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Personalized cardiorespiratory fitness and energy expenditure estimation using hierarchical Bayesian models

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ABSTRACT

Accurate estimation of energy expenditure (EE) and cardiorespiratory fitness (CRF) is a key element in determining the causal relation between aspects of human behavior related to physical activity and health. In this paper we estimate CRF without requiring laboratory protocols and personalize energy expenditure (EE) estimation models that rely on heart rate data, using CRF. CRF influences the relation between heart rate and EE. Thus, EE estimation based on heart rate typically requires individual calibration. Our modeling technique relies on a hierarchical approach using Bayesian modeling for both CRF and EE estimation models. By including CRF level in a hierarchical Bayesian model, we avoid the need for individual calibration or explicit heart rate normalization since CRF accounts for the different relation between heart rate and EE in different individuals. Our method first estimates CRF level from heart rate during low intensity activities of daily living, showing that CRF can be determined without specific protocols. Reference VO_2max and EE were collected on a sample of 32 participants with varying CRF level. CRF estimation error could be reduced up to 27.0% compared to other models. Secondly, we show that including CRF as a group level predictor in a hierarchical model for EE estimation accounts for the relation between CRF, heart rate and EE. Thus, reducing EE estimation error by 18.2% on average. Our results provide evidence that hierarchical modeling is a promising technique for generalized CRF estimation from activities of daily living and personalized EE estimation.

1. Introduction

Recent advances in ultra-low-power wireless and micro-electronic technologies are revolutionizing healthcare. Miniaturized and low-power wearable sensors allow users and professionals to monitor vital signs, activity and physiological signals in daily life environments, providing an unprecedented opportunity to delocalize healthcare from supervised settings, such as laboratories or hospitals, to unsupervised self-managed conditions, at home [26].

Mobile Health (mHealth) refers to the use of mobile devices for delivering health services. One of the main challenges of mHealth is to develop technologies and tools to gather quality, reliable and actionable information that empowers people in managing their health outside from hospitals or laboratory environments [19]. Low-power wearable sensing for mHealth promises to raise the quality of health monitoring in every-day life environments [13].

Much of the focus in the recent years has been on monitoring physical activity [9,1,36]. Lack of physical activity is one of the major health problems in most of the western world and, overall, is the 4th leading risk factor for global mortality. Lack of activity has been linked to the dramatic rise in obesity, diabetes and heart disease [17]. Thus, habitual physical activity and cardiorespiratory fitness (CRF) are among the most important determinants of health and wellbeing [40]. In the recent past, wearable sensing technologies have been used to objectively monitor human behavior, and started to provide unprecedented insights into the relation between physical activity and health. While energy expenditure (EE) is the most commonly used single metric to quantify physical activity, with many algorithms proposed in the recent past

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[33,9,1,21], CRF is not only an objective measure of habitual physical activity, but also a useful diagnostic and prognostic health indicator for patients in clinical settings, as well as healthy individuals [25].

Additionally, EE and CRF are tightly coupled when EE estimation is performed based on heart rate data acquired using wearable sensors. The inverse relation between heart rate and CRF is one of the main causes behind the need for individual calibration of heart rate monitors, since differences in CRF cause differences in heart rate but not in metabolic responses [31]. Thus, CRF estimation could both provide a relevant health marker and be used to personalize EE estimation models, improving estimation accuracy.

To date, the most commonly used measure for CRF level is the maximal oxygen uptake, or VO_2max. However, measures of VO_2max are rare in healthcare, due to safety concerns and laboratory infrastructure requirements. To tackle some limitations of VO_2max tests, *submaximal* test have been developed. Submaximal tests rely on the relation between heart rate and VO_2 at a certain exercise intensity, which is fixed by the strict exercise protocol that has to be executed [6,16,18]. Instead of performing a specific test that specifies exercise intensity at which heart rate is measured, we propose to use wearable sensor data to determine specific contexts (e.g. activity type and walking speed) and model the relation between heart rate in a specific context and CRF.

State of the art EE estimation models subdivide the estimation procedure into two steps. First, an activity is recognized. Secondly, an activity-specific regression model is applied to estimate EE [9,33]. Recent work showed that including physiological data and normalizing heart rate can further improve results [1,2]. Others, modeled the relation between EE and sensor data (e.g. accelerometer) while capturing commonalities across users of differing anthropometric characteristics [36,37] using a hierarchical approach. Thus, structuring sensor data at the first level of a hierarchical structure, and anthropometric data at the second level of a hierarchical structure.

In this work, we hypothesized that using hierarchical Bayesian regression we could model both the influence of anthropometric characteristics and CRF level on accelerometer and heart rate data, and the variation in parameters depending on the performed activity, as in activity-specific models for EE estimation. Thus, the flexibility of a hierarchical regression framework was used to estimate CRF and effectively personalize EE estimation models without the need for explicit heart rate normalization. In particular, this paper provides the following contributions:

1. We propose a hierarchical Bayesian model to estimate CRF level from accelerometer and heart rate data acquired using a single body-worn sensor during low intensity activities of daily living. Thus, the proposed model does not require specific laboratory tests or individual calibration. We show that low intensity activities of daily living (e.g. walking at 4 km/h) and heart rate data are sufficient to reduce CRF estimation errors by 27.0% compared to a model including anthropometric characteristics alone as predictors.
2. We extend previous work on EE estimation by proposing a hierarchical Bayesian model including non-nested group level parameters to simultaneously model the relation between activity type and EE, as well as between anthropometric characteristics, CRF and EE. Grouping by activity allows the model parameters to change as in activity-specific models. By including CRF among the group level parameters, we are able to account for the relation between CRF and heart rate and therefore personalize EE models. We show reductions in EE estimation error by 18.2% on average.

2. Related work

2.1. Maximal oxygen uptake

CRF is a well established and robust indicator of cardiovascular health and predictor of premature all cause mortality [8,14]. The most commonly used measure for CRF level is VO_2max. VO_2max is the maximal capacity of the individual's body to transport and use oxygen (O_2) during exercise. Direct measurement of VO_2 using gas analysis during maximal exercise is regarded as the most precise method for determining VO_2max [35]. Despite the indubitable importance of CRF for health, measurements of VO_2max in healthcare are rare, for different reasons. The test is time consuming, has to be performed by specialized personnel in a lab environment and expensive equipment is needed. The high motivation demand and exertion of subjects makes the test unfeasible in many patients groups [29].

2.2. Submaximal CRF estimation

To overcome these problems, many submaximal tests have been developed. Some are *non-exercise* CRF models, others are specific lab protocols performed while monitoring heart rate at predefined speeds (e.g. treadmill tests) or output powers (e.g. bike tests) [6,16,18], without requiring maximal effort. Several *non-exercise* models of CRF have been developed using easily accessible measures such as age, sex, self reported physical activity level, body composition [22,23]. Results typically provide decent accuracy at the group level [28]. However significant limitations apply at the individual level, since each individual is assumed to be equal to group averaged characteristics. Limited accuracy at the individual level is a common problem when physiological variables are not measured. Most *submaximal* exercise tests rely on the relation between heart rate and VO_2 at a certain exercise intensity, which is fixed by the strict exercise protocol that has to be sustained. Submaximal exercise tests should be re-performed every time CRF needs to be assessed and often require laboratory infrastructure.

