Relation Between Estimated Cardiorespiratory Fitness and Running Performance in Free-Living: an Analysis of HRV4Training Data

Marco Altini[1], Chris Van Hoof[2] and Oliver Amft[1]

Abstract— **In this work, we propose to use anthropometrics and physiological data to estimate cardiorespiratory fitness (CRF) in free-living and analyze the relation between estimated CRF and running performance. In particular, we use the ratio between running speed and heart rate (HR) as predictor for CRF estimation in free-living. The ratio is representative of fitness as lower HR at a given speed is expected for more fit individuals. Then, we analyze the relation between estimated CRF and running performance for 10 km, half marathon and full marathon runs. CRF estimation models were developed using lab-based VO_2max measurements. CRF estimates were obtained from data collected in unsupervised free-living in a sample of 532 runners for a period ranging between 1 and 8 months using the HRV4Training app. During the same period, running performance was determined for all runners. We show that the speed to HR ratio provides higher accuracy in CRF estimation compared to resting HR or no-physiological data (15% to 18% reduction in RMSE for person-independent models). Secondly, we found moderate to strong correlations between CRF estimated from free-living data and running performance (Pearson's $r = 0.56 - 0.61$). We conclude that estimating CRF in free-living using mobile technology and data integration can be a valuable tool to support individualized training plans and to track fitness and performance outside laboratory settings.**

I. INTRODUCTION AND RELATED WORK

In the past few years, ubiquitous sensing technologies showed unprecedented insights into the relation between physical activity, health and performance [1]. A multitude of wearable devices and mobile applications have been developed to support recreational and professional athletes in tracking their workouts. Physiological data, including heart rate (HR) and heart rate variability (HRV) have been used to monitor athletes fitness levels as well as recovery from previous workouts [2].

Due to fast paced technological developments and integrations between different platforms and services (e.g. public APIs), increased availability of multivariate data streams acquired from mobile applications and wearable sensors (e.g. GPS, accelerometer, physiological data), new applications and techniques have been developed. Smartphone-based measurements have become popular [3], as smartphone-integrated sensors could be used, e.g. GPS to track distance and photoplethysmography to track physiological data using the phone's camera and flash light as light source [4], [5].

While several mobile applications and wearable sensors have been released on the market in the recent past, typically providing users with estimates of calories burnt, steps taken (e.g. Fitbit) and workouts data such as distance, time, speed, heart rate, etc. (e.g. Garmin), all important metrics reflecting individual behavior, limited work has been carried out to provide insights on the individual's actual health and performance status outside of laboratory settings. In particular, cardiorespiratory fitness (CRF) can potentially provide more information for both health and sports applications, as it is a key health parameter [6], [7], [8] and performance indicator in endurance sports [9], [10].

Current gold standard and practice for CRF measurement is direct measurement of oxygen volume (VO_2 in ml/min) during maximal exercise (i.e.VO_2max). However, VO_2max tests are affected by multiple limitations. Medical supervision is required and the test can be risky for individuals in non-optimal health conditions. Sub-maximal tests have also been developed [11], typically requiring to measure HR while running at a certain speed or biking at a certain intensity. HR while performing a specific activity in laboratory settings, is discriminative of CRF levels due to the inverse relation between HR and CRF [12], with more fit individuals typically showing lower HR at a given workout intensity. Commercial devices, for example some sport watches paired to HR monitors [13] (e.g. Polar devices), provide CRF estimation using a regression model including HR at a predefined running speed as predictor. A few methods have been recently proposed to estimate CRF using wearable sensor data acquired in free-living [7], [8], [14], [15], without the need for laboratory tests. Using wearable sensors in free-living to estimate VO_2max is a novel approach that could be applied to a larger population compared to maximal or sub-maximal laboratory tests.

