Use of Smartphone Accelerometers and Signal Energy for Estimating Energy Expenditure in Daily-Living Conditions

Martine Duclos[1,2], Gérard Fleury[3], Romain Guidoux[2], Philippe Lacomme[4], Nicolas Lamaudière[1], Pierre-Henri Manenq[5], Ludivine Paris[2], Libo Ren[4] and Sylvie Rousset[*,2]

[1]*Université d'Auvergne, CHU Clermont Ferrand, Serv Med Sport & Explorat Fonct, 63003 Clermont-Ferrand, France*

[2]*INRA, Unité de Nutrition Humaine UMR 1019, CRNH d'Auvergne, 63009 Clermont-Ferrand, France*

[3]*Laboratoire de Mathématiques (UMR CNRS 6620), Campus des Cézeaux, 63177 Aubière Cedex, France*

[4]*Laboratoire d'Informatique (LIMOS, UMR CNRS 6158), Campus des Cézeaux, 63177 Aubière Cedex, France*

[5]*ALMERYS, 46 rue du Ressort, 63967 Clermont-Ferrand Cedex 9, France*

Sylvie Rousset

Abstract: This paper aims to introduce an efficient predictive function for total energy expenditure (TEE) in everyday life using dedicated mass-market sensors similar to those found in widespread smartphones and tablets. Our research encompasses the design of a TEE estimation model using the smartphone accelerometer with a new signal-to-energy transformation function. The main idea of this study consists in using the signal intensity instead of the activity recognition, since the signal intensity of the accelerometer is related to the amplitude of activities. The performance of the proposed function is estimated using a smartphone-based implementation and evaluated compared to references (the scenario associated with compendium MET values, Armband® and Actiheart®) under controlled conditions (CC) for 3.5 hours, and to both devices in free-living conditions (FLC) over a 12-hour monitoring period. The experiments were carried out with 12 volunteers in CC and 30 volunteers in FLC. The TEE mean gap in absolute value between the function and the three references (scenario, Armband® and Actiheart®) was 3.5%, 6.6% and 14.1% in CC, and 14.1% and 15.0% according to Armband® and Actiheart® in FLC, respectively.

Keywords: Accelerometry, controlled conditions, daily-living physical activities, discretization method, energy expenditure, free-living conditions, smart-energy computing, smartphone.

INTRODUCTION

The smartphone is a mobile device that has now become a powerful data collection platform due to the number of built-in sensors and the recent advances in electronic technologies over the last decade. The application domains of the platform range from environmental observation to on-body monitoring. Environmental observation applications can be extended to urban area sensing, e.g., the collection of real-time traffic information with a GPS, ambient noise measurement with a microphone, or climate change with a barometer [1]. In contrast, on-body monitoring applications include wearable sensor systems for personal health monitoring in clinical and fitness trials [2]. Moreover, by processing data collected by smartphones, the users can be characterized and then receive a fine-tuned personalized service.

*Address correspondence to this author at the INRA, Unité de Nutrition Humaine UMR 1019, CRNH d'Auvergne, 63009 Clermont-Ferrand, France; Tel: +33 (0)4 73 62 46 79; E-mail: rousset@clermont.inra.fr

A CHALLENGING PROBLEM IN NUTRITION: EVALUATION OF ENERGY EXPENDITURE

In this paper, we introduce a smartphone accelerometer-based approach for daily energy expenditure estimation. The quantification of daily energy expenditure could improve personal health through better management of the relationship between energy intake and expenditure. Among the numerous publications on the theoretical prediction of physical activity energy expenditure and physiological parameter recordings, data gathering in various experimental conditions has received a considerable amount of attention. Methods for energy expenditure estimation encompass:

1. Questionnaires to determine the frequency, duration and intensity of activities performed in free-living conditions;
2. The minute-by-minute recording of heart rate [3-4];
3. The doubly-labeled water technique [5-6];
4. Indirect calorimetry measured either in calorimetric chambers or using a portable tool to determine O_2

2211-551X/15 $58.00+.00

consumption and CO_2 production, capable of precisely estimating energy expenditure on the basis of these two parameters over a continuous period of time [7-8];

5. Dedicated electronic sensors that measure heart rate and body temperature with published or unpublished algorithms for total energy expenditure (TEE) estimation. These approaches include the utilization of Actiheart®, Actigraph®, ActiReg®, RT3® or Armband® sensors; and

6. Accelerometry techniques based on accelerometers that provide an "overall dynamic body acceleration" (ODBA) [9]. The first published method based on accelerometers was first introduced by Cavagna *et al.* (1963) for humans [10], and the literature dealing with humans on this and related techniques is extensive.

Among these methods, the third and fourth methods provide accurate measurements and are considered to be the gold standard. However, they involve costly medical material, and biochemical analyses are not feasible in the context of epidemiological studies. Some recent dedicated electronic devices have obtained good results for TEE estimation by combining the collection of several variables such as body acceleration, heart rate, body temperature, heat flux and impedance. Nevertheless, the majority of those dedicated sensor devices has to be directly attached to the subjects' bodies, which could be a problem for some people. Recently, accelerometry has emerged as an inexpensive and reliable means for estimating TEE and physical activity level [11-12].

Mellone *et al.* (2012) focused on mass-market sensors, similar to the smartphone sensor [13]. The authors draw attention to the specific statistical treatment to be applied in the pre-processing phase, which is common to all statistical treatment of any real-life data. The authors reported that measurement systems could use smartphones, the most ubiquitous electronic consumer device in the world. Smartphones have become attractive for TEE estimation since: (1) they can be equipped with a variety of sensors, including accelerometers; (2) they can be kept in the pocket instead of being attached to the user's body, which is less bothersome [14]; and (3) they are part of people's daily lives since people tend to carry their phones everywhere they go [14]. Therefore, many studies have been recently carried out on this topic using smartphones.

To estimate energy expenditure due to physical activity in human subjects using accelerometry data, many recent studies deal with physical activity recognition methods. Since most of this research is based on the analysis of acceleration signals to classify the data into different types of physical activities (such as standing, walking and running), the energy expenditure estimation could consequently be made using, for example, the standard reference for the measurement of physical activity - metabolic energy expended - calculated in Metabolic Equivalent Tasks (METs) [15]. Activity and intensity level recognition are the key points for accelerometry-based TEE estimation. A wide variety of accelerometry-based activity recognition methods have been developed [16]. Some of them are based on the use of features such as frequency (e.g., Fourier transformation or wavelet transform), signal-magnitude area, autoregressive coefficients, tilt angle or parameters such as averages, standard deviations and correlations. Others use a classification approach with machine-learning techniques such as Bayesian networks, support vector machines and artificial neural networks.

CONTRIBUTION OF SMARTPHONE TECHNOLOGY IN BIOLOGY AND MEDICAL RESEARCH

It should be noted that the creation of the smartphone application required the utilization of the marketplace, which defines *de facto* a new business model for the operating system provider [17] and, subsequently, an efficient new way to make these research algorithms available to patients for a small amount of effort. The total number of smartphones was over 491 million in 2012, compared to 139 million in 2008 [18]. Since smartphones are widely-used mobile computers, they offer a convenient alternative to standard data gathering systems and promote new approaches that contribute to redefining medical education and information distribution, which can be seen in the wide variety of medical domains covered by publications over the last five years.

