Cardiorespiratory fitness estimation in free-living using wearable sensors

Marco Altini[a], Pierluigi Casale[b], Julien Penders[b], Oliver Amft[c]

[a]altini.marco@gmail.com +31 6 46375742, Signal Processing and Systems, Eindhoven University of Technology, Den Dolech 2, Eindhoven, NL and Bloom Technologies, Agoralaan Building Abis 2.13, 3590 Diepenbeek, Belgium
[b]imec The Netherlands, High Tech Campus 31, 5656AE, Eindhoven, The Netherlands
[c]Chair of Sensor Technology, University of Passau, Innstrasse 41, 94032, Passau, Germany

Abstract

Objective: In this paper we propose artificial intelligence methods to estimate cardiorespiratory fitness (CRF) in free-living using wearable sensor data.

Methods: Our methods rely on a computational framework able to contextualize heart rate (HR) in free-living, and use context-specific HR as predictor of CRF without need for laboratory tests. In particular, we propose three estimation steps. Initially, we recognize activity primitives using accelerometer and location data. Using topic models, we group activity primitives and derive activities composites. We subsequently rank activity composites, and analyze the relation between ranked activity composites and CRF across individuals. Finally, HR data in specific activity primitives and composites is used as predictor in a hierarchical Bayesian regression model to estimate CRF level from the participant's habitual behavior in free-living.

Results: We show that by combining activity primitives and activity composites the proposed framework can adapt to the user and context, and outperforms other CRF estimation models, reducing estimation error between 10.3% and 22.6% on a study population of 46 participants.

Conclusions: Our investigation showed that HR can be contextualized in free-living using activity primitives and activity composites and robust CRF estimation in free-living is feasible.

Keywords: context recognition, topic models, Bayesian models,

1. Introduction

In the past few years, ubiquitous sensing technologies showed unprecedented insights into the relation between physical activity and health [1]. Wearable sensors are getting more and more widespread due to improvements in miniaturization, battery capacity and user experience design, reaching ubiquitousness in the quantified-self community and being rapidly adopted by the general population. Due to fast paced technological developments and increased availability of multivariate data streams acquired from wearable sensors (e.g. accelerometer, physiological data), new computational and artificial intelligence applications and techniques have been developed. When deployed in unsupervised free-living settings computational and artificial intelligence techniques can help shedding light on the complex relation between human behavior and health, ultimately driving behavioral change and better health outcomes [2, 3, 4, 5].

Wearable sensors have great potential for accurate physical activity monitoring in daily life [3, 2]. However, artificial intelligence capabilities of current systems and devices are limited, with almost all solutions focusing on behavioral aspects of physical activity such as steps, activity type and energy expenditure [6, 7]. On the other hand, cardiorespiratory fitness (CRF) is a marker of cardiovascular and cardiorespiratory health, and therefore is a key health parameter that could be estimated using state of the art technologies and computational methods [8, 9, 10].

CRF is defined as the ability of the circulatory and respiratory systems to supply oxygen during sustained physical activity and is considered among the most important determinants of health and wellbeing. 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 [8]. Epidemiological research has shown that in both individuals affected by disease [11] and healthy individuals [12, 13] higher level of CRF

2

resulted in better outcomes in term of slower disease progression, lower risk of cardiovascular disease as well as lower risk of all cause mortality. Thus, knowledge of CRF can be key in managing a healthy lifestyle.

Current practice for CRF measurement is direct measurement of oxygen volume (VO_2 in ml/min) during maximal exercise (i.e. VO_2max), the gold standard. 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. Less risky submaximal tests have also been developed [14]. Submaximal tests to estimate CRF typically require measuring heart rate (HR) while running at a certain speed or biking at a certain intensity. The inverse relation between HR at a certain exercise intensity, fixed by the strict exercise protocol that has to be sustained, and fitness, is the rationale behind this approach.

In this work, we propose to use artificial intelligence methods to estimate CRF using wearable sensor data acquired in free-living. We rely on the inverse relation between HR and fitness, but without the need for specific exercise protocols in laboratory settings. We aim at using computational techniques to automatically determine contexts in which HR can be interpreted, without any supervision from the user, and in free-living. Our hypothesis is that physiological data, for example HR, in free-living settings is not only affected by activity primitives such as walking, but by a combination of activity primitives and more abstract activity composites such as social interactions, working, etc. We define context as a combination of activity primitives and activity composites. Thus, we propose a method to determine both activity primitives and activity composites, to contextualize HR. Finally, after determining the user's context, we use contextualized HR to estimate person-specific CRF in a hierarchical Bayesian model. By using a non-nested hierarchical Bayesian model, parameters can vary depending on the activity performed, therefore being more flexible than models requiring specific activities. This paper provides the following contributions:

3

1. We propose a context recognition framework to contextualize HR and estimate CRF based on contextualized HR in free-living. First, we use topic models (TMs) to derive activity composites. Secondly, we rank activity composites to determine which activity composites are best suited for CRF estimation. Finally, we use HR data in specific contexts (i.e. activity primitives, walking speeds and activities composites) as a predictor in a hierarchical Bayesian model to estimate CRF.

2. We show the effectiveness of the proposed approach to estimate CRF on a dataset including 14 days of unsupervised free-living recordings from 46 participants and reference VO_2max acquired in laboratory conditions. CRF estimation error was reduced between 10.3% and 22.6% compared to alternative methods.

2. Related work

2.1. Wearable sensors and artificial intelligence to monitor physical activity

Energy expenditure is the most commonly used metric to quantify physical activity. Accelerometers and HR monitors are the most commonly used single sensor devices in epidemiologic studies and consumer products. Different methods have been developed in the past to monitor physical activity using such accelerometer and HR monitors. Typically, accelerometer-based systems rely on the relation between motion intensity close to the body's center of mass and energy expenditure. Using a single accelerometer prevents discriminating upper and lower body movement, e.g. biking and arm exercises, leading to large estimation error for activities not involving whole body motion. For example, Crouter et al. [15] had to remove biking activities from their evaluation, due to the inability of their system to capture physical activity when there is limited motion close to the body's center of mass.

Recent work showed that introducing artificial intelligence methods, activity type can be reliably detected with wearable sensors, opening new opportunities for physical activity monitoring [17, 18, 19, 20, 21]. Similarly, several activity

4

trackers and wearable sensors have been released on the market in the recent past, typically providing users with estimates of calories burnt and steps taken (e.g. Fitbit). While activity type, energy expenditure, steps, etc. are important, they reflect only individual behavior, but do not provide insights on the individual's actual health status. CRF can potentially provide more information on an individual's health status, being a marker of cardiovascular and cardiorespiratory health, and therefore a key health parameter [8, 9, 10]. Thus, our work aims at moving beyond quantification of human behavior, and towards quantification of health status as derived by CRF.