The relation between VO_2max and running performance has been investigated several times in laboratory settings, sometimes with conflicting results [9], [10]. VO_2max estimation in free-living to track performance over a broad population with different fitness levels has never been investigated before. Technological advances make it finally possible to monitor longitudinally physiological data in free-living with minimal burden on the user, enabling new opportunities beyond laboratory settings. Monitoring training progress using free-living estimates, without the need for additional protocols, could provide individuals with an effective tool for individualized training and motivation.

In this work, we first analyzed different CRF estimation models relying on anthropometrics data only, anthropometrics and physiological data at rest as well as anthropometrics and physiological data during exercise, proposing the speed to HR ratio as predictor able to minimize estimation error.

[1]M. Altini and O. Amft are with ACTLab, University of Passau, DE altini.marco@gmail.com
[2]C. Van Hoof is with imec, Leuven, BE

Then, we used the HRV4Training app [5] to collect resting HR and HRV data, training summaries (HR during exercise, distance, duration, elevation gain for each workout) and a user anthropometrics (age, weight, height and gender) for a total of 532 runners. We used HRV4Training data to derive running performance over 1 to 8 months as well as to estimate VO_2max according to the lab-validated CRF estimation models. Finally, we compared estimated VO_2max and running performance by integrating data from additional services. Our contribution is therefore twofold:

- We show that CRF estimation error can be reduced by 15% and 18% when using the speed to HR ratio as predictor, with respect to anthropometrics data only and resting physiological data respectively.
- We show moderate to strong correlations between free-living CRF estimates and running time (Pearson's $r = 0.56 - 0.61$), consistently for distances between the 10 km and the full marathon, highlighting how estimated VO_2max can potentially be used to track individual performance outside laboratory settings.

II. METHODS AND DATA COLLECTION

We used lab data and acquired data in free-living settings. Lab data included measurements of HR at sub-maximal intensities (rest and running at different speeds), used as predictors for VO_2max estimation, as well as a VO_2max test. Free-living data included training summaries (HR, speed, distance, time), resting physiological measurements (HR and HRV) and runner anthropometrics (age, gender, height and weight). VO_2max estimation models developed in the lab were used to estimate VO_2max from free-living data and investigate the relation with running performance, also derived from training summaries in free-living.

A. Laboratory data: VO_2max modeling

Participants for laboratory studies were 48 (22 male, 26 female), age 25.0 ± 6.2 years, weight 67.8 ± 10.4 kg, height 173.3 ± 9.1 cm, BMI 22.5 ± 2.3 kg/m^2 and VO_2max 44.8 ± 7.2 ml/min. Written informed consent was obtained, and the study was approved by the ethics committee of Maastricht University. HR data were acquired using the ECG Necklace, a platform configured to acquire one lead ECG data at 256 Hz, and three-axial accelerometer data at 32 Hz. Reference CRF was determined as VO_2max, by means of an incremental test on a cycle ergometer [16] using a indirect calorimeter that analyzed O_2 consumption and CO_2 production. Two laboratory protocols were performed. The first protocol included simulated activities performed while wearing a portable indirect calorimeter and the ECG Necklace. Activities included in this study were: lying down and running (treadmill flat at 7, 8, 9, 10 km/h). Activities were carried out for a period of at least 4 minutes. The second protocol was a VO_2max test providing reference data for CRF.

B. Free-living data: VO_2max estimations

Runners were not recruited but downloaded the HRV4Training application from the Apple Store and agreed to provide collected measurements for research purposes via a consent form embedded in the application. Instructions were provided to reproduce conditions similar to measurements at rest in laboratory settings. HR and HRV duration was configurable between 1 and 5 minutes. The HRV4Training app is used for morning measurements at rest, and integrates with other commonly used services to retrieve actual workouts data and training summaries. Thus, training summaries including HR, speed, time, distance and elevation gain were acquired using Strava's public APIs. Each user voluntarily linked HRV4Training to Strava to retrieve training summaries in the HRV4Training application.

