Heart rate modelling as a potential physical fitness assessment for runners and cyclists

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Abstract. Assessment of physical fitness of endurance athletes is usually performed by means of standardized exercise protocols in specialized laboratories. The recent development of devices measuring heart rate, power output, speed, etc. raises the possibility to assess the fitness level from data collected on the field. We propose a model based on cardiac parameters identification on training activities. Identified parameters prove to allow for heart rate simulations that match measurements with an average root mean square error of 4 beats/min for cycling activities for which power output and heart rate were provided and 6 beats/min for running activities for which the heart rate was provided and power output was estimated based on global positioning system (GPS) tracking.

Keywords: fitness assessment, system modeling, heart rate, power output

1 Introduction

Improvement of sport performance is dependent on physiological adaptations amongst others. These training adaptations are of particular importance for endurance athletes like cyclists and runners. Training optimization requires knowledge about how humans adapt to workout sessions. This knowledge can be seen as a model linking training workout characteristics to fitness level. Such system modeling approaches have been refined for at least four decades [1]. Although models are well described and increasingly used instead of relying solely on the empirical experience of coaches [2], they are unable to provide physiologically relevant parameters.

The athlete adaptation model takes as inputs quantifiable training workload $w(t)$ to predict the fitness level $fl(t)$ evolution over time as represented in the upper part of Fig. 1. Building and evaluating such a model requires input-output instances. Inputs are easy to gather thanks to the emerging tendency of athletes to log all their activities on a server by using their smartphone, sport watch or bike computer. On the other hand, endurance fitness is multifactorial

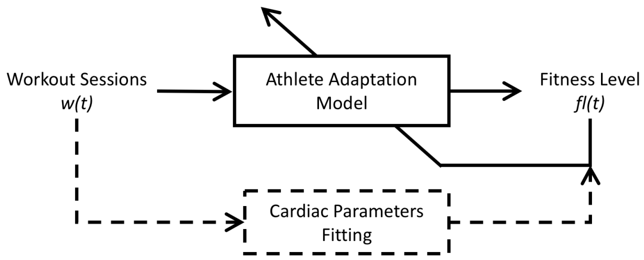

Fig. 1. Conceptual model of the human adaptation to workout sessions. The bottom part illustrates how objective measurements help to fit the athlete's adaptation model.

(cardiovascular, metabolic, endocrine, ...) and quantitative metrics are not directly available. Currently, the evaluation of the endurance fitness is assessed by incremental exercise protocols performed in specialized laboratories[4].

This work aims to provide a methodology that will help inferring the fitness level from workout sessions data themselves. For this purpose, a parametric heart rate model is proposed (see bottom part of Fig. 1).

The main principle is that a lower heart rate observed for a given intensity of exercise indicates a better endurance fitness level [7] but the kinetics of heart rate increase at the onset of exercise, or decrease after the discontinuation of exercise are also modified by the training process. Our intuition is that the assessment of physiological parameters explaining cardiac adaptations during the training sessions might provide relevant information regarding the fitness level of endurance athletes. As it could be able to give daily personal feedback, such a model is potentially very helpful for monitoring the physiological adaptations to training on a regular basis and without requiring a standardized laboratory protocol.

The validity of the proposed heart rate model will be assessed by simulation with cyclists' data for which we have instant power output and heart rate measurements. The model will then be re-used with runners' activities. For the latter, the power output needs to be estimated as it is not directly measured during the run.

2 Methods

This paper proposes a parametric heart rate model that describes the relationship between an athlete instant power output $po(t)$ and his heart rate $hr(t)$ as it is illustrated in Fig. 2. The model parameters can be identified to best reproduce heart rate measurements on a single activity.

2.1 Heart Rate Model

Steady state The steady state heart rate HR_{ss} refers to the heart rate that is reached after stabilisation at constant power output PO. The relationship

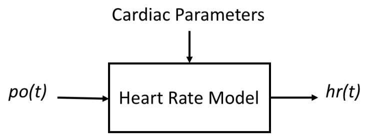

Fig. 2. Parametric heart rate model

between steady-state heart rate and power output is athlete-dependent and is known to be very close to linear as long as the heart rate is below its maximum value called maximum heart rate HR_{max} [5]. Higher power output is achievable for short periods of time but the heart rate will remain at HR_{max}. The three athlete-time specific parameters describing the steady state relationship are resting heart rate HR_{rest} in beats/min [bpm], the maximum heart rate HR_{max} in [bpm] and the slope coefficient m in [bpm/watt] following the equation

$$HR_{ss}(PO) = \begin{cases} HR_{rest} + m * PO, & \text{if } HR_{rest} + m * PO < HR_{max} \\ HR_{max}, & otherwise. \end{cases}$$

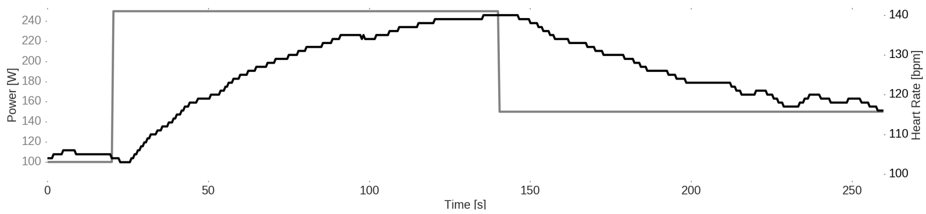

Fig. 3. Segment of ergometer measurement that shows the exponential-looking heart rate response to power steps.

