Cardio-respiratory fitness estimation from heart rate and body movement in daily life

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RESEARCH ARTICLE

Cardiorespiratory fitness estimation from heart rate and body movement in daily life

Alberto G. Bonomi,[1] Gill A. ten Hoor,[2] Helma M. de Morree,[1] Guy Plasqui,[3] and Francesco Sartor[1,4]

[1]*Patient Care and Measurements Department, Philips Research, Eindhoven, The Netherlands;* [2]*Department of Work and Social Psychology, Maastricht University, Maastricht, The Netherlands;* [3]*Department of Nutrition and Movement Sciences, Maastricht University, Maastricht, The Netherlands; and* [4]*College of Health and Behavioural Sciences, Bangor University, Bangor, United Kingdom*

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Bonomi AG, ten Hoor GA, de Morree HM, Plasqui G, Sartor F. Cardiorespiratory fitness estimation from heart rate and body movement in daily life. *J Appl Physiol* 128: 493–500, 2020. First published January 30, 2020; doi:10.1152/japplphysiol.00631.2019.—Low cardiorespiratory fitness (CRF) increases risk of all-cause mortality and cardiovascular events. Periodic CRF assessment can have an important preventive function. The objective of this study was to develop a protocol-free method to estimate CRF in daily life based on heart rate (HR) and body acceleration measurements. Acceleration and HR data were collected from 37 subjects (men = 49%) while they performed a standardized laboratory activity protocol (sitting, walking, running, cycling) and during a 5-day free-living monitoring period. CRF was determined by oxygen uptake ($\dot{V}O_{2max}$) during maximal exercise testing. A doubly labeled water-validated equation was used to predict total energy expenditure (TEE) from acceleration data. A fitness index was defined as the ratio between TEE and HR (TEE-pulse). Activity recognition techniques were used to process acceleration features and classify sedentary, ambulatory, and other activity types. Regression equations based on TEE-pulse data from each activity type were developed to predict $\dot{V}O_{2max}$. TEE-pulse measured within each activity type of the laboratory protocol was highly correlated with $\dot{V}O_{2max}$ (r from 0.74–0.91). Averaging the outcome of each activity-type specific equation based on TEE-pulse from the laboratory data led to accurate estimates of $\dot{V}O_{2max}$ [root mean square error (RMSE): 300 mL O_2/min, or 10%]. The difference between laboratory and free-living determined TEE-pulse was 3.7 ± 11% (r = 0.85). The prediction method preserved the prediction accuracy when applied to free-living data (RMSE: 367 mL O_2/min, or 12%). Measurements of body acceleration and HR can be used to predict $\dot{V}O_{2max}$ in daily life. Activity-specific prediction equations are needed to achieve highly accurate estimates of CRF.

NEW & NOTEWORTHY This is among the very few studies validating, in free-living conditions, a method to estimate cardiorespiratory fitness using heart rate and body acceleration data. A novel parameter called TEE-pulse, which was defined as the ratio between accelerometer-determined energy expenditure and heart rate, was highly correlated with maximal oxygen uptake ($\dot{V}O_{2max}$). Activity classification and the use of activity-selective prediction equations outperformed previously published methods for estimating $\dot{V}O_{2max}$ from heart rate and acceleration data.

activity classification; energy expenditure; maximal aerobic power; $\dot{V}O_{2max}$

Address for reprint requests and other correspondence: A. G. Bonomi, Patient Care and Measurements, Philips Research, HTC 34, 5656AE, Eindhoven; The Netherlands (e-mail: alberto.bonomi@philips.com).

INTRODUCTION

Cardiorespiratory fitness (CRF) represents the functional capacity of the pulmonary, cardiovascular, and skeletal muscle systems to perform everyday activities that require sustained aerobic metabolism (5). CRF has traditionally been an important parameter in the sports and clinical settings. For athletes, CRF is an essential index of aerobic capacity (18) and a good predictor of endurance performance (8). In the clinical setting, fitness testing is used for diagnostic, prognostic, and therapeutic applications, such as exercise prescription (4, 5). Moreover, CRF testing is important in the general population to allow for evaluation of progress during an exercise intervention program and to stratify cardiovascular risk in asymptomatic adults (4, 21). Low CRF increases the risk of all-cause mortality and cardiovascular events (15). CRF testing can therefore have an important preventive function.

The most widely recognized measure of CRF is maximal oxygen uptake ($\dot{V}O_{2max}$). The gold standard for measuring $\dot{V}O_{2max}$ is via open-circuit spirometry during a maximal exercise test. Maximal exercise testing implies that participants are to reach volitional exhaustion. Although it provides the most accurate determination of CRF, reaching maximal exertion may not always be desirable or feasible (4, 5), and the subject needs to be well motivated (20, 25). Moreover, it is not safe for everyone to undergo maximal exercise testing in the absence of medical supervision and emergency equipment (27).

