Phone in the Pocket: Pervasive Self-Tracking of Physical Activity Levels

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Abstract

Mobile (smart)phones prevail in our daily life activities, and in our research we aim for it to provide pervasive services for wellness. Therefore, we assess the phone's feasibility to unobtrusively, continuously and in real-time track its user's physical activity and the resulting energy expenditure (EE). Activity Level Estimator (ALE) is an Android OS application developed for that purpose. We have assessed the accuracy of ALE against the BodyMedia SenseWear (SW) device and the gold standard for EE estimation, *i.e.*, an indirect calorimetry (IC) method. ALE has mean accuracy of 86% (vs. SW) to 93% (vs. IC) for walking, and in 24h it underestimates EE by 23% ALE is currently used for a long-term behavioral trends study with the University of Geneva students and faculty.

Introduction

Nowadays, we are are less active and more sedentary, mainly due to the lack of time and motivation. Risks related to sedentary lifestyle relate to, *e.g.*, cardiovascular diseases, osteoporosis, cancers, psychological disorders, and the most commonly witnessed current epidemic of overweight and obesity (Cavill, 2006; Bernstein 1999; Varo, 2003). As the primary prevention, WHO recommends at least 150 minutes of a moderate-intensity, or at least 75 minutes vigorous-intensity of physical activity in the week, where the activity is to be performed in bouts of at least 10 minutes duration (WHO, 2010).

At the same time, we witness the emerging trend of use of high-end personal mobile phones, that people carry around almost all the time (Dey, 2011). Many sports and fitness applications are already available for phones, but they are disruptive as they use external devices, or require manual entry of the activities. The identified gap in the existing approaches is lack of use of mobile phone and its built-in sensors for an accurate, pervasive monitoring of physical activities performed along the persons daily life activities and for provisioning of an encouraging feedback. Towards this end, we develop Android OS based application called Activity Level Estimator (ALE) and evaluated it against gold standard methods, as reported in this paper.

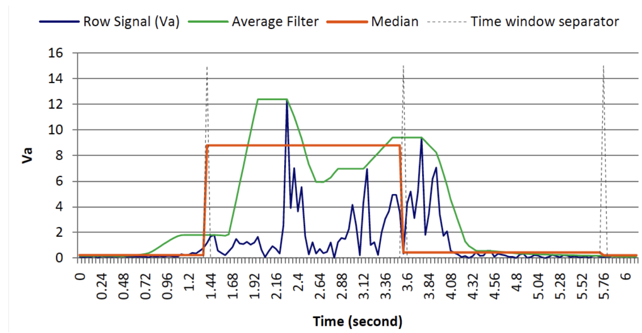

Figure 1: Ex. Deriving the Median Acceleration Density.

Methods and Results

The algorithm employed in the studies and preliminary evaluation results in lab and outdoors, are as follows.

The Algorithm

The body acceleration is monitored by the 3D accelerometer build-in in the Android OS mobile phone (freq. 40 Hz). The raw accelerometer readings are compensated for the gravity factor, clearing off the influence of the phone orientation. After this, ALE derives a vector of acceleration *Va* (m/s2), filters it (for noise removal) and scales it (for better discrimination of levels), then it calculates a median acceleration density during a predefined observation time interval (ΔT = 2s) (Fig. 1). Finally, it compares this result with the levels *predefined* for given physical activity levels. Each level matches to a *Metabolic Equivalent of Task* (MET) (Ainsworth, 2000), which relate to a given *energy expenditure* (EE) of a person, given her gender, age, height and weight (details in (Hausmann, 2010; Hausmann, Wac 2011)).