2.3. CRF estimation in free living

Both maximal and submaximal tests to estimate CRF are affected by important limitations. A more ideal solution, which possibly would be applicable to a larger population, is to estimate VO_2max during activities of daily living, without the need for a predefined exercise protocol. Towards this direction, Plasqui and Westerterp [30] showed that a combination of average heart rate and activity level over a period of 7 days correlates significantly with VO_2max. However, by averaging over several days, the relation between average heart rate and activity counts depends on the amount of activity performed by the participants. Tonis et al. [34] explored different parameters to estimate CRF from heart rate and accelerometer data in laboratory settings. However, no models to extract these parameters in daily life (e.g. activity type to detect walking or walking speed estimation models) are presented. In their work, VO_2max reference was not collected, but also estimated from walking data.

2.4. EE estimation

Recent work on EE estimation relying on wearable sensor data proposed activity-specific models as an improvement to previously used single or branched regression models [9,1,33]. Activity-specific EE estimation models consist of a two-step process, where first an activity is recognized, and then an EE

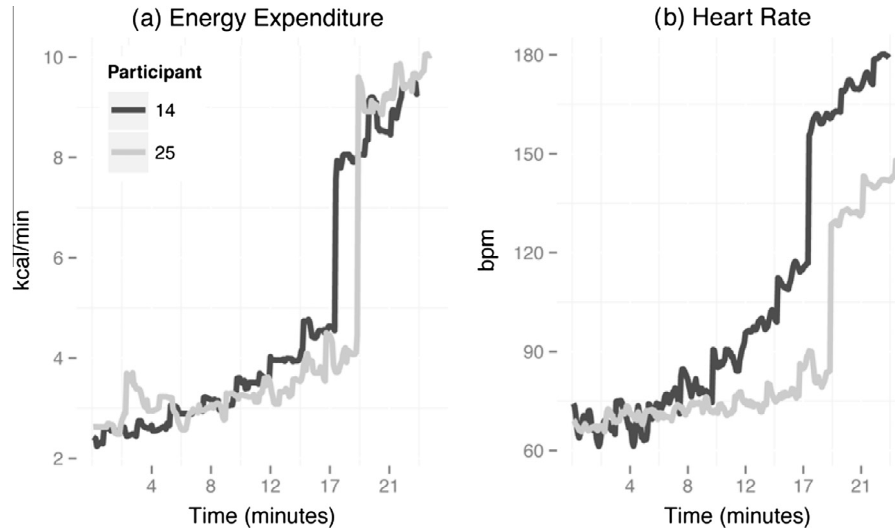

Fig. 1. Relation between EE and heart rate in different participants during a sequence of different physical activities. (a) Absolute EE levels are similar due to similar body weight. (b) heart rate differs significantly between participants due to different CRF level (VO_2max participant 14 is 2104 ml/min, VO_2max participant 25 is 3130 ml/min).

estimation model is applied. Algorithms combining accelerometer and heart rate data consistently provided improvements compared to accelerometers alone [1,33]. However, decomposing the EE estimation process into activity-specific sub-problems is not sufficient to take into account the different relation between heart rate and EE in different individuals. During moderate to vigorous physical activity, differences in heart rate between persons performing the same activity are mainly due to CRF. However, differences in CRF level do not cause different metabolic responses [31] (see Fig. 1). Thus, when estimating EE using heart rate data, individual calibration is necessary to deal with CRF-related differences between individuals [11]. For many practical applications personal calibration is not feasible since it would require every user to perform a suitable fitness test, and other personalization techniques would be preferable. We recently introduced a methodology to automatically normalize heart rate. By estimating a normalization parameter that describes heart rate at a certain workload during low intensity activities of daily living [2,4,5] we could personalize EE estimates. The methodology was based on the tight relation between CRF and heart rate at a certain workload, which is also the basis of sub-maximal CRF tests. In our previous work we required explicit heart rate normalization by estimating a normalization parameter representative of CRF, such as the heart rate while running at a certain intensity. In this current work, we propose a novel model in which, instead of normalizing heart rate, we take the source of between-individual variability in heart rate, i.e. actual CRF into account. To this aim, we collected reference CRF as measured by a VO_2max test and developed a model for personalizing EE estimation without the need for explicit heart rate normalization. We hypothesized that CRF could account for the varying relation between heart rate and EE in different individuals by acting as a group level predictor in a hierarchical Bayesian model.

2.4.1. Hierarchical models

Activity-specific EE models are typically implemented using linear regression models. Linear regression can be extended to capture commonalities across a population using a hierarchical linear model [20]. Hierarchical techniques use linear models at levels within (*individual* level) and across (*group* level) participants. In the remaining of this paper, we use the term *group level* parameters to indicate parameters at the second level of a hierarchical structure. These parameters are the ones influencing the relation between predictors at the first level of a hierarchical structure and the outcome variable. We refer to parameters at the first level of a hierarchical structure as *individual level* parameters [20]. These models were introduced in EE literature by Vathsangam et al. [37]. At one level the authors included participant specific parameters relating inertial sensor features to EE. At a second level they captured the inter-dependence of different person-specific parameters (e.g. anthropometric characteristics) using a (second) regression model. However [37], the authors limited their analysis to walking activities and accelerometer data, for EE estimation.

In this work, we hypothesized that hierarchical Bayesian models could be used to accurately model individual and group level differences in CRF level from wearable sensor data during activities of daily living. We expected that estimated CRF could be used to personalize heart rate-based EE estimations in order to improve the estimate accuracy. Additionally, we use the flexibility of a hierarchical regression framework to model both the influence of anthropometric characteristics and CRF level parameters on accelerometer and heart rate data, as well as the variation in parameters depending on the performed activity, as in activity-specific models.

3. Methods

In this section we describe our approach to CRF and EE estimation, as illustrated in Fig. 2. We use wearable sensor data, accelerometer X_{acc} and heart rate X_{hr}, together with anthropometric characteristics X_{ant} (e.g. height, body weight, etc.) as input to our models. CRF y_c is estimated from heart rate X_{hr} during low intensity activities of daily living, i.e. contexts s, simulated in the lab. For example, a context s can be walking at 4 or 6 km/h. Heart rate measured during a specific context is used together with anthropometric characteristics X_{ant} in a Bayesian regression model to estimate CRF y_c. Subsequently, we use the predicted CRF y_c as input for the second level of a hierarchical Bayesian model, to estimate EE y_{ee}. The hierarchical modeling accounts for variance in CRF between individuals and allows for more accurate EE estimation.

We introduce three hierarchical regression models, to estimate walking speed, CRF and EE, as shown in Fig. 3. Details on the notation and modeling technique are provided in Appendix A. We indicate group level predictors as U and individual level predictors as X.