Because of the difficulties associated with maximal exercise testing, many submaximal tests have been developed to estimate CRF (27). Estimation of $\dot{V}O_{2max}$ from submaximal tests is based on the linear relationships between oxygen uptake ($\dot{V}O_2$) and either mechanical power output or heart rate (HR) (19). Tests require the participants to undergo an activity protocol and may require specific exercise equipment and trained personnel (27). Some submaximal tests like the Astrand–Rhyming cycle test or the McArdle step test are suitable for self-evaluation, which means that the test is relatively safe and simple to perform (27). However, the accuracy and reproducibility of the estimates provided by such methods is lower than that offered by direct measures of $\dot{V}O_{2max}$.

Assessment of CRF during everyday activities may be very promising for enabling constant tracking of CRF in an unobtrusive manner, as it would simplify self-assessment by removing the need for exercise equipment typical of submaximal fitness testing. In recent years, estimates of CRF have been

attempted using simultaneous measurements of heart rate and body acceleration collected with wearable sensors during laboratory activities such as walking and running. These methods are based on the inverse relationship between CRF and heart rate for a specific activity type and at a certain intensity (1). Contextual information, namely which activity was carried out and at what intensity, could be estimated from the pattern of body acceleration (10). However, free-living validations have seldom been carried out, and the proposed CRF prediction models often require input data from activities of standardized intensity (2, 3, 30, 32).

The goal of the present study was to estimate CRF by means of a method based on heart rate and body acceleration applicable in free-living conditions, which therefore does not require data from predefined activities. The aim was threefold: *1*) develop a fitness index that could reflect the $\dot{V}O_2$ versus heart rate relationship of a subject by combining acceleration-based estimates of energy expenditure with heart rate data; *2*) develop activity-specific $\dot{V}O_{2max}$ prediction models based on the proposed fitness index; and *3*) validate the presented approach in free-living conditions and compare it to a previously published method (24) that does not take into account the types of activity carried out by the subject to estimate CRF.

METHODS

Study population. A total of 40 subjects were included in this study. Volunteers were recruited via leaflets, posters, and e-mail within the facilities of Maastricht University. Volunteers could take part in this study if they were between 18 and 55 yr, had a body mass index between 18 and 28 kg/m^2, and did not have any impediments in performing habitual physical activity. Volunteers who suffered from any chronic disease (e.g., diabetes or cardiovascular or pulmonary diseases), had cognitive or physical impediments, were taking any medication affecting the hormonal and metabolic systems, or might have been pregnant or lactating were excluded from this study. All participants were given plenty of time to read the study information and ask clarification before providing written informed consent. Because 3 volunteers dropped out, we have analyzed and presented data of 37 participants. The study protocol was approved by the Medical Ethical Committee of Maastricht University in conformity with the Declaration of Helsinki.

Study protocol. The study protocol included four visits to the laboratory for each volunteer. During the first visit, subject characteristics were measured. Body weight was measured on an electronic scale (Mettler Toledo ID1 Plus, Giessen, Germany) to the nearest 0.01 kg. Height was measured to the nearest 0.1 cm (SECA Mod. 220, Hamburg, Germany). Body volume was determined by underwater weighing. During the underwater weighing, residual lung volume was measured with the helium dilution technique (Volugraph 2000, Mijnhardt, Bunnik, The Netherlands). Total body water was determined with deuterium dilution according to the Maastricht protocol (31). Body composition was calculated from body mass, body volume, and total body water with Siri's three-compartment model (28). Fat mass and fat-free mass were calculated and expressed as percentage of body weight.

During the second visit to the laboratory, a direct measure of participants' CRF was performed by means of a maximal exercise test to determine $\dot{V}O_{2max}$. The third visit consisted of a laboratory routine of standardized everyday activities at least 48 h after the second visit. The participants were asked to refrain from any high-intensity physical exercise during the 24 h before testing. Participants were also asked to be well-hydrated and have consumed their last meal 2 h before starting all tests. At the fourth visit, participants were asked to wear a heart rate and an activity monitor for 5 consecutive days to measure their activity patterns in free-living conditions.

Maximal oxygen uptake exercise test. Participants were asked to bring suitable clothing for sport activities (e.g., a pair of shorts, a t-shirt, and trainers) and wear a chest-belt HR monitor (RS800CX, Polar Electro, Kempele, Finland) set to record HR data at 1 Hz. Participants were then equipped with a facemask connected to an expiratory volume and gas analyzer (Omnical, Maastricht Instruments, Maastricht, The Netherlands) and asked to ride a cycle ergometer (Excalibur, lode, The Netherlands). Participants started with a 5-min warm-up at 100 W for men and 75 W for women. At the end of the warm-up phase, the load increased by 50 W every 2 min and 30 s until the respiratory exchange ratio (RER) was greater than 1. When RER $>$ 1, the workload was increased by 25 W per stage until participant exhaustion occurred. Participants were asked to maintain a pedaling rate of 70 revolutions/min or higher, and the test was stopped when the participants could no longer keep a cadence greater than 60 revolutions/min. Criteria for a successful $\dot{V}O_{2max}$ test were as follows: an RER $\geq$ 1.1 and a maximal HR (HR_{max}) recorded during the test $>$90% of the age-predicted HR_{max} [calculated using the following equation: $208 - (0.7 \times \text{age})$] (29). Only one test did not meet these criteria, and the subject was excluded from the analysis.

