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SVELTE: Evaluation device of energy expenditure and physical condition for the prevention and treatment of obesity-related diseases through the analysis of a person's physical activities

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Abstract

Physical activity (PA) level is a key element in the prevention and the treatment of several chronic diseases. In adults, low PA levels and sedentary behaviors are linked to higher risks of developing cardiovascular diseases (e.g. high blood pressure), type 2 diabetes and several types of cancers. In addition, PA is an essential component for the treatment of obese people and for the prevention of elderly's loss of physical autonomy. In this context, the SVELTE project objectives were to develop new solutions to objectively measure one's fitness level on one hand, identify a subject's PA behavior in day-life conditions and its associated energy expenditure on the other hand. A few prototypes (including a multi-captor device linked with 3-axial accelerometer and magnetometer) were developed. The prototypes can store several days of data, are non-intrusive and easy to use for the subject. Several annotated databases have been collected and used to develop algorithms. These algorithms can (i) assess the overall fitness level of a subject, (ii) identify postures and types of PA performed throughout the day, and (iii) estimate the energy expenditure related to this daily PA. A clinical study protocol involving 120 subjects (obese and non-obese) wearing the sensors in their everyday life during 2 weeks is ongoing and has the purpose to validate the performances of the energy expenditure algorithm.

1. Introduction

One's usual level of physical activity (PA) has an impact on the risk of development of several non-communicable chronic diseases. For adults, low levels of PA significantly increase the risk of developing cardiovascular disease, obesity or type 2 diabetes, and have been linked to higher mortality rates at population levels [1]. In the case of elderly, PA plays a role in their ability to stay physically independent.

Historically, relationships between PA and health have been studied through the measurement of the energy expenditure (EE) related to physical activity (PAEE) [2]. However, reference methods to measure PAEE are not easy to use routinely in free-living conditions or require preliminary individual calibrations for each subject [3]. Motion sensors such as accelerometers are being increasingly used as alternatives, but the posture and the nature of movements involved in different types of PA strongly affect the relationship between actimetry data and PAEE [4]. Furthermore, in free-living conditions, the position of the device can

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hardly stay exactly the same at all times, which further affects PAEE estimates.

In the meantime, there is a growing body of evidence that the type, duration and frequency of activities constituting the overall PA of an individual may be an important factor to consider in addition to PAEE to understand the links between PA and health. In particular, sedentary behaviors have recently been shown to be additional risk factors for health. Existing motion devices often fail to capture these behaviors as well as low intensity PA, the main activities in everyday life.

In the framework of the TecSan 2009 call, the SVELTE project objectives were to develop an innovative solution based on motion sensors to quantify physical activity or inactivity, in terms of typology and energy expenditure. Two low-intrusiveness wearable prototypes and companion softwares were developed: the first to estimate physical activity and energy expenditure in daily life conditions and the second to calculate a snapshot of a person's physical condition at the time of the test (Diagnoform test, see www.diagnoform.com). The three main objectives of the project were:

- to have a robust identification of postures and physical activities;
- to develop algorithms linking the different types of physical activities and energy expenditure;
- to offer sensors with a high-level of autonomy.

2. Material and methods

To reach its objectives, the SVELTE project was structured into three parts.

2.1. Part 1 – Data acquisition and development of algorithms in controlled conditions

The first part dealt with the construction of an annotated database, with information relevant both to PA and EE. Sixty-five subjects performed a set of standardized physical activities (e.g. standing, sitting, walking, cycling on an indoor bicycle, etc. Fig. 1), during 4 hours, in laboratory conditions at the CRNH. Subjects were equipped with several motion sensors (MotionPod, MOVEA, each composed of tri-axial accelerometer and magnetometer), placed on different positions on the body (chest, waist, wrist, ankle...), two commercially available accelerometers devices (RT3 uni-axial, and Actigraph GT3X tri-axial) and a combined mono-axial accelerometer and heart-rate monitoring device (ActiHeart). The actual EE was simultaneously measured by indirect calorimetry (based on gaseous analysis of O_2 and CO_2). This database consists in the signal of the motion sensors (captured at 100 Hz), together with the corresponding annotations (actual posture or activity) and the EE measurements.

