding further measurements like heart rate as additional input.

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Modeling the acute physiological response to cycling exercise: the blood lactate concentration challenge

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Introduction

Bioenergetics models describe the energy sources utilization/depletion/restoration within the athlete's body. In the real-world practice, measurements of pulmonary oxygen consumption VO_2 and blood lactate concentration $[La]_b$ can be used as indexes for the energy released by means of the aerobic and anaerobic-lactacid pathways respectively [6]. We can use theoretical approaches like virtual models (VM) in the attempt to predict the impact of a generic power output distribution P_{MEC} on exercising human body.
In modeling bioenergetics, despite the great amount of work done, literature lacks of an accurate description of the behavior of the lactate concentration during cycling exercise. On the top of that, since lactate and oxygen availability are (somehow [7]) linked together, we should admit that an accurate model for the pulmonary oxygen consumption is missing as well. This work wants to present our recent attempts in modeling the VO_2 and the $[La]_b$ during cycling exercise. The focus of this manuscript is on lactate concentration, that constitutes a real challenge for bioenergetics model developers.

Previous work

Modeling bioenergetics is not a new challenge and has been tackled before by exercise physiologists and model developers. Literature is fulfilled by models that aim at predicting both VO_2 and $[La]_b$ kinetics during cycling exercise. Nevertheless, available virtual models are seldom written in a convenient mathematical form. We selected 6 models of human bioenergetics and we adapted them to cycling exercise. To test the ability of the models in reproducing the major features of VO_2 and $[La]_b$, we compared the simulated results with cardiopulmonary and blood data as collected on 10 trained cyclists (9 M, mean(SD), age=32(8)y, VO_{2MAX}=57(10) mlO2min^{-1}, MAP=4.4(0.7) Wkg^{-1}) performing an incremental to exhaustion long graded test (starting at 0W 90 rpm of freewheeling, then 100 W increasing 40W every 4 min). Model parameters were optimized by means of a Particular Swarm

Optimization (PSO) algorithm [1]. We expressed the goodness-of-fit between simulated and experimental data as an overall correlation coefficient R^2 and a Root Mean Squared Error RMSE.

Model 1 is the simplest model for VO_2 and based on the first-order basic formula with known efficiency [5]. The modeling process resulted in: 1 state variable (i.e. VO_2), 1 input (i.e. P_{MEC}), 1 parameter.

Model 2 is a model for VO_2 as derived from the previous one, but with unknown efficiency. The modeling process resulted in: 1 state variable (i.e. VO_2), 1 input (i.e. P_{MEC}), 4 parameters.

Model 3 includes the internal work contribution as introduced in [2]. Internal work contribution is function of the cadence *w*, then the cadence becomes one of the inputs of the system. The modeling process resulted in: 1 state variable (i.e. VO_2), 2 inputs (i.e. P_{MEC}, *w*), 4 parameters.

Model 4 extends the previous but with unknown VO_{2max}, VO_{2b}, PVO_{2max}. As a consequence, the modeling process resulted in: 1 state variable (i.e. VO_2), 2 inputs (i.e. P_{MEC}, *w*), 6 parameters.

Model 5 is for VO2 and $[La]_b$, as taken from [4] and adapted to cycling exercise. The model aims at predicting the blood (B) and the muscular (M) lactate concentration. The modeling process resulted in: 3 state variables (i.e. VO_2, $[La]_b$, $[La]_M$), 2 inputs (i.e. P_{MEC}, *w*), 13 parameters.

Model 6 is taken from [3] and it has been adapted for $[La]_b$ kinetic. The levels of the vessels (i.e. *h* and *l*) are additional state variables. The modeling process resulted in: 3 state variables (i.e. VO_2, $[La]_b$, l, h), 2 inputs (i.e. P_{MEC}, *w*), 14 parameters.

Results

Results are reported here for a representative subject. In Figure 1 and 2, results are reported for the models 5 and 6 respectively. Table 1 summarizes the results of the statistical analysis for all the models.

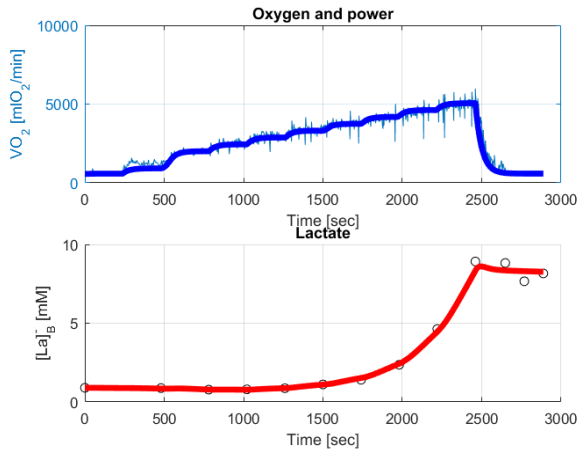
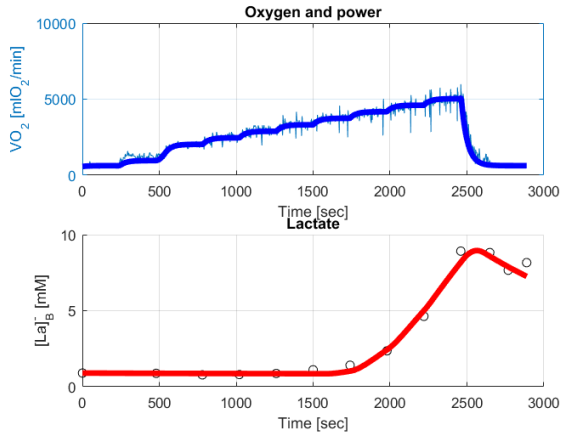


Figure 1: Results for model 6 are reported here (representative subject). In the upper graph, the blue thick lines are the simulated data (model) and the light blue thin lines are experimental data for VO_2. In the lower graph, red thick lines are the simulated data (model) and the black thin circular markers are the experimental data for $[La]_b$.



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Model	Ref.	Iter. [n]	RMSE VO_2 [mlO_2/min]	R^2 VO_2 [%]	RMSE $[La]_b$ [mM]	R^2 $[La]_b$ [%]	tCPU [s]
1	[5]	30	114	87	-	-	22
2	-	30	463	39	-	-	31
3	[2]	30	143	92	-	-	48
4	-	30	318	85	-	-	74
5	[4]	30	409	91	99	99	189
6	[3]	30	378	92	99	99	365

Table 1: Different model fitting results with actual data are reported for an incremental to exhaustion test for a representative subject. Number of iterations of the PSO algorithm (iter.), root mean square error for pulmonary oxygen consumption and blood lactate concentration (RMSE VO_2 and RMSE $[La]_b$) and CPU computational time (tCPU) are reported for the 6 different bioenergetics models.

