Estimating Internal Power in Walking and Running with a Smart Sock

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***Abstract*—The aim of this study is to investigate whether it is possible to estimate internal power in walking and running with a smart sock which is equipped with textile pressure sensors. Since commercially available smart socks are already used by runners to classify injury-prone running styles, such as running with low cadence and heel-striking, incorporating power measurement into the socks would make the usage of a separate power meter obsolete. While walking and running with different velocities and gradients on a treadmill, four subjects wore a pair of smart socks as well as a Stryd power meter as a reference system. The measurements from the pressure sensors were used to train regression algorithms, such as linear regression, trees of linear regressions (M5P), random forest, and k-nearest neighbors (KNN) to predict power. Preliminary results after a total of 42 runs show that depending on the actually used regression algorithm correlation coefficients between 0.75 and 0.99 and a mean absolute error between 1.5 and 21.8 Watts could be achieved. Although these results appear promising, the number of participants and test runs must be increased significantly in order to arrive at valid conclusions.**

Keywords–Smart textile; Smart socks; Running; Internal power.

I. Introduction

Together with measuring training volume, determining intensity is one of the most important measures to quantify physical stress or training load on athletes [1] which can subsequently be used to prescribe and adapt training [2] as well as make predictions [3]. While in the past heart rate or velocity have been mainly used to gauge intensity, we can nowadays observe an increased use of power meters in distance running [4]. They are superior to heart-rate measurements since they react instantly and are not prone to cardiac drift, and they are better than deriving the intensity from the velocity because changing external conditions such as wind and hills can be taken into account [5].

Commercially available power meters, such as Stryd [6] or RunScribe [7] are based on inertial measurements units and designed as small footpods, which are mounted directly on the shoe. With the increasing popularity of smart textiles in sports, such as Sensoria's smart socks [8] or Hexoskin's smart garments [9], it seems promising to investigate whether it is basically possible to estimate power in walking and running with a smart sock equipped with textile pressure sensors [10]. Incorporating power measurement into the socks would make the usage of a separate power meter obsolete.

The remainder of this paper is structured as follows. In Section 2 we review the related work, in Section 3 we describe the study design, then we continue with a discussion of the results in Section 4, and conclude with Section 5, in which we briefly summarize our findings and discuss possible future work.

II. Related Work

Because power is defined as the derivative of work, it is sufficient for our discussion to first deal with the determination of work while walking or running. Cavagna [11] measures the 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 and air. Forward and vertical velocities are then calculated by integrating the force signals, which allows determining the kinetic energy in forward and upward directions, as well as the potential energy caused by the vertical displacement of the center of mass. However, as this only gives external work, i.e., it does not take into account the energy needed to swing the legs and arms, internal energy is determined by means of a cinematographic analysis [12] which calculates the kinetic and potential energy of the body segments relative to the center of mass.

Since this is difficult to perform outside a controlled laboratory environment, van Dijk and van Megen [5] 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 [13] or running economy, nor does it consider walking where the energy cost varies as a function of velocity. Contemporary power meters

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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 [14].

Oks et al. [15] show that ground contact time can be adequately measured with a smart sock system with piezo-resistive knitted structures. One sock has six pressure sensors to gather the data. Validation was performed for walking, race-walking and running with an optical system as well as a force plate. Petz et al. [10] 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. Smart sock systems are also used for gait analysis and foot pressure control for human locomotion and to detect excessive pronation and supination [16][17]. Again, the system consists of piezo-resistive sensors and conductive lines knitted in. Foot strike patterns are important characteristics in human locomotion. The strike types – heel strike, mid foot and fore foot strike [18][19] – can be classified with a smart socks system [20].

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.

III. Methods

In this section we describe how we gathered the training data from numerous runs on a treadmill and show how we processed the data so that it could be fed into the machine learning suite to derive regression algorithms.

A. Participants

Four recreational runners (two male, two female) took part in our study. The runners' age is between 18 and 28 (average age: 26.5, SD=0.5) and their weekly running volume is between 10 and 20 kilometers. All of them are heel-strikers. In total, 42 test runs have been gathered so far. The study is still work in progress and therefore the number of participants and test runs is quite small.

B. Study design

Participants had to wear a pair of smart socks [10] (Figure 1), as well as a Stryd sensor together with a Garmin Fenix 3 sports watch to record the power data from the Stryd power meter (Figure 2). They were then instructed to walk or run 100 meters on a treadmill with velocities of 4 km/h, 6 km/h, 8 km/h, and 10 km/h, each velocity with different gradients (0, 4, 6, and 8 percent).

For each run, we measured and recorded the power output with a Stryd sensor, as well as the sensor data from the smart sock system, which in addition to the pressure measurements also contains rotation and acceleration, which, however, are not yet used in the analysis. Using various regression algorithms, we then predicted the power measurement given by Stryd with sensor data gathered with the smart sock. We used the Stryd sensor instead of a test setup with a force plate such as in [11][12], or a metabolic cart because our aim is simply to find out whether a correlation between pressure measurements from the socks and internal power can be found and according to Cerezuela-Espejo et al. [4] there is a close relation between power output and VO2.