Evaluation: Walking Activities

In the user study we have assessed the accuracy of ALE for walking activity. We have used the BodyMedia SenseWear (SW) device and an indirect calorimetry (IC) method to compare with. The participants were healthy volunteers of both sexes, of different age (23-31), height and weight, and they were wearing their casual clothes and shoes. We have asked them to walk a) on a flat surface in a building (using

SW); b) on a relatively flat parking surface outdoors (SW), c) on a treadmill (SW and IC). Each time we asked user to walk around 5 minutes at different speeds, from 3 to 6 km/h. ALE has mean accuracy of 86% (vs. SW) to 93% per a minute (vs. IC) for different speeds of walking.

Evaluation: Daily Life Activities

We aim to accurately, pervasively monitor of physical activities performed along the persons daily life activities, hence, we have also conducted a long-term ALE evaluation along an arbitrary three days with a randomly selected study participant (31 years old male), accumulating in total 30 hours of data. We have instructed the participant to follow usual daily life activities while wearing SenseWear and ALE, putting these off when sleeping. We present example results of this validation in (Fig. 2). We have added some annotations into figures for activities like driving, shopping and working.

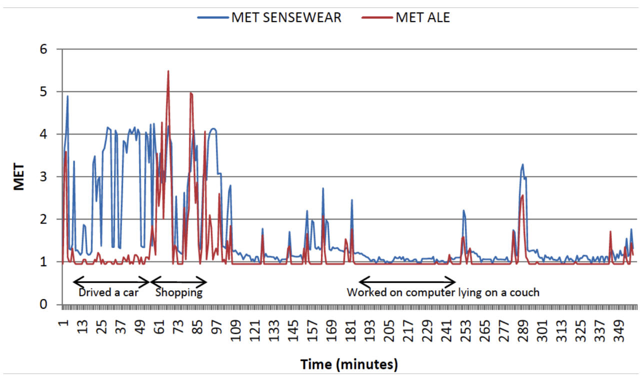

Figure 2: Evaluation for Daily Life Activities (6 hrs)

ALE tends to underestimate MET by 23% in 24h. From data we conclude that ALE does underestimate EE for sedentary activities like watching TV, lying on a couch and working on computer, We think that SW is able to estimate EE for these physical as well as cognitive activities because of its additional sensors like temperature and galvanic skin response. ALE was not able to detect that because, except arm, the participant did not move. However, the shopping activity was detected by ALE almost as accurately (average MET 1) as by SW (1.2 MET).

Application Interface

ALE is developed for Android OS (min. v.2.1) and uses phone's build-in 3D accelerometer. ALE starts at the system start-up and runs continuously in the background of the OS, even when the phone is not used and the screen is locked. A simple GUI was created to manage the user settings and follow the results in real-time - ALE displays four color bars (one an activity level) corresponding to the duration of an activity (Fig. 3) in the current day (*i.e.*, since midnight). The scale of the displayed figures can be adjusted via a touch interface. We have made the choice to not display the sedentary level because the time spend for this activity is generally much longer comparing the other activity levels, and it proved not to be motivating to display it. The GUI displays kcal burned as computed for all activity levels and the EE in kcal as predicted for the current 24h.

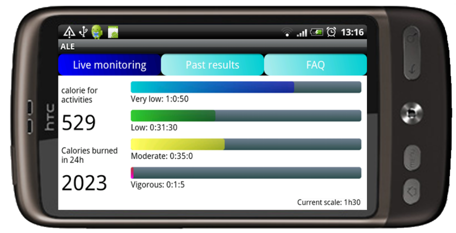

Figure 3: First GUI for the ALE prototype

Conclusion

One of the most important assumptions taken in our research is a minimum obtrusiveness of the proposed activity level estimation solution to the user, and its prevalence through the users daily life activities. Our study has limitations with respect to number of participants and limited time for ALE evaluation, and as such, it may be difficult to generalize these findings, however we find the preliminary results very encouraging. We are preparing more experiments and more user studies, which will enable us to improve our application and include *e.g.*, biking activity. We plan to conduct more studies applying ALE in the user's daily activities, and we are deploying ALE for a long-term behavioral trends study with the University of Geneva students and faculty.

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