# Human Energy Expenditure Models: Beyond State-of-the-Art Commercialized Embedded Algorithms

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**Abstract.** In the present study, we propose three new energy expenditure (EE) methods and evaluate their accuracy against state-of-the-art EE estimation commercialized devices. To this end, we used several sensors on 8 subjects to simultaneously record acceleration forces from wrist-located sensors and bio-potentials estimated from chest-located ECG devices. These subjects followed a protocol that included a wide range of intensities in a given set of activities, ranging from sedentary to vigorous. The results of the proposed human EE models were compared to indirect calorimetry EE estimated values (kcal/kg/h). The speed-based, heart rate-based and hybrid-based models are characterized by an RMSE of 1.22 ± 0.34 kcal/min, 1.53 ± 0.48 kcal/min and 1.03 ± 0.35 kcal/min, respectively. Based on the presented results, the proposed models provide a significant improvement over the state-of-the-art.

**Keywords:** energy expenditure, walking/running speed, human model, physical activity monitoring.

## 1 Introduction

The rapidly increasing prevalence of overweight and obesity is a worldwide health problem. Due to the associated serious medical conditions, it is estimated that obesity already accounts for up to 7% of healthcare costs in EU. Moreover, this value increases when considering the costs to wider economy associated with low productivity lost output and premature health problems [1]. At the simplest level, obesity results from a disturbed energy balance that reaches equilibrium only in an obese state. This situation occurs when energy intake is high and EE (physical activity) is low. Despite advances in dietary, exercise-based, behavioral, pharmacological and bariatric surgical approaches, lifestyle intervention remains the cornerstone of the prevention and treatment of obesity [2]. EE measurements are important indicators to consider for the estimation of spontaneous physical activity, as well as energy intake when body weight is stable (i.e., when EE equals energy intake).

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Numerous laboratory methods can be used to estimate whole-body EE at rest and during exercise such as detailed activity/food diary [3], isotopic measurements [4], and direct and indirect calorimetry methods [5]. These methods have advantages and drawbacks that make them more appropriate in one situation or another, but, because of their cost, technical difficulties, or infrastructure, none of them is suitable for daily-life EE monitoring. To overcome this issue, other methods, based on approaches such as pedometry, actigraphy or electrocardiography have been proposed. These methods use human kinetic models based on diverse parameters; namely step counts, heart rate (HR), speed, weight, sex, etc. The resulting EE estimation of such models might be sufficient for several applications. However, most of them are characterized by biased and inaccurate instantaneous EE values and necessitate specific calibration protocols.

Recent studies have presented new approaches which combined long-term wearable miniaturized sensors and activity-specific EE models [6-7]. These approaches first classify the physical activity of the subject, and then apply an activity-specific EE model. However, the evaluation of these models is not clear or is poorly documented. Moreover, the EE model inputs vary from activity class, through subject's anthropometric parameters and subject's fitness indicators, to precise calibration values and HR [8-9]. A clear overall picture of the accuracy of such EE models is therefore required.

In the present study, we propose three different human activity-specific EE models and evaluate their accuracy. These models range from two simple models based on (i) the subject's estimated speed and anthropometric parameters (speed-based model), (ii) instantaneous fitness parameters (HR-based model), or a (iii) multimodal model using estimated speed, anthropometric parameters and fitness parameters (hybrid-based model). The performance of these three models is evaluated with respect to gold standards (treadmill speed and body energy expenditure estimated from indirect calorimetry) and compared to published human EE models embedded in commercial devices.

## 2 Method

The following section describes the database and the protocol used in this study. It also describes the different proposed human speed and EE models. Finally, it contains the evaluation procedure and the statistical tools used to quantify the performance of the proposed models and to compare them against commercialized EE monitors.

### 2.1 Database and Protocol

In order to develop various human EE models, acceleration forces from CSEM's proprietary wrist-located sensors and bio-potentials estimated from chest-located dry electrodes were recorded simultaneously over 8 healthy male subjects. The distribution of the subjects' anthropometric parameters is shown in **Error! Reference source not found.**. The subjects followed a standardized protocol that included a wide set of activities, ranging from sedentary to vigorous, recorded in laboratory settings.