Conclusions

The number of iterations was kept constant, so we can make comparisons between models, but we know that PSO algorithms need a lot of iterations to find a best solution. In particular, models 5-6 needed more that 30 iterations.

The 1st to 4th models fail to predict VO_2 the progressive increase in oxygen consumption typical of the hard intensity exercise (slow component). In heavy and severe intensity domains the on- versus off-kinetics of VO_2 is known to be asymmetric because the EPOC, that cannot be predicted with the use of a simple model of oxygen dynamics.

From the $[La]_b$ point of view we report that none of all the models available in the literature are free of limitations. Although models 5 and 6 provided with a *nearly perfect* correlation (R^2>99%) with experimental data, we know that in predictive simulations they fail in their purposes (we do not show predictive simulations here).

Indeed, this work can be a call for more accurate models for the $[La]_b$ dynamics in response to an exercise. The work is promising as we can catch the major features of the behavior of the dynamics, but we cannot say that we can use the model with confidence when

predicting $[La]_b$ values in response to an exercise that is much different from the one with which we performed the parameter optimization. In this case we made use of an incremental to exhaustion protocol: this kind of test is very hard to reproduce because 1) the lactate dynamics is very slow at high intensities, 2) there are no recovery phases. Another limitation, is that $[La]_b$ data cannot be collected in a non-invasive way. In the best cases we can collect 1 blood sample per minute, form the same sampling site. We would need a method for continuously monitoring $[La]_b$ during exercise (e.g. infrared spectroscopy). Summarizing, we can say that: prediction on the impact of a generic power output distribution on VO2 and $[La]_b$ is an important issue and can rely on a theoretical approach like VMs; nevertheless, models describing VO2 and [La]b dynamics during exercise are present in the literature, but they all show limitations and pitfalls. To overcome these limitations, exercise physiologists and model developers should work side by side to develop a robust model for $[La]_b$. The best model would be the one which identifies and selects all-and-only the relevant aspects of the real system and is the simplest one among models with equal predictive power.

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The evolution over 4 years of a female cycling champion is revealed by the Athlete Performance Passport

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Introduction

The APP or Athlete Performance Passport, is the register of a complete set of parameters that describe the Power-Duration curve, also called the Mean Maximal Power or the Record Power curve. Training load, training quality, training at altitude, incidence of competition, and many other external factors cause expected or inexpected evolution of the APP. In the first part we will describe the Extended Critical Power model used to obtain the prominent parameters. These are Maximal 5" sprint power (P5"), Maximal Aerobic Power (MAP), Maximal Power at 20' (P20'), Critical Power (CP), Total Anaerobic Work Capacity in excess of CP (AWC) and Total Work Capacity in excess of MAP (SAWC).

In the second part we show the year-by-year evolution of the APP for an international class female cyclist for the years 2013 to mid' 2016. We will see an almost steady increase in the aerobic power related parameters, and an almost constancy in the anaerobic components.

In the third part we analyze the quarter-by-quarter evolution and we find the reason that this rider systematically peaks in the third quarter i.e. July-September.

Previous work

This work is somewhat similar to the work of J. Pinot and F. Grappe, "A six-year monitoring case study of a top-10 Grand Tour finisher" [1].

All details of our iqo2- extended critical power model were presented in ICCS 2015 and can be found on [2].

Results

Yearly evolution

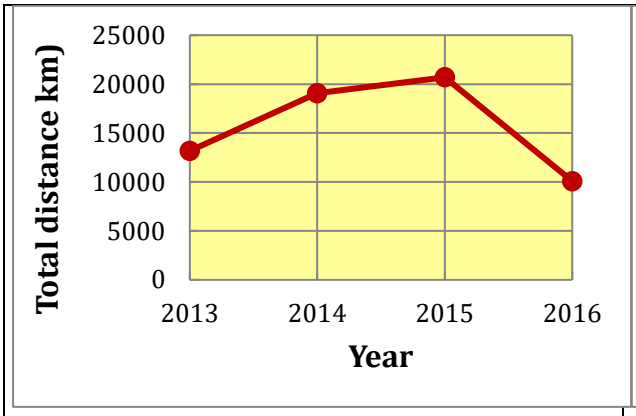

Figure 1. Total distance registered. Approximately 20000 km in a normal full year. For 2013 only the first 3 quarters were registered. For current year 2016 only the first 2 quarters are yet available.

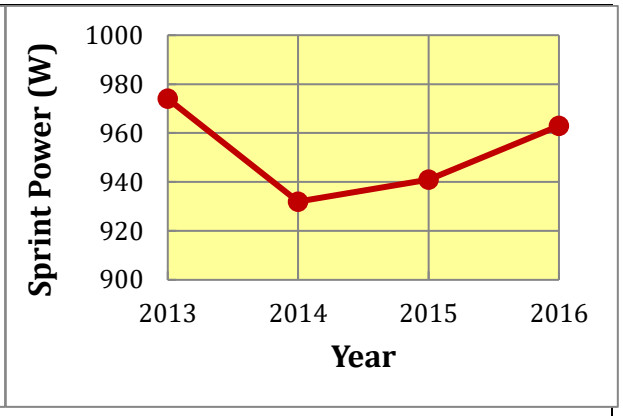

Figure 2. Sprint power (maximal power during 5 seconds).

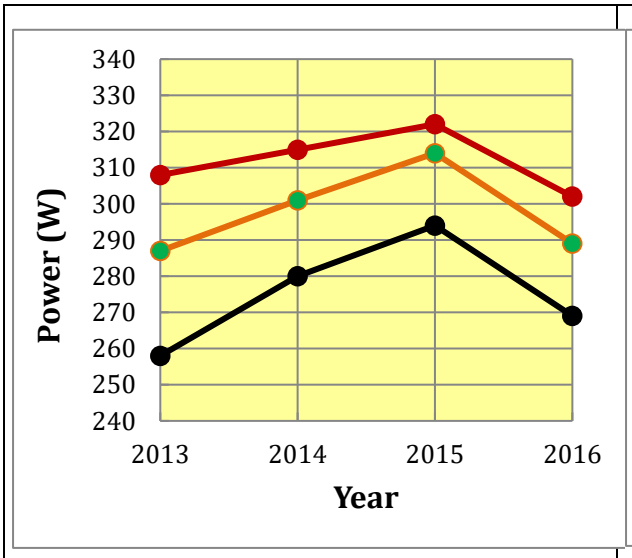

Figure 3. Maximal aerobic power (upper), Power per 20 minutes (middle) and critical power (lower).