Following a top down approach, we propose a hierarchical Bayesian model to estimate EE (see Fig. 3.c). We consider $i = 1, \ldots, n$ sensor data samples, $p = 1, \ldots, np$ participants and

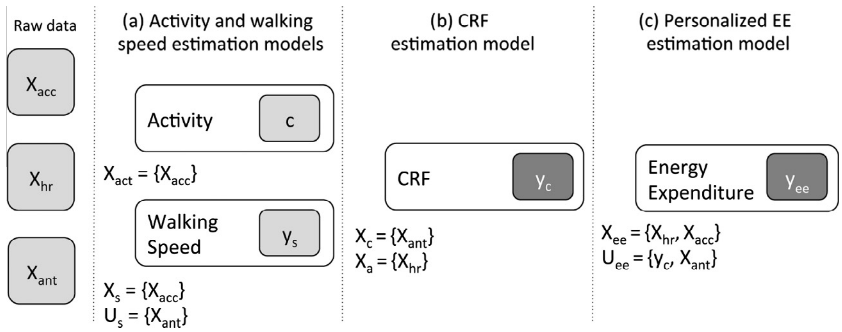

Fig. 2. Block diagram of the proposed CRF and EE estimation approach. (a) Activity type and walking speed are estimated from sensor data of a wearable device (X_{acc} and X_{hr}). (b) CRF is estimated from heart rate during low intensity activities of daily living, such as walking, as derived from models (a), together with anthropometric characteristics X_{ant}. X_a consists in heart rate during predefined contexts (for example walking at 4 km/h), and therefore requires activity c and speed y_s information. (c) EE is derived by combining X_{acc}, X_{hr}, X_{ant} and CRF y_c in a hierarchical model, as shown in Fig. 3. Data flow is left to right. At each processing block, indicated by vertical dashed lines, we indicated which data streams are received from the previous processing blocks.

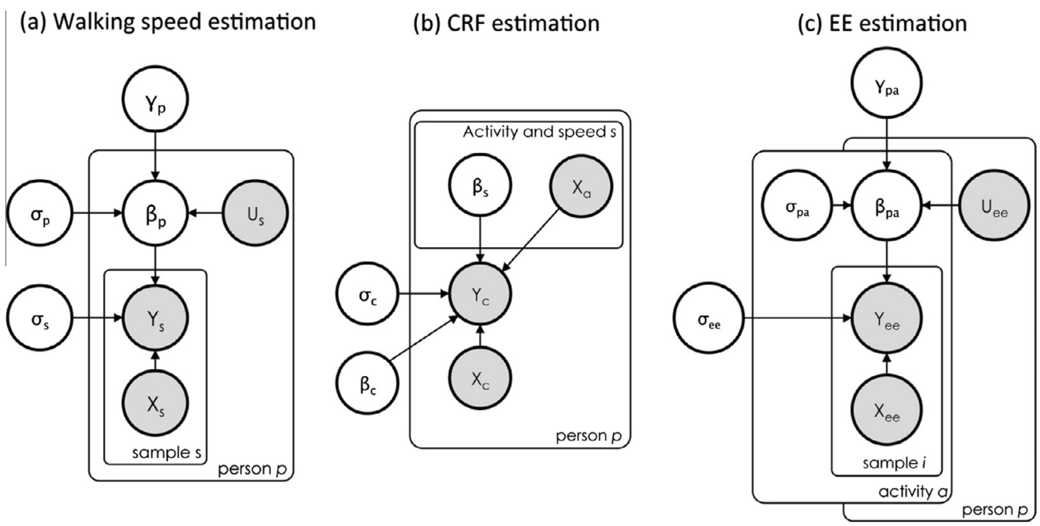

Fig. 3. Proposed hierarchical models in plate notation. (a) Walking speed estimation. Parameters β_p vary depending on the person's anthropometric characteristics U_s. (b) CRF estimation. Parameters β_s vary by activity and speed. (c) EE estimation. Parameters β_{pa} are allowed to vary depending on the performed activity as well as on the persons' anthropometric characteristics and CRF U_{ee}. The two groupings are non-nested. Estimated CRF y_c from model (b) is used as group level parameter U_c for model (c). Hyperparameters are not shown for clarity.

$a = 1, \ldots, T$ activities. Individual level parameters β_{pa} are influenced by both activity type a (which is the nature of activity-specific models) and the participants' anthropometric characteristics X_{ant} and CRF y_c, however the grouping by activity and by participant are non-nested:

$$
\begin{aligned}
& y_{ee_i} \sim N(X_{ee_i}\beta_{i[pa]}, \sigma^2_{ee}), \\
& i = 1, \ldots, n \quad a = 1, \ldots, T \quad p = 1, \ldots, np \\
& \beta_{pa} \sim N(U_{ee_p}\gamma_{pa}, \Sigma_{pa}) \\
& a = 1, \ldots, T \quad p = 1, \ldots, np \\
& X_{ee_i} = [1, X_{acc_i}, X_{hr_i}] \in \mathbb{R}^{n\times(K+1)} \\
& i = 1, \ldots, n \\
& U_{ee_p} = [1, X_{ant_p}, y_{c_p}] \in \mathbb{R}^{np\times(L+1)} \\
& p = 1, \ldots, np \\
& \gamma_{pa} \sim N(\mu_{\gamma_{pa}}, \sigma^2_{\gamma_{pa}})
\end{aligned}
$$

where the matrix X_{ee} is of dimension $n \times (K+1)$ and include K individual-level predictors such as heart rate X_{hr} and accelerometer features X_{acc}, over n data samples. U_{ee} is the matrix of dimension $np \times (L+1)$ and include L group level predictors controlling the individual level parameters β_{pa}. The predictors U_{ee} include anthropometric characteristics X_{ant} (e.g. *body weight*) and the estimated CRF y_c, for np participants. The hyperparameter matrix γ_{pa} is of dimension $(L+1) \times (K+1) \times T$, where T is the number of activities. Σ_{pa} is the $(K+1) \times (K+1)$ covariance matrix representing the variation of intercepts and slopes in the different groups. $\mu_{\gamma_{pa}}$ and $\sigma_{\gamma_{pa}}$ indicate hyperparameters for group level parameters γ_{pa}.

Estimated CRF y_c as included in the EE estimation model is shown in Fig. 3b and consists in a hierarchical Bayesian model allowing only heart rate coefficients to vary by group, and can be described as:

$$
\begin{aligned}
& y_{c_p} \sim N(X_{c_p}\beta_c + X_{a_p}\beta_{s[p]}, \sigma^2_c), \quad p = 1, \ldots, np \\
& s = 1, \ldots, R \quad p = 1, \ldots, np \\
& X_{c_p} = [1, X_{ant_p}] \in \mathbb{R}^{np\times(D+1)} \\
& p = 1, \ldots, np \\
& X_{a_p} = [X_{hra_p}] \in \mathbb{R}^{np\times 1} \\
& p = 1, \ldots, np \\
& \beta_s \sim N(\mu_{\beta_s}, \sigma^2_{\beta_s})
\end{aligned}
$$

where the matrix X_{c_p} of individual level attributes is of dimension $np \times (D+1)$ (i.e. *body weight*, *height*, *age*, *sex*). The associated parameters β_c do not vary. Contexts s are a set of combined activity types and walking speeds (e.g. *walking at* 4 km/h, etc.), which control the parameters β_s for the attributes X_a. X_a consists of heart rate during predefined contexts s (indicated as X_{hra_p}), and is of dimension $np \times 1$. μ_{β_s} and σ_{β_s} indicate hyperparameters for group level parameters β_s.

