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Estimation of physical activity monitored during the day-to-day life by an autonomous wearable device (SVELTE project)*

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Abstract— **Physical activity (PA) and the energy expenditure it generates (PAEE) are increasingly shown to have impacts on everybody's health (e.g. development of chronic diseases) and to be key factors in maintaining the physical autonomy of elderlies. The SVELTE project objective was to develop an autonomous actimeter, easily wearable and with several days of autonomy, which could record a subject's physical activity during his/her daily life and estimate the associated energy expenditure. A few prototypes and dedicated algorithms were developed based on laboratory experiments. The identification of physical activity patterns algorithm shows good performances (79% of correct identification), based on a trial in semi-free-living conditions. The assessment of the PAEE computation algorithm is under validation based on a clinical trial.**

I. INTRODUCTION

Daily physical activity (PA) and sedentary behaviors are more and more pointed at for the role they play in everybody's health. In particular, insufficient physical activity can be either responsible for, or an aggravating factor of, non-communicable chronic diseases. As stated in the World Health Organization report [1], people have four major domains with opportunities to be physically active: at work, for transport, in domestic duties, and in leisure time. Consequently, physical inactivity is obtained when very little or no physical activity is performed in any of these four domains. For adults, diseases at concern with a lack of physical activity are diverse. Obesity is obviously favored by physical inactivity and sedentary habits, on top of inadequate food consumption. The weight control of obese people can be improved by an increase of physical activity on a weekly basis. Low levels of physical activity have an impact on the risk of cardiovascular diseases, a few cancers and Type 2 diabetes mellitus. The WHO estimated that about "10–16% of cases each of breast cancer, colon and rectal cancers and diabetes mellitus, and about 22% of ischaemic heart diseases" are caused by physical inactivity [1]. In addition, it has been suggested that physical activity can relieve depression, anxiety and stress, or even lower back pain, although the precise mechanisms involved are not exactly known. In elderly people, physical activity is thought to improve balance and reduce the risk of fall, hence leading to a better physical autonomy and their possibility to live longer at home.

Historically, studies on links between physical activity and health have focused on monitoring PA levels and PA energy expenditure (PAEE). The currently available most efficient methods to measure PAEE include doubly labeled water (DLW) and indirect calorimetry [2]. DLW, the gold standard in the field, only provides PAEE measurements integrated over extended periods of time (>2 weeks) and is highly costly, preventing it from being used in routine. Indirect calorimetry on the other hand can provide measurements at high temporal resolution, but uses complex and quite 'cumbersome' machinery. Therefore, practical alternatives to monitor PAEE in free-living conditions are required; miniaturized accelerometry devices are being increasingly used for this purpose. However, currently existing devices often fail to overcome the problem of the relationships between acceleration signal and PAEE being inconsistent between different types of PA (cycling EE being particularly difficult to estimate) [3]. The present paper focuses mostly on the retrieval of PA.

Importantly, relatively to human beings' health, monitoring PA or PAEE do not provide the same type of information, since PA can be characterized by different aspects: the type of physical activity (walking or cleaning the windows), the frequency to which it is practiced (twice a day to and from the work or once monthly), its intensity (walking pace for instance) or its duration (5 minutes or 2 hours continuously). The contribution of each of these components to the overall health benefits one can get from PA remains to be determined. In addition, most studies to date, have been focusing onto heavy work or leisure activities; yet, the larger part of daily PA of many people is made up of low or very-low intensity PA.

The objectives of the SVELTE project were to develop a device, which could be at the same time highly wearable, user-friendly, autonomous for several days (both for data and energy), and capable of monitoring a subject's PA on his/her day-to-day life, automatically identifying different types of PA and estimating PAEE with robustness and precision. This paper is structured as follows: in section II, the methods

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developed to convert the raw signal into physical activity are explained. In section III, the databases used for the development of the data treatment and for the validation of the algorithms are presented. Section IV shows the results obtained in terms of physical activity in semi-free conditions while section V is a discussion.

II. DATA TREATMENT

A. Signal acquisition

The MOVEA SA firm developed an inertial sensor, named MotionPod of the size of a rubber gum. It includes a triaxial accelerometer and a triaxial magnetometer, together with the accompanying microelectronics and a BlueTooth link. Signal is captured at a 200 Hz. The MotionPod communicates with a MotionLog, which can store data from one or a few MotionPods. This allows one subject to simultaneously wear several MotionPods on different parts of the body. The sensor itself is relatively small (33x22x15mm, 14g), non-invasive and is easily wearable, either with straps or in a pocket. The raw measured signal includes the acceleration in three dimensions (A_x, A_y and A_z) and the magnetic field in three directions (M_x, M_y and M_z). Two dedicated treatment chains were developed to process the signal and allow its interpretation (1) into postures or PA and (2) into energy expenditure.

