Activity-specific Step Counting and Energy Expenditure Models using 3D Wrist Acceleration

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CSEM developed a new physical activity profiling toolbox embedded in a wrist-located device. This toolbox includes step counting and energy expenditure models. Their performances, according to gold-standard validation, provide a significant improvement over the state of the art (total EE relative error of 5.5% against 26.8% for ActiGraph GT1M®) and represent a step forward for most of commercial wellness and training wearable devices.

Originally used by sports and physical fitness enthusiasts, pedometers are now becoming popular as an everyday exercise monitor and motivator (*e.g.* a total of 10'000 steps per day for an active lifestyle [1]). Because the distance of each person's step varies, a user-dependent calibration is usually required if presentation of the distance covered is desired (odometer). In the latest trends, step counters are being integrated into an increasing number of portable consumer electronic devices such as music players and smartphones. Energy expenditure (EE) measurements are important indicators to consider for the estimation of physical activity in combination with the energy intake to keep the body weight stable. The most used EE estimated methods are detailed activity/food diary, isotopic measurements, and direct and indirect calorimetry methods. Due to their cost, technical difficulties, or infrastructure requirements, none of them is suitable for daily-life EE monitoring. To overcome this issue, a large variety of methods based on diverse approaches (such as pedometry, actigraphy or electrocardiography) have been proposed. However, most of them are characterized by biased and inaccurate EE estimates that need specific user-dependent calibration protocols. CSEM has recently developed human activity-specific step counting and EE models. These calibration-free models based on subject's activity require 3D acceleration signals at the wrist and anthropometric parameters (e.g., weight and height) as inputs. The 3D accelerometer signals recorded on the wrist device are used for three purposes: physical activity classification, step count, and EE estimation.

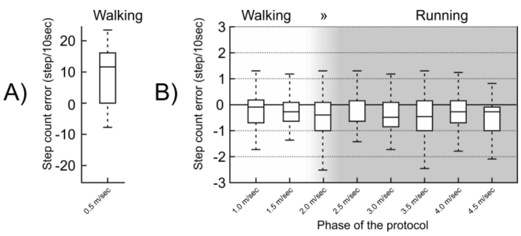

Figure 1: Performance of the step count model for each walking/running speed. Each distribution shows the 25th and 75th percentiles (lower and upper bounds of the box), the median (line within the box), and the minimum and maximum (lower and upper lines) values. Panel A displays the results for very slow walking, while panel B displays the results for walking to running.

Physical activity classifier—Several features are extracted from the accelerometer signals. These include signal strength, rhythmicity, and frequency stability among others. These features are used as predictors in a classification tree whose nodes depict different likelihoods for each activity. This tree was trained with a wide range of physical activities.

Step count model—This process starts by classifying the identified activities in two groups: rhythmic and non-rhythmic activities. Based on the result, a spectral analysis or a time-domain analysis is performed and the corresponding steps estimated from the time-window frequency (cadence) or single step is computed and added to the total step count.

Energy expenditure model—This human EE model is activity-dependent. For the activity classes *Rest* and *Other*, it uses a constant value of MET. For the activities classify as *Walk* and *Run*, it uses the so-called SPE2AR model, which uses a walking/running forward speed [2].

The performance of these two models and their activity classification sub-model were evaluated with respect to gold standards (ActiGraph GT1M® step counts, total energy expenditure estimated from indirect calorimetry) for a fixed protocol with activities including lying down, standing, sitting, walking, and running. The results are shown on Figures 1 & 2.

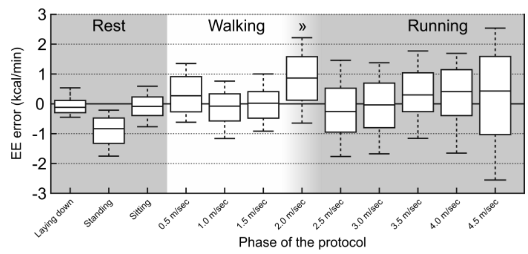

Figure 2: Performance of the EE model for each activity. The distributions have the same meaning as Figure 1.

Based on the presented results, we conclude that the proposed model for step count and EE offer a high accuracy as compared to off-the-shelf commercialized devices for walking and running activities at speeds larger or equal to 1.5m/s. More precisely, we achieve performance values of 0.71±0.06step/10s for the step-count model and 1.22±0.34 kcal/min and a total EE relative error of 5.52% for the EE. These performances improve by an order of magnitude most of the commercial solutions based on actimetry sensor (total EE relative error of 26.8 % for ActiGraph GT1M®). However, rhythmic low-speed activities (walking at 0.5m/s) introduce misclassifications that limit the overall performance of the device. This limitation is being addressed by CSEM in the frame of its on-going research activity.

[1] G. C. Le Masurier, C. L. Sidman, C. B. Corbin, "Accumulating 10,000 steps: does this meet current physical activity guidelines?," Res. Q. Exerc. Sport, vol. 74, no. 4, pp. 389–394, 2003

[2] R. Delgado-Gonzalo, *et al*., "Human Energy Expenditure Models: Beyond State-of-the-Art Commercialized Embedded Algorithms," Digit. Hum. Model. Appl. Heal. Safety, Ergon. Risk Manag. Lect. Notes Comput. Sci., vol. 8529, pp. 3–14, 2014