Medical research based on smartphone technologies over the last five years can be divided into four main classes (Table **1**):

1. Class 1. **Educational applications** that favor good practices by patients and good training for medical staff;

2. Class 2. **New feedback mechanisms** that favor self-management and effective daily communication with a therapist. The smartphone is used as a new means of communication in this type of research field;

3. Class 3. N**ew complementary measures** to help avoid costly medical material;

4. Class 4. **Preventive healthcare** using a smartphone as part of an information system dedicated to prevention.

For each class, one or two recent publications are introduced with the objective of providing a key for the classification of smartphone-based applications in the area of medical research, not as a final aim but, instead, as the first step in a classification.

Nes *et al*. (2012) defined a Web-based intervention (classes 1 and 2), delivered by a smartphone to support patient self-management with type-2 diabetes [19]. One objective of the study was to evaluate the role of the daily reports and the situational feedback for the purpose of stimulating self-management. The authors demonstrated that feedback *via* a smartphone could be a feasible intervention for such patients and that an Internet connection made it possible to submit daily reports about eating behavior, medication taking, physical activity and emotion online, favoring a fast connection with a therapist. Franc *et al*. (2011) revealed similar results within a telemedicine context [20] and concluded that remote transmission of results also leads to better monitoring in diabetic patients (class 1).

Patrick *et al*. (2014) provided the theoretical rationale and intervention design of the Social Mobile Approaches to Reduce weighT (SMART) study [21]. The theoretical considerations they introduced are not limited to the special system they proposed but encompass any mobile health system where goal and feedback are the cornerstones of efficiency (classes 1 and 2). Mobile health systems must account for the change in social cognitive theory (SCT) that claims that behavior is reciprocally influenced by intrapersonal factors (including cognitive processes, affective processes and biological events) and physical and social environments [22]. One cognitive process in particular, self-efficacy, is considered to be the main process influencing intrapersonal factors related to learning and subsequent behavior change.

The recent publication of Jenny (2013) corroborates that even if the sensor of one smartphone cannot be as precise as a dedicated specific (but frequently costly) sensor, the degree of precision is sufficient for the measurement of knee flexion angle (class 3) [23]. The comparative statistical study was carried out using the measures made by the smartphone application and the navigation system, with no significant difference from a clinical point of view. The authors reported that this "technology may be used to monitor the rehabilitation course by the physiotherapist or even the patient him- or herself, avoiding unnecessary postoperative visits". This remark is very similar to the widespread conclusions of publications in class 2. It should be noted that the authors draw our attention to the case of very obese patients where it could be assumed that a distortion of the measurement process could occur.

Mellone *et al*. (2012) provided an overall discussion on the smartphone sensors' capacities given the widely-used Timed Up and Go test to access balance and mobility (class 3) [13]. Authors felt confident that mass-market accelerometer embedded into a basic smartphone could provide high quality measurement as regards as a commercial dedicated unit. An instrumented Timed Up and Go test (TUG) makes use of a measurement system that has proved to be sensitive to a wide range of pathologies. As stressed by the authors, mobile sensing research was previously based on specialized mobile devices and could now be carried out "using mobile phones, which are indeed the most ubiquitous consumer electronic devices in the world". Their study was done on over 19 subjects. Their results encourage researchers to accept the fact that mobile phones can be an efficient way to obtain acceleration measurements, and prove that the algorithm they introduced is more effective than the algorithm that classifies TUG phases and identifies heel strikes. To the best of our knowledge, this publication is the first one that demonstrates that a mass-market accelerometer embedded in a basic smartphone is capable of providing high-quality measurements that are comparable to those of a dedicated commercial device. The authors draw attention to the specific statistical treatment used in the preprocessing phase, which is common to all statistical treatments of any real-life data.

Datta *et al*. (2011) investigated a new research area by defining the first smartphone-based system dedicated to the global surveillance of the population of the state of Illinois (US) using data gathered by school nurses (classes 2 and 4) [24]. The smartphone is not only a way to gather data but also provides a user-friendly interface to enable report visualization. mCHOIS is, to the best of our knowledge, the first smartphone-based system used by the Illinois Department of Human Services to be included in the School Health Program. The authors reported that the system contributed to the democratization of health data management since mobile technology has the potential to revolutionize telemedicine and to make patient-centric medical computing a reality. The publication of Doherty *et al*. (2014) is original in that the authors simultaneously captured both real–world human activity patterns by accelerometry and GPS, and perceived emotions at a fine temporal scale to associate activity type, localization and mood [25]. The main results of this study are the development of a novel method to survey participants in a more affordable and less burdensome manner. This type of survey will allow studying the impact of other contexts and to understand their effects on behaviors and health.

CONTRIBUTION OF SMARTPHONE TECHNOLOGY TO THE EVALUATION OF ENERGY EXPENDITURE

Among the above-mentioned methods using smartphone accelerometers, Miluzzo *et al*. (2008) presented a mobile phone application related to activity recognition [26]. Their

Table 1. Recent medical publications based on smartphone technologies.

References	Domain	Objective	Sensor Used
[19]	Educational applications	Evaluation of feedback with a smartphone	Web connection
[20]	Educational applications	Telemedicine	
[21]	New feedback mechanisms Educational applications	Obesity reduction	Web connection
[23]	New complementary measures	Knee flexion angle measurement	Positional sensor
[13]	New complementary measures	Comparative study of smartphone accelerometers with dedicated ones	Accelerometers
[24]	New feedback mechanisms Preventive healthcare	Obesity surveillance	Web connection GPS, camera
[25]	Educational applications	Tracing human activities in a natural environment	Positional sensor Accelerometers

activity classifier model consists of two components: a preprocessor and a classification algorithm. The preprocessor collects raw accelerometer data and then calculates the mean, standard deviation and number of peaks to extract features. The classification algorithm is based on a decision tree using a training process. The training data is collected from ten human subjects. The proposed application is able to distinguish sitting, standing, walking and running activities. Brezmes *et al*. (2009) described a k-nearest neighbors algorithm for real-time recognition of some basic activities including walking, sitting, standing and stair climbing [27]. The activities are identified using a set of features obtained from training records for each activity on a single data record. The k-nearest neighbors algorithm uses the Euclidean distance between current data and the data from the previously classified activity. It correctly identified ambulatory and postural changes with 90% and 70% accuracy, respectively. Yang (2009) presented a decision tree model for activity recognition using data processing and smoothing techniques to reduce the special noise present in phone-collected accelerometer data [28]. This author explored an orientation-independent feature extracted from vertical and horizontal components in acceleration for six physical activities: sitting, standing, walking, running, driving and bicycling. The model is provided by the training data using a decision tree with simple time-domain features. It is compared to a k-means clustering method on a large set of one week's unlabeled accelerometer data. All three of these studies collected acceleration data from a Nokia N95 phone.