More precisely, it consisted in three 3-minute phases of resting (lying down, standing up and sitting) and 3-minute walking/running phases (from 0.5 m/s to exhaustion; with steps of 0.5 m/s).

In order to validate both the human EE models and their human walking/running speed sub-models, gold standard measurements were simultaneously recorded, namely the speed values labelled $v_{ref}$ obtained from a treadmill (Technogym's Excite® Med), the HR values labelled $HR$ obtained from an ambulatory ECG monitoring device, and the EE values labeled PMETAMAX obtained from a Cortex's METAMAX® 3B device (accuracy of ±2.1% MET or kcal/kg/h) using an embedded indirect calorimetry approach. An Actigraph's GT1M® device is also measuring the EE simultaneously.

Before recording each subject, the oxygen (O2), carbon dioxide (CO2) analyzers and the atmospheric pressure and air volume sensors were calibrated using a medical grade calibration gas with known concentrations and known total volume. The air of the room was also taken into account in the indirect calorimetry computation.

**Table 1.** Subjects' anthropometric parameters

| Characteristic | μ±σ (N = 8) | Range |
|---|---|---|
| Age [years] | 35.95 ± 6.74 | 27 - 46 |
| Height [m] | 1.82 ± 0.07 | 1.72 - 1.95 |
| Weight [kg] | 75.88 ± 6.35 | 65 - 87 |

## 2.2 Activity Classification and Human Speed Estimation

In this study, the 3D accelerometer signals (x-, y- and z-axis) are used for two purposes: classification of activity and estimation of the speed. Firstly, these 3D signals are used to classify each subject's physical activity for every sample. In the context of this study, the considered classes of activities are: resting (subdivided in lying down, standing and sitting postures), walking, and running. The resulting activity-specific episodes were used to train an activity-specific human speed model based on common anthropometric parameters (i.e., weight, height and sex) and biomechanics principles. The proposed human EE models are finally trained by the resulting speed estimates (defined as $\hat{v}$) and the identified activity-specific episodes.

## 2.3 Human Energy Expenditure Models

**Speed-Based Model: SPE$^2$AR.** As previously mentioned, each timestamp (sampling frequency of 0.9 second) is first classified in one of the following categories: resting, walking or running. Then, a multi-linear regression is performed for each category taking into account the speed and anthropomorphic parameters. The resulting model is denoted as SPE$^2$AR (Speed-based Piece-wise Energy Estimation using AntRopomorphics). Formally, the regression model can be written as:

$$P_{\mathrm{SPE^2AR}} = \begin{cases} \alpha_{\mathrm{rest}}\, v + \beta_{\mathrm{rest}}\, w + \gamma_{\mathrm{rest}}\, h + \delta_{\mathrm{rest}}, & \text{if resting} \\ \alpha_{\mathrm{walk}}\, v + \beta_{\mathrm{walk}}\, w + \gamma_{\mathrm{walk}}\, h + \delta_{\mathrm{walk}}, & \text{if walking} \\ \alpha_{\mathrm{run}}\, v + \beta_{\mathrm{run}}\, w + \gamma_{\mathrm{run}}\, h + \delta_{\mathrm{run}}, & \text{if running} \end{cases} \tag{1}$$

where $v$ is the speed in km/h, $w$ is the weight in kg and $h$ is the height in cm.

**HR-Based Model: HEET.** A multi-linear regression is performed for each category using instantaneous HR values. These instantaneous HR values are obtained from applying an embedded R-wave detection algorithm to ECG signals. The resulting model is denoted as HEET (HR-based Energy EstimaTion). Formally, the regression model can be written as:

$$P_{HEET} = \begin{cases} \alpha_{\mathrm{rest}} HR + \beta_{\mathrm{rest}}\,, & \text{if resting} \\ \alpha_{\mathrm{active}} HR + \beta_{\mathrm{active}}\,, & \text{if active} \end{cases}, \tag{2}$$

where $HR$ is the instantaneous HR in $\mathrm{min}^{-1}$.