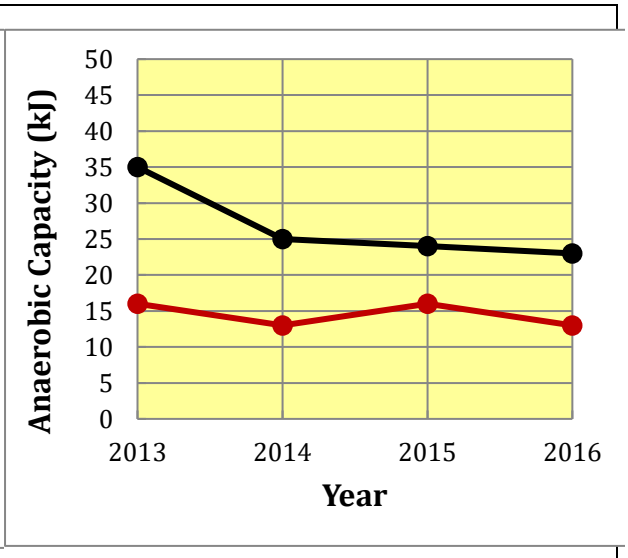

Figure 4. Anaerobic capacity in excess of MAP (lower) and Anaerobic capacity in excess of CP (upper).

Evolution by quarters

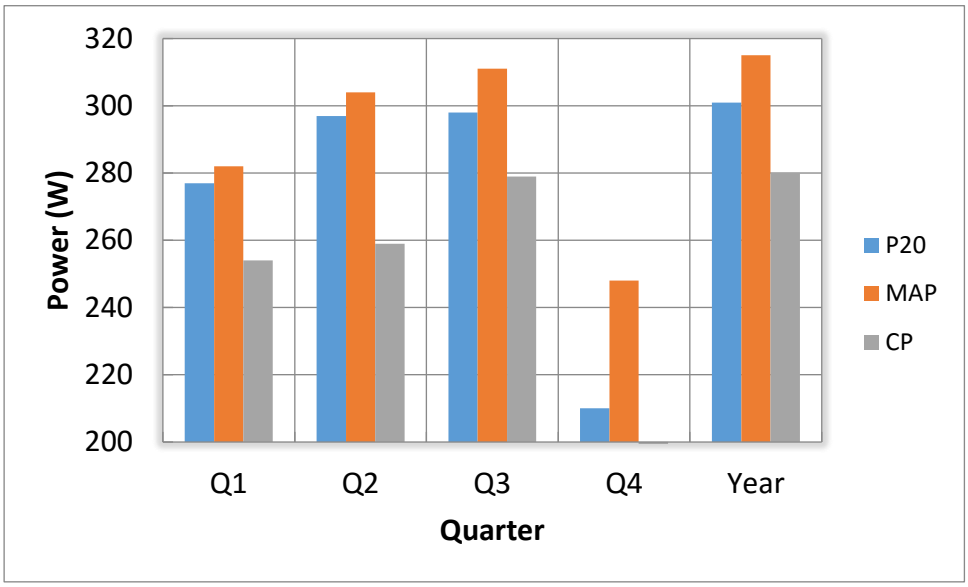

Figure 5. Evolution of the 3 principal aeobic power references during the year 2014.

Conclusions

The Athlete Performance Passport is a promising new tool to understanding and controlling the relation between the fundamental performance parameters, training or otherwise-induced improvements and race success.

Reference

[1] J.Pinot, F. Grappe, A six-year monitoring case study of a top-10 Grand Tour finisher" Journal of Sports Sciences, DOI: 10.1080/02640414.2014.969296

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Comparing Opposing Force Power Meters with SRM

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Introduction

This research is part of the Powerbike project at the University of Konstanz. This study would also fulfil requirements of a master thesis for the department of Sports Science at the same university.

Almost all professional cyclists use power meters (PMs) for their training. An increasing number of amateur athletes have started to adopt them as well. “Direct-force” power meters (DFPMs) are devices that measure the deformation caused by force on pedal(s), rear-wheel hub, crank(s), etc. At the moment, these devices are expensive for the average consumer. There are some power-estimating devices and applications that are much cheaper and hence attractive options for a non-professional to quantify training effort. These are also referred to as “opposing force” power meters (OFPMs). OFPMs do not measure forces directly but estimate power using data such as bicycle speed, wind speed, heart rate of the rider, elevation & gradient of the course, and so on. Most of these devices also factor-in anthropometric information such as body weight, age, sex, riding position, shoulder width, or a subset of these. Some also factor-in the type of bicycle, riding surface, tire pressure, etc.

Objective: This study aims to validate some chosen OFPMs for their accuracy of power measurement, based on ground truth measurements using an industry standard SRM PM.

Methods: We shortlisted four commercially available DFPMs for our experiment: a heart rate-sensor based system (Powertap), two speed-sensor based systems (Velocomputer, Sigma) and one wind-sensor based device (Powerpod). These devices were set up on a road bike. To test these devices, we charted a 33 km-long route that included a steady climb that lasted longer than 15 minutes and a flat section as well.

Results

The Velocomputer device had to be excluded from the study as it was outputting false values for power data and generally unreliable with little to no support from the manufacturers.

Figure 1 shows the 30s-smoothed data of the four power meters. We see visually that there is some degree of correlation between the NDFM PMs with the SRM device in certain sections of the ride i.e., mainly the climbing and flat sections. Detailed results within the sub-sections of the ride are more promising.