Kwapisz *et al*. (2011) presented an Android-based data collection platform with a predictive model that could recognize six activities with a high degree of accuracy [29]. In their studies, data are collected at 20 Hz with an accelerometer from 29 subjects performing different daily activities. The model is implemented using a feature generation process that consists in dividing data into 10-second segments. Each segment is analyzed to capture the repetitive motions involved in the activities. The model was then tested using the same group of subjects. Anguita *et al*. (2012) proposed a hardware-friendly approach for activity recognition using a smartphone sensor [30]. Their method adapted the standard support vector machine (SVM) and used fixed-point arithmetic for computational cost reduction. The authors used a Samsung Galaxy S2 smartphone to collect data at a rate of 50 Hz from 30 human subjects performing the predefined activities. The results are compared with the traditional SVM, and their method makes it possible to improve computational costs with similar accuracy. Anjum and Ilyas (2013) evaluated different machine-learning algorithms for activity recognition, including naive Bayes, decision tree, k-nearest neighbors and SVM [31]. They then developed a smartphone application that implemented a decision tree algorithm to detect seven different activities. Data collection was performed on a Samsung Galaxy Y phone at 15 Hz with ten human subjects. The collected data was divided into two classes: the first class including the data of a group of four people was used for training the activity recognition model; the second one including the data from other volunteers was used for activity classification.

Most studies have considered activity recognition as a supervised learning problem. However, one of the most critical points for supervised learning is the definition of the training dataset, which is a labor-intensive job. Several authors have recently commented that the major drawback is due to short periods of an activity or to the boundary of consecutive activities, making it difficult to differentiate between activities. Moreover, the number of activities should be established during the classification step. The regeneration of a training dataset is necessary when the number of activities is changed. The number of activities in daily life strongly depends on the human subject and cannot be fixed. That is the reason for using an unsupervised learning approach, making it possible to avoid the regeneration of a training dataset [14]. Therefore, Kwon *et al*. (2014) and Huynh (2008) stated that unsupervised techniques are desirable. They are useful for short-term activities and crucial for long-term activities as it is difficult to remember and to assign the correct activities [14, 32]. Some authors have proposed an unsupervised approach based on models that allow recognition of daily routines in data collected from four inertial sensors. Li and Dustdar (2011) analyzed the feasibility and potential benefits of incorporating unsupervised learning methods into activity recognition [33]. They proposed a hybrid activity recognition process that utilizes the results of subspace clustering to identify different groups of activities. Trabelsi *et al*. (2013) presented a recognition model based on the hidden Markov model in a regression context for the joint segmentation of multivariate time series of human activities [34]. Data is collected using three accelerometers and the results of the proposed method are compared with well-known supervised classification approaches.

Recently, Kwon *et al*. (2014) and Alvarez de la Conception *et al*. (2014) worked on human activity recognition [14, 35]. Kwon *et al*. (2014) proposed an unsupervised learning method for activity recognition using smartphones. They provided a new method for recognizing activities without using training datasets. Their model runs directly on the data collected from smartphone sensors and functions, even if the number of activities is unknown. Moreover, the number of activities can be determined by the Caliński-Harabasz index. In this study, data was collected at a 50 Hz sampling rate and a simple low-pass filter was applied to eliminate noise.

Our previous study on TEE estimation in which we proposed a prediction function with a fast Fourier transform for activity recognition was also based on human-activity recognition using smartphone accelerometers [12]. Forty-two volunteers who were studied either in controlled conditions (CC) or in free-living conditions (FLC) collected accelerometry data at 6 Hz using Android smartphones (Samsung Galaxy xCover and LG Nexus 4). TEE estimations from activity recognition were compared with those of two research devices (Armband® and Actiheart®) in both experimental conditions. Activity recognition was 73.3% in controlled conditions, and the TEE gap between the function and Armband® or Actiheart® was 7.0% and 16.4% in CC, respectively. TEE gaps were larger in FLC (17.0% and 23.7% between the function and Armband® or Actiheart®, respectively). The proposed function can only recognize activities that last more than 8 seconds. However, activities were more varied and discontinuous in FLC than in CC. For this reason, function performance was lower in FLC.

This paper presents a new TEE estimation model using the smartphone accelerometer with a new signal-to-energy transformation function. The main idea of this work consists in using the signal intensity instead of the activity recognition. The signal intensity of the accelerometer is related to the amplitude of the activities. Our research consisted in studying how the signal intensity could be proportionate to the intensity of activities. The proposed model makes it possible to avoid the disadvantage related to the activity recognition-based methods. The rest of this paper is organized as follows. The Materials and Methods section describes the proposed model. The computational results and the comparative studies are presented in the Results section, which is followed by a discussion and conclusion.

MATERIALS AND METHODS

Definition of a Function-to-Energy Expenditure Estimation in Real-Life Conditions

This research was carried out in three steps (Fig. **1**):

- **Initialization:** assignment of MET values to each activity, recruitment of volunteers and design of a smartphone prototype to record accelerometry data;
- **Study in controlled conditions:** creation of a 3.5-hour physical activity scenario that provides a TEE reference for the function development. TEE generated by the scenario was calculated from the sum of METs associated with activities. Data was collected by using the smartphone prototype, Armband® and Actiheart®. A first TEE comparison between the scenario, Armband®, Actiheart® and the function was performed;
- **Study in free-living conditions:** The same type of data as in CC was acquired for a day in FLC. The TEE estimation function was adjusted for spontaneous activities of daily living.

Volunteer Characteristics

Several factors including age, sex, height and weight were taken into account for determining a representative sample of the French population. Two groups of volunteers were recruited in Clermont-Ferrand (France). They were normal-weight and from 18 to 60 years old. Their body mass indexes (BMI) ranged between 18.5 and 25 kg.m^{-2}. They were free of cardiovascular or locomotion diseases. During the preliminary visit, they signed an informed consent form and passed a resting electrocardiogram validated by a cardiologist. The protocol was approved by the French Committee for the Protection of Human Subjects (Sud-Est VI). It was registered under the references 2012-A00809-34 and 2013-A00188-37 in the ANSM system, and under the references NCT01995253 and NCT01995162 in Clinical Trials. Detailed characteristics of the volunteers in CC and FLC are presented in Table **2**.

The FLC group was composed of two subgroups of six and 24 volunteers. Data from the first FLC subgroup and from the CC group were used to create the TEE estimation function. Data from the second FLC subgroup made it possible to test the function with independent datasets.