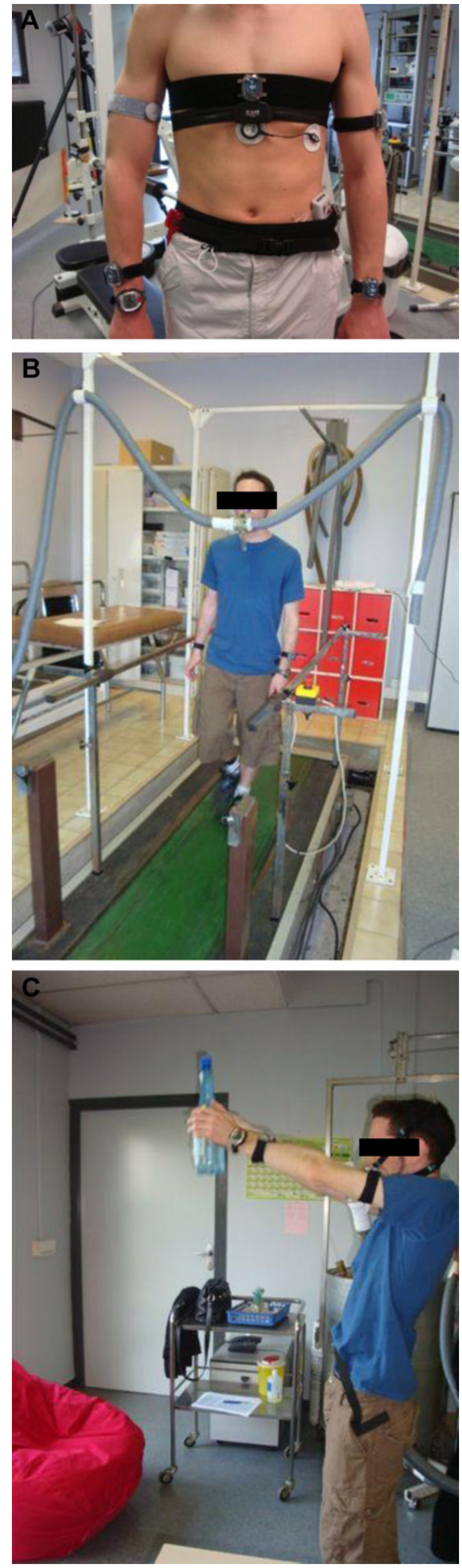

Fig. 1. Snapshots of subjects equipped with different motion sensors and actimeters during the database creation (4 hours of activity performed by 65 subjects). A. Sensors positioned on the subject's body. B. Walking. C. Bottle displacement.

Advanced signal processing methods and algorithm development were implemented to derive gait classification and estimate EE from the raw motion signals. The treatment chain (Fig. 2) included sampling, filtering, identification with Gaussian Model Mixtures, classification and graph based decision

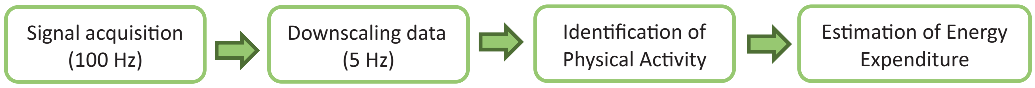

Fig. 2. Illustration of the data treatment chain from the motion sensor signal acquisition to the identification of the subject's posture, hence its PA, followed by the calculation of the estimated EE.

methods; it was developed by the CEA-LETI and Telecom Paris Tech. The developed software allows real-time monitoring of the motion sensor signal and identification of the PA. An initial validation of the algorithms was performed on the database by cross-validation to estimate the confusion matrix and thus the efficiency of the algorithm to successfully retrieve the activity.

2.2. *Part 2 – Test of the algorithms in free-living conditions*

A second database was built to validate the algorithms previously developed in laboratory conditions against data collected in semi-free living conditions. It was built under CRNH supervision, with technological developments of the motion sensors performed by Movea (controller of two motion sensors). Twenty

Fig. 3. Snapshots captured during four of the nine activities monitored during the Diagnoform evaluation test of physical condition (performed by 38 subjects). A. The subject has to stand up and sit down on a chair as many times as possible during 45 seconds. B. The subject is sitting against the wall, with the legs forming an angle of 90°, as long as possible. C. The subject is doing push-ups against the wall as many times as possible during 45 seconds. D. The subject is walking as fast as possible during 6 minutes. For more details, see www.diagnoform.com.