2.2. CRF estimation in laboratory settings

VO_2max is regarded as the most precise method for determining CRF [22]. Despite the indubitable importance of CRF in health, measurements of VO_2max are rare since they require specialized personnel and expensive equipment. The high motivation demand and exertion of the participants makes the test unfeasible in many patients groups [23]. As an alternative, many non-excercise and

Figure 1: Relation between body weight, HR and CRF for participants with similar body size (weight and height) characteristics. *a*) Positive relation between VO_2max and body weight disappears when participants with similar body size characteristics are considered. *b*) Negative relation between VO_2max and HR while walking holds on a subset of participants with similar body size, and can potentially be used to discriminate CRF levels.

submaximal models have been developed. Non-exercise modellaboratory-baseds

of CRF use easily accessible characteristics such as age, gender and self-reported physical activity [24, 25]. However, for individuals with similar characteristics, CRF levels cannot be discriminated, as shown in Fig. 1. Submaximal tests have been developed to estimate VO_2max during specific protocols while monitoring HR at predefined workloads [14]. Contextualized HR, e.g. HR while performing a specific activity in laboratory settings, is discriminative of CRF levels between individuals with similar characteristics, due to the inverse relation between HR and CRF [26] (see Fig. 1). Commercial devices, for example some sport watches paired to HR monitors [27, 28] (e.g. Garmin or Polar devices), provide CRF estimation using a regression model including HR at a predefined running speed as predictor. However, submaximal tests are still affected by limitations; the test should be re-performed every time CRF needs to be assessed, often requires laboratory infrastructure and specific activities to be performed [29].

While some devices and methods were developed to provide CRF estimation while performing intense exercise or under laboratory settings, very few systems and algorithms developed up to now focus on providing CRF estimation in free-living settings [26]. Using wearable sensor in free-living to estimate VO_2max is a novel approach. The estimation could be applied to a larger population compared to maximal or submaximal laboratory tests. Individuals not performing sports could still benefit from knowing more about their health status, via estimates of CRF, and potentially be motivated to take up a more active lifestyle.

2.3. CRF estimation in free-living

Preliminary work explored the relation between physical activity as expressed by a step counter, and CRF [30]. While number of steps can provide useful insights, the relation between HR and oxygen uptake at a certain exercise intensity cannot be exploited using motion based sensors. Plasqui et al. [26] showed that a combination of average HR and level of motion over a period of seven days correlates significantly with VO_2max. However, the relation between average HR and activity counts depends on the amount of activity performed

6

[26]. Tonis et al. [31] explored different parameters to estimate CRF from HR and accelerometer data during activities of daily living simulated in laboratory settings. However VO_2max reference and free-living data were not collected.
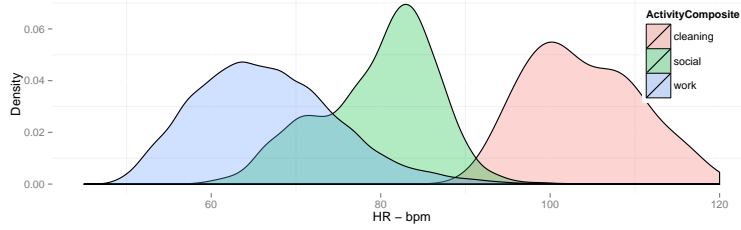

Figure 2: Density plot of HR data during the activity primitive *sedentary*, occurring in different *activity composites*, i.e. *cleaning, social, work*. Although the activity primitive *sedentary* occurs in all activity composites, HR differs consistently across activity composites. Thus, detecting activity composites can improve interpretation of HR in free-living, and therefore provide more accurate CRF estimation. Activities composites were manually annotated.

When moving towards free-living settings, HR is more difficult to interpret, since activities vary depending on the different lifestyles people adopt. However, contextualizing HR in free-living settings using pattern recognition and artificial intelligence methods opens an opportunity to bring sub-maximal tests to uncontrolled free-living conditions.

2.4. Artificial intelligence for context recognition

We hypothesized that HR in free-living settings is not only affected by activity primitives but by a combination of activity primitives and more abstract activity composites. Thus, we consider as context a combination of activity primitives and activity composites. For example, HR during the activity primitive *sedentary* changes substantially depending on the context in which such activity is performed. HR during social interactions is higher than during work for sedentary activities, possibly due to the higher physiological stress involved in talking and interacting with other people, as shown in Fig. 2. Thus, CRF estimation models might benefit from inclusion of activity composites representing

7

additional factors present in free-living (e.g. psychological stress, interactions with other people, etc.).

Various pattern recognition and artificial intelligence methods have been proposed to determine context and activities in literature. Typically, activities are thought of in a hierarchical manner, starting from activity primitives, to more abstract activity composites [32].

An example of activity primitives can be a set of postures and locomotion activities, such as: *lying down, sedentary, dynamic, walking, biking* and *running*, as determined using supervised methods in previous research [16]. On the contrary, higher level contextual information, such as activity composites, require a different recognition approach. Such activities are personal and need unsupervised methods able to discover different patterns in each individual, depending on their behavior. A possible solution is the use of TMs [33]. In activity recognition, TMs were applied to discover activity composites from activity primitives [34]. Recent work investigated the impact of multiple TMs (in particular LDA, latent Dirichlet allocation) parameters for activity composites discovery, showing promising results [35] for recognition of abstract activity composites.

In our previous work [36], we proposed a method to determine which activity composites are better suited to interpret HR for one individual. For example, we determined in which activity composites HR was more representative of HR normalization parameters used to personalize EE estimates. Our approach consisted of ranking activity composites based on features in order to compare them across participants. In this work, we extend our method to the relation between HR during activity composites and VO_2max. We aim at finding for each individual specific contexts where HR is representative of CRF in free-living, using an unsupervised approach. Then, we use contextualized HR to predict CRF without the need for laboratory tests or specific exercises.

8

3. Approach

Following a top down approach, CRF y_{CRF} was estimated from contextualized HR $\overline{HR}_{ctx*}$ and anthropometric characteristics by a hierarchical Bayesian regression model, as shown in Fig. 3. Contextualized HR $\overline{HR}_{ctx*}$ refers to HR during specific activity primitives, speeds and *relevant activity composites*. We used features from accelerometer X_{acc}, HR X_{hr}, location X_{coo} and anthropometrics X_{ant} as input to our context recognition and CRF estimation models. Activity primitives c were used together with stay regions sr as input for LDA topic discovery to obtain activity composites. Activity composites were ranked to find the most relevant ones for CRF estimation, referred to as *relevant activity composites* (see Sec. 3.3 for details). The procedure to determine activity primitives, speeds, activity composites, and therefore contextualized HR $\overline{HR}_{ctx*}$ is shown in Fig. 4.

In the remaining of this section, we detail the approach and provide an example. We consider *walking* at 3 and 5 km/h as exemplary activity primitives and speeds. Thus, to determine contextualized HR, we consider HR data while *walking* at 3 and 5 km/h during *relevant activity composites*.