Design of a Scenario in Controlled Conditions

Volunteers in the CC group performed each of the nine activities several times according to the activity scenario: sitting, slow, normal and brisk walking, climbing and descending stairs (eight floors), standing, slow running and taking public transportation (tramway, Table **3**). The duration of each activity varied from 10 seconds to 20 minutes. The scenario was repeated twice. The duration of the full scenario was approximately 3.5 hours. Volunteers were informed by the researcher of the beginning and the end of each activity. The 12 volunteers made it possible to obtain a set of 12 scenarios where the sequence of activities was identical to the sequence given by a theoretical scenario, but where the durations were submitted to slight variations. Volunteers simultaneously wore a smartphone in their left front pants pocket (Samsung Galaxy xCover or LG Nexus 4) that collected data, the Actiheart® (Cambridge Technology Ltd., Papworth, UK) and the Pro3 SenseWear Armband®

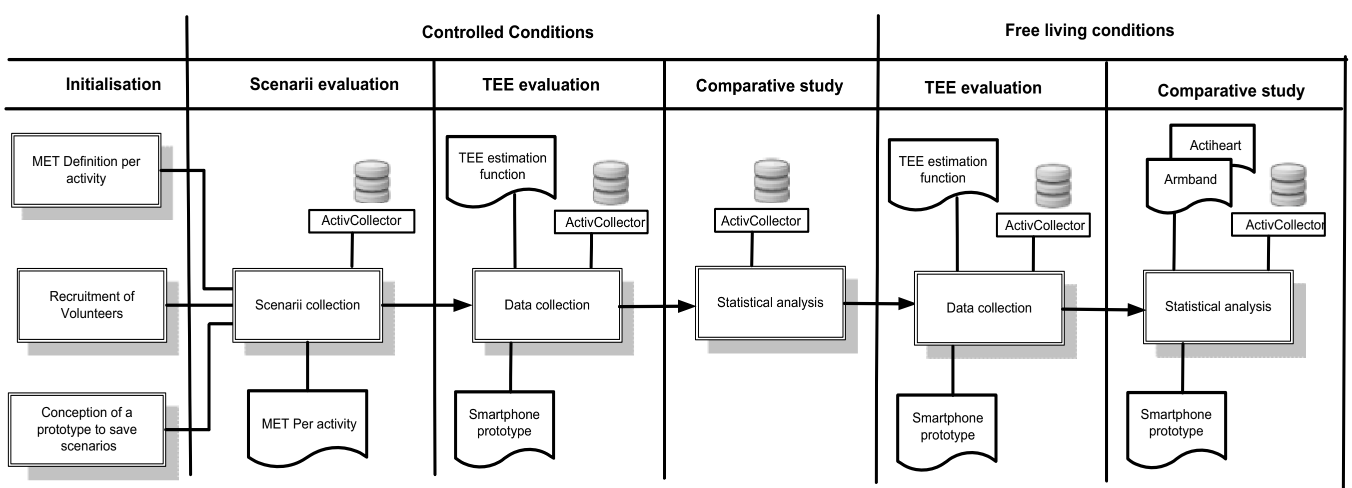

Fig. (1). Experimental approach.

(Bodymedia version 6.0) monitors. Researchers recorded the start and the duration of each activity.

Protocol in Free-Living Conditions

Volunteers in the second group wore the same devices as those in the first group for a full day, either during the week or over the weekend. They performed spontaneous activities either at home, at work or outdoors, depending on the volunteers' lifestyles and wishes. The volunteers wore the devices during the daytime and recorded their activities themselves. The mean recording duration was approximately 12.5 hours.

Table 2. Volunteer characteristics (mean ± SD).

Characteristics	Controlled Conditions		Free-Living Conditions	
Sex	Males	Females	Males	Females
n	6	6	15	15
Age (year)	34.2 ± 10.7	34.0 ± 10.3	33.6 ± 10.8	32.5± 7.9
Height (cm)	173.8 ± 1.6	171.0 ± 8.8	173.9 ± 7.0	165.6± 8.1
Weight (kg)	68.5 ± 3.0	61.2± 4.7	69.3 ± 6.5	59.6 ± 9.2
BMI (kg m^{-2})	22.7 ± 1.2	21.0 ± 0.9	22.9 ± 1.4	21.6± 2.1

Table 3. Theoretical scenario.

Order	Activity	Duration	Order	Activity	Duration
1	Sitting	5 min	14	Standing	5 min
2	Walking	10 s	15	Tram	7 min
3	Descending stairs	20 s	16	Walking	1 min
4	Walking	1 min	17	Standing	2 min
5	Slow walking	2 min	18	Running	2 min
6	Brisk walking	2 min	19	Walking	3 min
7	Walking	6 min 45s	20	Slow walking	2 min
8	Climbing stairs	3 min	21	Walking	13 min
9	Sitting	5 min	22	Brisk walking	3 min
10	Descending stairs	3 min	23	Walking	2 min
11	Walking	2 min	24	Climbing stairs	20 s
12	Standing	5 min	25	Walking	10 s
13	Tram	7 min	26	Sitting	20 min

TEE Estimation Based on the Activity Scenario

In CC, the energy cost of each activity was estimated using Metabolic Equivalent Tasks (METs) [15]. For example, one MET is the energy cost at rest and two METs correspond to an activity requiring the double of the resting energy expenditure (REE). The top of Table **4** lists the general MET values of the scenario activities.

As stressed by the physical compendium, MET values for each activity are general and there may be considerable individual variations. MET values have to be corrected according to REE expressed in ml.kg^{-1}.min^{-1}. We used Harris and Benedict's equations to estimate REE [36]. The best MET approximation can be obtained using:

$$METc(a) = (METg(a) \times 3.5\ ml.kg^{-1}.min^{-1}) \ / \ REE$$

where $METg(a)$ is the general MET value of activity a provided by the compendium (see Table **4**), 3.5 is the mean volume of O_2 consumed for the rest period in ml.kg^{-1}.min^{-1}, $METc(a)$ is the personalized MET value and REE is the rest energy expenditure computed by Harris and Benedict's equations in ml.kg^{-1}.min^{-1}.

For men, REE (kcal.d^{-1}) = 66.473 + 13.7516*Weight (kg) + 5.0033*Height (cm) – 6.755*Age (y)

For women, REE (kcal.d^{-1}) = 655.0955 + 9.5634*Weight (kg) + 1.8496*Height (cm) – 4.6756*Age (y)

We then converted kilocalories per day to ml O_2.kg^{-1}.min^{-1}:

REE (ml.kg^{-1}.min^{-1}) = (REE (kcal.d^{-1})*1000)/(1440*5*Weight)

Table **4** also gives the METc(a) values for volunteers in the first group. These METc(a) values were used to estimate energy expenditure for scenarios.

Data Collection and Numerical Experiments

Numerical experiments were done using a client-server architecture where the smartphone (client) collects data from volunteers and a server ensures TEE estimation after reception of data. To favor fair future comparative studies, all population data composition and all TEE data gathered during experiments are available on the ActivCollector website at the following address: https://activcollector.clermont.inra.fr/home/publications/nrjsiDocument7 [37].

A set of 44 data files were collected using smartphones from 42 volunteers divided into two groups: 12 data files for approximately 3.5 hours in CC; 32 files for 12.5 hours collected from 30 volunteers (two volunteers collected datasets on two different days) in FLC. The Actiheart® and the Armband® monitors each generated a data file with all measurements, which were used as references for TEE estimation.

Development of the TEE Estimation Function

The objective is to take advantage of the embedded smartphone accelerometers to provide a TEE estimation model with a new signal-to-energy transformation function using an adapted learning mechanism.

As stressed in [12], a predictive function can be described by $TEE^{f(\eta,d)} = TEE^{g(\eta)} \times \varepsilon(d)$ where:

- $TEE^{g(\eta)}$ is a supervised function in controlled conditions, which gives an estimation of the energy produced by accelerations η (where $\eta_t = (x_t, y_t, z_t)$ are the accelerometry values on the three axes at instant *t*). Datasets were collected at 6 Hz by the accelerometer;
- ε is an unsupervised function that depends on the total duration of the experiment d and encompasses both CC and FLC.

Table 4. Energy expenditure per activity for each volunteer in controlled conditions, function $METc(a)$.

