Estimating Internal Power in Walking and Running with a Smart Sock

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The Presenter

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Agenda

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- Related Work
- Methods
  - Participants
  - Study Design
  - Devises
  - Data Processing
- Results and Discussion
- Conclusion and Future Work

Introduction

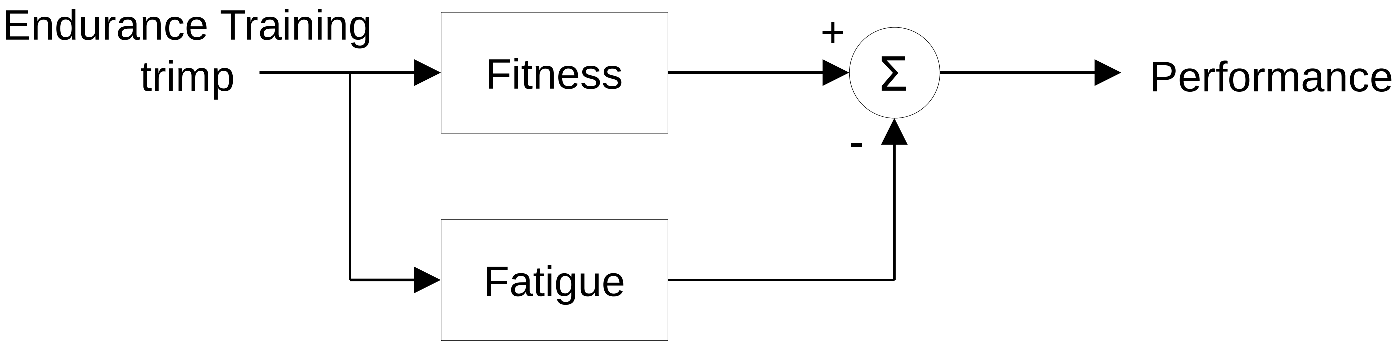
- Why do we measure intensity in endurance sports?
  - Athletes and coaches need to **quantify the training load** or stress caused by a workout or competition, to be able to make sure that their training is according to the prescribed training plan, adapt their training or plan, and to make predictions.
  - Training load depends on **volume** and **intensity**:
    - Volume: distance covered, elapsed time, …
    - Intensity: heart-rate, velocity, pace, power, …

Introduction

- As early as 1990, Morton et al. define the **training impulse** (trimp) as
  - $trimp = D\ x\ e^{bx}$, where
    - D: duration of training session in minutes
    - $x = \left(\frac{HR_{ex}-HR_{rest}}{HR_{max}-HR_{rest}}\right)$ denotes the percentage of heart rate reserve
    - HR_{ex} is the average heart rate during exercise;
    - HR_{rest} means the resting heart rate; HR_{max} is the maximum heart rate; and
    - the weighting factor e^{bx} corrects bias introduced from long training at low heart rate, b is a gender-specific parameter, 1.92 for men, 1.67 for women