Laboratory and free-living test. Participants were asked to undergo a series of standardized physical activities in randomized order. After sitting down for 5 min, the participants walked on a treadmill at three different speeds: 3, 4.5, and 6 km/h for 3 min; ran on a treadmill at two different speeds: 7 and 9 km/h for 3 min; and cycled on a cycle ergometer at three different intensities: 30, 50, and 65% of maximal power output as recorded during the $\dot{V}O_{2max}$ test for 3 min. Each activity was followed by at least 3 min of recovery standing upright, except for cycling, where the recovery was sitting down on the saddle. A new activity was started, after the 3 min of recovery, when the HR of the participant was $\leq$5% HR reserve. HR reserve was defined as follows: (HR – resting HR)/(HR_{max} – resting HR). The resting HR and HR_{max} used to calculate the HR reserve were those determined before and during the $\dot{V}O_{2max}$ test. Participants were provided with a heart rate monitor via a chest strap (RS800CX, Polar Electro, Kempele, Finland) and an activity monitor ($Tracmor_D$, Philips DirectLife, Amsterdam, The Netherlands) placed at the wrist. Data from the HR monitor and activity monitor were collected at 1 and 20 Hz, respectively. This physical-activity measuring equipment was worn during the entire duration of the laboratory protocol as well as during a free-living observational period of 5 consecutive days, during the daytime. Participants were asked to follow their habitual activity patterns.

Data processing. Data from the $Tracmor_D$ activity monitor and the HR monitor were synchronized and processed to extract features representing motion intensity, energy expenditure, and HR during the activity tasks included in the laboratory protocol as well as during the free-living monitoring period. Motion intensity was defined as activity counts per minute (Cnts), as previously described (12, 22), by processing the acceleration signal in overlapping windows of 60 s (overlap rate: 10 s). The physical activity level (PAL) and total energy expenditure (TEE) were determined from Cnts according to a doubly labeled water-validated equation (12). TEE was calculated by multiplying estimates of PAL by basal metabolic rate, as predicted from subjects' characteristics using a previously published equation (13).

Definition of a fitness index. A fitness index, named TEE-pulse, was defined by combining acceleration and HR data. A TEE-pulse parameter was calculated as the ratio between TEE and HR for each analysis window (60 s). This value was designed as highly indicative for oxygen pulse, which is a popular index of physical performance and correlates with $\dot{V}O_{2max}$ (26).

Activity classification. Activity classification was carried out to describe the context in which measurements of TEE-pulse occurred and generate activity-type selective equations to predict $\dot{V}O_{2max}$ from TEE-pulse. This allowed for the development of specific equations to

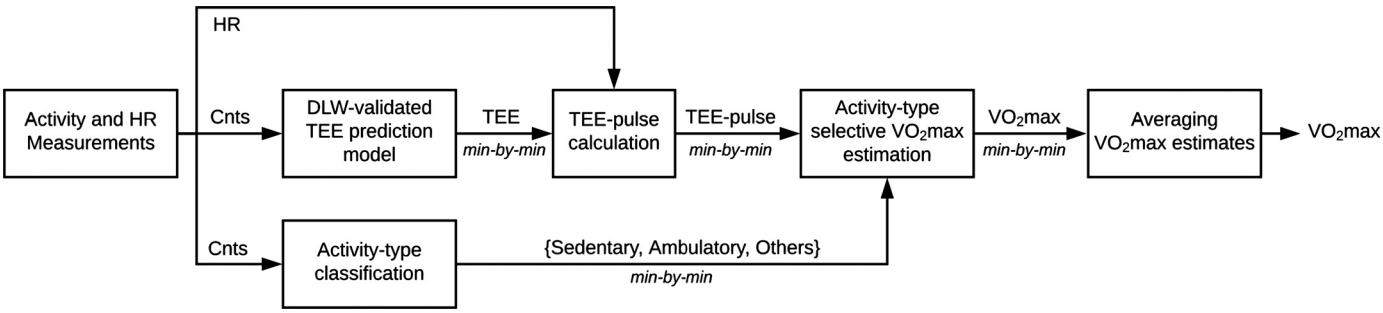

Fig. 1. Schematic representation of the processing steps to compute maximal oxygen uptake ($\dot{V}O_{2max}$) from measurements of body movement and heart rate (HR). Cnts, activity counts per minute; DLW, doubly labeled water; TEE, total energy expenditure; TEE-pulse, the ratio between TEE and HR.

relate TEE-pulse to $\dot{V}O_{2max}$ for each category of activity. Activity classification was carried out by determining whether the measured data belonged to three activity categories: sedentary, ambulatory, or other. This distinction was based on a set of Cnts thresholds determined using a linear grid-search algorithm on the collected laboratory data. According to the laboratory protocol, the sedentary category identified sitting and standing still data, the ambulatory category identified walking and running data, and the other category identified cycling data. The outcome of the grid-search algorithm was two Cnts thresholds that would discriminate sedentary versus other activities and other versus ambulatory activities, respectively. The accuracy of this activity classification method was evaluated based on laboratory data.