3.1. CRF estimation

The CRF estimation y_{CRF} was derived by a hierarchal Bayesian regression model. Parameters modeling the relations between $\overline{HR}_{ctx*}$ and y_{CRF} vary depending on the context *ctx*. We denote the estimation model as:

$$y_{CRF_p} \sim N(X_{CRF_p}\beta_{CRF} + X_{ctx[p]}\beta_{ctx[p]}, \sigma^2_{CRF}), \tag{1}$$

$$ctx = 1, \ldots, R \quad p = 1, \ldots, np$$

$$X_{CRF_p} = [1, X_{ant_p}] \in \mathbb{R}^{np \times (D+1)}, \quad p = 1, \ldots, np$$

$$X_{ctx} = [\overline{HR}_{ctx*}] \in \mathbb{R}^{np \times 1} \quad p = 1, \ldots, np$$

where matrix X_{CRF_p} is of dimension $np \times (D+1)$. np is the number of participants, while D the number of anthropometric characteristics X_{ant_p} for a person

p, which includes *body weight*, *height*, *age* and *sex*. The associated parameters β_{CRF} do not vary by context *ctx* since they are relative to a person and remain the same across different activities. Contexts *ctx* are a set R representing a combination of activity primitives and speeds during *relevant and activity composites*, as shown in Fig. 3. In our example, contexts are $R = 2$, i.e. walking

at 3 or 5 km/h during *relevant activity composites*, and control the parameters β_{ctx} for the predictor $\overline{HR}_{ctx*}$. By letting the parameters β_{ctx} vary, users are not constrained to one specific activity. Instead, the model will provide a CRF estimate y_{CRF} depending on the available activity primitives and speeds. Details on the model parameters estimation procedure are reported in Sec. 5.
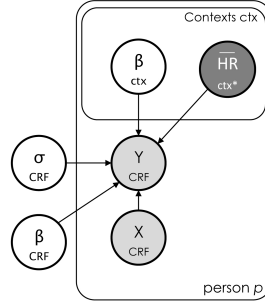

Figure 3: Hierarchical Bayesian model in plate notation. Parameters β_{ctx} vary by context *ctx* and model the relation between contextualized HR $\overline{HR}_{ctx*}$ and CRF y_{CRF}.

3.2. Context recognition

In this section we introduce our context recognition architecture to determine contextualized HR $\overline{HR}_{ctx*}$, as shown in Fig. 4. Activity composites were discovered using LDA. LDA is a generative probabilistic model which discovers K *activity composites*, from S time windows of N words y_n. For activity recognition, words y_n are typically basic building blocks for activity composites, such as activity primitives. In our implementation we used stay regions and activity primitives (see Sec. 5) as words y_n. Accelerometer features X_{acc} were used to derive activity primitives c_i combining a Support Vector Machines (SVM) classifier and subsequent Hidden Markov Models (HMM) used to smooth transitions
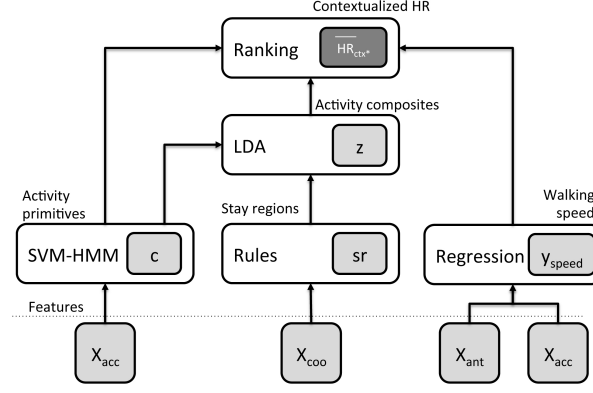
10

Figure 4: Proposed approach to determine contextualized HR $\overline{HR}_{ctx*}$. LDA uses histograms of activity primitives c and stay regions sr to discover a set of activity composites, which are ranked to determine *relevant activity composites*. Contextualized HR $\overline{HR}_{ctx*}$ is shown in the top block, and is determined by combining activity primitives, activity composites and speed. $\overline{HR}_{ctx*}$ is used as input for the CRF estimation model detailed in Fig. 3.

between activities. The hidden states corresponded to the real activity composites, c_i, while the observable states are the ones recognized by the SVM. *Stay regions* were derived from GPS coordinates X_{coo} using time and distance thresholds (see Sec. 5). According to the generative process, for each word y_n, we first draw the activity composite z_n. z_n is a scalar $z \in 1 : K$ indicating the activity composite for time window n. Each assigned activity composite z_n is derived from a multinomial distribution defined by the parameter θ_s. θ_s is the distribution over activity composites for time window s:

$$\theta_s \sim \text{Dir}(\alpha) \quad 1 \leq s \leq S \tag{2}$$

$$z_n \sim \text{Mult}(\theta_s) \quad 1 \leq s \leq S, \quad 1 \leq n \leq N \tag{3}$$

LDA defines θ_s as a Dirichlet distribution with hyperparameter α. Then, another multinomial is used to choose a word y_n, conditioned on the activity composite z_n, $p(y_n|z_n)$:

$$y_n \sim \text{Mult}(\beta_{z_n}) \quad 1 \leq n \leq N \tag{4}$$

11

Where β is defined as the probability of each word $n \in 1 : N$ for topic z. The joint distribution can be specified as:

$$p(y, z, \theta, \phi | \alpha, \beta) =$$

$$\prod_{s=1}^{S} \int p(\theta_s, \alpha) \prod_{n=1}^{N} \sum_{z=1}^{K} p(z_{sn|\theta_s}) p(y_{sn} | z_{sn}, \beta) d\theta_s \tag{5}$$

We were interested in estimating the distributions of the parameter θ_s. Multiple activity composites were derived by LDA in each time window s, each activity composite being assigned a probability. For each time window we considered only the activity composite maximizing θ_s, indicated hereafter as z_s, the window's main activity composite.

3.3. Relevant activity composites

During the training phase, the HR for activity primitives and speeds was computed for each main activity composite z_s and participant par. Accelerometer features X_{acc} were used to estimate walking speed as $y_{speed} = X_{speed} \beta_{speed} + \epsilon, X_{speed} = \{X_{acc}, X_{ant}\}$. The resulting matrix HR_{ctx} is of dimension $K \times npar$, where K is the number of activity composites and $npar$ is the number of participants. LDA-derived activity composites do not include semantics and cannot be compared across participants. To overcome the problem of comparing activity composites, we characterized them with a set of features T which we used to rank activity composites, as in [36]. In order to provide a generalized method that is applicable to new participants, we chose features T that are independent of a person's lifestyle, for example, $T_1 \in T$ could be *the relative time spent sedentary in each activity composite* for the different participants. Regardless of what a person's lifestyle is, it will always be possible to order LDA-derived activity composites by feature T_1, e.g. *the relative time spent sedentary in each activity composite*. Then, HR_{ctx} was ranked by feature T_1, providing a way to investigate the relation between the HR in different activity composites and CRF, across participants. The ranking orders HR_{ctx} by values of T_1 from

12

maximum to minimum. Since we are interested in highlighting commonalities across activities composites, ranked HR_{ctx} are smoothed by a moving average, resulting in $\overline{HR}_{ctx}$. As a result, we obtain an array of k ranked HR values per participant. We conclude the training phase by determining which feature in T maximizes Pearson's correlation between $\overline{HR}_{ctx}$ and CRF. We define the vector of correlations r_T for a set of TN features in a context *ctx*. Thus, for each context *ctx*, we have:

$$r_T = \{r_{rank_{T1}}, \ldots, r_{rank_{TN}}\}, \tag{6}$$

$$r_{rank_i} = r(\overline{HR}_{ctx_{par=\{1,\ldots,npar\},i}}, CRF_{par=\{1,\ldots,npar\}}) \tag{7}$$

Where r_{rank_i} is the correlation between the vector of contextualized HR $\overline{HR}_{ctx}$ and CRF, among all participants *par* for a feature T_i in a context *ctx*. The activity composite providing the highest correlation was selected, i.e. the first element of the $\overline{HR}_{ctx}$ vector across individuals and CRF, to determine which feature T_i results in activity composites most representative of CRF. Thus, the feature $T_i = \max r_{Tctx}$ showing the highest correlation between $\overline{HR}_{ctx}$ and CRF is chosen to determine *relevant activities composites*.