B. Signal processing to estimate the PA

Fig. 1 shows the diagram of the signal processing applied to obtain PA during the acquisition session. The treatment chain starts from the raw measurements of A_x, A_y, A_z, M_x, M_y and M_z at 200Hz. The data reader decimates the signal to 25Hz, and keeps only the accelerometry data (A_x, A_y and A_z). As shown by [4], a frequency of 20Hz allows a correct identification of PA; the decimation allows the calculations to be shorter. The features of the accelerometry signal are calculated at 1Hz: energy, mean frequency and an index of the scattering of the frequencies. Presently, nine postures or physical activities can be recovered from the signal processing. These activities are the following: (1) lying down, (2) sitting down, (3) slouching, (4) standing, (5) walking, (6) stalling, (7) running, (8) indoor cycling and (9) outdoor cycling. Each PA (noted A) is modeled with a Gaussian mixture model of two Gaussian, assuming that the samples (the observation vector $O(t)$) are i.i.d. :

$$p_A\big(O(t_0{:}\,t_{M-1})\big) = \prod_{m=0}^{M-1} p_A\big(O(m)\big)$$

$$p_A\big(O(m)\big) \rightarrow \sum_{n=0}^{1} c_{A,n} N\big(\mu_{A,n}, \sigma_{A,n}\big)$$

The sextuplet $\{c_{A,1}, \mu_{A,1}, \sigma_{A,1}, c_{A,2}, \mu_{A,2}, \sigma_{A,2}\}$ defines the 6 p.d.f. parameters and are obtained for each activity A thanks to an expectation-maximization algorithm on the SVELTE1 database (see section III for the details of the databases). The parameters for the outdoor cycling were calculated on the SVELTE2 database because it was performed only during that clinical trial.

Afterwards, in the case of a new observation vector, the PA assigned to this observation, noted $\hat{A}$, is the one with the greatest probability among the 9 activities. After that step, a graph analysis is performed with the aim to filter the succession of PA (see [5] or [6] for more details). A mapping of PA is used to classify the 9 activities into classes of activities as used for the energy expenditure estimation. Finally, the analyzed PA is written in a csv file for further analysis (from day to day, or in link with the subject's notes on his/her activities).

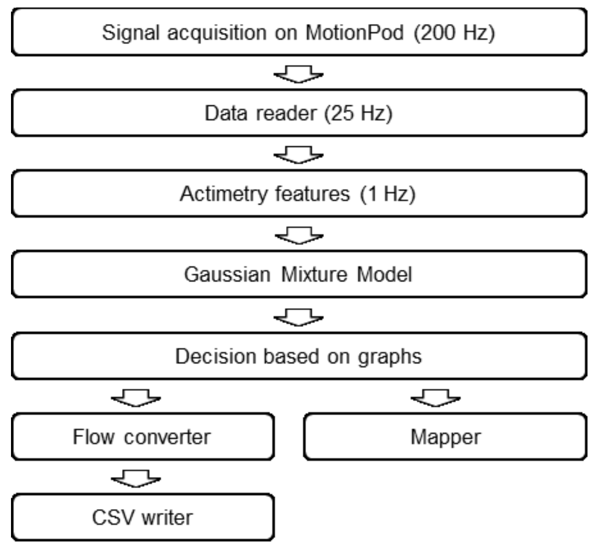

Figure 1. Diagram of the SVELTE treatment chain to estimate PA from raw motion signals.

III. DATABASES

For the purpose of the development of the system developed in the SVELTE project, a few databases were developed.

A. Laboratory measurements (SVELTE1 database)

A database was acquired in laboratory conditions in the CRNH Rhône-Alpes. A total of 65 subjects were invited to follow an activity path, including 23 standardized physical activities or postures during 2 hours (e.g. lying down, sitting in a chair, sitting at a desk typing on a computer, lifting a weight up and down, standing up still, cleaning the windows, sweeping the floor, walking, riding an exercise bicycle, running on a training set). The posture slouched has been identified as an intermediary between laying down and sitting down. Slouching is happening in a couch or in a chair, when the subject is not straight, it is a relaxed posture.The time spent in each activity was about 5 minutes except for lying down, which lasted for 45 min during which resting metabolism was measured through indirect calorimetry (see below). During the activity session, each participant wore a few devices: (1) one Stayhealthy RT3 (based on triaxial accelerometry), (2) one Actigraph GT3X (triaxial accelerometry), (3) one Camntech Actiheart and (4) up to eight Movea MotionPods. The first three devices are commercially available and provide data on physical activity and/or energy expenditure. Simultaneously, subjects were wearing a mask, which allows measuring their actual energy expenditure by indirect calorimetry based on analysis of O_2 and CO_2 volumes.