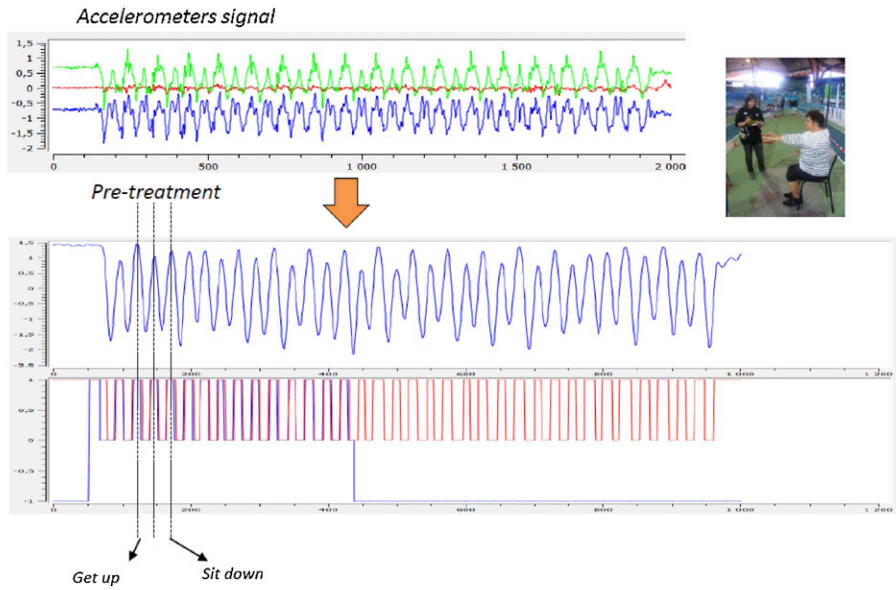

Fig. 4. Depending on the activity tested, the accelerometers or magnetometers signal are analysed. A pre-treatment (such as filtering) is applied on the signal followed by the classification step. The final score of the activity is then attributed.

subjects performed different types of PA in the city of Lyon (France) during 3.5 hours. Subjects were equipped with two Motionpods (worn on the right hip and ankle), one Actigraph and one Actiheart. The activities undertook by the subjects were typical of those experienced in everyday-life, such as being transported in a bus, waiting for a metro, walking up and down stairs, or actually riding a bicycle. Subjects were instructed to perform activities at their own pace. Annotations were precisely written down by an observer and were used to assess the performances of the algorithms previously developed to identify postures.

Validation of the EE estimation algorithm is currently ongoing, through a clinical trial involving 120 subjects wearing the device during two weeks in their everyday-life. For half of them, doubly labeled water (DLW) methods will provide an independent value of the average daily PAEE (DLW is considered being the golden-standard). The other half measurements are used for repeatability check. Every subject is also asked to document an activity notebook providing indications on her/his activities throughout the trial.

2.3. Part 3 – Developing and testing the fitness level assessment tool

In a third phase of the project, the initial algorithms were extended to allow an automatic scoring of the Diagnoform test (Fig. 3). The latter was developed and implemented by the Ligue Nord-Pas-de-Calais d'Athlétisme (LNPCA) as a funny practical estimation of one subject's physical condition (in the sense of fitness level) relatively to its age group (arms and legs strength, endurance, body flexibility. . .). A database associated with these activities was completed by 38 subjects wearing Motionpods. Dedicated algorithms to score the tests were developed to interpret the motion sensors signals (Fig. 4). The associated software was developed and implemented latter on a smartphone, leading to an easy use and interpretation of the tests results. An additional data collection campaign is currently ongoing to validate the user-friendliness and efficiency of the SVELTE software in combination with a smartphone. These data are collected during large scale events (such as the "fitness and nutrition days").