As an example, we consider as contexts *ctx* walking at 5 km/h during activity composites with the maximum relative time spent sedentary, i.e. *relevant activity composites*, as shown in Fig. 5. We first determine the vector of k elements HR_{ctx}, representing the mean HR while walking at 5 km/h in each LDA-discovered activity composite. Then, HR_{ctx} are ranked based on the feature T_i maximizing the correlation on our training set (i.e. *the relative time spent sedentary in each activity composite*), to determine $\overline{HR}_{ctx*}$. The first element of the ranked and smoothed $\overline{HR}_{ctx}$ vector, is the contextualized HR $\overline{HR}_{ctx*}$, used as input for CRF estimation.
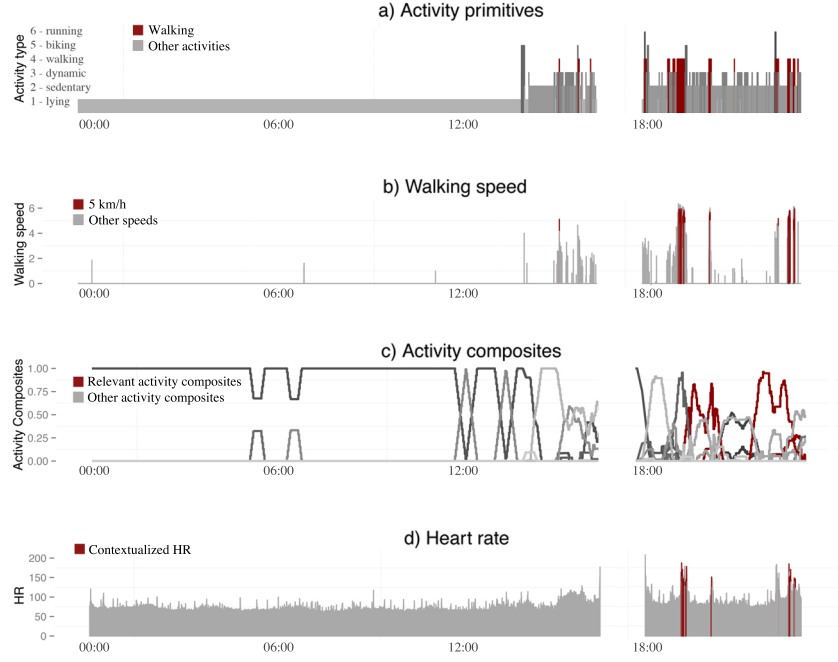
13

Figure 5: Exemplary diagram of the procedure to determine contextualized HR $\overline{HR}_{ctx*}$. Plots show 24 hours of free-living data for one participant. For this illustration, we selected as activity primitive and speed *walking at 5 km/h during relevant activity composites*, and highlighted them in red. *a*) Recognized activity primitives, as detected by the combined SVM and HMM classifier. *b*) Walking speed y_s, determined when walking is detected, using a linear regression model. *c*) Activity composites determined by LDA and defined by the distribution of activity primitives and stay regions over 15 minutes windows. Relevant activity composites are determined using the procedure detailed in Sec. 3.3, maximizing the correlation between HR and CRF. *d*) Contextualized HR $\overline{HR}_{ctx*}$ is determined as the mean HR while walking at 5 km/h during *relevant activity composites* in this example, and highlighted in red. $\overline{HR}_{ctx*}$ is used to estimate CRF, as shown in Fig. 3. Between 17 and 18 hours no data are present since the sensor was being charged.

14

4. Evaluation study

4.1. Participants and data acquisition

Participants were 46 (21 male, 25 female), age 24.7±4.9 years, weight 68.6± 10.9 kg, height 172.8±8.9 cm, BMI 22.9±2.5 kg/m^2 and VO_2max 3020.8±668.9 ml/min. Written informed consent was obtained, and the study was approved by the ethics committee of Maastricht University. The sensor platform used was an ECG Necklace, a platform 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, close to the body's center of mass. The ECG Necklace was worn during laboratory protocols and free-living. Additionally, during free-living each participant carried a Samsung Galaxy S3 used to record GPS coordinates at 5 minutes intervals. Reference CRF was determined as VO_2max, by means of an incremental test on a cycle ergometer [37] using a indirect calorimeter that analyzed O_2 consumption and CO_2 production. The dataset considered for this work contains 507 days of data collected from 46 participants in free-living, thus for each participant we acquired about 11 days of accelerometer, ECG and GPS data. Compared to the two-week protocol, available data per participants varied between 7 and 14 days, due to participant availability, sensor failures and power outages, as participants forgot to recharge, causing data losses. Nevertheless, we consider that the recordings were sufficient to capture the behavior of each participant. 75 hours of laboratory recordings including reference VO_2, VCO_2, acceleration, ECG and VO_2max were also obtained for model validation.

4.2. Experiment design and validation procedure

We collected data in free-living and laboratory settings and evaluated four approaches to CRF estimation. All approaches were evaluated with respect to reference CRF measured by means of a VO_2max test carried out on a cycle ergometer. In the remaining of this paper, we will use the following terminology to characterize the four estimation conditions that were used for comparison; a) *anthropometrics*: no HR data was used, b) *no-context*: HR in free-living was

15

Figure 6: ECG Necklace and Samsung S3, the wearable sensor and phone used to collect accelerometer ECG and GPS data in this study. The ECG Necklace was worn during laboratory protocols and free-living recordings close to the body's center of mass. The Samsung S3 was carried during free-living only.

used directly to estimate CRF, c) *primitives*: HR in free-living was contextualized using activity primitives and speed, d) *composites*: HR in free-living was contextualized using activity primitives, speed and *relevant activity composites*.

265   Two laboratory protocols were designed and implemented for each participant on two separate days to avoid the maximal fitness test to affect physiological parameters during less intense activities and vice versa. Additionally, each participant wore the ECG Necklace in free-living for 14 days. All results on CRF estimation were obtained from the free-living data, whereas the laboratory 270 data was used to derive the models, as detailed in the next Sections.

     Data from laboratory protocols were used to develop supervised methods for activity type recognition and walking speed estimation. Activity type recognition and walking speed estimation models were deployed in free-living and used as building blocks to contextualize HR. Additionally reference VO_2max was 275 collected under laboratory protocols to validate the proposed CRF estimation models. Data collected in free-living were used to determine contextualized HR and use contextualize HR as predictor for CRF estimation. CRF estimation models including contextualized HR as predictor relied on; laboratory-validated activity type recognition and walking speed estimation models, stay regions de- 280 termined without supervision in free-living (see Sec. 5) and activity composites determined using LDA, in free-living.