**Hybrid-Based Model: QI²Hybrid.** Our multimodal hybrid model combines both previous models into a single expression with the addition of two quality indicators labelled as $p_{\mathrm{SPE^2AR}}$ and $p_{\mathrm{HEET}}$ (speed and HR values). Once both models have been properly calibrated, QI²Hybrid (Quality Indicator Hybrid) model can be written as:

$$P_{\mathrm{QI^2Hybrid}} = p_{\mathrm{SPE^2AR}} P_{\mathrm{SPE^2AR}} + p_{\mathrm{HEET}} P_{\mathrm{HEET}}, \tag{3}$$

where $p_{\mathrm{SPE^2AR}}$ is the probability of $P_{\mathrm{SPE^2AR}}$ producing a better estimate than $P_{\mathrm{HEET}}$ and $p_{\mathrm{HEET}}$ is the probability of $P_{\mathrm{HEET}}$ providing a better estimate than $P_{\mathrm{SPE^2AR}}$. Note that the relation $p_{\mathrm{SPE^2AR}} = 1 - P_{\mathrm{HEET}}$ always holds. These quality indicators are defined as

$$p_{\mathrm{SPE^2AR}} = 1 - Q_{\mathrm{HR}} \frac{\mathrm{RMSE_{SPE^2AR}}}{\mathrm{RMSE_{HEET}} + \mathrm{RMSE_{SPE^2AR}}} \tag{4}$$

and

$$p_{\mathrm{HEET}} = 1 - p_{\mathrm{SPE^2AR}}\,, \tag{5}$$

where $0 \leq Q_{\mathrm{HR}} \leq 1$ is a value that informs about the quality of the current estimation of the HR value, and $\mathrm{RMSE_{HEET}}$ and $\mathrm{RMSE_{SPE^2AR}}$ are the root mean squared errors of the HEET and SPE²AR models, respectively. Note that in the extreme case, when $Q_{\mathrm{HR}} = 0$, the estimation of the EE is completely based on SPE²AR model:

$$P_{\mathrm{Hybrid}} = P_{\mathrm{SPE^2AR}}. \tag{6}$$

Analogously, when $Q_{\mathrm{HR}} = 1$ the estimation of EE is based on the convex combination of both methods relative to their performance:

$$P_{Hybrid} = \frac{\mathrm{RMSE_{HEET}}}{\mathrm{RMSE_{HEET}} + \mathrm{RMSE_{SPE^2AR}}} P_{\mathrm{SPE^2AR}} + \frac{\mathrm{RMSE_{SPE^2AR}}}{\mathrm{RMSE_{HEET}} + \mathrm{RMSE_{SPE^2AR}}} P_{\mathrm{HEET}}. \tag{7}$$

Note that all EE models are expressed in MET or in kcal/kg/h.

**Statistical Analysis.** In order to deal with the limited number of subjects (N=8) in the database, a leave-one-out cross validation procedure is applied to the entire database in order to fit the EE models and to evaluate their respective performance with respect to the ground truth values (METAMAX® 3B values). That is, the parameters of each model are estimated using N-1 subjects and validated against the remaining one, and this procedure is iterated for each subject. The two quality indicators $p_{\mathrm{SPE^2AR}}$ and $p_{\mathrm{HEET}}$ are obtained in the same manner. Concerning SPE$^2$AR, the coefficient of determination ( $R^2$) distribution equals $0.96 \pm 0.02$ , whereas for HEET and QI$^2$Hybrid models, the $R^2$ distributions equal $0.92 \pm 0.05$ and $0.96 \pm 0.02$.

For the evaluation of the performance over the entire database of the proposed models, three performance indicators are defined: the distribution of the absolute and relative errors and the distribution of the RMSE. These distributions are characterized by their mean μ and standard deviation σ. In order to compare our results with other studies, MET values are converted into kcal/min. Table 2 defines these three performance indicators.

**Table 2.** Description of the performance indicators

| Performance indicator | Equation |
|---|---|
| Absolute energy error [kcal] | $\lvert E_{\mathrm{METAMAX}} - \hat{E} \rvert$ |
| Relative energy error [%] | $\lvert E_{\mathrm{METAMAX}} - \hat{E} \rvert / E_{\mathrm{MetaMax}}$ |
| Root mean squared error (RMSE) [kcal/min] | $w \times \sqrt{\frac{\int \lvert P_{\mathrm{METAMAX}} - \hat{P} \rvert^2}{\Delta t}}$ |

Here, $E_{\mathrm{METAMAX}}$ is the total energy measured by METAMAX® 3B, which equals $w \times \int P_{\mathrm{METAMAX}}\, dt$. $\hat{E}$ is the total energy estimated by the proposed models, which equals $w \times \int \hat{P}\, dt$. RMSE provides insight on the instantaneous error, while absolute and relative energy errors show how the errors accumulate over time. When these errors are accumulated over the entire recording sessions, they are referred as total EE errors.

