ESTIMATING WHOLE-BODY MECHANICAL POWER IN RUNNING BY MEANS OF SIMULATED INERTIAL SENSOR SIGNALS

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The purpose of this study was to identify the potential of inertial sensor information to estimate whole-body mechanical power (WBP) in running. We recorded three-dimensional (3D) whole-body kinematic and kinetic data of eleven male subjects by means of optoelectronic motion capturing and an instrumented treadmill at speeds between 2.0 and 3.5 m/s. We simulated 3D acceleration and gyroscope signals for 15 segments of the whole body from marker trajectory data. We calculated one statistical model for each subject to estimate WBP from a set of 279 predictor variables derived from simulated sensor signals. Overall, WBP was estimated with root mean square errors between 4% and 20%. This highlights the potential of inertial sensor signals to estimate WBP. Nonetheless, in its current form, the method requires too many sensors for practical applications.

KEYWORDS: wearable sensors, running mechanics, machine learning.

INTRODUCTION: Recent advances in wearable sensor technology provide new possibilities for biomechanical research. Especially for running, small size motion sensors allow for analyses in the field of the athletes' action.
The methods in studies using these sensors range from rather simple approaches, e.g. to determine foot strike pattern by means of two foot-mounted accelerometers (Giandolini et al., 2014) to more elaborate techniques and variables (Brahms, Zhao, Gerhard, & Barden, 2018). In these studies, the foot trajectory is calculated by means of combined gyroscope and accelerometer data from foot-mounted inertial measurement units (IMU).
A biomechanical parameter, which is of interest for both research and applied sciences such as performance diagnostics, is mechanical whole-body power. In cycling, power is a well-established objective parameter for athletic performance. In running, however, pace – measured by means of global navigation satellite system (GNSS) – is the most common performance metric. Nonetheless, pace does not consider changes in running style or the running environment (e.g. slope) that might affect the intensity of the run.
There are several approaches to calculate power in running. Arampatzis et al. (2000) compared four different methods regarding their accuracy. The most accurate methods were those taking the ground reaction forces (GRF) into account. Both, vertical and horizontal GRF were accurately estimated by means of IMU data (Neugebauer, Collins, & Hawkins, 2014; Thiel et al., 2018; Wouda et al., 2018). Thus, it seems possible to estimate the power in running from inertial sensor data, even though published research in this area is scarce.
Therefore, this study aimed to identify the potential of wearable inertial sensors to accurately estimate mechanical whole-body power in running.

METHODS: Eleven healthy male subjects (age: 27.1 ± 3.8 years, height: 182.1 ± 7.3 cm, mass: 80.1 ± 11.0 kg, BMI: 24.1 ± 1.7 kg/m²) performed running trials on an instrumented treadmill measuring three-dimensional GRFs (1000 Hz, Treadmetrix, Park City, UT, USA). Kinematic data of the whole body was captured by means of a three-dimensional motion capturing system (250 Hz, Vicon MX40, Vicon, Oxford, UK). Marker trajectories and GRFs were low-pass filtered with a cut-off frequency of 12 Hz.
We analysed different running velocities (2.0, 2.5, 3.0 and 3.5 m/s) at a self-selected cadence as well as an increased (+10%) and decreased (-10%) cadence (only at 2.5 m/s), set by means of a metronome. We captured at least 30 consecutive strides for each condition.
The least absolute shrinkage and selection operator (LASSO) as it is implemented in Matlab (R2018a, The Mathworks Inc., Natick, MA, USA) was used to compute the statistical models

to estimate whole-body power as the response variable from the predictor variables (Tibshirani, 1996). The tuning parameter λ was chosen as it minimises the mean squared error after five-fold cross-validation.

Since this was a proof of concept study, no physical IMU system was used. Instead, virtual acceleration and angular velocity signals were computed from kinematic data similar to Tong and Granat (1998). From the three-dimensional virtual IMU data, maximum, minimum and mean for each of the 15 segments of a rigid full body model over each stride were calculated. In addition, ground contact time, duty-cycle (i.e. ground contact divided by stride time), running speed, body mass and height were included, resulting in a total of 279 predictor variables.