General	Activities (METg(a))					
	Walking	Brisk Walking	Running	Sitting	Standing	Tram(1)
METg(a)(2)	3.50	4.30	6.00	1.40	1.80	1.60
Individual Volunteer	**Activities (METc(a))(3)**					
1	3.41	4.19	5.85	1.36	1.75	1.56
2	4.14	5.08	7.09	1.65	2.13	1.89
3	3.74	4.59	6.41	1.50	1.92	1.71
4	3.73	4.58	6.39	1.49	1.92	1.70
5	3.60	4.43	6.17	1.44	1.85	1.65
6	3.58	4.40	6.13	1.43	1.84	1.64
7	4.14	5.08	7.09	1.65	2.13	1.89
8	4.27	5.25	7.33	1.71	2.20	1.95
9	3.60	4.43	6.17	1.44	1.85	1.65
10	3.69	4.53	6.32	1.47	1.90	1.68
11	3.97	4.88	6.81	1.59	2.04	1.82
12	3.78	4.64	6.48	1.51	1.94	1.73

(1)The tram transportation value is associated with the mean MET values of sitting and standing activities. All the volunteers sat and stood for half the time in the tram.
(2)General metabolic equivalent (in METs) values given by the physical compendium [15].
(3)Individual metabolic equivalents calculated from general metabolic equivalents and individual characteristics.
MET values associated with scenario activity durations were used to estimate TEE in CC. This estimation was not possible in FLC because many of the activity records completed by the volunteers themselves were not sufficiently accurate.

Estimation of the Function g with the Supervised Learning Process

The function g leads to the supervised learning methods for which the most important thing is the training dataset. The generation of a training dataset is considered to be tedious and labor-intensive by numerous researchers. Twelve datasets in CC and six datasets in FLC make it possible to define the function g:

$$TEE^{g(\eta)} = \frac{\sigma(\gamma)+3}{4} \times W \times d$$

where:

- $\sigma(\gamma)$ is the standard deviation of the module (m.s^{-2}) computed on the whole recording;
- W is the body weight of the volunteer (kg);
- d is the duration of the recording (s).

The unit of g is then kg.m.s^{-1}. This function is not tuned for activity recognition but provides a measurement of the "energy" of the signal $\sigma(\gamma)$.

The linear expression $\sigma(\gamma) \times C1 + C2$ was introduced into the model assuming that $C1$ is the constant linked to the physical activity energy expenditure, and $C2$ is related to the resting energy expenditure. The 12 datasets in CC and the first six in FLC allow us to estimate that $C1 = 1/4$ and $C2 = 3/4$.

Estimation of the Function ε with the Unsupervised Learning Process in Free-Living Conditions

The function ε depends on the recording duration d (in seconds) and on two coefficients α and β:

$$\varepsilon = \left(1 - \frac{d}{24 \times 3600} \times \alpha\right) \times \beta$$

These coefficients were determined from the 18 datasets described above. $\alpha \approx 0.4855$ and $\beta \approx 0.000713$ were computed by minimizing the sum of square errors compared to Armband® TEE estimations:

$$\min \sum_{i=1}^{n} (TEE_i^{armband} - TEE_i^{f(\eta,d)})^2$$

where $n = 18$ is the number of volunteers, $TEE_i^{armband}$ is the TEE estimation provided by Armband® for the volunteer i, and $TEE_i^{f(\eta,d)}$ is the TEE estimation provided by our function for the volunteer i.

To conclude, the predictive function is:

$$TEE^{f(\eta,d)} = TEE^{g(\eta)} \times (0.000713 - 4.01 \times 10^{-9} d)$$

Statistical Analyses

The TEE estimation function was compared to three references: TEE calculated from the sum of the MET values

(TEE^{scenario}), TEE given by Armband® (TEE^{armband}) and Actiheart® (TEE^{actiheart}). First, the gaps between the TEE estimation function and the references are calculated using the following formula for the full recording in CC and in FLC:

$$gap(\%) = \frac{TEE^{f(\eta,d)} - TEE^{ref}}{TEE^{ref}} \times 100$$

In FLC, the absolute values of gaps were also calculated on intermediate times: after 4, 6, 8 hours of recording. A multiple ANOVA (MANOVA) was then carried out on these gaps to determine if there was an effect of recording time over gaps, and if the gaps with Actiheart® and Armband® were generally different over recording times.

Secondly, t–tests and paired t-tests were performed on absolute values of gaps to determine if the gaps were different or not from 0, and to compare the gap levels between them. SAS 9.4 software was used to perform the t-tests and MANOVA.

RESULTS

Performance Evaluation of the Proposed Function in Controlled Conditions

Table **5** shows a comparative study of TEE estimation between the proposed approach (denoted $TEE^{f(\eta,d)}$) and the following three references: TEE^{scenario}, TEE^{armband} and TEE^{actiheart}.

In CC, the gap between $TEE^{f(\eta,d)}$ and TEE^{scenario} was 3.5 ± 2.5%, which was significantly different from zero ($t = 4.94$, $p = 0.0004$). An average gap of 3.5% remains very low since it was obtained with a mass-market accelerometer embedded into a basic smartphone.

It should be noted that the 12 datasets were used to create the function, and the results in Table **5** are therefore more a post mortem analysis than an estimation of the predictive function performance. The gap between $TEE^{f(\eta,d)}$ and TEE^{armband} was 6.6 ± 4.3% ($t = 5.1$, $p = 0.0003$); the gap between $TEE^{f(\eta,d)}$ and TEE^{actiheart} was 14.1 ± 7.7% ($t = 6.2$, $p < 0.0001$). All these gaps were significantly different from zero. However, the gap between $TEE^{f(\eta,d)}$ and TEE^{actiheart} was greater than the other two ($TEE^{f(\eta,d)}$ *vs* TEE^{armband}: $t = -2.9$, $p = 0.01$, and $TEE^{f(\eta,d)}$ *vs* TEE^{scenario}: $t = 4.1$, $p = 0.001$). No individual gap between the proposed function and scenario was higher than 10% (Table **5**). Only two gaps between the function and Armband® were higher than 10% but lower than 20%. The gaps relative to Actiheart® were larger. Thus, six gaps were higher than 10% and two other gaps were higher than 20%.

Comparison of TEE Estimations Given by the Three References in CC

The comparison of references, two-by-two, showed that the difference in absolute value between TEE^{armband} and TEE^{scenario} was significant: 5.9 ± 5.8% ($t = 3.5$, $p = 0.005$), and larger between TEE^{actiheart} and TEE^{scenario}: 13.9 ± 5.7% ($t = 8.4$, $p < 0.0001$). Thus, the TEE evaluation per scenario was closer to that of Armband than to that of Actiheart. The most disparate estimations occurred between Armband and Actiheart: 15.0 ± 8.1% ($t = 6.4$, $p < 0.0001$).

Table 5. TEE estimated by the proposed function and the references in CC – gaps between them (%).