**Comparison with Commercialized EE Estimates.** The comparison against commercial estimates is based on a limited set of published academic studies. Only the Actigraph's GT1M provided real-time EE estimates that could be simultaneously acquired during the recordings. To provide a fair comparison, we contrast the published measures against appropriate test conditions within our protocol (e.g. walking episodes compared to low intensity activities).

# 3 Results

## 3.1 Performance of the Three Proposed Models

The overall performance of the activity-specific speed model is characterized by an RMSE distribution of 0.114 ± 0.063 km/h. The performance of the proposed activity-specific EE models (SPE2AR, HEET and QI2Hybrid models) is shown in Table 4 in terms of absolute, relative and RMS errors.

**Table 3.** Performance of activity-specific EE models

| EE model | Total EE absolute error distribution (μ±σ) | Total EE relative error distribution (μ±σ) | RMSE distribution (μ±σ) |
|---|---|---|---|
| SPE$^2$AR | 17.91 ± 9.32 kcal | 5.52 % ± 2.21 % | 1.22 ± 0.34 kcal/min |
| HEET | 18.80 ± 9.40 kcal | 6.17 % ± 3.08 % | 1.53 ± 0.48 kcal/min |
| QI$^2$Hybrid | 14.57 ± 8.47 kcal | 4.45 % ± 2.30 % | 1.03 ± 0.35 kcal/min |

Fig.1 displays an example of the evolution of EE during the execution of the different tasks included in the experimental protocol. The EE evolution of each model is compared to the ground truth EE values measured by METAMAX® 3B. Panels A and B represent the estimated EE values from SPE$^2$AR, HEET and QI$^2$Hybrid models, respectively. Resting (lying down, standing and sitting postures), walking and running episodes are alternately displayed in gray and white areas. In this case, the subject starts to run at the 21:50.6 minute which is 50.6 sec after starting the 2 m/s step.

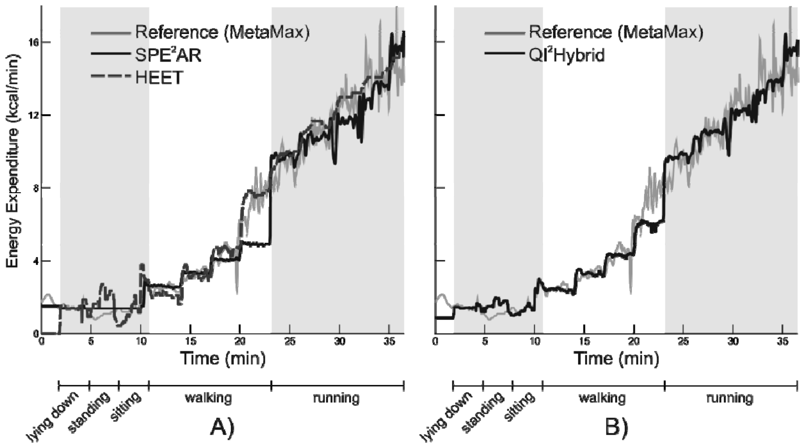


**Fig. 1.** Evolution of estimated EE values (in kcal/min) and ground truth values of a subject over the entire protocol. Panel A displays the results from SPE$^2$AR and HEET, while panel B display the results from QI$^2$Hybrid.

Fig 2 displays the absolute error distribution of QI2Hybrid with respect to the activity class for the same subject (see Fig. 1 B). The resting-, walking- and running-specific error distributions are characterized by mean and standard deviation values of -0.20 ± 0.41 kcal/min, 0.17 ± 0.77 kcal/min and -0.03 ± 0.91 kcal/min, respectively. The first two distributions are bimodal and significantly biased. Moreover, the error distribution during running is characterized by unbiased values ($p<0.05$).