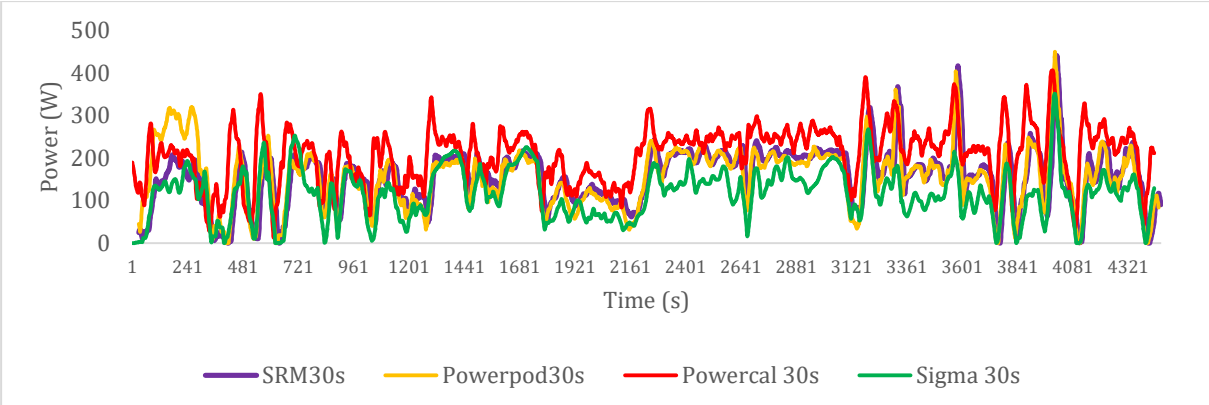

Figure 1: Graph of power data of the three NDFM PMs along with SRM data for the 75-minute test ride

Table 1 shows a brief look at the results of the 33km test ride.

	Powercal	Powerpod	Sigma	SRM
Average Power (W)	208.47	155.59	116.76	155.86
Error (%)	33.76	-0.18	-25.09	
RMS Error (W)	63.83	41.86	71.87	
Relative RMS Error (%)	448.70	117.00	331.09	
Signal to Noise Ratio	7887.00	362544.50	3283.73	
Peak SNR	16.78	20.45	15.76	

Table 1: Summary of results for the entire duration of the test ride
Error% is given by (Relative Error):(Actual Power) expressed as a percentage
RMS Error stands for Root Mean Square Error of the 30-s smoothed data
Peak Signal to Noise Ratio is given by the expression $20\log_{10}$*[max(Actual Power):(Relative RMS Error)]*

Conclusions

The Powerpod turned out to be the most accurate OFPM of the three. However, it is not accurate enough to be used as a power meter for the purpose of research. The device may be used to measure wind-properties in order to help model power better.

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Modeling Altitude Training Benefits with the Record Power Profile in Professional Cyclists

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Introduction

Assessing fitness changes of athletes is challenging in elite sports (Muller et al. 2000) : tests require a high level of validity, reliability, accessibility and specificity (Hopkins 2000). Frequent maximal testing sessions are not possible since it would alter the training program and induce additional fatigue. In cycling, different protocols (e.g. cycle ergometer, velodrome, uphill…) have been proposed (Paton and Hopkins 2001) but recently the constant use of validated powermeters during training and racing makes the power output (PO, W) available and permits to model the hyperbolic relationship between the different record PO and time durations; the so-called "Record Power Profile" (RPP) (Pinot and Grappe 2011).

Altitude training is now widely used in endurance sports (Millet et al. 2010) including in cycling but, to date, there is a scarcity of data on the beneficial or deleterious effects of such intervention in professional cyclists (Garvican et al. 2007; Hahn and Gore 2001). Field evaluation is always difficult, especially during the overloaded competitive period. By using RPP, one may detect fitness changes induced by an altitude training camp. Therefore, the purpose of this study was to assess the performance gains after an altitude training camp in professional cyclists by the mean of the RPP.

Methods

20 professional cyclists (age: 29.1 ± 4.2 years, weight: 66.3 ± 6.8 kg, height: 1.79 ± 0.08 m) performed 15 days of training either by sleeping at an altitude of 2 058 m and training between 490 and 2 642 m (H Hypoxia, n = 7) or by sleeping and training near sea-level (N Normoxia; n = 13). The training content was 17 training sessions, 3.1 ± 1.8 h/session. They performed 12 low intensity training (under the first ventilatory threshold) and 5 high intensity training (above the second ventilatory threshold).

The RPP was modeled from the PO of each rider over four different periods (pre: four weeks prior the intervention period, in: during the altitude camp, post1-2: two weeks after the training camp, post3-4: two weeks after post1-2) in order to assess the change during and

after the altitude training at different times since it is known that altitude leads to a decrease in aerobic power (Wehrlin and Hallen 2006) and that the time course of the post-altitude adaptations is not linear (Chapman et al. 2014).

Figure 1: Evolution of the record power profile for the group that lived in altitude