Activity type a is recognized from a set of T activities $A = a_1, \ldots, a_t$, using Support Vector Machines (SVM). Implementation details can be found in Section 5. Walking speed estimation y_s is shown in Fig. 3.a and consists of a hierarchical Bayesian model allowing accelerometer features X_{acc} to vary depending on anthropometric characteristics X_{ant}:

$$
\begin{aligned}
& y_{s_i} \sim N(X_{s_i}\beta_{i[p]}, \sigma_s^2), \\
& i = 1, \ldots, n \quad p = 1, \ldots, np \\
& \beta_p \sim N(U_s\gamma_p, \Sigma_p) \\
& p = 1, \ldots, np \\
& X_s = [1, X_{acc}] \in \mathbb{R}^{n \times (K+1)} \\
& i = 1, \ldots, n \\
& U_s = [1, X_{ant}] \in \mathbb{R}^{np \times (L+1)} \\
& p = 1, \ldots, np \\
& \gamma_p \sim N(\mu_{\gamma_p}, \sigma_{\gamma_p}^2)
\end{aligned}
$$

where the matrix X_s is of dimension $n \times (K+1)$ and includes K individual-level accelerometer features X_{acc}, over n data samples. U_s is the matrix of dimension $np \times (L+1)$ and includes L group level predictors controlling the individual level parameters $\beta_{i[p]}$. The predictors U_s are the anthropometric characteristics X_{ant} such as *body weight* and *height*. The hyperparameter matrix γ_p is of dimension $(L+1) \times (K+1)$. Σ_p is the $(K+1) \times (K+1)$ covariance matrix representing the variation of intercepts and slopes in the different groups. μ_{γ_p} and σ_{γ_p} indicate hyperparameters for group level parameters γ_p.

4. Evaluation study

4.1. Participants and data acquisition

Participants were 32, characteristics are reported in Table 1. Written informed consent was obtained, and the study was approved by the ethics committee of Maastricht University. Participants were selected to have a wide range in physical activity levels and CRF. Measurements were obtained using an ECG Necklace, a low power wireless platform which was configured to acquire one lead ECG data at 256 Hz, and three-axial accelerometer data at 32 Hz. The ECG Necklace was worn on the chest, during all recordings, since the chest showed to be an optimal location for EE estimation in previous research comparing multiple on body sensor locations [3]. Participants were equipped with an indirect calorimeter consisting of a mouthpiece and nose clip. Expired air was continuously analyzed for O_2 consumption and CO_2 production (Oxycon-β), from which EE was derived [38].

Table 1
Participants characteristics, mean and standard deviation (SD).

Characteristic	Female Mean ± SD	Male Mean ± SD	All Mean ± SD
Number	17	15	32
Age (y)	24.6 ± 2.5	23.7 ± 1.6	24.2 ± 2.1
Height (cm)	167.1 ± 5.9	177.0 ± 6.3	171.8 ± 7.8
Weight (kg)	60.4 ± 6.8	72.5 ± 11.1	66.1 ± 10.8
BMI (kg/m^2)	21.6 ± 2.4	23.1 ± 3.5	22.4 ± 3.7
VO_2max (ml/min)	2534.2 ± 488.5	3518.6 ± 401.2	2995.6 ± 667.0

4.2. Experiment protocol

Participants reported at the lab on three separate days and after refraining from drinking (except for water), eating and smoking in the two hours before the recordings. Two laboratory protocols were performed. The first protocol included simulated activities of daily living performed while wearing a portable indirect calorimeter. Activities included: lying down resting, sitting, sitting writing, standing, cleaning a table, sweeping the floor, walking at different speeds (treadmill flat at 2.5, 3, 3.5, 4, 4.5, 5, 5.5, 6 km/h) and running at different speeds (treadmill flat at 8, 9, 10 km/h). The second protocol was a VO_2max test. VO_2max was determined during an incremental test on a cycle ergometer [24], thus providing reference data for CRF level, biking activity and EE while biking. Finally, anthropometric measurements including the participant's body weight, height and body fat were performed. Body fat was assessed using doubly labelled water [39]. Depending on lab and participant availability, the protocols were carried out in different days. Activities were carried out for a period of at least four minutes, always in the same order. Participants were allowed to rest between activities. Rest periods were normally between one and two minutes.

4.3. Statistics and performance measures

CRF estimation models were compared against models including anthropometric characteristics to describe individual variability. Our hierarchical EE estimation approach including estimated CRF as group level predictor was compared against two other estimation methods. First, we compared against state of the art activity-specific EE models including accelerometer and heart rate features but without CRF estimation. In literature, activity-specific EE models showed performance superior to other linear and non-linear EE estimation methods [1,10] and therefore were selected as baseline for our proposed method. Secondly, we compared against hierarchical models including actual CRF (referred to as *CRF measured*) as a predictor. Hierarchical models including actual CRF serve as a lower boundary indicating the theoretical RMSE that is achievable.

Models were derived using data from all but one participants, and validated on the remaining one (leave-one-participant-out cross validation). The same training set, consisting of data from all participants but one, was used to build feature selection, activity recognition, walking speed estimation, CRF estimation and EE estimation models. The remaining data (from one participant) was used for validation. This procedure was repeated n (n = number of participants) times, and results were averaged. Performance of the activity recognition models was evaluated using the class-normalized accuracy = $\frac{1}{N_a}\sum_{c=1}^{N_a}\frac{recognized_a}{relevant_a}$, where N_a is the total number of classes, and $recognized_a$ and $relevant_a$ are the number of correctly identified and total instances for activity a, respectively. Results for walking speed are reported in terms of Root-mean-square error (RMSE) where the outcome variables was speed in km/h. Results for CRF and EE estimates are reported in terms of RMSE, mean absolute percentage error (MAPE) and explained variation (R^2), where the outcome variables were VO_2 in ml/min and EE in kcal/min respectively. Paired t-tests were used to compare RMSE between models. Significance was assessed at $\alpha < 0.05$.

5. Implementation

5.1. Pre-processing

The dataset considered for this work contains about 88.6 h of annotated data collected from 32 participants, consisting of reference VO_2, VCO_2, three axial acceleration, ECG and VO_2max during laboratory recordings. A continuous wavelet transform based beat detection algorithm was used to extract RR intervals from ECG data, which output was manually examined to correct for missed beats. Breath-by-breath data acquired from the indirect calorimeter was resampled at 0.2 Hz. EE was calculated from O_2 consumption and CO_2 production using Weir's equation [38]. The first 1 or 2 min of each activity were discarded to remove non-steady-state data. Activities were grouped into six clusters to be used for activity classification. The six clusters were *lying* (lying down), *sedentary* (sitting, sitting writing, standing), *dynamic* (cleaning the table, sweeping the floor), *walking* (treadmill flat at different speeds), *biking* (cycle ergometer) and *running* (treadmill flat at different speeds).