These statistical results are obtained using a Krustal-Wallis one-way analysis of variance between the estimated and ground truth EE values for each class of activities (resting, running and walking).

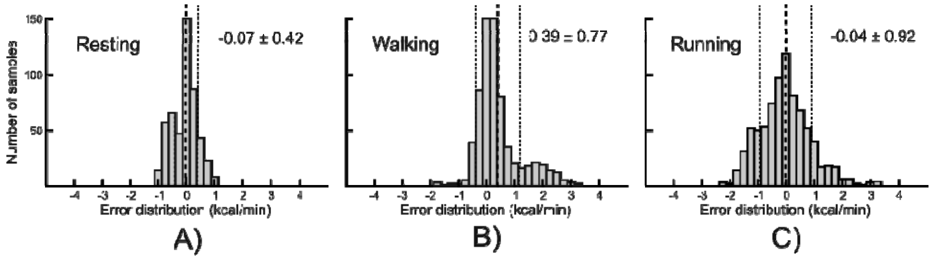


**Fig. 2.** Example of QI$^2$Hybrid error distributions with respect to activity (resting in panel A, walking in panel B and running in panel C). The results correspond to the one showed in Fig. 1 B.

The distribution of EE errors with respect to each 3-minute phases obtained with QI$^2$Hybrid over the entire database is showed in Fig. 3. Resting (lying down, standing and sitting postures), walking and running episodes are alternately displayed in gray and white areas. The subject-dependent walking-to-running transition zone is also displayed. As for the error distributions showed in Fig. 2, the overall distributions associated with resting and walking activities are significantly biased. Moreover, the overall distributions associated with running activities are characterized by unbiased values ($p<0.05$). These statistical results are also obtained using a Krustal-Wallis one-way analysis of variance between the estimated and ground truth EE values for each class of activities (resting, running and walking).

## 3.2 Commercial off-the-Shelf EE Monitoring Devices

The performance of typical off-the-shelf EE monitoring devices is not necessarily accurate (particularly the instantaneous value) but suffices for several applications. Despite their low complexity, the estimation algorithms are proprietary or unpublished. Moreover, the results displayed by the graphic user interface of these devices remain difficult to interpret (e.g., EE per epoch or activity). The following section presents an overview of some available systems, compares, if possible, their performance with our proposed appropriate model. This evaluation is divided into the following methodologies: pedometry, actigraphy, electrocardiography and photoplethysmography.

**Pedometry.** Used originally by sports and physical fitness enthusiasts, pedometers are now becoming popular as an everyday exercise measurer and motivator. They record how many steps a subject has walked during that day. Some pedometers will also erroneously record movements other than walking, such as bending to tie one's shoes, or road bumps incurred while riding a vehicle. Because the length of each person's step varies, an informal calibration, performed by the user, is required if presentation of the distance covered in km is desired (odometer).

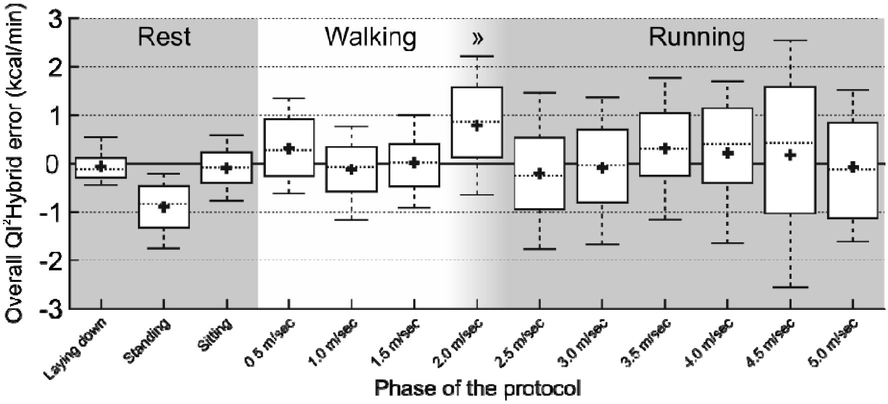


**Fig. 3.** QI2Hybrid EE performance with respect to specific tasks on the entire database. Resting, walking, running and walking/running transition zones are also displayed in alternate grey and white areas. Each distribution shows the mean (bold cross), the median (dotted line), the $25^{th}$ and $75^{th}$ percentile (lower and upper bounds of the box) and the minimum and maximum (lower and upper lines) values.