The purpose of this database is four-fold: (1) eight MotionPods are worn at different places of the body, such as the waist, the ankle, the chest, the wrist, the leg, the arm … to determine which sensor location allows the best recognition of the postures; (2) the three commercially available devices measure the same activity set, which allows to compare the performances of different sensors to estimate the PA; (3) the Camntech Actiheart being considered as the state-of-the-art EE meter provides a reference for EE, see [7] ; (4) the actual EE measured by indirect calorimetry is an independent measurement of what ideally should be provided by the SVELTE method. The database is annotated, which means that the beginning and end of each PA is precisely delimited, hence the MotionPod signals are linked to the corresponding PA.

B. *Semi-controlled conditions for the validation of the physical activity identification algorithm (SVELTE2 database)*

A second database was developed at CRNH Rhône-Alpes, with the aim to be more representative of real-life physical activity patterns. For this reason, an activity path was created in the city of Lyon (France), including a variety of postures and activities, among which sitting down, standing up and walking were obviously represented as in the SVELTE1 database, but this time it was performed in town. Additional activities were climbing up and down stairs, being transported in a car, in a bus, in the tram, (in the latter two either sitting down or standing), waiting for the public transportation, being transported on an automated stairs (either passively or actively climbing up and down), riding a bicycle on a flat ground, or up and down a slope. A total of 20 subjects were asked to perform this activity set at their own pace. Each person wore a few sensors: one Movea MotionPod worn at the hip, one Camntech Actiheart and one Actigraph GT3X. During the 3.5 hours duration of the activities, one research assistant noted precisely the beginning and end of each PA. A third database is under collection, mostly related to EE.

IV. Results

A. *Detection of the postures and PA on the laboratory measurements (SVELTE1 database)*

After a sensitivity study, data from the MotionPod worn at the hip was chosen to be the raw signal input of the treatment chain. A few different models were tested to interpret the motion sensors signals. For instance, models with 4 PA were tested (lying down, sitting, standing, walking), but they had the disadvantage of not being comprehensive enough for the day-to-day life. A model including more PA was adopted which includes these 4 activities plus slouching, stalling, running and cycling. The good detection rate (or confusion matrix) on the SVELTE1database was calculated as the average for all N subjects. Actually, $N-1$ subjects are used to learn the Gaussian Mixture Models, and the performances (i.e. the capacity to identify correctly the PA, as is mentioned in the annotations) are calculated on the N^{th} subject. The overall good detection rate is the mean of these performances for all subjects. The larger the good detection rate, the better the PA is recognized based on the motion signals. The good detection rate for all activities is 79.3%. Table 1 shows the details for the eight PA (the outdoor cycling was added afterwards with the SVELTE2 database). The good detection rate ranges between 55% for sitting down, to more than 90% for lying down, walking and running. For clarity reasons, figures have been rounded in Table 1, but not the very low quantities, thus the sum of detection is not strictly 100% as presented here.

Activities performed	Physical activities identified (categories of the model) in %							
	Lying down	*Slouching*	*Sitting down*	*Standing*	*Walking*	*Cycling*	*Stalling*	*Running*
Lying down	**92.7**	4.6	0	$7.1e^{-2}$	0	0	2.7	0
Slouching	3.7	**87.8**	3.0	5.4	0	0	$2.0\ e^{-2}$	0
Sitting down	0	3.0	**55.4**	37.1	0	0.2	4.1	0.1
Standing	0	0.5	5.5	**89.3**	0	0	4.7	0
Walking	0	0	$3.6e^{-3}$	$4.8e^{-2}$	**97.4**	0.4	1.1	1.0
Cycling	0	0	$3.2e^{-2}$	$9.6e^{-2}$	1.5	**84.9**	13.3	0.1
Stalling	0	0	2.0	30.1	1.5	1.4	**65.0**	$5.5\ e^{-2}$
Running	0	0.7	0	0.3	3.1	0	3.3	**92.6**