3. Results

The results obtained in the framework of the first part of the project, i.e. signal processing methods and posture-recognition were previously presented in a number of communications [5–8]. Overall, the performances of the implemented algorithm can be calculated on the database for posture identification. The confusion matrix gives figures between 65% and 97% for the posture identification. The lowest figures illustrate the confusion between sitting down and standing up, or between indoor cycling and stalling, which stays rather sensible and may not impact too strongly the balance of energy expenditure.

The posture-recognition algorithms were tested on the actimetry signals captured during the semi-free living conditions. For activities close to the ones used during the algorithm development (laying down, standing, sitting down, slumping/slouching, walking, running, stalling), the recognition algorithm performed well (Table 1). Correct classification rates were 97% for lying, 66% for sitting, 67% for slumped, 78% for walking (14% of walking is recognized as stalling/pacing), 49% for stalling/pacing, 95% for running, and 68% for cycling (except downhill: 10.2%). Some confusion still occurred with stalling interpreted partly as walking, or slumping partly identified as lying down. In both cases, these errors can be considered as rather sensible. The "standing still" position was mostly identified as "stalling" (79%) due to subjects not staying perfectly still. New activities, which were not included in the development database (e.g. climbing stairs, standing in a bus, sitting down in a car) resulted in relatively sensible classifications: for instance,

Table 1
Performance of the posture classification algorithm in classifying data collected during a guided activity trail in the streets of Lyon performed at the pace of the subject. *n* is the number of points for each type of activity (5 Hz).

Activity performed \Detected as (in %)	Lying down	Slouching	Sitting on a chair	Standing still	Pacing/Stalling	Walking	Running	*n*
Lying on a bed	**97.1**	2.0	0.0	0.0	0.8	0.0	0.0	3581
Slouching in an armchair	21.2	**69.5**	5.4	0.0	3.2	0.5	0.3	3574
Sitting at a desk	0.0	4.9	**66.3**	9.4	17.8	1.5	0.2	3583
Standing still	0.0	0.0	0.0	**13.0**	79.2	7.8	0.0	1200
Pacing/Stalling indoors	2.1	0.0	0.0	1.7	**48.8**	40.5	0.4	7279
Walking the streets (flat, up, down)	0.0	0.0	2.7	1.2	14.4	**77.9**	3.3	4,3527
Running in the street	0.0	0.0	0.0	0.0	5.1	0.0	**94.9**	3506
Walking upstairs	0.9	0.6	6.3	0.9	19.8	67.8	3.7	5465
Walking downstairs	0.0	0.0	0.0	0.0	1.8	56.5	41.8	2684
Standing in a vehicle (bus, tramway, subway)	0.0	0.1	3.3	1.2	91.9	3.4	0.1	1,4341
Sitting in a vehicle (car, bus, tramway, subway)	14.7	22.8	28.2	1.1	25.0	3.7	4.6	2,8814

The bold figures in the table correspond to the correct identification of PA.

climbing the stairs was interpreted mainly as walking (around 90%) and residually as running. However, errors remained with the identification of posture when the subject was sitting down in a vehicle. Additional results can be found in [9,10] and [11].

4. Discussion

Understanding the links between fitness level, physical activity/inactivity, PAEE and health is a prerequisite to develop strategies and assess their performances to prevent and treat several non-communicable diseases as well as the loss of physical independence in elderlies. Studies aiming towards this goal require the development of tools to objectively quantify of all these parameters in free-living conditions. The solutions developed during the SVELTE project provide such tools. The device used (MotionLog and MotionPod) was relatively easy to use, presented minimal discomfort for the subject compared to previously existing methods (e.g. heart-rate monitor) and have enough autonomy to be used over several days without data discharge. The algorithms developed during the project now enable to identify the daily PA recorded by the actimetry sensors to be broken down into discrete activity types (postures). In addition, the posture-recognition algorithm should also prove to be useful in improving PAEE estimates by integrating activity-specific considerations in the calculations of PAEE. Such PAEE prediction models have been developed during the project and the ongoing clinical trial will provide the data required to formally test their accuracy and precision. The SVELTE tools pave the way to more detailed analysis of actimetry data collected in free-living conditions over extended period of times, especially with respect to low intensity or sedentary behaviour.

Acknowledgments

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