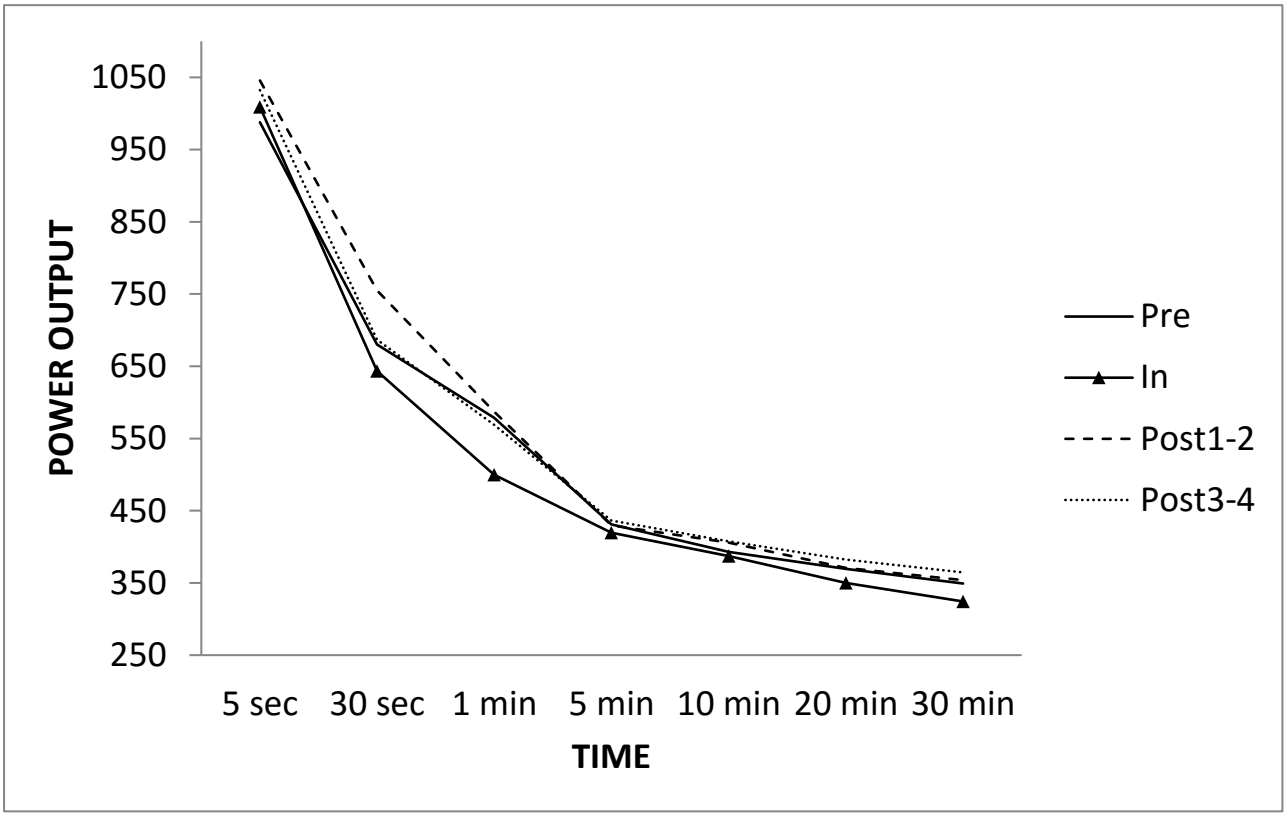

Figure 2: Comparison of the "Record Power Profile" aerobic component for the groups that lived in hypoxia (H) vs. in normoxia (N)

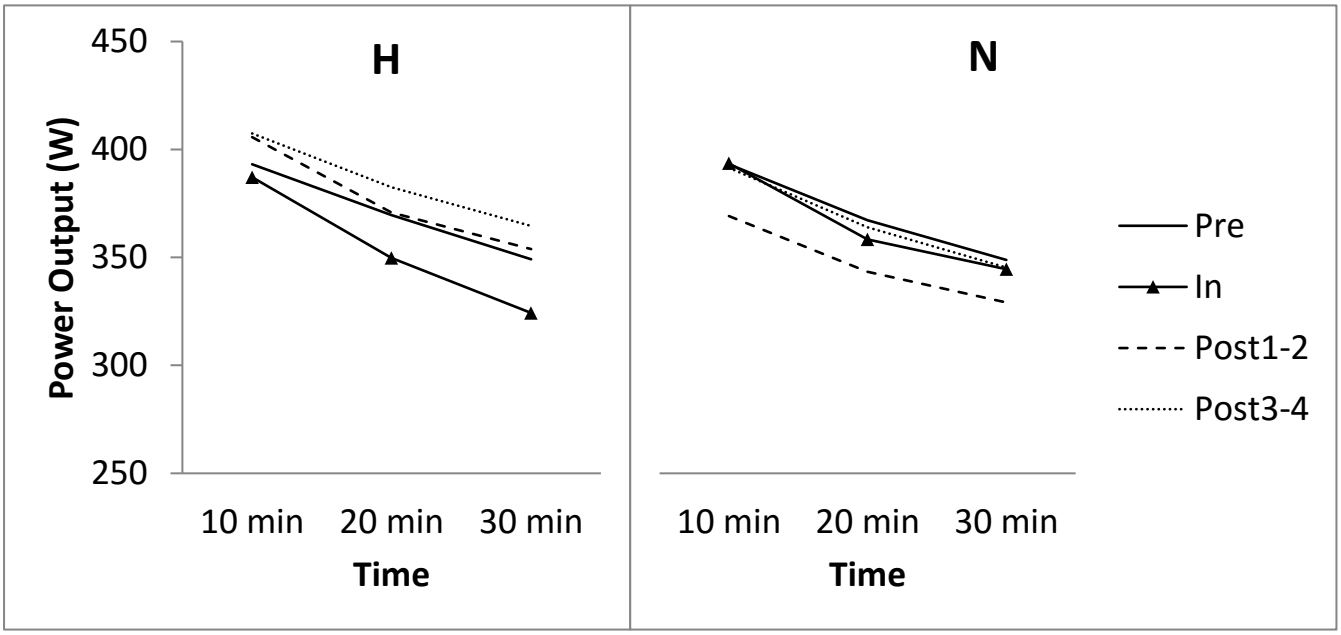

Figure 3: Comparison of the "Record Power Profile" anaerobic component for the groups that lived in hypoxia (H) vs. in normoxia (N)