Statistical analysis. The processing steps to compute $\dot{V}O_{2max}$ from measurements of body movement and heart rate are shown in Fig. 1. The predictive value of TEE-pulse to predict CRF was assessed by correlation analysis between $\dot{V}O_{2max}$ and TEE-pulse data for each of the group of activity tasks included in the laboratory protocol. Activity-type selective equations were developed to relate TEE-pulse to $\dot{V}O_{2max}$ using the laboratory data. Leave-one-subject-out (L1SO) cross-validation on the laboratory data was used to determine the robustness of prediction error by means of bias, mean absolute error (MAE), and root mean square error (RMSE) and percentages. The $\dot{V}O_{2max}$ prediction equations developed for each activity type using laboratory data were in a later stage applied to free-living data. An aggregated estimate of $\dot{V}O_{2max}$ was obtained for each subject by averaging the minute-by-minute predictions based on TEE-pulse according to the classified activity type in both laboratory as well as free-living settings. A Bland–Altman plot was used to represent $\dot{V}O_{2max}$ prediction accuracy on both laboratory data and free-living data. Furthermore, reproducibility of the aggregated TEE-pulse for the same subject between laboratory and free-living conditions was evaluated by correlation analysis.

As a benchmark, a previously published approach (23, 24) was applied to the free-living data to assess the validity of the presented method. In brief, Plasqui et al. (23, 24) developed a $\dot{V}O_{2max}$ estimation method based on HR and Cnts measured using a wearable device during a 7-day monitoring period in free living. $\dot{V}O_{2max}$ was determined by a maximal incremental test on a bicycle ergometer in the laboratory. The ratio between HR and Cnts calculated on a minute-by-minute basis in free living was averaged for each subject to determine an individual fitness index (HR/Cnts). This parameter was used to predict $\dot{V}O_{2max}$ in combination with subject characteristics selected by stepwise multilinear regression (gender, age, height, and body weight). This method was different from the one proposed in our study because it did not group data according to context (e.g., by clustering data according to activity type) before estimation of $\dot{V}O_{2max}$.

RESULTS

Subjects' characteristics and CRF information are presented in Table 1. From the 37 participants that successfully completed the laboratory and $\dot{V}O_{2max}$ test, 4 male and 4 female subjects did not complete the free-living part of the trial because of lack of compliance with the measurement protocol (during the 5-day monitoring period, less than 32 h of valid HR and acceleration data were available).

Activity classification. Activity classification based on Cnts thresholds was achieved with 78% accuracy in laboratory settings. The outcome of the activity classification method for each activity task included in the laboratory protocol is presented in Table 2.

Evaluation of TEE-pulse in the laboratory settings. For each activity task included in the laboratory protocol, the acceler-

Table 1. *Characteristics of the study population*

	Men			Women		
	Means SD	Min	Max	Means SD	Min	Max
Age, yr	25 ± 5	19	36	25 ± 3	20	33
Height, m	1.81 ± 0.07	1.63	1.91	1.70 ± 0.05	1.59	1.81
BW, kg	76.9 ± 8.7	58.3	95.8	61.1 ± 5.3	52.3	74.6
BMI, kg/m^2	23.5 ± 2.5	17.6	28.1	21.1 ± 1.9	18.6	25.8
%FM	14.4 ± 4.4	6.8	23.7	18.0 ± 4.7	11.8	28.0
%FFM	85.6 ± 4.4	76.3	93.2	82.0 ± 4.7	72.0	88.2
HR_{max}, beats/min	191 ± 8	179	208	195 ± 12	160	213
W_{max}, W	287 ± 37	231	366	216 ± 35	144	288
$\dot{V}O_{2max}$ BW, mL $O_2 \cdot kg^{-1} \cdot min^{-1}$	45.7 ± 6.1	36.0	62.6	40.0 ± 6.6	27.0	52.6
$\dot{V}O_{2max}$, mL O_2/min	3,490 ± 435	2,727	4,212	2,435 ± 381	1,490	3,159

No. of subjects: n = 37 (18 men; 19 women). BMI, body mass index; BW, body weight; %FFM, fat-free mass as percentages; %FM, fat mass percentage; HR_{max}, maximal heart rate; $\dot{V}O_{2max}$, maximal oxygen uptake during the maximal exercise test; W_{max}, maximal power output.

Table 2. *Confusion matrix describing how the different activity tasks included in the laboratory routine were clustered in each activity type by the activity identification method*

		Walk			Run		Cycle		
Activity Type Clustering	Sit Rest	3 km/h	4.5 km/h	6 km/h	7 km/h	9 km/h	30%	50%	65%
Other	38	7	0	0	0	0	96	95	90
Sedentary	61	0	0	0	0	0	0	0	0
Ambulatory	1	93	100	100	100	100	4	5	10

Data represent percentages of duration for each activity task categorized according to the class on each row. Cycle Watts expressed in % of maximal power output.

ometer and HR-based fitness index (TEE-pulse) was highly and significantly correlated to $\dot{V}O_{2max}$. TEE-pulse obtained during running showed the strongest correlation with $\dot{V}O_{2max}$ (r ranging from 0.89–0.91, $P < 0.05$) compared with walking and cycling (r ranging from 0.74–0.85, $P < 0.05$) (Fig. 2).

