Journal of Biomedical Informatics 56 (2015) 195–204

Contents lists available at ScienceDirect

Journal of Biomedical Informatics

journal homepage: www.elsevier.com/locate/yjbin

Personalized cardiorespiratory fitness and energy expenditure estimation using hierarchical Bayesian models

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ARTICLE INFO

Article history:
Received 21 November 2014
Revised 23 March 2015
Accepted 8 June 2015
Available online 14 June 2015

Keywords:
Cardiorespiratory fitness
Energy expenditure
Hierarchical Bayesian models
Heart rate
Accelerometer

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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http://dx.doi.org/10.1016/j.jbi.2015.06.008
1532-0464/

[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