Figure 1. Smart socks with sensors and data acquisition unit provide the independent variables for the analysis.

Figure 2. The dependent variable power output is measured with the Stryd sensor and recorded on a Garmin watch.

C. Devices

Measurements were performed on a Technogym MYRUN treadmill. Our smart socks developed by Petz et al. [10] (see Figure 1) have three piezo-resistive sensors placed according to the foot strike pattern, six conductive lines and a data acquisition unit. One sensor (referred to as MTB1) is placed in the left front, one sensor (MTB5) is in the right front and the third sensor (Heel) is located in the heel part of the sock. The sensors are sampled at a rate of 160 Hz and the recorded data is transferred to an Android smartphone and stored as a CSV file.

The Stryd power meter (firmware version 2.0.2) is connected to a Garmin Fenix 3 sports watch (firmware version 5.40) that stores power data and cadence. The Garmin watch stores data in the .fit file format and uploads the recordings

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to the Garmin Connect website. We use the FIT File Explorer [21], version 2.3, to retrieve the data from the .fit file.

D. Data Processing

After collecting the smart sock data from the smartphone and power data as well as cadence from the .fit file, we calculate an arithmetic mean over the measured sensor values to generate features for the regression analyses (Figure 3).

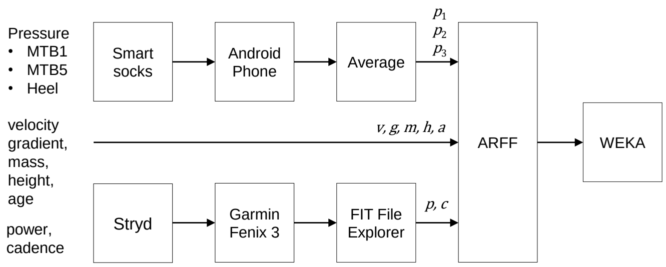

Figure 3. Devices and data processing.

Since we use the WEKA machine learning suite [22], the features are stored in the Attribute Relation File Format (ARFF). To process the data, ten input variables have been considered from the smart socks, and two input variables from the Garmin watch along with the output from Stryd. These are averages of the three sensor pressure sensors (MTB1 (p_1), MTB5 (p_2), heel (p_3), cadence (c) and power (p). Additionally, velocity (v) of the run, gradient (g), and related user information such as age (a), height (h), and mass (m) are also recorded. The units of measurements are shown in the ARFF file which looks as follows:

```
@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
% ...
```

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 neighbours. In WEKA, we used the default settings for each regression algorithm, as well as tenfold cross-validation.

IV. 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. Hence, we can find out whether estimating power with the smart sock offers any added value at all. Even a simple linear regression with v, g, and m as independent variables ($p = 23.220v - 0.0568m - 0.3489g - 24.2518$) is able to approximate the Stryd data quite well (see Tables I and II for correlation coefficients and mean absolute errors).

Next, we want to predict the power output based solely on the signals coming from the pressure sensors. 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 $p = 1.8752m - 0.0468p_1 - 0.0356p_2 + 0.1679p_3 - 290.0082$ ($r = 0.75$).

Since the cost of locomotion and therefore power is quite different for walking and running [23], with a U-shaped curve and a distinct minimum at the preferred walking speed of approx. 1.3 $\mathrm{m\,s^{-1}}$, while it remains constant across running speeds, 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.

Random forest and KNN achieve even better results (see Tables I and II). However, both methods are not able to extrapolate and therefore – with our limited data set – will perform poorly for power data outside of 61 to 206 Watts.

TABLE I. Correlation coefficients.

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

Since steps can be easily detected and derived from either acceleration or pressure signals which is done in [10], we could determine cadence c and estimate the power output with $p = 0.0323m + 2.9232c$ ($r = 0.98$). Currently, we use cadence data from Stryd. Combining c with the pressure readings does not improve the result ($p = -0.6921m + 0.0143p_2 - 0.0437p_3 + 3.2741c + 38.0002$, $r = 0.98$), which means that we can predict Stryd's power data with cadence and mass alone quite well.

TABLE II. Mean absolute errors.

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

However, this is certainly only possible when running on a treadmill without external influences, such as headwind or tailwind and the uniform nature of the running surface. Deriving VO2 and hence power from step-rate alone is well known and, e.g., used in pedometers [24].

V. Conclusion and Future Work

In this paper, we described how to estimate internal power using smart socks equipped with three piezo-resistive pressure sensors.

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. However, given the right regression algorithm, the estimation is also not much worse which means that it can provide power data without GPS, which would be the case under dense foliage or indoors.

Basing the estimation on cadence, which can be derived from the pressure sensors, gives – at least under ideal conditions – a better result than using the average pressure data. However, 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 be applicable.

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.

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