Transient Response It appears from exercise laboratory measurements on ergometers (a segment of measurement is illustrate in Fig. 3) that a power step upward leads to a new steady state heart rate that is reached after a few seconds. The exponential-looking shape of the heart rate curve in response to power steps suggests this phenomenon can be roughly described by a first order differential equation :

$$\frac{dHR(t)}{dt} + \frac{1}{\tau_r} HR(t) = PO(t)$$

with τ_r an athlete-specific time constant. It will be shown below that this assumption allows for accurate simulations.

In a time frame $[t_0, t]$ where power output is constant, the solution of this equation is given by

$$HR(t) = HR(t_0) + (HR_{ss}(PO(t)) - HR(t_0))e^{-\frac{t}{\tau_r}}.$$

In the discrete over-sampled time domain, an iterative form given by

$$HR(t+1) = HR(t) + \frac{1}{\tau_r}(HR_{ss}(PO(t)) - HR(t))$$

can be used.

As there is no reason to assume equality between rise time τ_r and fall time τ_f. The equation is allowed to differ for increasing and decreasing heart rate and becomes

$$HR(t+1) = \begin{cases} HR(t) + \frac{1}{\tau_r}(HR_{ss}(po(t)) - HR(t)), & \text{if } HR_{ss}(po(t)) \geq HR(t) \\ HR(t) + \frac{1}{\tau_f}(HR_{ss}(po(t)) - HR(t)), & \text{if } HR_{ss}(po(t)) < HR(t). \end{cases}$$

The heart rate transient response is thus captured by two athlete-time specific parameters which are τ_r and τ_f.

2.2 Runners Power Output Estimation

Running activities are provided as timestamped geolocalized points with elevation that was corrected using elevation maps. The elevation can be derived with respect to the curvilinear horizontal distance to get the slope. The runner velocity is also derived from locations and timestamp. Both are smoothed using factors that were chosen to give best simulation accuracy. It is assumed that the smoothing factors are not athlete- or activity- specific.

Minetti et al [6] show that the energy cost of running does not depend on the speed but only on the distance. It also gives the energy cost of running EC as a function of the slope relative to the runner's weight in [J/m/kg]. As velocity $v(t)$ and slope were evaluated, the runner's power output $PO(t)$ is

$$PO(t) = EC(slope).v(t)$$

in [w/kg].

Cardiovascular Drift Intra-session workload results in fatigue that induces increased heart rate for the same power output[5, 8]. The increase is assumed to be proportional to the energy expenditure from the beginning of the activity. The power output can then be replaced in the above equations by

$$PO(t) + k_f \int_{t_0}^{t} PO(t)dt$$

with k_f being the athlete's sensitivity to fatigue. This intuitive formulation might not be accurate but proved to help the heart rate model to better fit activities measurements.

2.3 Fitting of the Athlete's parameters

The model that was described contains three parameters that account for the steady state relationship (HR_{rest} [bpm],HR_{max} [bpm] and m [bpm/watt]); two that account for heart rate transient response (τ_r and τ_f [s]); and one that accounts for the athlete's sensitivity to fatigue (k_f coefficient). Those parameters are identified on an activity from which heart rate $HR(t)$ and power output $PO(t)$ are known or estimated. Given the power output $PO(t)$, a set of cardiac parameters can result in a simulation $\widehat{HR(t)}$ that can be compared to the heart rate measurement $HR(t)$. The six parameters are tuned to minimize the mean square error between simulation and measurement using a non-linear optimization algorithm known as Nelder-Mead method [9].

2.4 Data

In most modern activity tracking platforms (Nike+, Runkeeper, Strava, Garmin Connect, Endomondo, TrainingPeaks, ...), activities are shared as tuples of geolocalized points associated with timestamps recorded by athletes with their device. They can potentially record more parameters like heart rate, cycling power, cadence, accelerations, temperature or baro-metric pressure.

The cardiac model was first fitted to 72 cycling activities of three cyclists containing instant power output and heart rate measures sampled every second. The power was measured with a torque meter in the crankshaft of their bikes.

The same was done with 234 running activities of two runners containing heart rate and geolocalized points. Instant power output was estimated based on based on global positioning system (GPS) tracking coordinates.

3 Results and Discussion

Cardiac parameters that were identified on activities with the described methodology enable accurate heart rate simulation on the same activity taking solely the instant power measure or estimation as input. Heart rate simulations differ from heart rate measurements with an average root mean square error of 4 bpm for the 72 cycling activities recorded with the use of a power meter. On average, a root mean square error of 6 bpm was observed for the 234 running activities.

Fig. 4 and 5 show respectively cycling and running activities simulation examples with measurement curves that were used.