TABLE I. Performances of the PA identification on the SVELTE1 database

B. *Identification of PA in semi-controlled conditions (SVELTE2 database)*

The SVELTE2 database was then interpreted with the previously developed algorithm (see Fig. 1, [8], [9] and [10]). The motion signal is interpreted in terms of PA for each of the 20 subjects during the 3.5 hours duration of the trial. The succession of PA is reconstructed and compared to the truth (i.e. the notes taken by the observer during the trial). The matrix of good detection rate can be calculated. Some activities performed during the SVELTE2 clinical trial were similar to activities performed during the SVELTE1 clinical trial, it is for instance: lying down, sitting down on a chair or walking. For these activities, the identification of the PA is rather good. Figures vary between 49% for stalling to 97% for lying. Intermediate scores were obtained for sitting down (66%), slouching (67%), walking (78%) and running (95%).

The percentages written in bold in Table 1 represent the good detection rate. Confusion between different PA may occur: for instance, the subject being slouched in an armchair was identified as lying down in 21% of the time and as sitting down in 5% of the time.

The distinction between lying down, slouching and sitting is probably not so clear/consistent between subjects and is one limitation of the algorithm. There is also such confusion between standing and stalling, probably in the case where the subjects were not strictly still. In the SVELTE2 database, new activities were introduced, such as climbing stairs. The current PA model includes 9 PA, which means that each new activity will be classified in one of the 9 classes of PA. Presently, climbing the stairs is identified mainly as walking (68% of the time) or stalling (20% of the time). Going down the stairs is identified mainly as walking (57%) and running (42%). Standing in a vehicle is overwhelmingly identified as stalling (92%), while sitting in the same vehicles is identified in the same proportions as slouching, sitting and stalling (between 23% and 28%).

C. *Examples of one-day-physical activity for contrasting behaviors*

As a proof of concept, the SVELTE algorithm was used to profile the PA of four subjects with contrasting life-styles over an entire day. Fig. 2 illustrates how the daily PA can be different for a variety of reasons and depends on the subject.

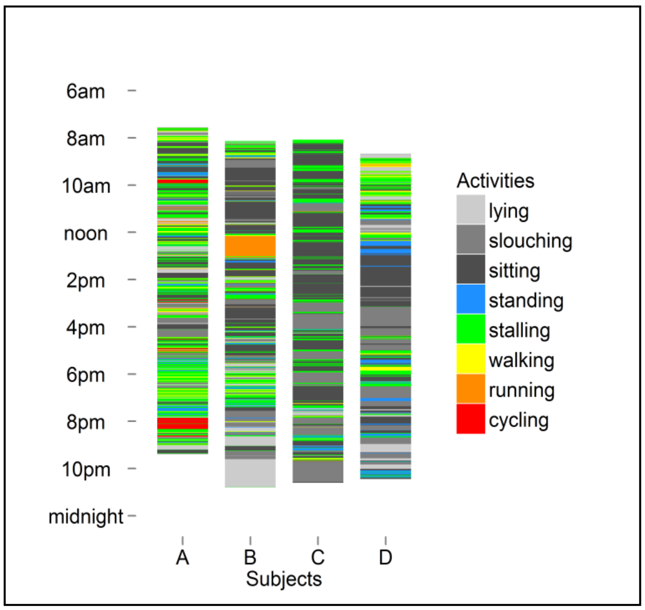

Figure 2. Reconstructed physical activity for four subjects with contrasting life-styles : (A) a subject being active all day long, (B) a subject with a desk-based professional occupation but jogging over lunch-break, (C) a subject with a sedentary professional occupation, and (D) a retired person active in the morning (grocery, market) and inactive in the afternoon and evening.

V. Discussion

The SVELTE project objectives were to develop a wearable sensor, based on motion sensor, allowing the day-to-day estimation of human PA and PAEE. The sensor was developed and proved to be usable by individuals in their daily life for 15 days without problems. The PA algorithms provide valuable information on the subject's activity although tests in semi free-living conditions revealed some confusions between certain types of PA. An EE calculation algorithm integrating the results of the PA identification process has been designed and validation is still ongoing. Despite some inherent uncertainties, due to the use of a single motion sensor to identify a variety of PA, from lying down to be transported in public transportation, the SVELTE device and associated algorithms should provide a useful objective tracer of one's activity on a day-to-day basis [10]. Such tool is essential in order to improve the design and to evaluate the efficiency of interventions targeting PA practices at individual or population levels.

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