Activity-type selective equations to estimate $\dot{V}O_{2max}$ in the laboratory settings. Table 3 shows the accuracy of the activity-type selective equations developed to predict $\dot{V}O_{2max}$ from TEE-pulse using laboratory data. The ambulatory-type equation showed the lowest $\dot{V}O_{2max}$ estimation error as determined by L1SO cross-validation (RMSE = 11.7%). For each subject included in the laboratory group, an aggregated $\dot{V}O_{2max}$ prediction was obtained by averaging the minute-by-minute $\dot{V}O_{2max}$ estimates as provided by each activity-type selective prediction equation. Figure 3 shows the relationship between measured and predicted $\dot{V}O_{2max}$ ($r = 0.89$) and the error bias and RMSE obtained during training of the model, as well as a Bland–Altman plot of the comparison between the measured and predicted $\dot{V}O_{2max}$. The aggregated TEE-pulse data showed a $\dot{V}O_{2max}$ estimation error in laboratory settings with a bias of 9 mL O_2/min (0.3%), MAE of 234 mL O_2/min (7.9%), and RMSE of 300 mL O_2/min (10.1%) according to the L1SO cross-validation.

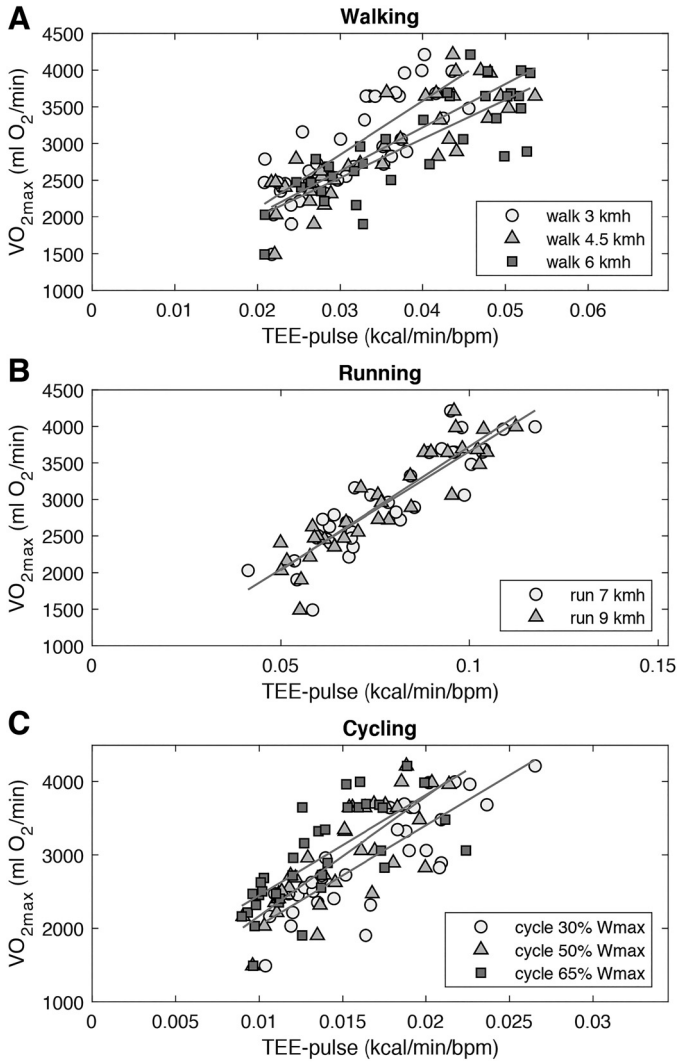

Fig. 2. Correlation between the ratio between total energy expenditure and heart rate (TEE-pulse) and maximal oxygen uptake ($\dot{V}O_{2max}$) for different activities included in the laboratory protocol. *A*: walking. *B*: running. *C*: cycling.

$\dot{V}O_{2max}$ estimation on free-living data. Table 4 shows the outcome of the activity classification when applied to free-living data. Because of the habitual activity behavior of the test participants, a very different distribution of data between activity types was observed compared with the laboratory recordings. The daily average TEE-pulse was highly correlated ($r = 0.85$) to the mean TEE-pulse measured in the laboratory (Fig. 4). Activity-selective equations used to estimate $\dot{V}O_{2max}$ from TEE-pulse in free-living conditions showed an error bias of 165 mL O_2/min (5.5%), MAE of 302.5 mL O_2/min (10.2%), and RMSE of 367 mL O_2/min (12.4%). Figure 3 shows the correlation ($r = 0.88$) and the Bland–Altman plot describing the accuracy of the presented method to predict $\dot{V}O_{2max}$ from free-living data.