Absolute whole-body power was calculated from the sum of the dot products of joint moment and joint angular velocity vectors:

$$P = \sum_{j=1}^{n} \left| \overrightarrow{M_j} \cdot \overrightarrow{\omega_j} \right|$$

in which $\overrightarrow{M_j}$ and $\overrightarrow{\omega_j}$ are the moment and the angular velocity, respectively, of the j-th joint calculated from inverse dynamics (Sanno, Willwacher, Epro, & Brüggemann, 2018). From this equation the mean power over each stride, i.e. the time between two consecutive right heel-strikes, was calculated as response variable.

Eleven statistical models were trained with the data of ten subjects always leaving out one subject. These models were separately validated using the data of the remaining subject. To determine the models' accuracy, we calculated the root-mean-square error (RMSE), mean absolute deviation (MAD) and Bland and Altman's limits of agreement (LoA) between measured power and the models' estimates (Bland & Altman, 1986).

RESULTS: After checking for outliers, a total of 2829 strides from the 11 participants were included with at least 30 strides for each participant in each condition. The measured power ranged between 4.09 W/kg and 10.97 W/kg with a mean of 6.97 W/kg. The accuracy varied considerably between models. The model trained for subject 4 showed the highest agreement with the measured values (LoA: ±0.43 W/kg, RMSE: 0.31 W/kg, MAD: 0.18 W/kg, compare table 1). Estimates with the lowest accuracy were present for the subject 6 (LoA: ±1.16 W/kg, RMSE: 0.65 W/kg, MAD: 0.50 W/kg) and subject 5 (LoA: ±0.80 W/kg, RMSE: 1.15 W/kg, MAD: 0.34 W/kg) respectively. The RMSE of the most accurate model (subject 4) was 4.2%, while the RMSE of the least accurate model (subject 5) was 20.1% of the measured mean power values.

The minimum number of predictor variables ranged between 206 and 269. BMI, height, stride duration, mean acceleration of the left thigh and velocity were most frequently present in the five highest normalized coefficients, thus having the highest impact on the model estimates. For all models at least one signal of each of the 15 simulated IMUs was present in the predictor subset.

Table 1 Root mean square error (RMSE), mean absolute deviation (MAD) and limits of agreement (LoA) of the differences between measured values (M ± SD) and model estimates for all models as absolute values [W/kg] and percentage of measured mean power [%]

Model for Subject	Measured Power [W/kg]	LoA [W/kg]	LoA [%]	RMSE [W/kg]	RMSE [%]	MAD [W/kg]	MAD [%]	LoA Rank	RMSE Rank	MAD Rank	Predictor Variables
1	7.51 ± 1.42	0.49	6.5	0.88	11.7	0.20	2.7	4	8	3	229
2	7.93 ± 1.30	0.76	9.6	0.91	11.5	0.29	3.7	7	9	7	257
3	6.94 ± 1.36	0.53	7.6	0.32	4.6	0.22	3.2	5	3	5	220
4	7.43 ± 1.27	0.43	5.8	0.31	4.2	0.18	2.4	1	2	1	258
5	5.71 ± 1.02	0.80	14.0	1.15	20.1	0.34	6.0	8	11	9	259
6	6.99 ± 1.32	1.16	16.6	0.65	9.3	0.50	7.2	11	6	11	251
7	7.31 ± 1.33	0.47	6.4	0.34	4.7	0.21	2.9	2	4	4	252
8	7.07 ± 1.14	0.49	6.9	0.30	4.2	0.20	2.8	3	1	2	206
9	6.17 ± 1.09	0.80	13.0	0.48	7.8	0.32	5.2	9	5	8	223
10	7.70 ± 1.36	1.05	13.6	0.84	10.9	0.43	5.6	10	7	10	218
11	6.13 ± 1.06	0.63	10.3	1.12	18.3	0.25	4.1	6	10	6	269