16

4.2.1. Laboratory protocols

Participants reported at the lab on three separate days and after refraining from drinking, eating and smoking in the two hours before the experiment. Two laboratory protocols were performed. The first protocol included simulated activities performed while wearing a portable indirect calorimeter. Activities included: lying down, sitting, sit and write, standing, cleaning a table, sweeping the floor, walking (treadmill flat at 2.5, 3, 3.5, 4, 4.5, 5, 5.5, 6 km/h) 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 biking and CRF. The third day was used for anthropometric measurements including the participant's body weight, height and body fat assessed using doubly labelled water [38].

4.2.2. Free-living protocol

Participants worn the ECG necklace for 14 consecutive days in free-living and manually annotated their activity composites in a paper diary. Participants were instructed to annotate activity composites as they occurred during the day and to annotate only activity composites such as going to work, sleeping, commuting, etc. Annotated activity composites were not used for model development since activity composites were derived using LDA, and therefore without supervision from activity primitives, as detailed in Sec. 3 and Sec. 5. The annotations were only used to interpret the LDA and CRF estimation results as detailed in the discussion, Sec. 7. Activity composites can only be determined from free-living data, since they cannot be simulated under laboratory conditions. Participants carried a Samsung S3 phone and were instructed to charge both the ECG Necklace and phone and to change electrodes daily.

4.2.3. Statistics and performance measures

All models were derived using 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

17

and CRF estimation models. The remaining data was used for validation. The procedure was repeated for each participant and results were averaged. LDA models were built on data from the participant to be validated, since no reference or training set are necessary. Performance of the activity recognition models was evaluated using the class-normalized accuracy, in laboratory recordings. Results for walking speed estimation and CRF estimation are reported in terms of Root-mean-square error (RMSE) and Pearson's correlation (r), where the outcome variables were speed in km/h and CRF in ml/min respectively. Paired t-tests were used to compare RMSE between models.

5. Implementation

5.1. Context recognition

5.1.1. Features

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 due to 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 results from our previous work [19], using a different dataset. Selected features were: *mean of the absolute signal, inter-quartile range, median, variance, main frequency peak, low frequency band signal power*. Accelerometer features for walking speed estimation were: *mean of the absolute signal, inter-quartile range, variance, main frequency peak, high frequency band signal power*. HR was determined from RR intervals extracted from raw ECG data and averaged over 15 seconds windows.

5.1.2. Activity primitives

Laboratory activities were grouped into six clusters to be used for classification of activity primitives. The six clusters were *lying* (lying down), *sedentary* (sitting, sit and write, standing), *dynamic* (cleaning the table, sweeping the floor), *walking*, *biking* and *running*. Activity primitives were derived combining

18

a SVM and HMM. For the SVMs, we used a Gaussian radial basis kernel (cost function parameter C = 1). Parameters were set based on previous work from our group [21]. The HMM is defined by parameters $\lambda = (\pi, A, B)$; where π are the initial state probabilities, A is the transition probability matrix, defining the probability of transitioning between one activity to the other at time interval t. The HMM states corresponded to activity primitives. B is the emission matrix, which defines the probability of getting an emission at time t, given the state. We implemented the emission matrix B as $b_{ij} = 0.5 \iff i = j$, $b_{ij} = 0.1 \iff i \neq j$, while transitions probabilities A between actual states were derived from training data. Training data was the SVM classification result obtained with reference activity primitives manually annotated in laboratory settings.

5.1.3. Walking speed

Walking speed was estimated using a multiple regression model using as predictors the features listed in Sec. 5.1.1, together with the participant's *height*. Laboratory recordings on a treadmill while walking at different speeds were used to build participant-independent walking speed models.

5.1.4. Stay regions

Stay regions were computed from GPS coordinates according to time and distance thresholds, which were set to 60 minutes and 1 km according to previous literature [39]. The time threshold ensures that each stay region is a location where the participants spent a significant amount of time, while the distance threshold ensures that noisy recordings do not result into a multitude of stay regions being detected. GPS data was collected at 5 minutes intervals to conserve battery power. The relatively wide distance and time thresholds were chosen due to the low frequency of the GPS recordings.

5.1.5. Relevant activity composites

Input primitives for LDA were occurrences histograms of stay regions and activity primitives in each time window s. LDA hyperparameter α was set to

19

0.01, while segment size and number of topics k were set to 15 minutes and 20 topics respectively, based on results obtained in previous research [35]. Parameters were optimized using an implementation of the variational expectation-maximization algorithm proposed in [33]. HR during activities composites HR_{ctx} was ranked according to different features T: *amount of time spent in each activity composite*, *relative amount of time spent in each activity primitive for an activity composite, with respect to the total time spent in the same activity primitive across all activities composites* and *relative time spent in each activity primitive per activity composite*. These features were chosen since they can be computed across participants and activities composites regardless of the participant lifestyle or activity composite semantics. Ranked HR_{ctx} were correlated with CRF to determine which activities composites features were more representative of CRF. Ranking of HR_{ctx} values was smoothed by a moving average of 2 elements, i.e. over the first two ranked activity composites. The relevant activity composites discovery procedure was also evaluated independently of the participant. Contextualized HR HR_{ctx} was ranked and correlated with CRF for $np-1$ participants. The feature resulting as the most representative of CRF, i.e. the one for which correlation was maximized, was used to determine relevant activity composites for the left out participant. The procedure was repeated np times, where np was the number of participants.

5.2. CRF estimation

Hierarchical Bayesian models for CRF estimation introduced in Sec. 3 were implemented using R and JAGS. Posterior parameters estimations were performed by Gibbs sampling with 3 chains and 10000 iterations. The first 500 iterations were discarded (burn-in period). We consider reference VO_2max as CRF. We chose *walking* at different speeds as activity primitives normally carried out by most of the population. We evaluated our VO_2max estimation models using as predictor HR contextualized over a broad range of walking speeds, from 2.5 to 6 km/h. The hierarchical Bayesian model to estimate CRF also included the participant's weight, age, sex and height as predictors. We im-
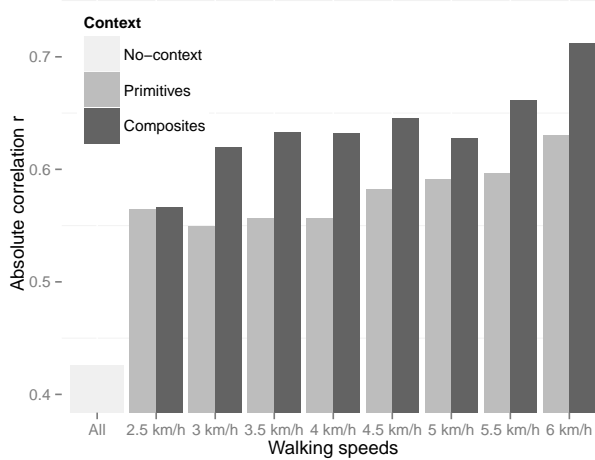
20

Figure 7: Correlation between HR and VO_2max. Correlation is lowest for *No-context* and were highest when activity composites (*Composites*) were used, compared to the condition were only activity primitives (*Primitives*) were considered. HR data during activity primitives and composites was acquired in free-living settings.

plemented the models listed in Sec. 4 for comparison, thus estimating VO_2max using anthropometric characteristics only (case *anthropometrics*), HR in free-living (case *no-context*), HR while walking at a certain speed (case *primitives*), and HR while walking at a certain speed *relevant activity composites* (case *composites*).