Activity-selective versus activity-independent $\dot{V}O_{2max}$ prediction equations. A previously published method (24) to process minute-by-minute Cnts and HR and subjects' characteristics for predicting $\dot{V}O_{2max}$ using free-living data was used as a benchmark for the current study. The following equation was produced by the stepwise multiple linear regression method:

$$\dot{V}O_{2max}(\text{mL } O_2/\text{min}) = b_0 + b_1 \times \text{sex} + b_2 \times \text{age} + b_3 \times \text{weight} + b_4 \times \text{HR/Cnts},$$

where $b_0 = 4{,}064$; $b_1 = -563$; $b_2 = -38.46$; $b_3 = 27.66$; $b_4 = -8{,}339.99$; sex is 0 for female subjects and 1 for male subjects; age is in years and weight is in kg; and all independent parameters were selected in the model with $P < 0.05$. A poor correlation ($r = 0.57$) was obtained between measured and predicted $\dot{V}O_{2max}$. The error analysis of this algorithm showed a larger MAE (514.8 mL O_2/min, or 17.4%) and RMSE (631 mL O_2/min, or 21.3%) compared with activity-selective equations. The proposed computational approach based on activity-type selective equations offered a 41% improvement in MAE and 42% improvement in RMSE.

Table 3. *Activity-type selective algorithms to predict cardiorespiratory fitness based on the TEE-pulse*

		Model		L1SO CV	
Activity Type	r	Intercept	Slope, cal/beat	Bias, mL O_2/min	RMSE, mL O_2/min
Other	0.82	517.5	150.06	−1.86	396.9
Sedentary	0.75	644.8	108.25	−4.55	461.9
Ambulatory	0.87	839.9	60.70	0.24	345.3

Intercept is the coefficient of the linear regression model linking the ratio between total energy expenditure and heart rate (TEE-pulse) to maximal oxygen uptake ($\dot{V}O_{2max}$). Slope is the coefficient of the linear regression model linking TEE-pulse as expressed in calories/beat to $\dot{V}O_{2max}$. Pearson correlation coefficient (r) between measured and predicted $\dot{V}O_{2max}$. L1SO , leave-one-subject-out cross-validation error statistics; RMSE, root mean square error.

DISCUSSION

The development of simple, inexpensive, and valid methods to assess CRF in the general population has been identified by the American College of Sports Medicine as a matter of paramount importance to enable innovative intervention programs to reduce the health-threatening effect of a low CRF and poor physical activity (4). Current maximal and submaximal exercise protocols are either too costly or impractical for the frequent and serial assessment of $\dot{V}O_{2max}$ (14, 27). In this study, we developed and validated a novel method based on acceleration and HR data measured using wearable sensors to estimate CRF without the need for a specific exercise protocol. The system is capable of identifying the contextual situation during which measurements of energy expenditure and HR are obtained to generate a fitness index and predict $\dot{V}O_{2max}$. The accuracy of this method was demonstrated in both laboratory and free-living settings, with $\dot{V}O_{2max}$ estimation error comparable to that reported in previous studies based on submaximal exercise protocols (27).

Some previous attempts have been made at producing protocol-free fitness assessment. Weyand and colleagues (32) used the ratio of the inverse foot-ground contact time to the HR during running at a steady speed to predict $\dot{V}O_{2max}$. The regression equation that they derived predicted $\dot{V}O_{2max}$ within 8.3% (4.7 mL $O_2 \cdot kg^{-1} \cdot min^{-1}$), with a 70.5% correlation coefficient ($r = 0.84$). The disadvantage of this method is that a certain activity (running on level ground at a constant speed) needs to be undertaken to enable the prediction. The model has only been tested during treadmill running, and outdoor running may not produce the same results. Furthermore, a model that is based on lower-intensity activities such as walking may be more widely applicable. Tönis and colleagues (30) have made an attempt at developing such a model but did not use a gold standard measure of $\dot{V}O_{2max}$ and did not test the method during daily living conditions, making the validity of this protocol questionable. More recently, Altini and colleagues (2, 3) have published a model to estimate CRF from accelerometer and HR data obtained during walking activities. The CRF predictions