5.2. Features extraction and selection

Features extracted from the sensors' raw data were used to derive all models. Activity recognition was performed to classify the six activity clusters previously introduced. Accelerometer data from the three axes were segmented in 5 s windows, band-pass filtered between 0.1 and 10 Hz, to isolate the dynamic component caused by body motion, and low-pass filtered at 1 Hz, to isolate the static component, due to gravity. Feature selection for activity type recognition was based on mutual information [7] and features were derived and selected from our previous work [1], using a different dataset. The complete feature set can be found in [1]. Selected features were: *mean of the absolute signal, inter-quartile range, median, variance, standard deviation, main frequency peak (i.e. mode of the frequency spectra), low and high frequency band signal power*. Heart rate was extracted from ECG data over 15 s windows. Anthropometric characteristics (*body weight*, *height*, *age*, and *sex*) were included in walking speed, CRF and EE estimation models.

5.3. Activity recognition

We implemented an activity recognition algorithm to classify the following clusters of activities: *lying*, *sedentary*, *dynamic*, *walking*, *running* and *biking*. Given the promising results in past research on activity recognition [1], we selected SVM as classifier. For the SVM, we used a gaussian radial basis kernel ($C = 1$).

5.4. Hierarchical Bayesian regression models

Hierarchical Bayesian models introduced in Section 3 were implemented using R and JAGS. Posterior estimations were performed by Gibbs sampling with 3 chains and 10,000 iterations. The first 500 iterations were discarded (burn-in period). Anthropometric characteristics were *height* for the walking speed model, *height*, *weight*, *age* and *sex* for the CRF estimation model and *weight* for the EE model. Additionally, EE models included CRF as group level parameter. Individual level features were accelerometer only for walking speed estimation models, accelerometer and heart rate for EE estimation models and heart rate features for CRF estimation models. Prior distributions for all parameters and hyperparameters were non-informative uniform distributions with $\mu = 0$ and $\sigma = 100$.

6. Results

Subject-independent class-normalized accuracy of the SVM was 92.7%. More specifically, the accuracy was 95.4% for *lying*, 95.2% for *sedentary*, 81.9% for *dynamic*, 96.3% for *walking*, 87.5% for *biking* and 99.7% for *running*. Walking speed estimation RMSE was 0.53 km/h.

Fig. 4 shows the relation between anthropometric characteristics and VO_2max, as well as the relation between heart rate and VO_2max for different activities. Correlation between heart rate and VO_2max was highest for running activities ($r = -0.71$), as shown in Fig. 4e. Correlation increased between $r = -0.52$ and $r = -0.66$ for increases in low intensity activities of daily living, e.g. for walking between 4 and 6 km/h, regardless of anthropometric characteristics.

Fig. 5 shows results of the CRF estimation model for three conditions. As a CRF estimation baseline we considered anthropometric characteristics (model referred to as *Ant* in Fig. 5) as predictors, resulting in RMSE of 382.3 ml/min ($R^2 = 0.56$). RMSE was reduced to 279.5 ml/min (26.9% error reduction, $p = 0.02 < \alpha, R^2 = 0.73$) and 279.2 ml/min (27.0% error reduction, $p = 0.02 < \alpha, R^2 = 0.74$) when including heart rate while walking at 4 km/h and 6 km/h respectively as predictors. Detailed results for men and women are shown in Table 2. While error is relatively higher for women, differences are not significant ($p = 0.25 > \alpha$ for *Ant*, $p = 0.73 > \alpha$ for *Walk* 4 km/h, $p = 0.30 > \alpha$ for *Walk* 6 km/h).

EE estimation results are shown in Fig. 6. For an EE estimation baseline we considered for this analysis state of the art activity-specific EE estimation models. Activity-specific EE estimation models (*no CRF*) included accelerometer and heart rate data as predictors and resulted in RMSE of 0.88 kcal/min ($R^2 = 0.94$). Additionally, we compared results obtained with the proposed hierarchical model (*CRF estimated*) to the theoretical case where actual CRF is available, instead of being estimated by our architecture (*CRF measured*). RMSE was reduced from the *no CRF* condition to 0.72 kcal/min (18.2% error reduction, $p = 0.003 < \alpha, R^2 = 0.95$) for *CRF estimated* and to 0.69 kcal/min (21.8% error reduction, $p = 0.002 < \alpha, R^2 = 0.96$) for *CRF measured*. In Table 3 we provide detailed results for moderate to vigorous activities only, since personalizing the relation between heart rate and EE during sedentary activities is not beneficial [4]. When including estimated CRF (Fig. 6, *no CRF* vs *CRF estimated*), EE RMSE was reduced from 0.61 kcal/min to 0.56 kcal/min for *dynamic* (8.9% error reduction), from 0.60 kcal/min to 0.55 kcal/min for *walking* (8.2% error reduction), from 2.18 kcal/min to 1.62 kcal/min for *biking* (25.5% error reduction) and from 1.36 kcal/min to 1.11 kcal/min for *running* (18.4% error reduction).

7. Discussion

In this work, we demonstrated that hierarchical Bayesian regression could be used to accurately model individual and group level differences in CRF estimated from heart rate data during low intensity activities of daily living. We also validated our hypothesis that such estimated CRF could be used to personalize heart rate-based EE estimation models in order to improve the estimate accuracy for different activities. We adopted hierarchical Bayesian models as a powerful and flexible extension to conventional regression frameworks, structuring our models into groups which are both nested and non-nested.

To estimate CRF, we relied on the relation between CRF and heart rate at a certain submaximal intensity (e.g. while walking). Heart rate parameters were allowed to vary by activity type and speed, in order to let the proposed CRF model provide estimates without constraining the participant in performing specific