6. Results

6.1. Activity primitives and walking speed

Activity primitives and walking speed were validated in laboratory settings. Class-normalized accuracy of the SVM-HMM activity recognition classifier was 95.8%. More specifically, accuracy was 98.2% for *lying*, 98.9% for *sedentary*, 83.5% for *dynamic*, 99.4% for *walking*, 96.5% for *biking* and 98.4% for *running*. Walking speed estimation RMSE was 0.37 km/h.

6.2. Relevant activity composites

Fig. 7 shows the absolute value of the correlation between HR and VO_2max for different contexts. HR in free-living was moderately correlated with VO_2max (comparison case *no-context*, $r = -0.43$). Correlation between HR and VO_2max in free-living was stronger for *walking* activity primitives, compared to no-context, ranging from -0.55 to -0.63. Correlation had a tendency to increase as speed increased, reaching the highest value for *walking* at 6 km/h. Fig. 8 shows results for VO_2max estimation models. RMSE between estimated and predicted VO_2max when no HR data was used (*case anthropometrics*) was 322.5 ml/min. The relation between contextualized HR $\overline{HR}_{ctx}$ (i.e. including *relevant*
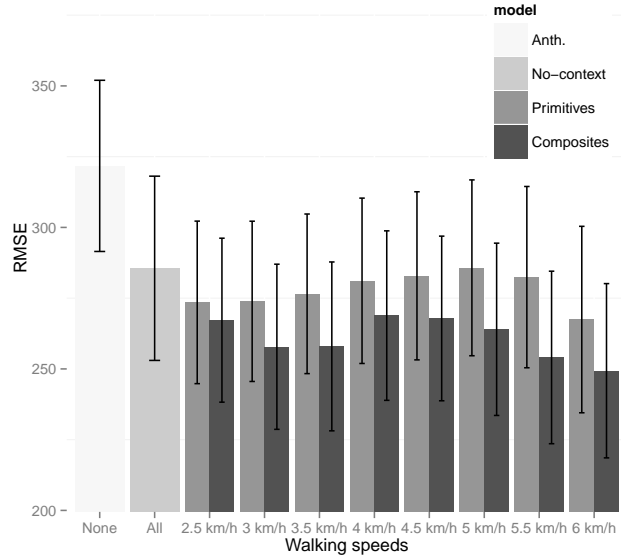

Figure 8: RMSE of CRF estimation in free-living against VO_2max reference. Error bars represent standard error. RMSE is highest for *Anth*, followed by *No-Context*, showing that not using HR data or using HR data without context produces larger errors in VO_2max estimation. A combination of activity primitives and activity composites (condition *Composites*) shows optimal results, i.e. the lowest RMSE across different walking speeds, compared to the condition were only activity primitives (*Primitives*) were considered. HR data used as predictors was acquired during activity primitives and composites performed without supervision in free-living settings.

activity composites) and VO_2max was maximized ranking activities composites by feature $T_i = $ *relative time spent sedentary within an activity composite*. Correlation ranged between -0.57 and -0.71, reaching the highest value for *walking* at 6 km/h. Thus, correlation was consistently improved when a combination of activity primitives and *relevant activity composites* was used to contextualized HR, compared to no-context and activity primitives only, as shown in Fig. 7.
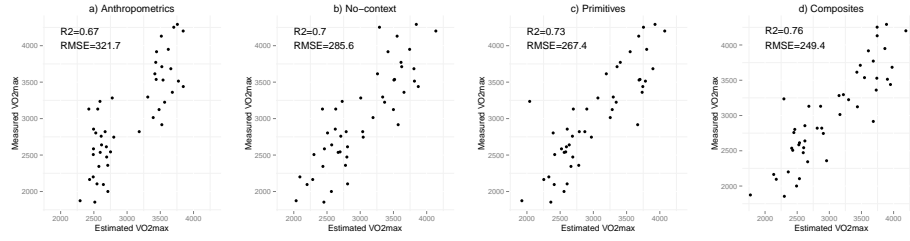

Figure 9: Estimated and measured VO_2max for the four conditions compared in this work. R^2 is increased and RMSE is reduced when adding more levels of contexts. The best results when VO_2max is estimated using HR contextualized by activity primitives and composites, as shown in *d*). HR data used as predictors was acquired during activity primitives and composites performed without supervision in free-living settings.

6.3. CRF estimation

RMSE was reduced to 286.3 ml/min (11.3% error reduction) when including free-living HR as predictor but no contextual information (case *no-context*). Estimation error was further reduced for case *primitives*, i.e. using the HR while walking at a certain speed as predictors. More specifically, RMSE varied between 287.3 and 267.6 ml/min, depending on walking speed. RMSE was reduced by 17.0% and 6.5% compared to *case anthropometrics* and *no-context* respectively, when the best model was used (i.e. walking at 6 km/h). Contextualizing HR by a combination of activity primitives and activity composites provided better accuracy than any other model. RMSE varied between 268.9 ml/min and 249.5 ml/min, depending on walking speed. A combination of activity primitives and activity composites always outperformed activity primitives alone, as shown in Fig. 8.

Activity primitives in free-living were recognized as follows: 44.5% lying, 36.4% sedentary, 9.5% dynamic, 5.4% walking, 3.8% biking and 0.4% running. The average walking speed in free-living over the entire dataset was 3.5 ± 1.5 km/h. Participants spent 71 ± 27 minutes per day in walking activities, 7 ± 5.4 minutes walking at 6 km/h.

Overall, combining activity primitives and activities composites provided error reductions up to 22.6%, 12.8% and 10.3% compared to *anthropometrics*, *no-context* and *primitives* respectively. Fig. 9 shows estimated and measured VO_2max for the four models compared in this study. Explained variance (R^2) and RMSE are reported, showing increased R^2 and reduced error as more context is included. For the latter figure, only the best performing models is shown for cases *primitives* and *composites*.

7. Discussion

Many methods have been developed to estimate VO_2max using data collected under supervised laboratory conditions or following strict protocols. However, to the best of our knowledge, this is the first work, which proposes to use pattern recognition and artificial intelligence methods to determine activity primitives and activity composites as contextual information, and then interpret HR data in free-living. We showed RMSE reductions of 22.6% compared to estimates derived using anthropometric characteristics only, and RMSE reductions up to 10.3% compared to estimates derived using activity primitives, highlighting the benefit of our context recognition method.