In Table 4, we present a comparison of the performances of the SPE2AR model and a standard pedometer against the same ground truth. For a fair comparison, the statistics of our methods are restricted over low-intensity exercise, that is, similar conditions in which the other method was tested.

**Table 4.** Comparison with a pedometry-based device for low-intensity exercises

| EE Model | RMSE |
|---|---|
| Walk4Life Elite | 5.0 kcal/6min [8] |
| **SPE$^2$AR** | **4.62 ± 1.76 kcal/6min** |

**Actigraphy.** Actigraphy is a non-invasive method of monitoring human rest/activity cycles. A small actigraph unit is worn by a person to measure gross motor activity. The unit continually records the movements it undergoes. Information on body position can be combined with motion data to increase accuracy. Movement is not directly related to metabolism, since movement type and conditions influence the estimation, and movement based methods cannot generally describe reliably the intensity of physical activity. Additionally, activity counts are defined differently by each sensor's manufacturer (i.e., Actigraph counts, and the equations derived from them, are not directly comparable to Actical or Actiheart counts). In Table 5, we present a comparison, in terms of relative energy, of SPE2AR with several commercial actigraphy-based solutions against the same ground truth.

**Table 5.** Comparison with actigraphy-based devices

| EE Model | Total EE relative error distribution (μ±σ) |
|---|---|
| Actigraph GT1M - Harris-Benedict (N=16) | 26.8 % [9] |
| Actical (N=19) | 17.8 % [9] |
| IDEEA (N=18) | 17.5 % [9] |
| Directlife (N=19) | 13.6 % [9] |
| Fitbit (N=16) | 28.7 % [9] |
| **SPE$^2$AR** | **5.52 % ± 2.17 %** |

In Table 6, we present a comparison, in terms of absolute and relative energy, of SPE$^2$AR with an GT1M device by Actigraph over the proposed protocol.

**Table 6.** Comparison with Actigraph GT1M for our experimental protocol

| EE Model | Total EE absolute error distribution (μ±σ) | Total EE relative error distribution (μ±σ) |
|---|---|---|
| Actigraph GT1M - Work energy theorem | 110.45 ± 49.50 kcal | 35.60 % ± 16.51 % |
| Actigraph GT1M - Vector magnitude | 127.85 ± 49.43 kcal | 40.99 % ± 14.68 % |
| **SPE$^2$AR** | **17.91 ± 9.32 kcal** | **5.52 % ± 2.17 %** |

**Electrocardiography.** Electrocardiography (ECG) is a bio-potential technique aiming at monitoring electrical activity of the heart and constitutes the gold standard technique to monitor HR. When the ECG monitoring systems are wearable, they are specifically referred as Holter systems. A large variety of alternative devices which monitor averaged HR values (one HR value over a specific time window) or heartbeat intervals based on bio-potential measurements exists. Their bio-potential sensors are based on gel, dry or textile electrode principles. There is also a family of strapless/wireless devices that temporally estimates fingertip bio-potentials using sensors embedded into watches (including Health Touch Plus by Timex, Vital by MIO and SmartHealth by Salutron).

In Table 7, we present a comparison, in terms of absolute energy, of HEET, QI$^2$Hybrid and two commercialized HR-monitoring devices. For a fair comparison, the statistics of our methods are restricted over low-intensity exercises, that is, similar conditions in which the other methods were tested. It is important to mention that the database used in Erdogan study [10] was dedicated to overweight and obese subjects during low-intensity exercises.

**Table 7.** Comparison with electrocardiography-based devices for low-intensity exercises

| EE Model | Total EE absolute error distribution (μ±σ) |
|---|---|
| Polar S810i™ (N=43) | 0.5 ± 0.5 kcal/min [10] |
| SenseWear Pro Armband ™ (N=43) | ~2.5 ± 1.1 kcal/min [10] |
| **HEET** | **0.85 ± 0.41 kcal/min** |
| **Hybrid** | **0.72 ± 0.31 kcal/min** |

**Photoplethysmography.** Photoplethysmography is an optical technology aiming at measuring tissue light propagation changes during cardiac cycle. In the daily activity monitoring context, the measurement of volumetric changes of microvascular bed of tissue due to blood flow is the target. This measure brings information on arterial pulsatility content. Wearable HR monitoring devices using this technology are already available on the market (including Nonin's Onyx 2, MIO's Alpha and Basis products). Unfortunately, to our knowledge, no peer-reviewed studies exist on the EE estimation performance based on this technology.