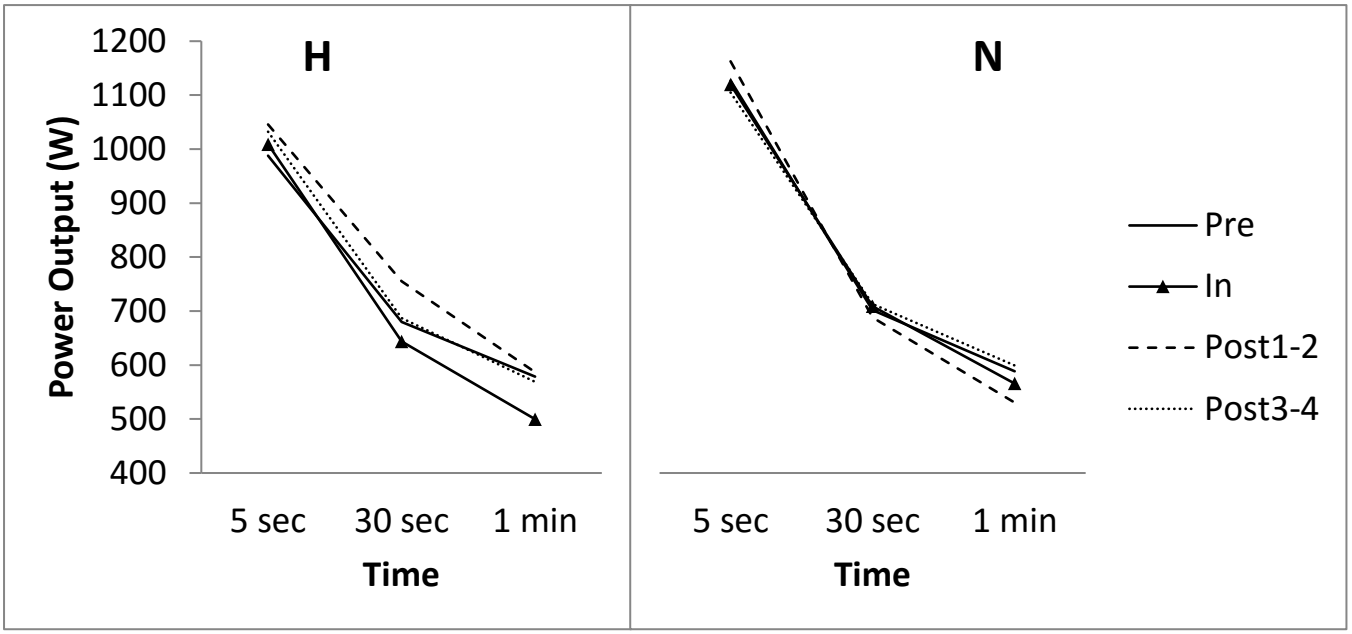

Table 1: Performance change (W and %) of the "Record Power Profile" anaerobic and aerobic components from pre- to post1-2 and post3-4 for the groups that lived in hypoxia (H) vs. in normoxia (N)

Anaerobic component			5 sec	30 sec	60 sec	Mean
Post 1-2	H	(W)	58	75	8	47.1
		(%)	5.9%	11.1%	1.4%	6.3%
	N	(W)	35	-13	-57	-12.0
		(%)	3.1%	-1.9%	-9.8%	-1.5%
Post 3-4	H	(W)	44	7	-10	13.8
		(%)	4.5%	1.0%	-1.7%	1.8%
	N	(W)	-22	11	11	0.0
		(%)	-1.9%	1.6%	1.8%	0.0%

Aerobic component			10 min	20 min	30 min	Mean
Post 1-2	H	(W)	13	1	5	6.0
		(%)	3.2%	0.3%	1.4%	1.7%
	N	(W)	-24	-24	-19	-22.2
		(%)	-6.0%	-6.4%	-5.6%	-6.0%
Post 3-4	H	(W)	14	13	15	14.2
		(%)	3.6%	3.5%	4.4%	3.8%
	N	(W)	-2	-3	-3	-2.8
		(%)	-0.4%	-0.9%	-1.0%	-0.8%

Conclusions

The mean increase in PO is larger in H than in N for both the anaerobic component at post1-2 (6.3 vs -1.5%) and for the aerobic component at post3-4 (3.8 vs -0.8%). These results are in line with the literature since short-term adaptive non-hematological responses to altitude training likely to improve muscle buffering capacity or glycolytic capacity have been reported (Gore et al. 2007; Mizuno et al. 1990) while the optimal post-altitude period for the aerobic capacity improvement seems delayed to weeks 3 and 4 (Millet et al. 2010; Chapman et al. 2014).

Altogether, this study shows the usefulness of the RPP as a modeling tool for monitoring fitness changes and for assessing the performance gains induced by altitude exposure in professional cyclists.

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Comparison between Maximal Lactate Steady-State, Critical Power and the Second Ventilatory Threshold detected by a Computer Algorithm

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Introduction

The exact determination of the anaerobic threshold is indispensable in the analysis and optimization of endurance performance, as it demarcates the bodies' boundary from a predominant aerobic to a predominant anaerobic energy metabolism. In the past, several biological parameters and determination concepts have been proposed to be more or less effective in determining the anaerobic threshold (Peinado, Rojo, Calderon & Maffulli, 2014). Unfortunately most of these concepts are limited by its subjective methodology. In recent years the critical power (CP) concept (Monod & Scherrer, 1965) has received increasing attention and is used alternatively for the anaerobic threshold (Bosquet, Larrouturou, Lheureux & Carter, 2011). However it remains questionable if this concept can be used as an alternative to other lactate threshold concepts. Furthermore it is expected that a more standardised and objective procedure in the determination of the second ventilatory threshold could lead to an improved validity when comparing it to the gold standard method of anaerobic lactate threshold determination.

Therefore, the aim of this study was to determine the second ventilatory threshold (VT_2) by an automated method as well as CP by three cycle ergometer tests and to compare them to the maximal lactate steady-state (MLSS).

Methods

13 recreational cyclists and one sedentary male (age: 41.1 yrs., height: 181 cm, weight: 75.6 kg, VO_{2max}: 57.2 ml/min/kg) completed a series of cycling tests, separated by at least 48h of recovery. The first test consisted of an incremental ramp exercise to exhaustion for the determination of VT_2. The remaining 4-5 tests were performed at different constant work rates (CWR) in order to determine CP and MLSS. Every CWR test lasted up to maximally 30 min or until volitional exhaustion. Lactate probes from the earlobe were taken every five minutes and at test termination. The intensity of each CWR test was related to body weight (range across subjects: 2.75 and 5.5 W/kg) and decreased or increased in steps of 0.25 W/kg. The test phase was completed when all of the following criteria were met:

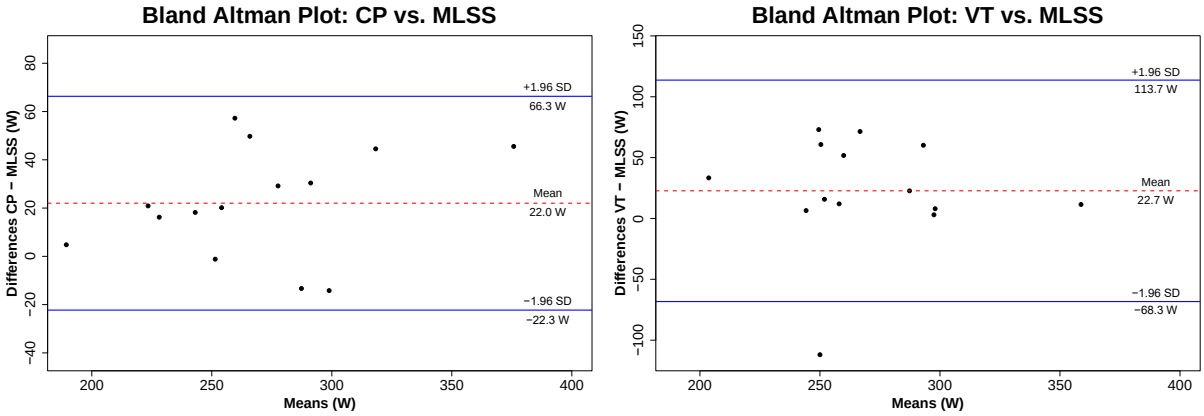
a) Every subject performed three CWR tests to volitional exhaustion before the end of the 30 minute cut-off time.
b) At least one 30 min test that showed a steady-state (< 1mmol/l) in blood lactate concentration from minute 10-30 and a CWR test at an intensity 0.25 W/kg higher than

the previous test that showed an increase in blood lactate concentration of more than 1mmol/l in the last 20 minutes (or less).