We hypothesized that the presence of a multitude of factors such as psychological stress, interactions with other people, etc. in free-living required a novel approach over the prior estimation attempts used in laboratory settings. In particular, HR in free-living is not only affected by activity primitives - as shown in the lab - but by both activity primitives and activity composites. Thus, developing computational methods able to incorporate knowledge of contextual information beyond activity primitives could potentially improve interpretation

24

of HR in free-living. Our results confirm the importance of activity composites in free-living. RMSE was consistently reduced over a broad range of walking speeds, as shown in Fig. 8. We translated the need for contextual information into a hierarchical model. In our previous work we introduced *relevant activity composites* for energy expenditure estimation [36]. We established *relevant activity composites* to relate discovered activity composites for which no supervised information exists, to behaviour-related HR.

In this work, we discovered individual activity composites of each user without identifying them. Measuring the composite discovery performance was not needed since we assessed the CRF estimation based on the LDA output. We determined which activity composites were better suited for CRF estimation by ranked them according to the correlation of selected features and HR. The approach simplified our study methodology as no activity composite annotations were required. However, discovered activity composite do not provide semantics and comparison between participants is challenging. Typically, activity composite of interest are isolated and further classified using supervised methods [34, 35], thus requiring prior knowledge of the activity composites to discover, effectively limiting the unsupervised nature of the method. Ranking allowed for comparison of activity composite specific features across participants, thus making the approach unsupervised and generalizable to new participants.

We found a strong relation between the *relative time spent sedentary in each activity composite* and CRF. A possible explanation for the relation between HR contextualized by activity composites ranked by *relative time spent sedentary in each activity composite* and CRF is that activities composites in which people spend most of their time sedentary are typically representative of a stable physiological condition, which might be more representative of their CRF level. On the contrary, short or infrequent activities might involve more stressful situations as well as more intermittent HR, causing cardiovascular responses which are not as reliable for HR interpretation [40]. An example of an activity composite that maximizes the relative time spent sedentary is *working at the office*. While most of the time while working at the office an individual is probably

25

sedentary, there can still be many periods of walking, that are therefore used to contextualize HR. In such periods, HR might be less affected by for example carrying loads, effects of previously performed intense exercise, walking hills, etc.) and therefore be more representative of CRF.

We relied on the inverse relation between HR at a certain workload and VO_2max, as often reported for laboratory protocols. However, by using a non-nested hierarchical approach, where parameters varied based on the activities, we did not constrain the participant in performing specific activities or walking at predefined speeds. Instead, based on the participant's preferred walking speed in free-living, the optimal parameters were used. The activity primitives chosen as free-living contexts were lying down and walking, for the following reasons. First, we aimed at activities commonly performed by healthy individuals. Secondly, the inverse relation between HR at rest or sleeping HR and CRF was already shown in previous research [41, 42], highlighting how this parameter can be valuable for VO_2max estimation. Finally, walking activities can be discriminated in intensity, by detecting walking speed, using simply an accelerometer. Determining the specific intensity of an activity is an important factor when trying to detect specific context in free-living, since detecting only activity type, if the activity can be carried out at different intensities, would not be sufficient to determine the same context for each individual. However, walking is an activity that can be accurately quantified in terms of both type (i.e. walking) and intensity (i.e. speed). On our free-living dataset, participants spent more than an hour per day walking (71 ± 27 minutes), and about 10% of walking activities involved walking at 6 km/h (7 ± 5.4 minutes). Thus, *walking* confirmed to be a common activity of daily life, and a good candidate to contextualize HR for CRF estimation. Noteworthy, RMSE for VO_2max estimation was not consistently reduced by including in the models HR collected while walking at higher speeds. Thus, highlighting the additional complexity of analyzing HR data in free-living.

Being able to accurately determine the user context in terms of activity type and intensity allows us to bring the principle used in laboratory-based submax-

imal tests (i.e. the inverse relation between HR measured while performing an exercise at a certain intensity, such as biking at a fixed power on a cycle ergometer, and VO_2max) to free-living settings. Contextualizing HR by means of activity primitives and speed improved correlation between free-living HR and CRF. Our approach builds on LDA and a hierarchical Bayesian model to discover activity composites and relating VO_2max to behavior in a probabilistic framework. As a result, RMSE for CRF estimation against VO2max reference was reduced up to 22.6%.

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. Estimating CRF continuously in free-living creates a feedback loop from measurements to lifestyle. CRF estimates may provide the basis for many adaptive applications supporting behavior change. Moreover, CRF is not only important for fitness applications, but to health and patient care too, as CRF has known associations to disease risk. Our investigation showed that robust CRF estimation in free-living is feasible, thus confirming that the applications described above are realistic.

Acknowledgment

References

[1] S. J. Marshall, E. Ramirez, Reducing sedentary behavior a new paradigm in physical activity promotion, American Journal of Lifestyle Medicine 5 (6) (2011) 518–530.

[2] M. Chan, D. Estève, J.-Y. Fourniols, C. Escriba, E. Campo, Smart wearable systems: Current status and future challenges, Artificial intelligence in medicine 56 (3) (2012) 137–156.

27

[3] F. Buttussi, L. Chittaro, Mopet: A context-aware and user-adaptive wearable system for fitness training, Artificial Intelligence in Medicine 42 (2) (2008) 153–163.

[4] W. H. Wu, A. A. Bui, M. A. Batalin, L. K. Au, J. D. Binney, W. J. Kaiser, Medic: Medical embedded device for individualized care, Artificial Intelligence in Medicine 42 (2) (2008) 137–152.

[5] C. C. Bennett, K. Hauser, Artificial intelligence framework for simulating clinical decision-making: A markov decision process approach, Artificial intelligence in medicine 57 (1) (2013) 9–19.

[6] C. V. Bouten, K. T. Koekkoek, M. Verduin, R. Kodde, J. D. Janssen, A triaxial accelerometer and portable data processing unit for the assessment of daily physical activity, IEEE Transactions on Biomedical Engineering 44 (3) (1997) 136–147.

[7] H. Vathsangam, A. Emken, E. T. Schroeder, D. Spruijt-Metz, G. S. Sukhatme, Determining energy expenditure from treadmill walking using hip-worn inertial sensors: An experimental study, IEEE Transactions on Biomedical Engineering 58 (10) (2011) 2804–2815.

[8] D.-c. Lee, E. G. Artero, X. Sui, S. N. Blair, Review: Mortality trends in the general population: the importance of cardiorespiratory fitness, Journal of Psychopharmacology 24 (4 suppl) (2010) 27–35.

[9] G. Plasqui, K. R. Westerterp, Accelerometry and heart rate as a measure of physical fitness: proof of concept., Medicine and science in sports and exercise 37 (5) (2005) 872–876.

[10] F. Sartor, G. Vernillo, H. M. de Morree, A. G. Bonomi, A. La Torre, H.-P. Kubis, A. Veicsteinas, Estimation of maximal oxygen uptake via submaximal exercise testing in sports, clinical, and home settings, Sports medicine 43 (9) (2013) 865–873.

28

[11] L. Thorsen, E. Skovlund, S. B. Strømme, K. Hornslien, A. A. Dahl, S. D. Fosså, Effectiveness of physical activity on cardiorespiratory fitness and health-related quality of life in young and middle-aged cancer patients shortly after chemotherapy, Journal of Clinical Oncology 23 (10) (2005) 2378–2388.

