Demonstration Paper: Personalized Physical Activity Monitoring on the Move

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ABSTRACT

Accurate Energy Expenditure (EE) estimation is key in understanding how behavior and daily Physical Activity (PA) patterns affect health. Mobile phones and wearable sensors (e.g. accelerometers (ACC) and heart rate (HR) monitors) have been widely used to monitor PA. In this paper we present a real-time implementation of activity-specific EE estimation algorithms, using an Health Patch and an iPhone. Our approach to continuous monitoring of PA targets personalized behavior and health status assessment, by automatically accounting for a person's cardiorespiratory fitness level (CRF), which is the main cause of inter-individual variation in HR during moderate to vigorous activities. The proposed system opens new opportunities for personalized health assessment in daily life, using ubiquitous devices.

Categories and Subject Descriptors

J.3 [**Computer Applications**]: Life & medical sciences—*Health*

General Terms

Algorithms, Experimentation

1. INTRODUCTION

To determine the links between PA and health, accurate quantification of habitual PA in ambulatory settings is essential. New technologies able to monitor objectively and non-invasively our behavior can provide unprecedented insights on these links. Among these technologies, ACC and HR monitors are the most widespread. The most advanced algorithms combine ACC and HR in activity-specific models, dividing the estimation process into two steps. First, the activity performed is determined. Secondly, an activity-specific equation is applied to estimate EE. However, regardless of the methodology used, HR-based algorithms typically require individual calibration to cope with the substantial inter-individual differences in the relation between HR and EE. During moderate to vigorous PA, differences in HR between individuals are mainly due to CRF. Thus, we propose a real-time implementation of an HR normalization procedure that, based on daily life activities, can automatically estimate CRF-related variance and personalize EE estimates.

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2. THE NEED FOR PERSONALIZATION

The main cause of differences in the HR-EE relation during activity is CRF. An individual with higher CRF (i.e. more fit), will have a lower HR during exercise. Fig. 1 shows the relation between HR and EE for two subjects. Given the similar body size, EE is almost the same, while HR is very different, due to higher fitness level of subject 20. Since EE is derived from HR, the outcome will be over or under-estimated. Individual calibration is not practically feasible since it requires each user to perform tests, using an indirect calorimeter. Thus, alternative methods to tackle the problem are needed to objectively and accurately estimate EE at the individual level, and not only as group averages. When normalizing HR, we are interested in the HR the different individuals would reach when performing the same activity, at the same workload. This HR at a constant workload is representative of CRF, and can be used to normalize HR. We selected running at $10 km/h$ as the constant workload (HR normalization factor), since running at 10 to 12 km/h could explain 88% of the variance in VO_2 max in past research [2], showing that it well represents CRF.

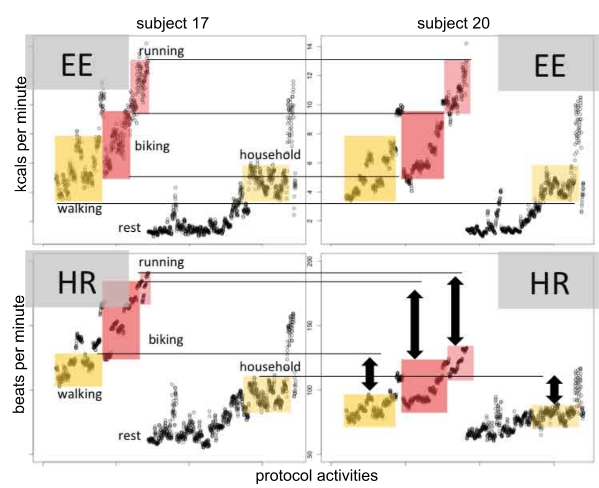

Figure 1: Relation between HR and EE for two subjects with similar body size but different CRF level.