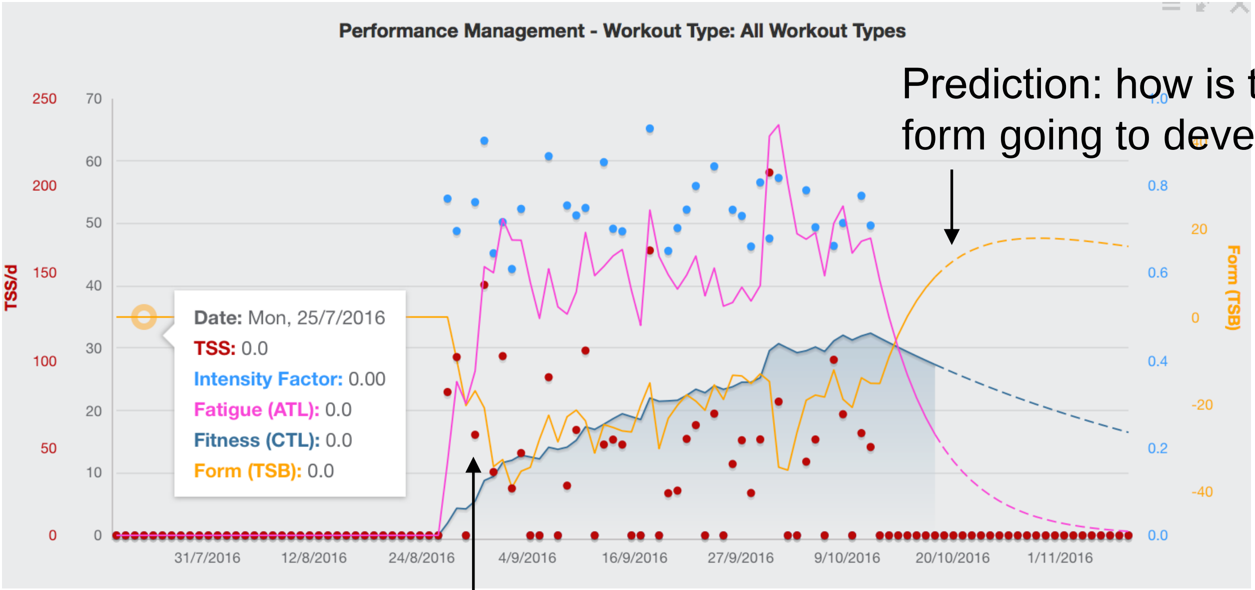
Introduction

- According to the 2-component systems model of training and performance, (Morton et.al 1990), each time a training is undertaken, fitness and fatigue, as well as **performance** are affected:



Introduction

– This model allows to prescribe and adapt training plans, as well as make **predictions**, e. g. www.trainingpeaks.com:



Prediction: how is the athlete's form going to develop?

Red dots represent training load (trimp)

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Introduction

- Intensity and hence training load can be calculated based on
  - Heart rate – reacts slowly, cardiac drift, influence of mental stress
  - Velocity, pace – does not consider wind, hills, nor the surface (track, grass, …)
  - Power – the gold standard in cycling

- Power meters in running, usually based on inertial measurement units
  - www.stryd.com
  - runscribe.com
  - www.garmin.com:

Introduction

- Smart textiles
  - Becoming increasingly popular in sports
  - E.g., www.sensoriafitness.com

- Is it possible to incorporate the power meter into the socks and make the usage of a separate power meter obsolete?

Related Work

- **Cavagna 1975** measures **external work** by means of a force plate to record the horizontal and vertical components of the resultant force applied by the body to the ground or air.
- **Internal work** (i. e., taking into account the energy needed to swing the legs and arms) is determined by means of a cinematographic analysis.

- Since this is difficult to perform outside a controlled laboratory environment, **van Dijk and van Megen 2017** assume the energy expenditure of running (Cr) which is based on indirect calorimetry with 0.98 J/kg/m and add the energy to overcome the air resistance, as well as the influence of uphill and downhill running.
- Of course, assuming a fixed Cr value does not allow for different running surfaces or running economy, nor does it consider walking where the energy cost varies as a function of velocity.

Related Work

- Contemporary power meters for running therefore combine both approaches: they estimate external power with accelerometers mounted on the subject and then assume a gross metabolic efficiency of around 25% to map mechanical energy to metabolic energy.

- **Oks et al. 2017** show that ground contact time can be adequately measured with a smart sock system with piezo-resistive knitted structures.

- **Petz et al. 2019** show that a smart sock system with three piezo-resistive pressure sensors can be used to detect steps and to make reasonable statements about the subject's activity.

Related Work

- Smart sock systems are also used for gait analysis and foot pressure control for human locomotion and to detect excessive pronation and supination (**Oks et al. 2017, Eizentals et al. 2019**).