In most activities, identified heart rate rising time constant τ_r was found to be smaller than heart rate falling time constant τ_f; with respective average values of 24 and 30 seconds. Sensitivity to fatigue was modeled with an additional power output in the range $[1; 6].10^{-5}$ [w/J]. Steady state heart rate parameters were more subject to intra- and inter-athlete variability. Resting heart rate HR_{rest} was found to be in the range $[60; 100]$ [bpm] that does not necessarily correspond to the conventional resting heart rate that is taken on a person laying down. The slope coefficient m was found in the range $[0.15; 0.45]$ [bpm/w].

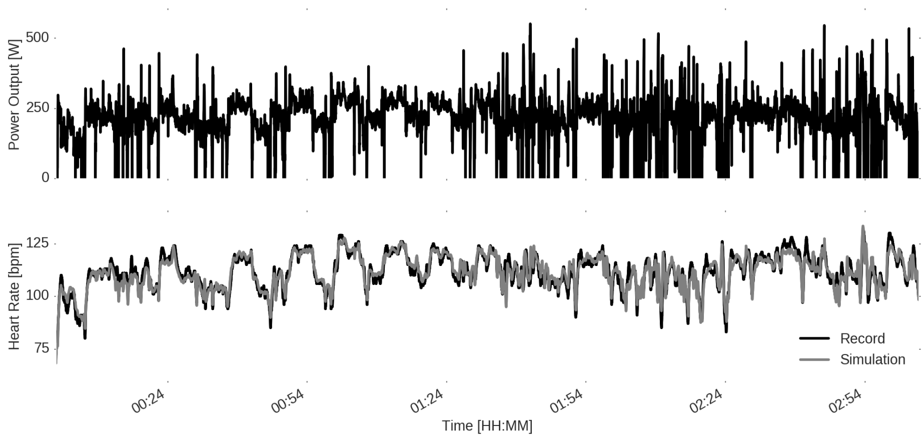

Fig. 4. Cycling activity. Top: Power measurement. Bottom: Simulated vs recorded heart rate

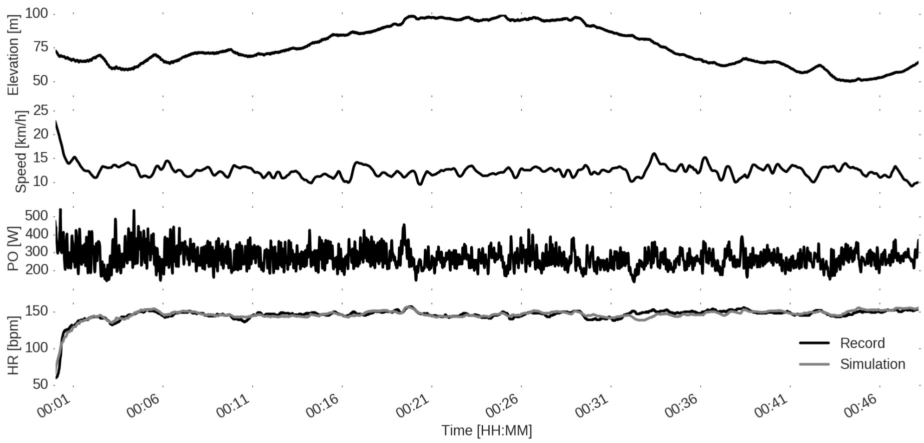

Fig. 5. Running activity. Plot 1 and 2: Elevation and speed measurements. Plot 3: Estimated power output computed on speed and slope (elevation's derivative). Plot 4: Simulated vs recorded heart rate

Although parameters identification proved to result in accurate simulations, their variability seems higher than what is expected from real cardiac parameters. The parameter variability over different activities taking place at different times during the year can be imputed to the athlete state (which is of interest) but other factors can be invoked:

1. The day-to-day heart rate variability that is believed to be around 2-4 bpm according to [5].
2. Exogenous information such as temperature or altitude that are not included in the model and are known to impact heart rate [5].

3. The methodology itself:
   – Given the model that was chosen, maximum heart rate is impossible to identify if it was not reached by the athlete during the activity.
   – Activities characteristics influence the expected accuracy of the parameters. For instance, steady state line coefficients are better estimated if activities sweep over a large range of power output.
4. Data accuracy or sensor model that are device-dependant and that were not discussed here.

How cardiac parameters are exactly linked to fitness levels or performances is not considered in this work. We rely on the fact that part of them are measured by coaches during standardized exercise in laboratory for the periodic follow-up of their athletes.

4 Conclusion

We identified a pressing need for objective fitness assessments based on data acquired on the field in training situations, in order to better understand human adaptation to physical training and to enable adaptive training plans. We propose a framework that provides the basis of a potential solution through cardiac parameters identification. Identified parameters prove to be sufficient for athletes heart rate simulation based on athletes power output for running and cycling activities.

In further research, parameters accuracy can be improved by including exogenous meteorological information in the heart rate model. Fixing parameters that are easy to obtain, like resting heart rate, might also help accuracy of the other parameters.

The natural continuation of this work would compare identified parameters to exercise laboratory measurements, or even more interesting, to athletes target performances such as race times.

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