We included in this analysis all runners that recorded trainings for at least 1 month. We included only runner trainings when a HR rate monitor was used, as HR data during exercise is required for our VO_2max estimation. Finally, we included in this analysis only users that ran one of the following events: 10 km, half marathon (21.1 km) or full marathon (42.2 km). The inclusion criteria yielded 532 runners (493 male, 34 female), 88581 physiological measurements at rest, and 24712 trainings including HR and GPS data, i.e 46 trainings and 70 physiological measurements per user on average. Mean age was 39.9 ± 8.0 years, mean weight was 72.5 ± 9.1 kg, mean height was 178.0 ± 7.3 cm and mean BMI was 22.8 ± 2.1 kg/m^2.

III. DATA ANALYSIS

A. Laboratory data: VO_2max modeling

CRF was estimated using multiple linear regression models and different sets of predictors collected in laboratory settings (see Sec. II-A). We compared the following three cases: *anth*, including anthropometrics data only (BMI, age and gender), *resting* including anthropometrics and physiological data acquired at rest, i.e. morning HR and HRV, *training* including anthropometrics, resting physiological data and the speed to HR ratio. The speed to HR ratio was used as it could be derived from free-living training summaries regardless of a runner HR and preferred running speed and is representative of fitness as lower HR at a given speed is expected for more fit individuals.

B. Free-living data: VO_2max estimations

Resting physiological data were acquired in free-living using HRV4Training's photoplethysmographic (PPG) measurement. PPG is an unobtrusive technique for detecting blood volume changes during a cardiac cycle and is often measured using reflection by illuminating the skin using a LED (e.g. the phone's flash) and detecting the amount of light that is reflected by a photodetector or a camera located next to the light source. Details on this method can be found in [5]. HR was computed as the mean HR over the measurement window. As HRV feature we used rMSSD as it was shown to be a clear marker of parasympathetic activity and often used to determine physiological stress due to training load [17]. rMSSD was computed as the square root of the mean squared difference between PPG peak to peak intervals.

Running performance was determined for each runner as the fastest time over distances between the 10 km and full marathon for the measurement period. Runners were also split into performance categories based on their best times. In particular, we created three categories: *slow* runners (10 km above 47.5 minutes, half marathon time above 1 hour and 45 minutes, full marathon time above 4 hours and 15 minutes), *fast* runners (10 km below 40 minutes, half marathon time below 1 hour and 30 minutes, full marathon time below 3 hours and 15 minutes) and *average* runners, including all remaining ones. Training summaries data were used to determine running performance as well as running HR and speed, used as predictors for VO_2max estimates. The speed to HR ratio was computed from training summaries and used as predictor for VO_2max estimation models.

IV. Results and Discussion

A. Laboratory data: VO_2max modeling

Results for leave one participant out cross-validation of VO_2max estimation models are shown in Fig. 1. Root mean square error (RMSE) for *anth* was 4.2 ± 3.0 ml/kg/min, while for *resting* was 4.1 ± 3.1 ml/kg/min and for *training* was 3.5 ± 2.8 ml/kg/min. Results are consistent with previous research on VO_2max estimation using sub-maximal HR, confirming that physiological responses to more intense exercise (e.g. the speed to HR ratio during running) consistently improve VO_2max estimation accuracy. In particular, participant-independent RMSE is reduced by 15% and 18% on our dataset when using *training* compared to *resting* and *anth* respectively.

B. Free-living data: Running performance and VO_2max estimations

Running performance derived from training summaries acquired in free-living was 48.8 ± 6.0 minutes for 10 km runs, 108.0 ± 15.9 minutes for half marathon runs and 225.0 ± 36.6 minutes for full marathons. Fig. 2 shows the relation between VO_2max estimated using the *training* model, i.e. the best performing VO_2max estimation model described in Sec. IV-A, and running performance. A moderate to strong inverse relation is visible for all running distances (Pearson's r ranging between -0.56 and -0.61). Finally, Fig. 2.d shows boxplots of the relation between estimated VO_2max and running category as defined in Sec. III-B, highlighting consistent differences between groups.