Volunteer	Duration (min)	1	2	3	4	Absolute Values of Gap (%) Between					
		TEE^{scenario} (kcal)	TEE^{armband} (kcal)	TEE^{actiheart}(kcal)	$TEE^{f(\eta,d)}$ (kcal)	1-4	2-4	3-4	1-2	1-3	2-3
1	200	654.5	740.1	531.0	683.7	4.5	7.6	28.8	13.1	18.8	28.2
2	201	666.4	684.7	545.0	650.0	2.5	5.1	19.3	2.7	18.2	20.4
3	192	694.6	698.5	752.8	750.1	8.0	7.4	0.4	0.5	8.3	7.7
4	208	596.2	662.7	512.4	587.0	1.5	11.4	14.6	11.1	14.0	22.7
5	203	707.2	710.9	638.9	700.3	1.0	1.5	9.6	0.5	9.6	10.1
6	195	719.3	714.4	551.6	680.9	5.4	4.7	23.4	0.7	23.3	22.8
7	202	643.6	677.5	628.0	693.2	7.7	2.3	10.4	5.3	2.4	7.3
8	203	686.4	662.3	793.3	668.0	2.7	0.9	15.8	3.5	15.6	19.8
9	195	689.5	791.4	816.9	682.3	1.0	13.8	16.5	14.8	18.5	3.2
10	202	714.7	691.4	807.3	748.0	4.7	8.2	7.3	3.3	12.9	16.7
11	203	619.7	624.2	523.0	601.9	2.9	3.6	15.1	0.7	15.6	16.2
12	208	612.2	703.2	667.4	615.9	0.6	12.4	7.7	14.8	9.0	5.1
			Mean gap (%):			3.5	6.6	14.1	5.9	13.9	15.0
			Standard deviation (%):			2.5	4.3	7.7	5.8	5.7	8.1

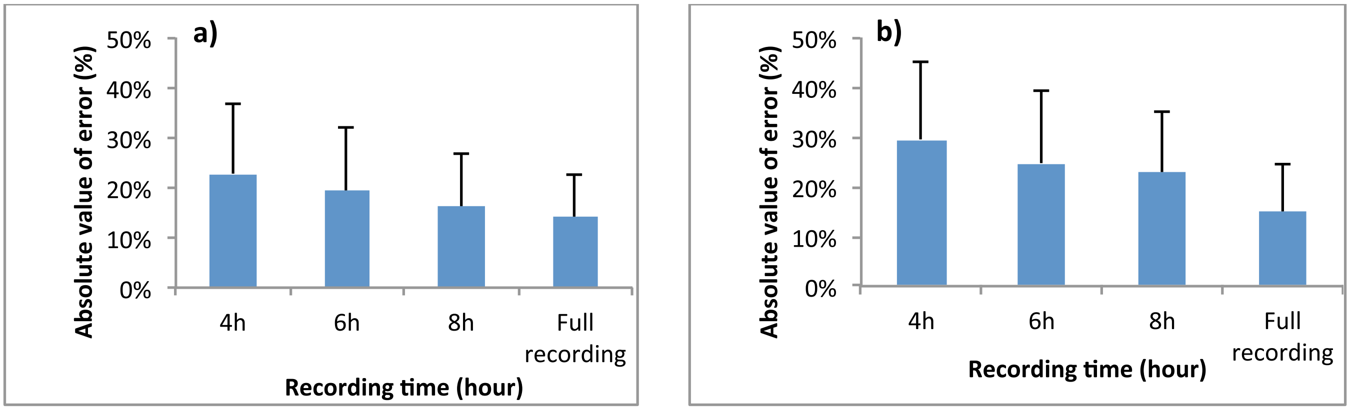

Fig. (2). Evolution of gaps according to recording time (mean ± standard deviation). **a**) Gaps between $TEE^{f(\eta,d)}$ and $TEE^{armband}$; **b**) Gaps between $TEE^{f(\eta,d)}$ and $TEE^{actiheart}$.

Performance Evaluation of the Proposed Function in Free-Living Conditions

In free-living conditions, the scenario cannot be considered as a reference because many records completed by the volunteers themselves were not sufficiently accurate. Thus, only gaps with Actiheart® and Armband® were considered. Fig. (**2**) shows the evolution of the gaps between $TEE^{f(\eta,d)}$ and TEE given by both references (Armband® and Actiheart®) according to the recording time. MANOVA showed that the gaps significantly decreased with increasing recording time ($F = 7.72$, $p = 0.0002$) without interaction between gap reference X time ($F = 1.59$, $p = 0.20$). The gaps calculated with these two references were globally not different over time ($F = 1.50$, $p = 0.21$). The gaps calculated over the full recording reached 14.1 ± 8.7% and 15.0 ± 9.9% with Armband® and Actiheart® TEE, respectively (Table **6**). They were significantly different from 0 ($t = 9.0$, $p < 0.0001$; $t = 7.7$, $p < 0.0001$) but not between them ($t = -0.3$, $p = 0.7$). The absolute maximal gap between $TEE^{f(\eta,d)}$ and $TEE^{armband}$ was reached for volunteer number 1 with a gap of about 35%, and the minimal gap was -0.6% for volunteer 5. As stressed in Table **6**, for ten data sets out of 32 (3, 4, 5, 6, 10, 11, 21, 27, 29 and 32), the gap was less than 10%. Conversely, the gaps concerning six other volunteers (1, 2, 20, 22, 24, 26) were greater than 20%.

DISCUSSION

In the present study, the performances of the function $TEE^{f(\eta,d)}$ for TEE estimation were compared with the results given by two portable devices (Actiheart® and Armband®) used in controlled and free-living conditions. Moreover, the controlled conditions made it possible to evaluate the TEE of activities monitored over a short period using MET values and compared it to $TEE^{armband}$ and $TEE^{actiheart}$. The comparison of the three references in controlled conditions showed that Armband and the scenario gave the closest TEE evaluations, whereas differences between Actiheart and the scenario or Armband and Actiheart were greater. In Rousset *et al*. (2014), errors in absolute value for Armband and Actiheart were calculated in a calorimetric room on 49 normal-weight adult volunteers. It was significantly lower for Armband (6.7%) than Actiheart (8.6%). Thus, $TEE^{armband}$ rather than $TEE^{actiheart}$ was close to the TEE given by indirect calorimetry. Therefore, Armband was used as the main reference in this publication.

The advantage of the study in free-living conditions was to estimate spontaneous and daily-living activity TEE for a longer period than in CC. The proposed function that takes only accelerometry into account with no information on the initial smartphone position provides a global absolute gap of about 14-15%, which was relatively close to the estimations provided by both devices. As stressed in previously published articles, the Actiheart® and Armband® performances were frequently evaluated against indirect calorimetry in CC and less often assessed against the doubly-labeled water technique in FLC. This technique provides a TEE measurement averaged over a 10-14-day period. Rousset *et al*. (2014) tested the validity of both devices against DLW in FLC in a sample of normal-weight adult volunteers for a 10-day period [38]. Armband® produced smaller errors in absolute value than Actiheart® (8.6% *vs* 12.8%). Thus, Armband® errors were lower than 10% in both CC and FLC for daily-living activities. For this reason, it was the main TEE reference to which $TEE^{f(\eta,d)}$ was compared. Regardless of the reference considered, the TEE gaps in FLC shown in this study were lower than those previously determined by an activity recognition function (14% *vs* 17% against Armband®; 15% *vs* 24% against Actiheart® [12]. The present function was less accurate than $TEE^{armband}$. To estimate TEE, Armband uses five sensors: accelerometry, body and near-body temperature, impedance and heat flux. The smartphone used only data collected by the accelerometer. Thus, the smartphone is at a disadvantage compared to Armband that has several types of sensors. However, the advantage of using a smartphone is that nearly everyone has a smartphone but few people have an Armband.