- Foot strike patterns are important characteristics in human locomotion. The strike types – heel strike, mid foot and fore foot strike – can be classified with a smart socks system (**Oks et al. 2017**)

- Since smart socks with pressure sensors have been previously successfully used to detect various gait-related parameters and to the best of our knowledge there are no studies trying to predict internal power with smart socks, the aim of this study is to investigate, whether it is possible to estimate internal power with a smart textile.

Methods

- Participants
  - 4 recreational runners (two male, two female)
  - Age between 18 and 28 (average 26.5, SD=0.5)
  - Weekly running volume between 10 and 20 kilometers
  - Heel strikers
  - 42 test runs so far (100 meters at a specified pace and gradient)

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Methods

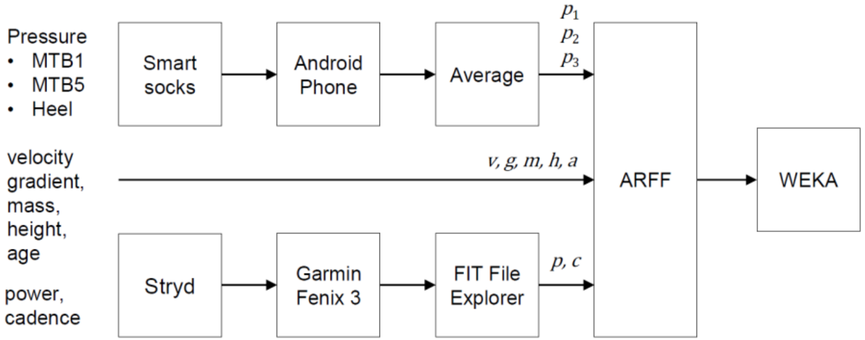
- Study Design
  - Participants wore smart socks with textile pressure sensors developed by Petz et al 2019.
  - Sensor data from the smart sock was recorded.
  - Power was measured with a Stryd sensor.
  - Subjects walk and/or ran 100 meters with velocities of 4 km/h, 6 km/h, 8 km/h, 10 km/h, each with different gradients (0, 4, 6, 8 percent).
  - Using various regression algorithms, we then predicted the power measurement given by Stryd with sensor data gathered with the smart sock.

Methods

- Devices
  - Measurements were performed on a Technogym MYRUN treadmill.
  - Smart socks developed by Petz et al 2019.
    - Three piezo-resistive pressure sensors (heel, left and right front)
    - Sampled with 160 Hz, 12 bits resolution
    - Data is transferred to a smart phone and stored as CSV file
  - Stryd power meter (firmware version 2.0.2)
  - Garmin Fenix 3 sports watch (firmware version 5.40) to store the power data from Stryd, uploads data to Garmin Connect
  - FIT File Explorer to extract power data from Garmin Connect

Methods

- Data Processing
  - Features for the regression analysis are
    - the arithmetic mean over the pressure data,
    - velocity, gradient, mass, cadence
    - height, age not used yet
  - Power is the dependent variable which we want to predict



Methods

- Data Processing
  - Data is then formatted as ARFF file for the WEKA toolkit:

```
@relation smartsocks
@attribute velocity numeric % v  km/h
@attribute mass numeric     % m  kg
@attribute height numeric   % h  cm
@attribute age numeric      % a  years
@attribute aveMTB1 numeric  % p1 mV
@attribute aveMTB5 numeric  % p2 mV
@attribute aveHeel numeric  % p3 mV
@attribute cadence numeric  % c  steps/min
@attribute gradient numeric % g  %%
@attribute watts numeric    % p  Watt

@data
4 80 1.75 27 2379 2369 2438 44 0 61
6 53 1.63 27 2980 2365 3006 63 0 105
% ...
```

Methods

- Data Processing
  - We then tried **different combinations of independent variables** and **different regression** algorithms to find out which combination performed best.
  - Since the number of instances in our data set is yet quite small and we want models that are computationally inexpensive, we go for simple algorithms such as
    - linear regression,
    - decision trees with regressions (M5P),
    - random forest and
    - K-nearest neighbors.
  - In WEKA, we used the default settings for each regression algorithm, as well as tenfold cross-validation.