Reported results are consistent with previous small-scale studies showing moderate to strong correlations between VO_2max and running performance [9], [10]. While it is clear that there is more to running performance than VO_2max, and other variables might serve as more accurate predictors in laboratory settings (for example lactate threshold and running efficiency [18], [9]), measuring these parameters requires laboratory infrastructure, expensive equipment and dedicate

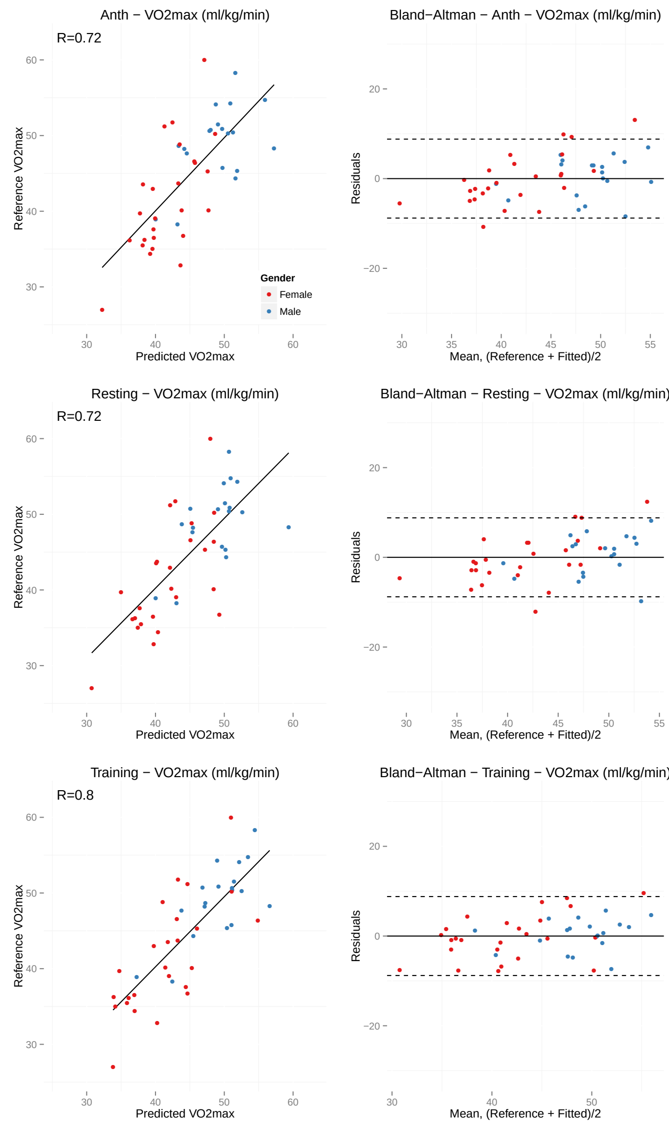

Fig. 1. Relation between estimated and measured VO_2max for the different models implemented based on the lab data. *Anth* refers to anthropometrics characteristics only, *Resting* includes anthropometrics, resting HR and rMSSD, *training* includes anthropometrics and the speed to HR ratio during running activities as predictors. Correlation between actual and estimated VO_2max is also reported for each analysis.

personnel. On the other hand, we showed that VO_2max can be estimated with good accuracy using the speed to HR ratio as predictor, which can be easily acquired using today's smartwatches and mobile phone applications. Additionally, we found the inverse relation between running performance and estimated VO_2max to be consistent across different running distances. We believe that the availability of metrics representative of running performance such as the proposed VO_2max estimate could help individuals keep track of their fitness level, effectively closing the loop between training and objective estimates of physical fitness and performance.