The performance of the present function was better in CC than in FLC. The distinctive feature of the two populations in CC and FLC is that all volunteers in CC have a highly significant amount of time assigned to walking activities. For the volunteers in FLC, there is an even spread of activities over time. For example, activity recordings showed that

Table 6. TEE estimations of the proposed function and the references in the FLC - gap between them.

Data Sets	Record Duration (min)	1 $TEE^{armband}$ (kcal)	2 $TEE^{actiheart}$ (kcal)	3 $TEE^{f(\eta,d)}$ (kcal)	Absolute Value of Gap (%) Between	
					1 and 3	2 and 3
1	645	2375.12	1666.51	1544.61	35.0	7.3
2	687	1024.52	1015.08	1239.78	21.0	22.1
3	558	905.46	907.84	994.31	9.8	9.5
4	871	2483.8	2039.88	2338.47	5.9	14.6
5	947	1705.65	1387.46	1696.03	0.6	22.2
6	935	1875.58	-	1720.22	8.3	-
7	747	1684.53	1288.97	1510.99	10.3	17.2
8	922	1339.21	1912.28	1186.03	11.4	38.0
9	669	1067.59	1075.23	1242.82	16.4	15.6
10	914	1424.8	1297.72	1360.71	4.5	4.9
11	797	1614.32	1324.2	1470.87	8.9	11.1
12	1000	2391.59	2224.99	2036.13	14.9	8.5
13	622	1021.95	-	1132.52	10.8	-
14	855	1318.71	-	1098.85	16.7	-
15	640	1613.21	-	1318.42	18.3	-
16	588	1743.92	1224.02	1426.18	18.2	16.5
17	728	1045.76	917.84	915.91	12.4	0.2
18	820	1193.68	1125.79	1316.27	10.3	16.9
19	857	1692.22	1248.41	1382.58	18.3	10.8
20	809	2714.92	2993.33	2069.82	23.8	30.9
21	947	1330.43	1121.24	1351.95	1.6	20.6
22	785	1400.76	1701.73	1739.46	24.2	2.2
23	530	1253.1	1479.17	1391.69	11.1	5.9
24	815	1803.15	1773	1268.88	29.6	28.4
25	545	1429.27	-	1234.95	13.6	-
26	894	2976.13	2243.58	1866.21	37.3	16.8
27	872	1621.32	1352.69	1504.92	7.2	11.3
28	628	1794.32	2562.17	1595.87	11.1	37.7
29	719	1426.25	1590.5	1509.62	5.9	5.1
30	656	1544.11	2140.04	1754.06	13.6	18.0
31	329	870.84	815.62	723.49	16.9	11.3
32	862	1347.41	1361.09	1387.92	3.0	2.0
			Mean gap (%):		14.1	15.0
			Standard deviation (%)		8.8	10.1

*: Some missing values were reported for Actiheart® due to unforeseen circumstances in free-living experiments.

housework or sports activities were carried out. Consequently, the predictive function cannot be as effective in FLC as in CC because the predictive function has been tuned using the activities chosen in controlled conditions where specific free-living activities are not take into account. For example, the housework or sports activities were not addressed in the study of controlled conditions. A second remark must be made concerning the recording time since short recordings generated higher gaps than long recordings. The validity of the predictive function was time-dependent and at least 8 hours of recording are required to obtain a reliable prediction.

CONCLUSION

A dedicated smartphone application was used to estimate total energy expenditure in real-life conditions. $TEE^{f(\eta,d)}$ provided an estimation of approximately 14% of the costly dedicated sensors, including Armband® and Actiheart®. The need for improving the function is still necessary, notably for the TEE prediction for short periods. On the basis of the TEE prediction and REE estimation, we will be able to estimate the mean intensity of physical activities for the period recorded. We will therefore know if the users are sedentary, little or moderately physically active. Our application would not only be useful for medical and research staffs for monitoring patients and volunteers in free-living conditions, but also for education and prevention. Education and prevention will be possible using both the ActivCollector site and the application to set goals, for example, to be less sedentary. ActivCollector can send personalized messages to the users to inform them about their mean level of physical activity and the guidelines. Before health problems such as cardiovascular disease occur, physical activity programs should be established and monitored by our application. Numerous studies utilize after-the-fact or generalized self-reports following engagement in light-intensity activities, or are limited to controlled experiments (i.e., where the natural environment and physical activity types are controlled in short-term studies) rather than everyday situations. The actual *in situ* experience during real-life experiments and the truly personal service mechanism is clearly defined for the purpose of generating health benefits. However, health benefits remain unexplored, especially in real-life conditions, and our research is now directed towards the estimation of such benefits on the long-term. Cognitive process analysis leads us to consider that monitoring behavior, receiving feedback, and reviewing relevant goals after obtaining feedback are central to self-management and behavioral control. Our application integrated these theoretical approaches and provided user-friendly interfaces that not only showed TEE results but also proposed physical activity goals.

The function of energy expenditure assessment permits to create a mobile application on daily-living physical activity. The validation has been carried out in a research program where all volunteers were subjected to a careful medical follow-up. A future application could be designed for the general public to raise awareness of a physical activity practice and sedentary behaviors. However none application could replace a visit to consult a doctor.

This study was carried out within the framework of an agreement with Almerys, an information technology company (France). A product is currently being designed for the purpose of developing an operational software suite and middleware for health-care mobile systems.

LIST OF ABBREVIATIONS

BMI = Body mass index

CC = Controlled conditions

FLC = Free-living conditions

TEE = Total energy expenditure

REE = Rest energy expenditure

MET = Metabolic equivalent task

SVM = Support vector machine

CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

ACKNOWLEDGEMENTS

Special thanks to the volunteers for their participation in this study and to Gail Wagman for correcting the English.

REFERENCES

[1] Akimura D, Kawahara Y, Asami T. Compressed sensing method for human activity sensing using mobile phone accelerometers. 2012 Ninth International Conference on Networked Sensing Systems (INSS); 2012 June 11-14; Antwerp, Belgium. http://www.inss-conf.org/2012/ pp. 1-4.

[2] Lyzwinski LN. A systematic review and meta-analysis of mobile devices and weight loss with an intervention content analysis. J Pers Med 2014; 4: 311-85.

[3] Spurr GB, Prentice AM, Murgatroyd PR, Goldberg GR, Reina JC, Christman NT. Energy expenditure from minute-by-minute heart rate recording: comparison with indirect calorimetry. Am J Clin Nutr 1988; 48:552-9.

[4] Baharestani H, Tompkins WJ, Webster JG, Mazess RB. Heart rate recorder. Med Biol Eng Comput 1979; 17:719-23.

[5] Schoeller DA, Ravussin E, Schutz Y, Acheson KJ, Baertschi P, Jequier E. Energy-expenditure by doubly labeled water - validation in humans and proposed calculation. Am J Physiol 1986; 250: R823-30.