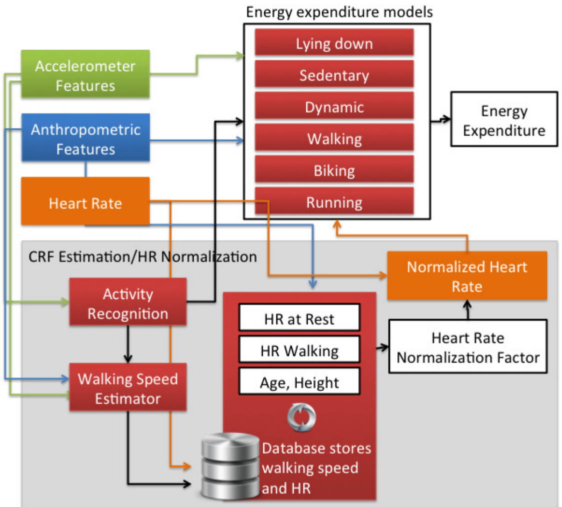

Figure 2: Personalized EE estimation system.

We implemented a system able to derive the CRF-related normalization factor automatically during daily life, by combining HR at rest and during walking activities, in order to predict an individual's HR while running at 10 km/h. The algorithm is able to self-adapt and learn from its user, without requiring any individual calibration. The derived HR normalization factor is used to normalize HR. Then, the normalized HR is used as a predictor for the activity-specific EE estimation equations (see Fig. 2).

3. SYSTEM ARCHITECTURE

The proposed solution is composed by two hardware components, imec's Health patch [3] and an iPhone. imec's Health patch was configured to acquire 128 Hz ECG and 32 Hz ACC, extract R-R intervals, and send HR and ACC via Bluetooth Low Energy. The software architecture is detailed in Fig. 2. We extended the architecture of activity-specific EE estimation algorithms, including the components necessary to estimate CRF and normalize HR. To automatically personalize the system, HR at rest and while walking, together with walking speed, are stored in a database on the phone. The medians of the last week of HR data in the different activities (rest, walking at 3 *to* 6 km/h) is used to recalculate the normalization factor daily. This way, changes in CRF will be automatically reflected in changes in normalized HR and used to properly estimate EE.

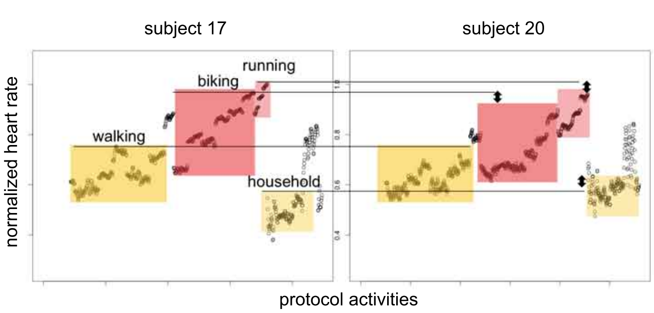

Figure 3: Qualitative result of the HR normalization procedure for the same subjects of Fig. 1.

Figure 4: iPhone app and imec's Health patch.

4. ALGORITHMS IMPLEMENTATION

Offline models were developed using data from 29 participants performing a wide set of PAs [1]. Online versions of the regression models (walking speed, normalization factor and EE estimations) use the same features as the offline versions, thus accuracy is not affected by the online implementation. On the other hand, the activity recognition model was modified to ease implementation on the phone. The system can recognize six clusters of activities (*lying, sedentary, dynamic, walking, biking* and *running*). Accuracy was 87%, compared to the 94% of the offline version, due to higher misclassification for *biking*. In future versions we plan to integrate GPS data to increase accuracy. Walking speed was estimated using ACC features and the individual's *height* (RMSE $= 0.28 \pm 0.09\, km/h$). Another regression model was built to predict the normalization factor using activities of daily living. The model relies on HR while *lying* resting and while *walking at 4, 5 and 6 km/h*, together with the individual's *height* and *age* (RMSE = 8.3 beats per minute). Actual HR measurements are then divided by the normalization factor. Fig. 3. shows a qualitative result of the effect of the HR normalization. We implemented six activity-specific EE linear models, and used the normalized HR, ACC and anthropometric features to estimate EE (RMSE $= 0.60\, kcal/min$). Reduction in error using the normalization factor ranged between 3 and 33% for the different clusters.

5. DEMO

Real-time activity recognition and personalized activity-specific EE estimates will be shown using an iPhone app, connected to imec's Health patch (see Fig. 4).

6. REFERENCES

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