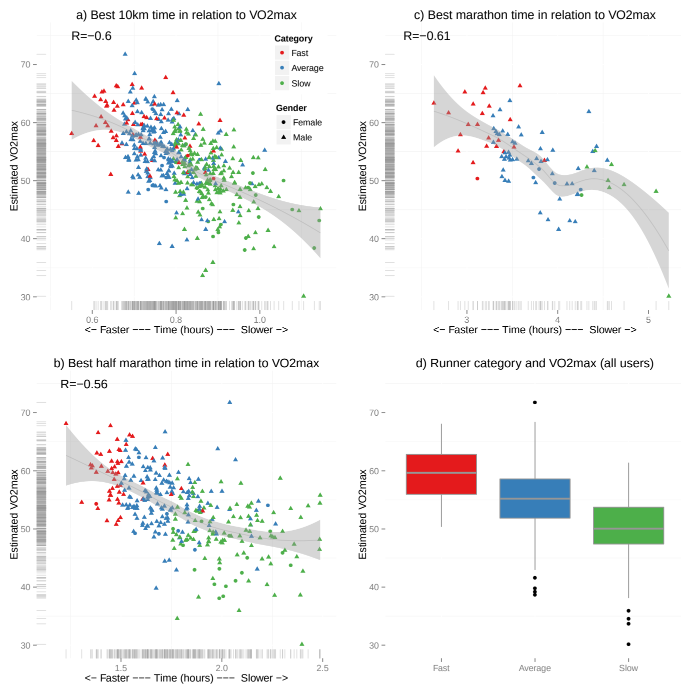

Fig. 2. Relation between running performance (racing duration for distances between the 10 km and the full marathon) and estimated VO_2max for data collected using the HRV4Training application in unsupervised free-living settings. A moderate to strong inverse relationship is shown independently of running distance. Distributions of VO_2max values and running performance are also shown.

V. CONCLUSIONS

In this paper we investigated the relation between estimated VO_2max and running performance in free-living. First, we used data acquired under laboratory settings to build and validate VO_2max estimation models and proposed the speed to HR ratio as predictor that can be easily computed from running workouts. We showed that VO_2max estimation error can be reduced by 15% and 18% with respect to anthropometrics data only and resting physiological data (HR and HRV) respectively. Then, we acquired free-living workouts data from 532 individuals over a period of up to 8 months using the HRV4Training application. Trainings were used to estimate VO_2max and running performance. We found a moderate to strong negative correlation between estimated VO_2max and running performance ($r = 0.56 - 0.61$), for all distances between the 10 km and the full marathon. Given the greater sample size compared to typical studies, we could provide confirmative insights on the feasibility of using sub-maximal HR to estimate fitness level in free-living, and use such estimated fitness level as a metric representative of running performance. Estimated VO_2max can potentially be used to track individual performance outside laboratory settings, driving motivation and helping athletes of all levels keep track of progress as well as adopt individualized training plans based on a person's physiological response to training. Our approach confirms the potential of mobile technology and data integration to provide relevant insights in free-living performance on the population level. Further work is needed to investigate individual variance.

REFERENCES

[1] S. J. Marshall and E. Ramirez, "Reducing Sedentary Behavior : A New Paradigm in Physical Activity Promotion," *American Journal of Lifestyle Medicine*, 2011.

[2] A. Jeukendrup, M. Hesselink, A. Snyder, H. Kuipers, and H. Keizer, "Physiological changes in male competitive cyclists after two weeks of intensified training." *International journal of sports medicine*, vol. 13, no. 7, pp. 534–541, 1992.

[3] E. Ozdalga, A. Ozdalga, and N. Ahuja, "The smartphone in medicine: a review of current and potential use among physicians and students," *Journal of medical Internet research*, vol. 14, no. 5, p. e128, 2012.

[4] C. G. Scully, J. Lee, J. Meyer, A. M. Gorbach, D. Granquist-Fraser, Y. Mendelson, and K. H. Chon, "Physiological parameter monitoring from optical recordings with a mobile phone," *Biomedical Engineering, IEEE Transactions on*, vol. 59, no. 2, pp. 303–306, 2012.