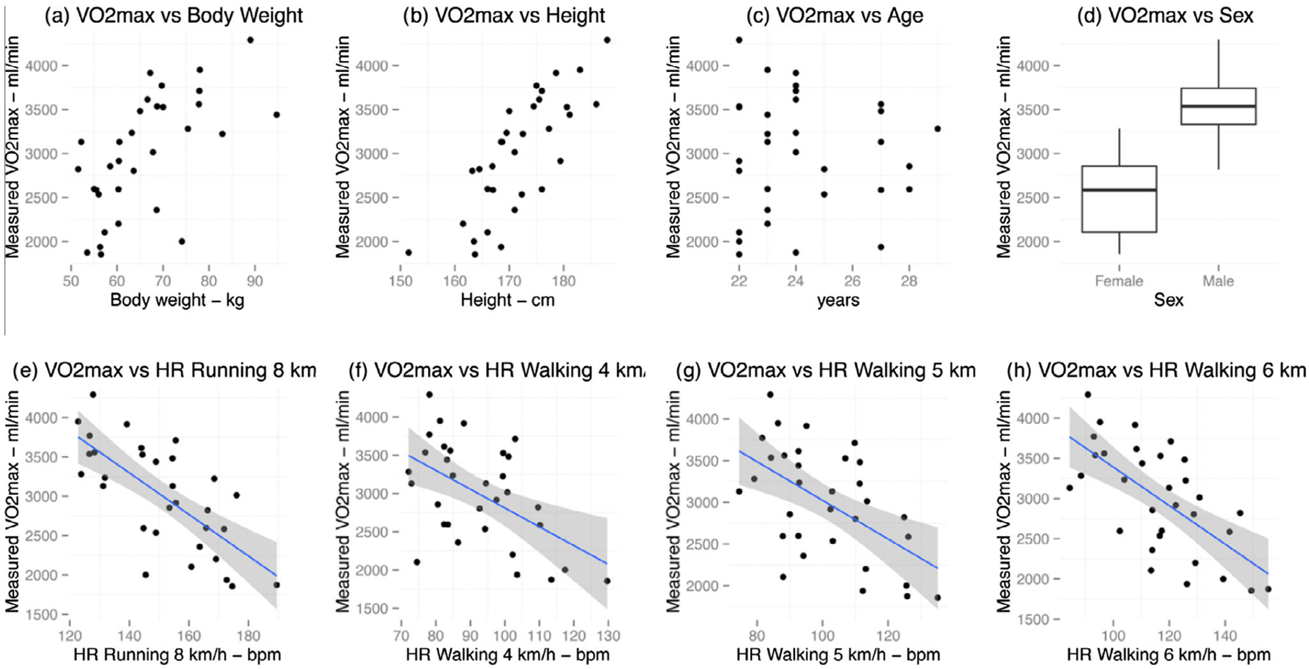

Fig. 4. (a–d) Relation between anthropometric characteristics and VO_2max. (e–h) Relation between heart rate and VO_2max for different activities. Regression line and 95% confidence intervals highlighting the inverse relation between heart rate at different activities intensities and VO_2max are shown in plots (e)–(h).

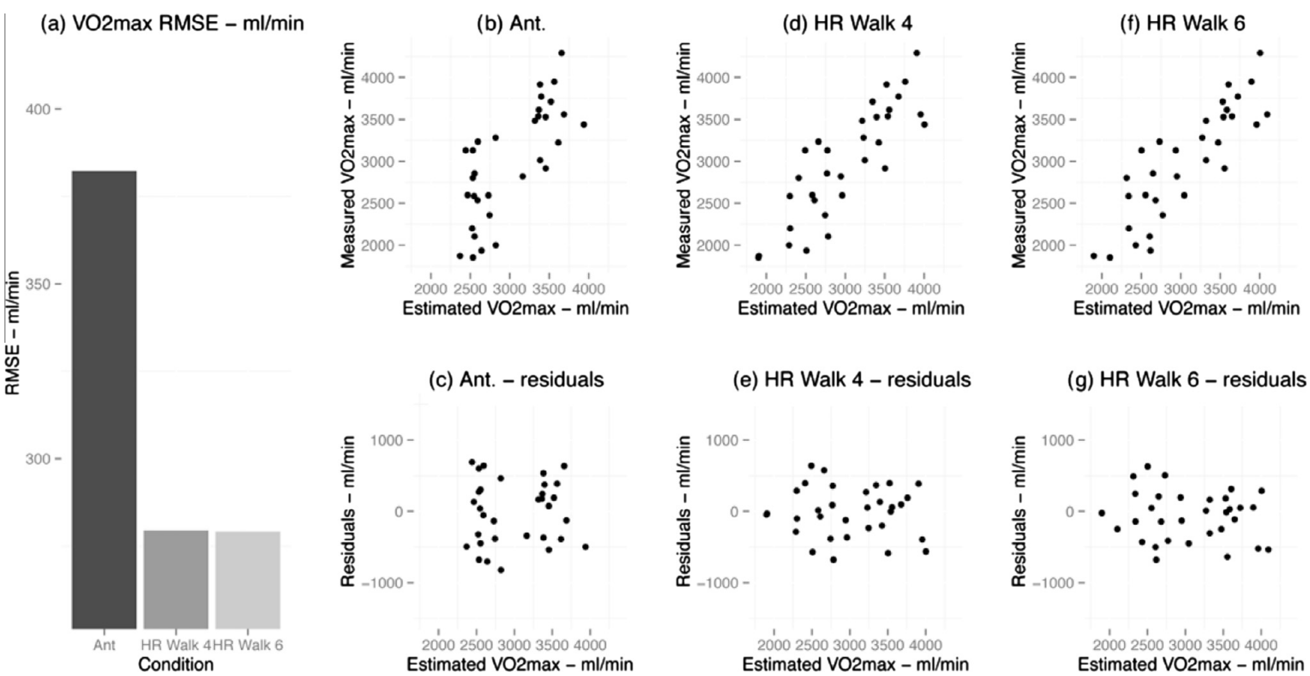

Fig. 5. (a) VO_2max estimation accuracy for different models over all participants. *Ant* does not include heart rate data but anthropometric characteristics only, *HR Walk* 4 and *HR Walk* 6 include heart rate while walking at 4 km/h and 6 km/h respectively. (b–g) Scatterplots and residuals plot for measured and estimated VO_2max according to the three models of plot (a).

activities or walking at predefined speeds, as normally done in submaximal laboratory tests. By using a hierarchical approach where parameters vary based on the activities performed by the participant, we also allow the CRF estimation model to use different parameters based on the participant activities, thus potentially increasing accuracy when more intense activities are performed. We chose walking speeds of 4–6 km/h for our analysis, since speeds close to this range were often reported as the average walking speeds in healthy individuals (5.3 km/h in [12] and 5 ± 0.8 km/h in [27]). We analyzed the impact of different features on CRF estimation, such as anthropometric characteristics, and the relation between heart rate while walking at different speeds. Anthropometric characteristics alone were shown to estimate CRF with in past research [22,23]. Our models confirm these findings, due to the high correlation between VO_2max and most anthropometric characteristics, such as *body weight*, *height* and *gender* (see Fig. 4). However, only when including in the models physiological data such as the heart rate, differences between

Table 2
CRF estimation results.

CRF model	Sex	RMSE (ml/min)	MAPE (%)
Ant	All	382.3	14.0
	Male	336.5	9.7
	Female	422.7	17.8
Walk 4 km/h	All	279.5	9.8
	Male	266.3	7.7
	Female	291.2	11.7
Walk 6 km/h	All	279.2	10.2
	Male	238.6	7.1
	Female	315.1	12.9

participants with similar anthropometric characteristics can be estimated. By including heart rate data while walking at 4 km/h to 6 km/h we could reduce RMSE up to 27.0%. Since CRF is a strong and independent predictor of all-cause and cardiovascular mortality, the proposed CRF estimation model could be used to provide accurate information about an individual's health without the need for laboratory infrastructure or specific tests.