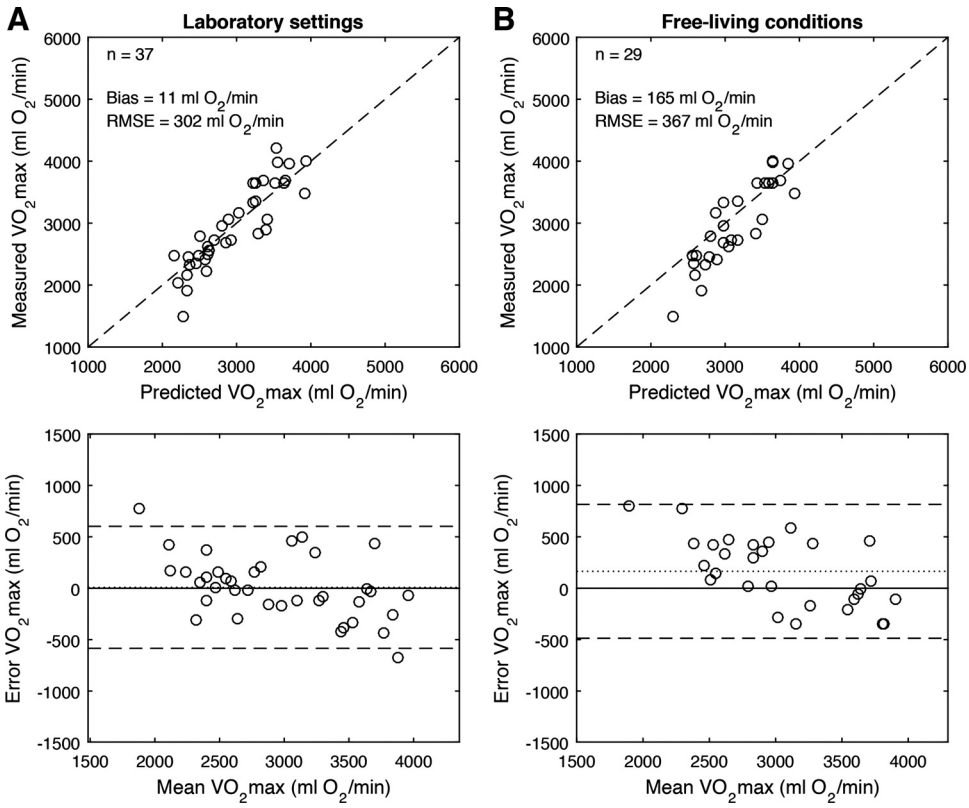

Fig. 3. Regression and Bland–Altman plots for the maximal oxygen uptake ($\dot{V}O_{2max}$) prediction models based on laboratory data (*A*) and then applied to free-living data (*B*). Dashed lines indicate 95% confidence interval, and dotted lines indicate the error bias. RMSE, root mean square error.

Table 4. *Output from the activity identification method applied to acceleration data recorded in free-living conditions*

Identified Activity Type	Duration per Participant, min			Duration per Participant, %		
	Mean ± SD	Min	Max	Mean ± SD	Min	Max
Others	1,138 ± 357	697	1,597	33 ± 9	21	44
Sedentary	990 ± 1,024	553	2,973	34 ± 17	19	65
Ambulatory	1,045 ± 457	401	1,634	30 ± 12	12	47

Numbers are minutes of wake-time monitoring (or %) spent in each activity category.

were compared with $\dot{V}O_{2max}$ measured during an incremental cycle ergometer test. The CRF estimation correlated well with the $\dot{V}O_{2max}$ reference measure ($r = 0.87$), the RMSE was ~280 mL O_2/min, and the mean absolute percentage error (MAE) was 10%. The model depends on walking at certain fixed speed, which may be impractical to observe in daily life. Plasqui and Westerterp (24) have developed a model that overcomes these issues. Participants wore an accelerometer and an HR monitor with a chest belt during waking hours for 7 days. Estimates of $\dot{V}O_{2max}$ were obtained by processing free-living acceleration and HR data. The resulting regression equation showed a good correlation between estimated and measured $\dot{V}O_{2max}$ ($r = 0.85$), and the standard error of the estimate was 14% (437 mL O_2/min). A similar approach was presented in a recent report (16) showing how daily energy expenditure and HR could be combined with anthropometric variables to predict $\dot{V}O_{2max}$ as derived by submaximal tests. The main disadvantage of those methods using free-living data to generate a fitness index from wearable sensor data is the high bias toward sedentary data, which is abundant during the monitoring period. Indeed, heart rate data from different daily activity types yield a dissimilar predictive value with respect to CRF, with moderate and vigorous intensity activities providing better fitness information than low-intensity activities (6).

The present study demonstrated that body acceleration and HR measurements collected in free-living conditions could be used to assess CRF with a MAE around 10% (302 mL O_2/min). A fitness index called TEE-pulse, developed to represent the relationship between energy expenditure and the HR response during physical activity, was highly correlated with $\dot{V}O_{2max}$. A substantial activity-type dependency in the relationship between TEE-pulse and $\dot{V}O_{2max}$ suggested the need for activity-specific prediction equations. Combining TEE-pulse with contextual information on activity type as derived from wearable sensor data allowed for the development of an accurate $\dot{V}O_{2max}$ prediction equation. The ratio between TEE and HR was proposed as a marker of fitness because for a given aerobic load, which can be quantified by energy expenditure or O_2 uptake, differences in HR significantly indicate variations in CRF between subjects (2, 19). Previous studies showed that the amount of O_2 uptake per heart beat (oxygen pulse) was highly correlated to $\dot{V}O_{2max}$ (26, 33) and that changes in CRF during training and detraining were remarkably indicated by concurrent changes in oxygen pulse at maximal as well as submaximal exercise levels (7, 17). These insights supported our hypothesis that TEE-pulse, as a surrogate measure for oxygen pulse, could be used to predict $\dot{V}O_{2max}$. TEE was estimated from physical activity measurements by converting activity Cnts to energy expenditure using a doubly labeled water-validated equation (12). This may represent a limitation of the method, as later studies showed that activity-dependent equations are recommended to improve accelerometer accuracy in providing TEE predictions from Cnts (9, 11). Whereas TEE estimates may have been incorrect at an absolute level, variations in TEE within each activity type may have maintained a large degree of validity to describe aerobic load and activity intensity. This can explain the strong between-activity dependency in the relationship between TEE-pulse and $\dot{V}O_{2max}$. Thus, the proposed activity-type dependent method to predict CRF may end up being unaffected by potential TEE estimation errors.