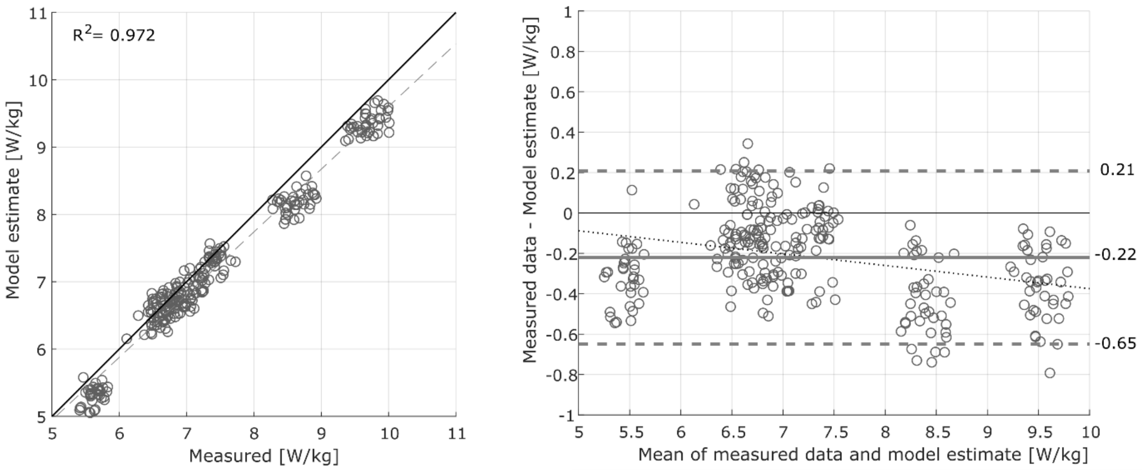

Figure 1: Correlation between measured power and model estimated power (left) and Bland-Altman difference plot (right) for model for subject 4 (estimates with the highest accuracy)

DISCUSSION: The purpose of this study was to explore whether it is possible to determine mechanical whole-body power in running solely by means of wearable sensors. Our results indicate that the accuracy of the estimated power values varies considerably among subjects. The measured range of our power values are in good accordance with those measured by other authors (Arampatzis et al., 2000).
Studies with a similar purpose used a certain number of subjects to train the models and multiple remaining subjects to validate the accuracy (e.g. Goulermas et al. 2005 used n=6 for training and n=2 for validation). However, for a small number of participants this can lead to randomly choosing unrepresentative subjects and over- or underestimate the overall capabilities of such a statistical model. With our approach we tried to reveal the overall possible range of accuracy for a small sample.
The high impact of running velocity on the model estimate can be attributed to the study design. Only level running was performed at different speeds and cadences. Early studies already revealed a strong correlation of running velocity and power (Fukunage, Matsuo, & Ichikawa, 1981). Uphill or downhill running might increase the relevance of other predictor variables.
Interestingly, both the most and the least accurate models were validated with subject data of two subjects with similar measured relative power, subject 4 and 6 respectively. However, subject 4 showed the lowest BMI and subject 6 the second highest. This could indicate a too high impact of the predictor variable BMI on the model estimate.
We found that the models require a high number of predictor variables, which makes the practical application difficult, since a high number of IMU sensors would need to be attached to the body. This would potentially impair the movements of runners and would increase the effort and time needed for data collection and monitoring.
Nonetheless, the model accuracy might be further improved and the number of sensors needed decreased by using more elaborate predictor variables or hybrid approaches which combine algorithms like the LASSO or artificial neural networks (ANN) and a biomechanical model (Ancillao, Tedesco, Barton, & O'Flynn, 2018).
This is especially important since the results of this study were based on simulated sensor signals. In practical applications, using actual sensors, the signals would be subject to noise, which would further negatively affect the accuracy of the estimates.

CONCLUSION: This study demonstrates that estimation of mechanical whole-body power in running without the use of direct methods to measure the GRF is possible with satisfying accuracy. However, for practical applications, improved models and methods are necessary to reduce the number of sensors needed and the results of this study need to be confirmed by studies using actual sensors.

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