[12] M. Wei, J. B. Kampert, C. E. Barlow, M. Z. Nichaman, L. W. Gibbons, R. S. Paffenbarger Jr, S. N. Blair, Relationship between low cardiorespiratory fitness and mortality in normal-weight, overweight, and obese men, Jama 282 (16) (1999) 1547–1553.

[13] S. N. Blair, J. B. Kampert, H. W. Kohl, C. E. Barlow, C. A. Macera, R. S. Paffenbarger, L. W. Gibbons, Influences of cardiorespiratory fitness and other precursors on cardiovascular disease and all-cause mortality in men and women, Jama 276 (3) (1996) 205–210.

[14] P. O. Åstrand, I. Ryhming, A nomogram for calculation of aerobic capacity (physical fitness) from pulse rate during submaximal work, Journal of Applied Physiology 7 (2) (1954) 218–221.

[15] S. E. Crouter, D. R. Bassett, A refined 2-regression model for the actigraph accelerometer, Medicine & Science in Sports & Exercise 42 (5) (2010) 1029–1037.

[16] L. Bao, S. Intille, Activity recognition from user-annotated acceleration data, in: Pervasive '04, Vol. 3001, 2004, pp. 1–17.

[17] A. G. Bonomi, Improving assessment of daily energy expenditure by identifying types of physical activity with a single accelerometer., Journal of Applied Physiology 107 (3) (2009) 655–661.

[18] E. Tapia, Using machine learning for real-time activity recognition and estimation of energy expenditure, in: PhD thesis, MIT, 2008.

[19] M. Altini, J. Penders, O. Amft, Energy expenditure estimation using wearable sensors: A new methodology for activity-specific models, in: Proceed-

ings of the Conference on Wireless Health, WH '12, ACM, New York, NY, USA, 2012, pp. 1:1–1:8.

[20] M. Altini, J. Penders, R. Vullers, O. Amft, Estimating energy expenditure using body-worn accelerometers: a comparison of methods, sensors number and positioning, Biomedical and Health Informatics, IEEE Journal of 19 (1) (2015) 219–226.

[21] M. Altini, P. Casale, J. Penders, O. Amft, Personalized cardiorespiratory fitness and energy expenditure estimation using hierarchical bayesian models, Journal of biomedical informatics 56 (2015) 195–204.

[22] L. Vanhees, J. Lefevre, R. Philippaerts, M. Martens, W. Huygens, T. Troosters, G. Beunen, How to assess physical activity? how to assess physical fitness?, European Journal of Cardiovascular Prevention & Rehabilitation 12 (2) (2005) 102–114.

[23] V. Noonan, E. Dean, Submaximal exercise testing: clinical application and interpretation, Physical Therapy 80 (8) (2000) 782–807.

[24] A. S. Jackson, S. N. Blair, M. T. Mahar, L. T. Wier, R. M. Ross, J. E. Stuteville, Prediction of functional aerobic capacity without exercise testing., Medicine and Science in Sports and exercise 22 (6) (1990) 863–870.

[25] B. M. Nes, I. Janszky, L. J. Vatten, T. Nilsen, S. T. Aspenes, U. Wisløff, Estimating vo2peak from a nonexercise prediction model: the hunt study, norway, Medicine and Science in Sports and Exercise 43 (11) (2011) 2024–30.

[26] G. Plasqui, K. R. Westerterp, Accelerometry and heart rate as a measure of physical fitness: cross-validation., Medicine and science in sports and exercise 38 (8) (2006) 1510–1514.

[27] M. R. Esco, E. M. Mugu, H. N. Williford, A. N. McHugh, B. E. Bloomquist, Cross-validation of the polar fitness test via the polar f11 heart rate monitor in predicting vo2max, Journal of Exercise Physiology 14 (2011) 31–37.

[28] S. Crumpton, H. N. Williford, S. O'Mailia, M. S. Olson, L. E. Woolen, Validity of the polar m52 heart rate monitor in predicting vo2max, Medicine & Science in Sports & Exercise 35 (5) (2003) S193.

[29] J. R. Ruiz, J. Ramirez-Lechuga, F. B. Ortega, J. Castro-Pinero, J. M. Benitez, A. Arauzo-Azofra, C. Sanchez, M. Sjöström, M. J. Castillo, A. Gutierrez, et al., Artificial neural network-based equation for estimating vo 2max from the 20m shuttle run test in adolescents, Artificial intelligence in medicine 44 (3) (2008) 233–245.

[30] Z.-B. Cao, N. Miyatake, M. Higuchi, K. Ishikawa-Takata, M. Miyachi, I. Tabata, Prediction of vo2max with daily step counts for japanese adult women, European journal of applied physiology 105 (2) (2009) 289–296.

[31] T. Tönis, K. Gorter, M. Vollenbroek-Hutten, H. Hermens, Comparing vo2max determined by using the relation between heart rate and accelerometry with submaximal estimated vo2max., The Journal of sports medicine and physical fitness 52 (4) (2012) 337–343.

[32] O. Amft, C. Lombriser, T. Stiefmeier, G. Tröster, Recognition of user activity sequences using distributed event detection, in: Smart Sensing and Context, Springer, 2007, pp. 126–141.

[33] D. M. Blei, A. Y. Ng, M. I. Jordan, Latent dirichlet allocation, the Journal of machine Learning research 3 (2003) 993–1022.

[34] T. Huynh, M. Fritz, B. Schiele, Discovery of activity patterns using topic models, in: Proceedings of the 10th international conference on Ubiquitous computing, ACM, 2008, pp. 10–19.

[35] J. Seiter, O. Amft, M. Rossi, G. Tröster, Discovery of activity composites using topic models: An analysis of unsupervised methods, Pervasive and Mobile Computing 15 (2014) 215–227.

[36] M. Altini, P. Casale, J. Penders, O. Amft, Personalization of energy expenditure estimation in free living using topic models, IEEE Journal of Biomedical and Health Informatics 19 (5) (2015) 1577–1586.

[37] H. Kuipers, F. Verstappen, H. Keizer, P. Geurten, G. Van Kranenburg, Variability of aerobic performance in the laboratory and its physiologic correlates, International journal of sports medicine 6 (04) (1985) 197–201.

[38] K. Westerterp, L. Wouters, L. W. van Marken, The maastricht protocol for the measurement of body composition and energy expenditure with labeled water., Obesity research 3 (1995) 49–57.

[39] Y. Zheng, L. Zhang, X. Xie, W.-Y. Ma, Mining interesting locations and travel sequences from gps trajectories, in: Proceedings of the 18th international conference on World wide web, ACM, 2009, pp. 791–800.

[40] E. Redding, M. Wyon, J. Shearman, L. Doggart, Validity of using heart rate as a predictor of oxygen consumption in dance, Journal of Dance Medicine & Science 8 (3) (2004) 69–72.

[41] A. Loimaala, H. Huikuri, P. Oja, M. Pasanen, I. Vuori, Controlled 5-mo aerobic training improves heart rate but not heart rate variability or baroreflex sensitivity, Journal of Applied Physiology 89 (5) (2000) 1825–1829.

[42] N. Uth, H. Sørensen, K. Overgaard, P. K. Pedersen, Estimation of vo2max from the ratio between hrmax and hrrest–the heart rate ratio method, European journal of applied physiology 91 (1) (2004) 111–115.