# 4 Discussion

## 4.1 Performance and Validation

The present study demonstrates that SPE2AR provides already an accurate estimate of EE with an average of 1.22 kcal/min across all activities and subjects. Since the model is based on two complementary modes (walking vs. running), the system produces an artifact when the subjects switch from one mode to the other. We can observe this interphase around the minute 22 within Fig. 1 A.

We observe that HEET provides an overall performance of 1.53 kcal/min (see Fig. 1 A), which is slightly worse than the one offered by SPE2AR. However, HEET does not experience any artifact in the interphase between the walking to running modes. The accuracy of the HR-based model might be explained by the fact that the HR values are estimated for every time stamp using a small amount of previous detected R-waves instead of using global averages. Moreover, we also observe the well-known phenomenon that the HR-based model has a bigger relative error for low HR. This can be noticed in the resting phases within Fig. 1 A (lying down, standing up and sitting).

Finally, the combination of both methods (QI2Hybrid) still exhibits a small jump at interphase between the running and walking phases. However, this discontinuity is mostly smoothed out by the contribution of the HR-based model (see Fig. 1 B). Moreover, the hybrid method provides a more robust estimation of the energy consumption for low values of HR (see lying down, standing up and sitting categories within Fig. 1 B). This is due to the fact that the speed-based method regularizes the variability introduced by the HR-based method. In Fig. 3, we can observe the behavior of the error distribution for the different tasks comprised in the protocol. It can be shown that the dispersion of the error increases as the activity becomes more vigorous. This is due to increase in the variance of the estimate of our method as well as the METAMAX® 3B (see Fig. 1 for a typical example). In particular, we observe this phenomenon in the width of the distributions shown in Fig. 2. The distribution in the resting category exhibits a sharp peak at zero, but it contains a second mode due to the poor estimation of the energy while standing (see Fig. 3). The error distribution becomes broader in the walking category, and a new secondary mode can be observed which corresponds to the transition towards running (see 2.0 m/sec in Fig. 3). Finally, the error distribution in the running category exhibits a Gaussian appearance with the largest support.

All three EE models have shown to adjust properly to the subjects of the database, being the mean coefficients of determination $R^2$ 0.96, 0.92 and 0.96. Moreover, the standard deviations of these coefficients are quite low (0.02, 0.05 and 0.05). This indicates that our statistical models are robust to the change of the training data.

### 4.2 Models versus Commercialized Devices

In view of these preliminary but promising results, it suggest that the proposed models, specially the one combining all source of information, seem accurate at low, moderate and high activity levels. In particular, the accuracy of our speed-based method has shown to be comparable to the one reported by Walk4Life for low-activity levels (see Table 4), and to improve by an order of magnitude most of the commercial solutions based on actigraphy (see Table 6). For a fair comparison, we also used an actigraphy-based method as control within out protocol (see Table 7). The results were in concordance with the ones reported by the referred study [9] (see Table 6).

As discussed, the HR-based method seems accurate even during stationary physical activities (see Fig. 1 A). Moreover, the accuracy of our methods using HR information have shown to be comparable to the ones reported by the state-of-the-art methods based on ECG (see Table 8).

Finally, the hybrid model consistently compensates for the deficiencies of the two models individually, producing a lower error estimate (absolute energy, relative error and RMSE) and a comparable standard deviation. Our EE estimation models embedded into wrist-located devices would produce EE estimate performance at the state-of-the-art level in an accurate, non-obtrusive, daily integrated, inconspicuous manner.

**Conclusion.** Based on the presented results, it is concluded that there is high potential to improve the performance of the off-the-shelf commercialized devices (in terms of energy expenditure estimation) by using one of the proposed models. The model selection should be dictated by the implemented type of embedded sensors such as 3D accelerometers, GPS (providing gold standard speed values), and/or dry electrodes.

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