Results and Discussion

- Since most runners nowadays routinely wear a GPS-enabled device such as a smart phone or sports watch, we first try to define a **baseline** by determining how well we can estimate power based on **velocity**, **gradient**, and **mass**.
- I.e., we want to find out whether estimating power with the smart sock offers any added value at all.

- Even a linear regression approximates the Stryd data quite well:
  - $p = 23.220v - 0.0568m - 0.3489g - 24.2518$ (r = 0.98; mean average error = 7.32 W)

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Results and Discussion

- What if we base our prediction on **pressure data** alone?
  - The linear regression model $p = 0.0418p_1 - 0.0385p_2 + 0.0915p_3 + 35.819$ ($r = 0.74$) can be minimally improved by additionally considering mass which gives $p = 1.8752m - 0.0468p_1 - 0.0356p_2 + 0.1679p_3$ ($r = 0.75$).
  - Non-linear regression-algorithms perform better:
    - Weka's M5P approximates a continuous function by building a decision tree where each leaf has a linear regression model; with p_1, p_2, p_3 as independent variables, the regression coefficient r is 0.88 with a mean average error of approx. $16\ \mathrm{W}$.
    - With random forest we get $r = 0.98$, and KNN achieves $r = 0.99$ with mean average errors of approx. $10\ \mathrm{W}$.

Results and Discussion

- If we base the estimation on **mass** and **cadence** (which can easily be retrieved from the pressure sensors, or an accelerometer), we can estimate the power output with
  - $p = 0.0323m + 2.9232c$ ($r = 0.98$, mean average error = $4.25\ \mathrm{W}$).
  - This is similar to the result achieved with velocity, gradient, and mass.

- Deriving VO2 and hence power from step-rate alone is well known and, e.g., used in pedometers.
  - certainly only possible when running on a treadmill or track without external influences, such as headwind or tailwind and the uniform nature of the running surface.

Results and Discussion

- Correlation coefficients for various combinations of independent variables and regression algorithms

Independent variables	*Linear regression*	*M5P*	*Random forest*	*KNN*
v, g, m	0.98	0.99	0.99	0.99
p_1, p_2, p_3	0.74	0.88	0.95	0.98
p_1, p_2, p_3, m	0.75	0.88	0.95	0.98
c	0.98	0.99	0.99	0.99
p_1, p_2, p_3, m, c	0.98	0.99	0.99	0.99

Results and Discussion

- Mean absolute errors for various combinations of independent variables and regression algorithms

Independent variables	*Linear regression*	*M5P*	*Random forest*	*KNN*
v, g, m	7.32	3.93	2.13	3.86
p_1, p_2, p_3	22.76	15.91	10.43	5.31
p_1, p_2, p_3, m	23.79	16.84	10.94	5.31
c	7.90	4.25	2.16	1.53
p_1, p_2, p_3, m, c	10.30	5.81	4.15	3.07

Conclusion and Future Work

- Under **ideal conditions** on a treadmill without any headwind or tailwind and on a uniform running surface, using the pressure sensors alone does not perform better than basing the estimation on velocity and gradient or cadence.
  - Given the right regression algorithm, the estimation is however not much worse which means that it can provide power data **without GPS**, which would be the case under dense foliage or indoors.
  - When **running on sand or grass or with headwind**, the assumption of approx. 0.98 J/kg/m is not valid anymore and using pressure data might provide a better estimation than the one based on cadence or GPS.

- Since the preliminary results seem promising, we plan to increase the number of participants, and perform more runs at different velocities and gradients as well as take different running surfaces such as sand or grass into account.