As a second contribution, we developed a two level hierarchical Bayesian model, where accelerometer and heart rate parameters were allowed to vary by activity-type, as in activity-specific EE models, and by anthropometric characteristics as well as CRF level. Previous work by our group [2,4] as well as others [33] showed that normalizing heart rate using a normalization parameter representative of CRF, such as the heart rate at a certain workload, could significantly reduce inter-person differences in heart rate and consequently improve EE estimation accuracy. The proposed hierarchical structure goes to the root of the problem, including estimated CRF level as a group level parameter able to control the relation between heart rate and EE. Since CRF is estimated from activities of daily living of varying intensity, no predefined test or laboratory calibration is necessary in order to improve EE estimation models. EE estimation RMSE was reduced by

Table 3
EE estimation results. Activity *All* includes lying, sedentary, dynamic, walking, biking and running activities. Reference EE is shown as mean ± standard deviation and was collected by indirect calorimeter. EE and RMSE are reported in kcal/min.

EE model	Activity	EE	RMSE	MAPE (%)
No CRF	All	4.98 ± 4.14	0.88	18.4
	Dynamic	2.64 ± 0.71	0.61	23.7
	Walking	3.96 ± 0.59	0.60	13.6
	Biking	10.50 ± 2.38	2.18	22.1
	Running	10.35 ± 1.85	1.36	13.2
CRF estimated	All	4.98 ± 4.14	0.72	16.2
	Dynamic	2.64 ± 0.71	0.56	21.2
	Walking	3.96 ± 0.59	0.55	12.0
	Biking	10.50 ± 2.38	1.62	15.6
	Running	10.35 ± 1.85	1.11	10.6
CRF measured	All	4.98 ± 4.14	0.69	15.7
	Dynamic	2.64 ± 0.71	0.54	20.6
	Walking	3.96 ± 0.59	0.52	11.3
	Biking	10.50 ± 2.38	1.48	14.3
	Running	10.35 ± 1.85	1.10	10.6

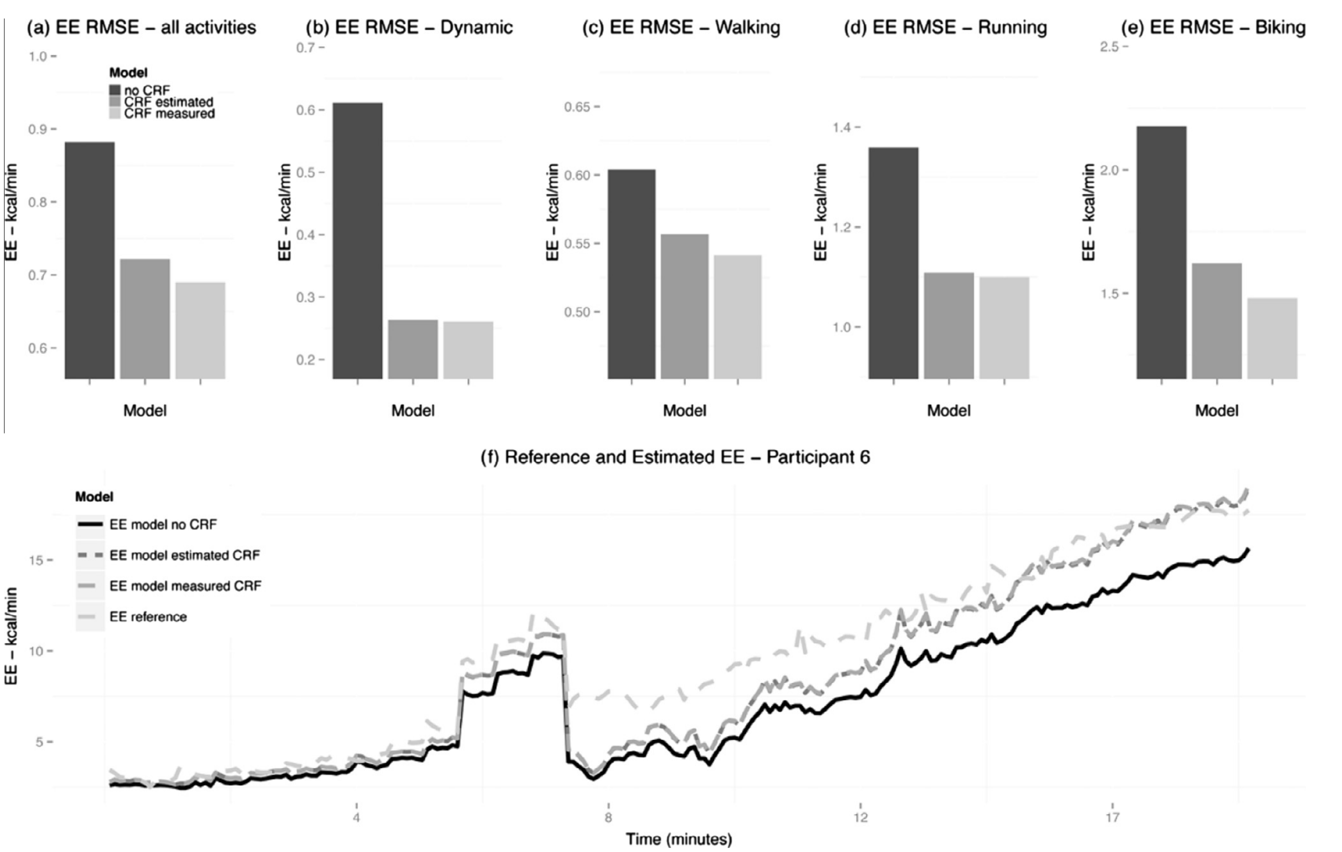

Fig. 6. EE estimation RMSE for (a) all activities averaged, (b) dynamic, (c) walking (d) running and (e) biking. Three models are compared, *no CRF*, indicating state of the art activity-specific EE models, *CRF estimated* indicating the proposed hierarchical Bayesian approach, where estimated CRF is used as group level parameter, and *CRF measured* which consists in the same model as *CRF estimated*, but including actual VO_2max as measured in the lab. *CRF measured* serves as a lower limit to the RMSE achievable by the proposed approach. (f) Effect of CRF in EE estimation for an unfit participant. Without CRF, EE was underestimated, due to the higher heart rate. Including CRF increased the EE estimate, therefore reducing RMSE. No difference appeared between EE estimation models using estimated or measured CRF for this participant. Reference EE is shown in light gray.

$8.9\%, 8.2\%, 25.5\%$ and 18.4% for dynamic, walking, biking and running activities respectively. In our models, we excluded sedentary activities. In previous work heart rate during sedentary behavior was not found to be beneficial in estimating EE. During sedentary behavior, heart rate is affected by other factors such as stress and emotions, and is typically weakly correlated with EE, and therefore often omitted for EE estimation [1,15]. While RMSE for biking and running is relatively high compared to other activities, larger errors are expected for intense activities. Nevertheless, we believe that the RMSE reductions compared to current state of the art methods (up to 25%) are practically relevant, especially as the proposed method does not require laborious individual calibration. Moreover, the estimation performance obtained in this work is close to the theoretical performance estimate using actual CRF level data as shown in Table 3. Thus, measuring heart rate in low intensity activities of daily living is sufficient to estimate CRF at sufficient accuracy to obtain optimal EE estimation results.