The MLSS intensity was defined as the highest intensity in which the lactate concentration did not rise more than 1 mmol/l in the last 20 minutes of the test. The critical power was calculated from the three tests to exhaustion by the 2-parameter critical power model adapted by Moritani, Nagata, deVries und Muro (1981). VT_2 was analysed by a self-programmed computer algorithm based on the determination method proposed by Beaver, Wasserman und Whipp (1986).

Results

Mean work rates were 257.9 ± 43.6 W, 279.9 ± 50.1 W and 280.6 ± 42.5 W (Mean ± SD) for MLSS, CP and VT_2 respectively. Bland Altman analysis between MLSS and CP revealed a mean bias of 22W with limits of agreement (LoA) between -22 and +66W. For MLSS and VT_2 the mean bias was 23W with LoA between -68 and 114W.



A paired t-test showed a significant difference between MLSS and CP (p = .003) but no significant difference for MLSS vs. VT_2 (p=.090). Pearson's Product Moment Correlation revealed a strong correlation between MLSS and CP (r=.893, p=<.001) and a weak correlation between MLSS and VT_2 (r=.419, p=.068).

Discussion

The aim of this study was to determine CP with three constant power tests to volitional exhaustion and VT_2 by a computer algorithm and compare these procedures to the gold standard method of MLSS determination.

Bland Altman analysis represents an adequate tool for demonstrating the amount of agreement between differing methods. In this study the accuracy to identify the MLSS is 18.9 ± 1.4 W. We therefore determined appropriate limits of agreement to lie between ± 20.2W. Bland Altman analyses revealed that an upward bias of 22W (CP) and 23W (VT_2) was evident. Unfortunately, the critical limits were more than two-fold for CP (± 44.3W) and four and a half fold for VT_2 (± 91W). Therefore, both CP and VT_2 determination methods are considered as invalid procedures for the determination of the MLSS.

Although testing for statistical differences and relationships showed partly promising results and are to some extent in line with other studies (Dekerle, Baron, Dupont, Vanvelcenaher und Pelayo (2003) Pringle und Jones (2002). However, they are not considered as appropriate procedures

for comparing differing methods and were merely conducted to demonstrate that these approaches can be misleading.
The here proposed computer based method for the detection of the second ventilatory threshold has shown not to be an ideal predictor of the maximal lactate steady-state. Further work has to be put into a new or modified computer algorithm to attain better results in the future. Also the determination of critical power by three laboratory tests seems to be an inadequate method for determining MLSS. However it should be considered that different CP models or field data collected from mobile power meters with more data points for the power time relationship curve could yield different, more reliable results.

Conclusion

In this study we show by the Bland Altman procedure that work rate at critical power and ventilatory threshold determined by a computer algorithm are not adequate methods for determining MLSS. Although significant results and high correlations could have been partly demonstrated, these measures do not account for the agreement between the methods and are considered inappropriate for this kind of research question.

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High cycling cadences allow for an increase in training volume monitored via blood lactate concentration

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Introduction

Top endurance athletes train 15 to 20 h per week. Selected endurance events seem to require even up to 30 h of training and up to 12 training sessions per week. In order to prevent glycogen depletion 70 to 90 % of the training volume is performed at intensities corresponding to blood lactate concentrations (BLC) up to 2 mmol l^{-1} [1]. The most efficient cadence in terms of VO_2 at low exercise intensities is in the range of 40 to 60 rpm [2]. Cadence related divergences in VO_2 converge as exercise intensity increases with small or no differences at peak power (P_{Peak}). The BLC is higher at higher cadences and low intensities and this difference increases furthermore with increasing intensity (3). The reason why competitive cyclists prefer cadences between 90 and 110 RPM is not clear.

The maximal lactate steady state (MLSS) depicts the highest BLC that can be maintained over time without a continual accumulation at constant 30 min workload. Based on the cadence specific MLSS of a female cyclist (age: 25 yrs, height: 1.72 m, body mass: 67 kg, P_{Peak}: 4.9 W kg^{-1}, VO_{2max}: 64.1 ml kg^{-1} min^{-1}) we simulated cadence dependent limits of sustainable cycling training volume. We tested the hypothesis that high cadences offer an advantage in terms of carbohydrate e.g. pyruvate and lactate oxidation (CHO) related to metabolic rate and sustainable training volume.

Previous work

We demonstrated that at incremental load tests the intensity related to P_{Peak} at which aerobic metabolism approaches complete dependence on carbohydrate oxidation as indicated by a respiratory exchange ratio (RER) near 1.0 was independent of cycling cadence irrespective of a higher BLC at 100 than at 50 RPM [3]. Furthermore, we found a higher MLSS at 105 than at 60 RPM with no differences in MLSS exercise intensity (I_{MLSS}) [1]. At I_{MLSS} RER is almost 1.0 indicating that the mitochondrial metabolism approaches saturation with pyruvate and lactate as metabolic substrate without much variability between the 10th and 30th min [4].

At BLC steady state (BLC_{SS}), the glycolytic pyruvate and lactate generation (Gly) equals CHO (Eq.1). CHO is defined by VO_2 times the amount of lactate and pyruvate combusted per unit VO_2 (Ox) and the fraction of the VO_2 utilized for CHO (relCHO). Gly and Ox depend on

VO_{2max}, exercise intensity and cadence [1].

Eq.1: Gly = Ox * relCHO = CHO

relCHO can be described as a nonlinear function of BLC_{SS} (Eq.2) [1,3,5-7].

Eq.2: $$relCHO = \frac{1}{1 + \frac{k_{CHO}}{BLC_{SS}^{n}}}$$

where k_{CHO} is the constant of the 50 % activation of CHO, functionally reflecting the activation of the pyruvate dehydrogenase of the whole body. With relCHO approaching saturation, the cadence specific k_{CHO} can be estimated by re-arranging Eq.2.