[5] M. Altini and O. Amft, "Hrv4training: Large-scale longitudinal training load analysis in unconstrained free-living settings using a smartphone application," in *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Aug 2016, pp. 2610–2613.

[6] D.-c. Lee, E. G. Artero, X. Sui, and S. N. Blair, "Review: Mortality trends in the general population: the importance of cardiorespiratory fitness," *Journal of Psychopharmacology*, vol. 24, no. 4 suppl, pp. 27–35, 2010.

[7] G. Plasqui and K. R. Westerterp, "Accelerometry and heart rate as a measure of physical fitness: proof of concept." *Medicine and science in sports and exercise*, vol. 37, no. 5, pp. 872–876, 2005.

[8] F. Sartor, G. Vernillo, H. M. de Morree, A. G. Bonomi, A. La Torre, H.-P. Kubis, and A. Veicsteinas, "Estimation of maximal oxygen uptake via submaximal exercise testing in sports, clinical, and home settings," *Sports medicine*, vol. 43, no. 9, pp. 865–873, 2013.

[9] L. Brandon and R. Boileau, "The contribution of selected variables to middle and long distance run performance," *Journal of sports medicine and physical fitness*, vol. 27, no. 2, pp. 157–164, 1987.

[10] C. C. Abad, R. V. Barros, R. Bertuzzi, J. F. Gagliardi, A. E. Lima-Silva, M. I. Lambert, and F. O. Pires, "10 km running performance predicted by a multiple linear regression model with allometrically adjusted variables," *Journal of Human Kinetics*, vol. 51, no. 1, pp. 193–200, 2016.

[11] P. O. Åstrand and I. Ryhming, "A nomogram for calculation of aerobic capacity (physical fitness) from pulse rate during submaximal work," *Journal of Applied Physiology*, vol. 7, no. 2, pp. 218–221, 1954.

[12] G. Plasqui and K. R. Westerterp, "Accelerometry and heart rate as a measure of physical fitness: cross-validation." *Medicine and science in sports and exercise*, vol. 38, no. 8, pp. 1510–1514, 2006.

[13] M. R. Esco, E. M. Mugu, H. N. Williford, A. N. McHugh, and B. E. Bloomquist, "Cross-validation of the polar fitness test tm via the polar f11 heart rate monitor in predicting vo2 max," *Age (yrs)*, vol. 24, pp. 5–1, 2011.

[14] M. Altini, P. Casale, J. Penders, and O. Amft, "Cardiorespiratory fitness estimation in free-living using wearable sensors," *Artificial intelligence in medicine*, vol. 68, pp. 37–46, 2016.

[15] M. Altini, P. Casale, J. Penders, G. ten Velde, G. Plasqui, and O. Amft, "Cardiorespiratory fitness estimation using wearable sensors: Laboratory and free-living analysis of context-specific submaximal heart rates," *Journal of Applied Physiology*, vol. 120, no. 9, pp. 1082–1096, 2016.

[16] H. Kuipers, F. Verstappen, H. Keizer, P. Geurten, and G. Van Kranenburg, "Variability of aerobic performance in the laboratory and its physiologic correlates," *International journal of sports medicine*, vol. 6, no. 04, pp. 197–201, 1985.

[17] D. J. Plews, P. B. Laursen, J. Stanley, A. E. Kilding, and M. Buchheit, "Training adaptation and heart rate variability in elite endurance athletes: opening the door to effective monitoring," *Sports medicine*, vol. 43, no. 9, pp. 773–781, 2013.

[18] E. Stratton, B. O'Brien, J. Harvey, J. Blitvich, A. McNicol, D. Janissen, C. Paton, and W. Knez, "Treadmill velocity best predicts 5000-m run performance," *International journal of sports medicine*, vol. 30, no. 01, pp. 40–45, 2009.