Personalizing a system goes beyond the inclusion of the individual's anthropometric characteristics in CRF or EE models, as shown by the increased accuracy of the proposed models. While our CRF estimation model could be applied to a wide population and provide feedback on health status, we expect that our EE normalization approach will be most useful for individuals having a moderately active lifestyle. Sports training devices, where users and trainers are interested in accurate EE estimation under moderate to vigorous workloads, could benefit from inclusion of CRF in the EE estimation models. Additionally, less active individuals willing to take up a more active lifestyle, or undergoing a physical activity intervention targeted in modifying behavior to increase level of activity, would also benefit. As a matter of fact, in the latter case CRF takes even a bigger role, since it typically changes faster in the transition from inactive to active lifestyle, and failing to capture these changes would result in higher errors in EE estimation. New opportunities for applications targeted at inducing behavioral change by creating a feedback loop involving objectively measured physical activity level and EE, as well as change in CRF and associated reduced risk of disease, could be developed building up on the proposed approach.

We recognize limitations in our study. Even though we developed an algorithm able to derive CRF during regular activities, by combining walking heart rate data with the subjects anthropometric characteristics, we tested it using laboratory recordings only. We consider that the evaluation with lab data is a necessary first step, which can be sufficiently covered with reference measurements of CRF and EE. We proposed activity recognition and walking speed estimation models to detect activity type and walking speed such that the proposed model could be deployed in free living. Some activities (e.g. dynamic and biking) were recognized with suboptimal accuracy, due to sensor positioning and high variability in movement involved, for example, during household activities. Nevertheless, activity recognition performance for walking activities used by our models was sufficiently high to obtain useful EE estimation performance. We consider these results promising for free-living deployment in further research. Additionally, while our participants population included a wide range of weight, height, BMI and was balanced between male and female, their limited age range prevents us from generalizing the results to other age groups. However, our CRF models provide RMSE comparable with ordinary submaximal tests [32] without requiring specific exercises or individual calibration. Another point of attention is the difference in accuracy of our CRF estimation model in men and women. The slightly higher error for women might be due to a combination of factors. For example, the higher VO_2max standard deviation suggests higher variability in the female population. Adding explanatory variables such as body fat, which is known to have an important role in VO_2max estimation [30] might reduce this error. However, our goal was to use basic anthropometrics that can be easily acquired without laboratory tests. Therefore we limited our analysis to body weight. However, given the small difference in RMSE for EE estimation models using either CRF estimated by our procedure (CRF estimated) or actual VO_2max (CRF measured), the higher error found for CRF estimation in women does not seem to negatively affect personalization of EE estimation models.

In this work, CRF estimation was used to model the relation between heart rate and EE in participants of different fitness level, effectively reducing EE estimation error during moderate to vigorous physical activities. No intense activities or laboratory tests were used for CRF estimation and EE personalization. Instead, heart rate during low intensity activities of daily living was used as a predictor in our models, which provides for the practical applicability of the proposed method. Additionally, we used only simple anthropometrics data, excluding body fat, to allow for the development of models which do not require parameters acquired under laboratory conditions. Our methodology could be applied to other problems in which the relation between physiological parameters (e.g. heart rate, galvanic skin response, respiration, etc.) and an outcome variable (e.g. energy expenditure, mental stress, disease progression, etc.) varies between individuals. By modeling the source of variation, in our case CRF, at the second level of a hierarchical structure, the relation between physiological data and the outcome variable is modeled. Consequently, no explicit normalization is needed that would require individual calibration.

8. Conflicts of Interest

The authors declare that there are no conflicts of interest for this work.

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Appendix A

In this section we clarify the mathematical notation used in this manuscript. We adopted the notation of [20]. Each sample, is indicated by an index. In the following equations we will use i to indicate the index. The classical linear regression model where the predicted variable is indicated by y_i and the array of K predictors is indicated by X_i, can be written in mathematical form as:

$$y_i = X_{i1}\beta_1 + \cdots + X_{ik}\beta_k + \epsilon_i, \quad \epsilon_i \sim N(0, \sigma^2), \quad i = 1, \ldots, n \tag{1}$$

X_{i1} is the constant term, while X_{i2} to X_{ik} are features, for example accelerometer or heart rate data. We assume independent normal distribution with mean 0 and standard deviation σ for ϵ. Eq. (1) can be written in compact form as:

$$y_i = X_i\beta + \epsilon_i, \quad \epsilon_i \sim N(0, \sigma^2), \quad i = 1, \ldots, n \tag{2}$$

Equivalently to Eq. (2), we can express the relation between predictors and predicted variables as:

$$y_i \sim N(X_i\beta, \sigma^2), \quad i = 1, \ldots, n \tag{3}$$

We adopted the latter notation for simplicity and reduced verbosity, especially when multiple parameters and levels are included in the models.

Hierarchical models are a generalization of linear regression models such as the one described in Eq. (3) in which parameters act at two levels. We use the term *group level* parameters to indicate parameters at the second level of a hierarchical structure. These parameters are the ones influencing the relation between predictors X and the outcome variable y. In the context of hierarchical modeling, parameters β are indicated as *individual level* parameters [20]. Individual level parameters β (i.e. the slopes and intercepts) are allowed to vary by group. Thus, additionally to the variables already introduced, we introduce the group index j and represent group membership as $j[i]$. We also introduce group level parameters as γ. Thus, we define a hierarchical model in which parameters β vary by group as:

$$y_i \sim N(X_i \beta_{j[i]}, \sigma^2), \quad i = 1, \ldots, n \tag{4}$$

In 4, individual level parameters β vary depending on the group j. If there are no group level predictors, β acts similar to indicator variables in standard regression. This is the case for example of our activity-specific EE models, where different coefficients are derived for each activity class, however there is no group level predictors. Individual level parameters β in this case can be expressed as:

$$\beta_j \sim N(\mu_\beta, \sigma_\beta^2), \quad j = 1, \ldots, J \tag{5}$$

where μ_β and σ_β^2 are hyperparameters. Alternatively, parameters β can also be estimated by higher level regression models, including group level parameters γ and a set L of group level predictors U. This is the case of EE estimation models where anthropometric characteristics such as body weight and height, are used as group level predictors U. The notation used in this case is the following:

$$\beta_j \sim N(U_j \gamma, \sigma_\beta^2), \quad j = 1, \ldots, J \tag{6}$$

$$\gamma \sim N(\mu_\gamma, \sigma_\gamma^2), \quad j = 1, \ldots, np \tag{7}$$

where γ is of dimension $K + 1 \times L + 1$, μ_γ and σ_γ^2 are hyperparameters.

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