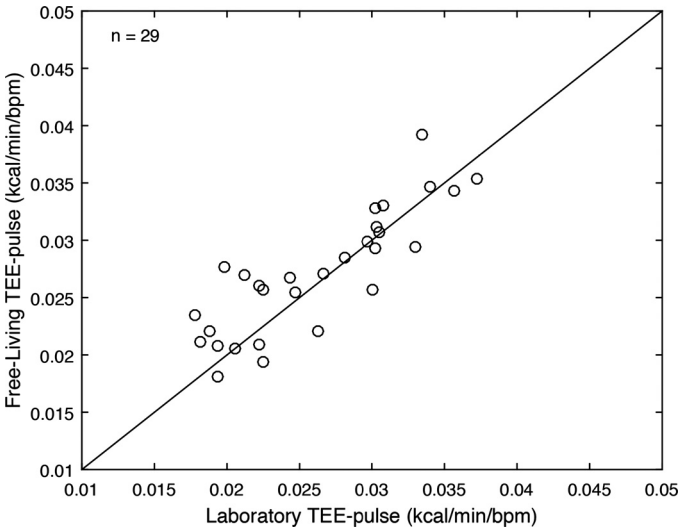

Fig. 4. Correlation between the mean ratio between total energy expenditure and heart rate (TEE-pulse) measured in the laboratory and free-living conditions.

Laboratory data showed that sedentary activities had a poorer predictive value than ambulatory ones for estimating $\dot{V}O_{2max}$. This is one of the reasons why body acceleration and HR measurements in free-living settings are not trivial to use when aiming at estimating CRF because of the large amount of sedentary data. Our study showed that laboratory-trained algorithms had a trend to overestimate $\dot{V}O_{2max}$ (from 5.5% error bias) in free-living conditions, even though the error bias was not significantly different from zero ($P > 0.05$). The reason for this overestimation trend cannot be imputed without information on activities carried out by the user in daily life. Eventually, errors that occurred in the activity identification process may have caused $\dot{V}O_{2max}$ overestimation. Despite these error biases, the RMSE of the prediction models showed comparable results in both laboratory and free-living settings. Future work should focus on enhancing the level of contextualization of HR and body movement data, for example, by considering activity duration and periods of cardiovascular adaptation and drift to

enhance the applicability of the laboratory-trained model on free-living data.

It remains undetermined whether the achieved accuracy performance would be sufficient for field applications. Specifically, the question on whether the $\dot{V}O_{2max}$ prediction model would be capable of tracking changes in CRF over time is unaddressed by our study. In the sports setting, $\dot{V}O_{2max}$ is used to predict performance and evaluate training effectiveness. Therefore, its accuracy and precision are key. A previous literature review of more than 70 submaximal protocols showed that standard errors (expressed in percentage of the mean $\dot{V}O_{2max}$) ranged from 3–27%, with a mean error of 11% (27). In our study we showed that in free-living conditions, the $\dot{V}O_{2max}$ estimation method offered a 10% mean absolute error and a 12% root mean square error. This gives us confidence that the presented method offers valuable predictions of CRF that are useful for categorizing individuals of different fitness levels, but intervention studies are needed to test the precision for tracking changes in $\dot{V}O_{2max}$.

In conclusion, measurements of body acceleration and HR can be used to predict $\dot{V}O_{2max}$ in daily life. Activity-type specific prediction equations achieved highly accurate estimates of CRF, with ~10% MAE and 12% RMSE. Future work should focus on extending the validity of the presented method with data from elderly and patient groups, as well as attempt to use free-living measurements to train the predictive parameters of the $\dot{V}O_{2max}$ estimation model to aim at improving the CRF estimation error even further.

GRANTS

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DISCLOSURES

A. G. Bonomi, H. M. de Morree, and F. Sartor are employed at Philips Research. None of the other authors has any conflicts of interest, financial or otherwise, to disclose.

AUTHOR CONTRIBUTIONS

A.G.B., G.A.t.H., G.P., and F.S. conceived and designed research; G.A.t.H. performed experiments; A.G.B. and H.M.d.M. analyzed data; A.G.B., G.A.t.H., G.P., and F.S. interpreted results of experiments; A.G.B. prepared figures; A.G.B., H.M.d.M., and F.S. drafted manuscript; A.G.B., G.A.t.H., G.P., and F.S. edited and revised manuscript; G.P. and F.S. approved final version of manuscript.

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