The total power (P_{TOT}) required to cycle at a given velocity is determined by power to overcome air- (P_{AIR}, Eq.3) plus rolling resistances (P_{ROLL}, Eq.4) [2,8].

Eq.3: $P_{AIR} = 0.5\ cd\ A\ k\ \rho\ v^3$

where cd is the drag coefficient, A the body surface area, k is the air resistance effective fraction of A, ρ is air density and v is cycling velocity.

Eq.4: $P_{ROLL} = M\ g\ v\ rrc$

where M is body mass plus bicycle mass, g is gravity and rrc is the rolling resistance coefficient.

Under the assumption that a daily glycogen turnover of 6 g per kg body mass indicates a critical margin of sustainable endurance training volume corresponding training limits can be simulated based on cadence specific MLSS and P_{TOT}.

Results

At 105 RPM the MLSS was 0.9 mmol l^{-1} higher than at 60 RPM (Fig.1) reflecting k_{CHO} values of 6.2 and 3.3 (mmol l^{-1})[3]. With 3.3 W kg^{-1} and 66.7 %, $P_{MLSS105}$ and $I_{MLSS105}$ related to P_{Peak} were approximately 8 % lower than P_{MLSS60} and I_{MLSS60} of 3.6 W kg^{-1} and 72.7 %, respectively. However, VO_2 and I_{MLSS} related to VO_{2max} were almost identical with 49.3 ml kg^{-1} and 76.8 % at 105 RPM and 49.0 ml kg^{-1} and 76.4 % at 60 RPM. This corresponded to cycling velocities of 10.2 and 10.5 m s^{-1} sustainable for 52.6 and 51.8 min equivalent to 33.7 and 33.2 km at 105 and 60 RPM, respectively.

Cycling at 105 RPM decreased power and v by 18.2 and 7.9 % at 2.0 mmol l^{-1} and 37.5 and 7.7 % at 1.5 mmol l^{-1}, respectively. No corresponding differences were seen in the VO_2. However, compared to 60 RPM cycling at 105 RPM increased the sustainable time of the latter metabolic rate by 23.9 % at 2.0 mmol l^{-1} and by 40.4 % at 1.5 mmol l^{-1} (Table 1).

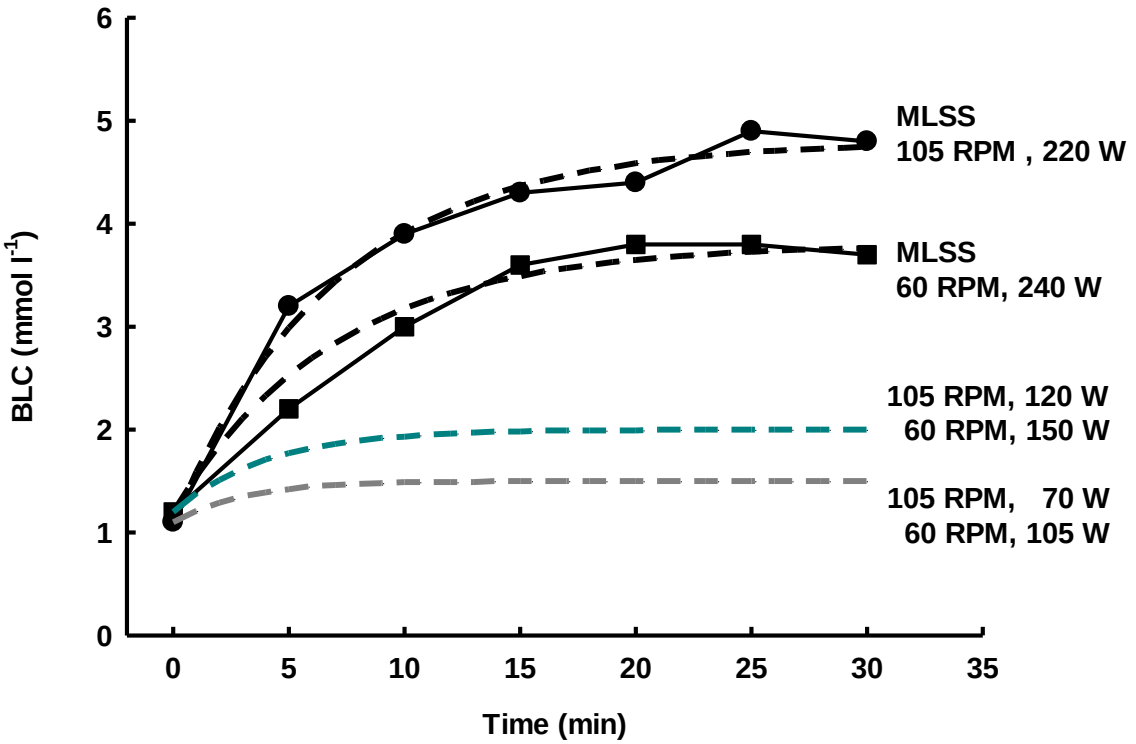

Figure 1: MLSS obtained and simulated BLC-response (dotted lines) to prolonged constant workload at training relevant BLC, 105 and 60 RPM

		105 RPM	**60 RPM**
	P (W kg^{-1})	1.8	2.2
	IP (% P_{Peak})	36.4	45.5
	VO_2 (ml kg^{-1} min^{-1})	33.2	33.7
2.0 mmol l^{-1}	IVO_2 (% VO_{2max})	52.6	51.8
	v (m s^{-1})	8.2	8.9
	T (min)	133.7	107.9
	D (km)	65.8	57.6
	P (W kg^{-1})	1.0	1.6
	IP (% P_{Peak})	21.2	31.8
	VO_2 (ml kg^{-1} min^{-1})	25.9	25.3
1.5 mmol l^{-1}	IVO_2 (% VO_{2max})	40.5	39.5
	v (m s^{-1})	7.2	7.8
	T (min)	277.9	198.0
	D (km)	120.0	92.7

Table 1: Simulated performance and metabolic response and sustainable training volume corresponding to BLC of 2.0 and 1.5 mmol l^{-1}

Conclusions

The present findings provide support for the concept of cycling at relative high cadences at low exercise intensity training. High cadences seem to preserve CHO at given metabolic rates and/or BLC levels during low intensity high volume training sessions allowing for substantially increased training volumes at exercise intensities dominantly utilized in endurance training of high performance athletes.

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