[6] Prentice AM. Applications of the doubly-labeled-water (H2O)-H-2-O-18 method in free-living adults. Proceedings of the Nutrition Society 1988; 47: 259-68.

[7] Vermorel M, Bitar A, Vernet J. Indirect calorimetry. 3. Check of the validity of gas exchange measurement in animals and humans. Cahiers des Techniques INRA 1995; 13: 659-81.

[8] Weir JB. New methods for calculating metabolic rate with special reference to protein metabolism. J Physiol 1949; 109: 1-9.

[9] Halsey LG, Shepard ELC, Wilson RP. Assessing the development and application of the accelerometry technique for estimating energy expenditure. Comp Biochem Physiol A Mol Integr Physiol 2011; 158: 305-14.

[10] Cavagna GA, Saibene FP, Margaria R. External work in walking. J Appl Physiol 1963 ;18 : 1-9.

[11] Khan AM, Lee Y-K, Lee SY, Kim T-S. A triaxial accelerometer-based physical-activity recognition *via* augmented-signal features and a hierarchical recognizer. IEEE Trans Inf Technol Biomed 2010; 14: 116672.

[12] Guidoux R, Duclos M, Fleury G, *et al*. A smartphone-driven methodology for estimating physical activities and energy expenditure in free living conditions. J Biomed Inform 2014; 52: 271-8.

[13] Mellone S, Tacconi C, Chian L. Validity of a smartphone-based instrumented timed up and go. Gait Posture 2012; 36: 163–5.

[14] Kwon Y, Kang K, Bae C. Unsupervised learning for human activity recognition using smartphone sensors. Expert Syst Appl 2014; 41: 6067-74.

[15] Ainsworth BE, Haskell WL, Herrmann SD, *et al*. Compendium of physical activities: a second update of codes and Met values. Med Sci Sports Exerc 2011; 43: 1575-81.

[16] Khan AM, Siddiqi MH, Lee SW. Exploratory data analysis of acceleration signals to select light-weight and accurate features for real-time activity recognition on smartphones. Sensors 2013; 13: 13099-122.

[17] Hsieh J-K, Y-C Hsieh. Appealing to Internet-based freelance developers in smartphone application marketplaces. Int J Inform Manage 2013; 33: 308-17.

[18] Guido G, Vitale A, Astarita V, Saccomanno F, Giofre VP, Gallelli V. Estimation of safety performance measures from smartphone sensors. Procedia Soc Behav Sci 2012 ; 54 : 1095 – 103.

[19] Nes AAG, van Dulmen S, Eide E, *et al*. The development and feasibility of a web-based intervention with diaries and situational feedback *via* smartphone to support self-management in patients with diabetes type 2. Diabetes Res Clin Pract 2012; 97: 385-93.

[20] Franc S, Daoudi A, Mounier S, *et al*. Telemedicine and diabetes: achievements and prospects. Diabetes Metab 2011; 37: 463-76.

[21] Patrick K, Marshall SJ, Davila EP, *et al*. Design and implementation of a randomized controlled social and mobile weight loss trial for young adults (project SMART). Contemp Clin Trials 2014; 37: 10-8.

[22] Bandura A. From thought to action: Mechanisms of personal agency. New Zeal J Psychol 1986; 15: 1-17.

[23] Jenny J-Y. Measurement of the knee flexion angle with a smartphone-application is precise and accurate. J Arthroplasty 2013; 28: 784-7.

[24] Datta AK, Sumargo A, Jackson V, Dey PP. mCHOIS: An application of mobile technology for childhood obesity surveillance. Procedia Comput Sci 2011; 5: 653–60.

[25] Doherty ST, Lemieux CJ, Canally C. Tracking human activity and well-being in natural environments using wearable sensors and experience sampling. Soc Sci Med 2014 ; 106 : 83-92.

[26] Miluzzo E, Lane ND, Fodor K, *et al*. Sensing meets mobile social networks: the design, implementation and evaluation of the CenceMe application. The 6th ACM Conference on Embedded Network Sensor Systems; 2008 November 4-7; Raleigh, USA; 337-50.

[27] Brezmes T, Gorricho J-L, Cotrina J. Activity recognition from accelerometer data on a mobile phone. Proceedings of the 10th International Work-Conference on Artificial Neural Networks: Part II: Distributed Computing, Artificial Intelligence, Bioinformatics, Soft Computing, and Ambient Assisted Living; 2009 June 10-12; Salamanca, Spain. Springer-Verlag Berlin, Heidelberg ©2009; pp. 796-9.

[28] Yang J. Toward physical activity diary: motion recognition using simple acceleration features with mobile phones. Proceedings of the 1rst International Workshop on Interactive Multimedia for Consumer Electronics, 2009 October 19-24; Beijing, China. Association for Computing Machinery; pp. 1-10.

[29] Kwapisz JR, Weiss GM, Moore SA. Activity recognition using cell phone accelerometers. ACM SIGKDD Explor Newsl 2010; 12: 74–82.

[30] Anguita D, Ghio A, Oneto L, Parra X, Reyes-Ortiz JL. Human activity recognition on smartphones using a multiclass hardware-friendly support vector machine. Proceedings of the 4th international conference on Ambient Assisted Living and Home Care 2012; Springer-Verlag Berlin, Heidelberg 2012; pp. 216-23.

[31] Anjum A, Ilyas MU. Activity recognition using smartphone sensors. First Workshop on People Centric Sensing and Communications; 2013 January 11-14; Las Vegas USA. pp. 914-19.

[32] Huynh DTG. Human activity recognition with wearable sensors. Ph.D. Thesis, 2008; TU Darmstadt, Germany.

[33] Li F, Dustdar S. Incorporating unsupervised learning in activity recognition. 25th AAAI Conference on Artificial Intelligence - Activity Context Representation; 2011 August 7-11; San Francisco, USA; WS-11-04 AAAI Workshops.

[34] Trabelsi D, Mohammed S, Chamroukhi F, Oukhellou L, Amirat Y. An unsupervised approach for automatic activity recognition based on hidden Markov model regression. IEEE Trans Autom Sci Eng 2013; 10: 829-35.

[35] Álvarez de la CMA, Soria MLM, Gonzalez-Abril L, Ortega RJA. Discrete techniques applied to low-energy mobile human activity recognition. A new approach. Expert Syst Appl 2014; 41: 6138-46.

[36] Harris JA, Benedict FG. A biometric study of basal metabolism in man. In Carnegie Institute of Washington 1919 (http://archive.org/download/biometricstudyof00harruoft/biometricstudyof00harruoft.pdf).

[37] Guidoux R. Conception et réalisation d'un système de gestion centralisée des données issues de projets de recherche clinique en nutrition humaine. Rapport de stage d'ingénieur en informatique. ISIMA, Clermont-Ferrand 2011. Available for download at: https://activcollector.clermont.inra.fr/resources/documents/guidoux-stage-2011-t1.pdf

[38] Rousset S, Fardet A, Lacomme P *et al*. Comparison of total energy expenditure assessed by two devices in controlled and free-living conditions. Eur J Sport Sci 2014. DOI:10.1080/17461391.2014.949309.

Received: November 4, 2014 Revised: January 5, 2015 Accepted: February 27, 2015