Rich Context Information for Just-In-Time Adaptive Intervention promoting physical activity*

F. Cruciani$^1$, C. Nugent$^1$, Member IEEE, I. Cleland$^1$, P. McCullagh$^1$

**Abstract**—Sedentary lifestyle and inadequate levels of physical activity represent two serious health risk factors. Nevertheless, within developed countries, 60% of people aged over 60 are deemed to be sedentary. Consequently, interest in behavior change to promote physical activity is increasing. In particular, the role of emerging mobile apps to facilitate behavior change has shown promising results. Smart technologies can help in providing rich context information including an objective assessment of the level of physical activity and information on the emotional and physiological state of the person. Collectively, this can be used to develop innovative persuasive solutions for adaptive behavior change. Such solutions offer potential in reducing levels of sedentary behavior. This work presents a study exploring new ways of employing smart technologies to facilitate behavior change. It is achieved by means of (i) developing a knowledge base on sedentary behaviors and recommended physical activity guidelines, and (ii) a context model able to combine information on physical activity, location, and a user’s diary to develop a context-aware virtual coach with the ability to select the most appropriate behavior change strategy on a case by case basis.

I. INTRODUCTION

Sedentary behaviors (SB) and inadequate levels of physical activity (PA) are two emerging health risk factors connected to metabolic and cardiovascular diseases, cognitive impairment and musculoskeletal diseases [1]. In developed countries, SB and physical inactivity are particularly significant in the older adults (age $\geq 60$) segment of the population [1]. The relevance of this issue has made the promotion of PA one of the clinical priorities for national healthcare systems [2]. To date, behavior change interventions aimed to reduce SBs and/or increase levels of PA still rely heavily on self-reported information [1][3]; the use of inertial sensors to objectively measure levels of PA is increasing [4], however there are very few smartphone applications which specifically target older adults [1][3]. The use of smart technologies and pervasive computing can be an appropriate channel to provide automatic and objective assessment of the levels of PA. While the perceived invasiveness of technology has been a significant adoption issue in the past in terms of acceptability of proposed solutions (particularly in certain age groups), recent trends suggest that a less obtrusive approach could leverage the growing diffusion of smartphones [5]. As such the delivery of behavior change interventions is becoming more popular through the use of smartphones and mobile apps [6][7] and automatic activity recognition through pervasive technologies can replace and enrich self-reported information. There is a solid underpinning in terms of research around activity recognition and context aware systems that can provide essential information for behavior change [8] and that can also be employed regarding the promotion of PA. Traditional approaches to activity recognition have shown high classification accuracy in controlled environments, however, their deployment in situ and their scalability still represents a significant challenge [9], hindering their application in large scale pilots for behavior change. Lack of large labeled datasets has traditionally represented an obstacle to *data-driven* approaches to activity recognition. Recent studies combining *data* and *knowledge-driven* approaches have shown promising results in realistic experimental set-ups, moving towards solutions that are applicable on a large scale [9]. In this work, we propose a combined *knowledge* and *data-driven* approach for the definition of a rich context information in smart environments with the objective of promoting behavior change. The aim of this work is to develop a personalized solution, deployable on a large scale which can support a behavior change intervention for SBs and PA without the need for intrusive monitoring equipment or configuration by end users.

II. RELATED WORKS

SBs and inadequate levels of PA are generally considered as two distinct objectives in behavior change interventions, given that they represent two separate health risk factors [1]. As such, studies in this area can be divided respectively to the single or joint goal of reducing sitting time and/or increasing levels of PA. Most studies have been based on information on PA such as the number of steps taken per day, or the time spent in sedentary activities such as watching TV. In most cases, the information relating to the user’s behavior is self-reported [1],[3] resulting in the risk of biased information [1]. Clearly, the automatic and objective assessment of levels of PA and detection of SBs using smart technologies can constitute a major benefit [1], [10]. When tackling the problem with older adults, step count is generally used as a valid metric of assessment [11]. Even though step count by itself does not provide information on the intensity of the activity, some studies have shown how the combination of step count with information on the Body Mass Index (BMI) can be used to assess low, moderate and intense PA based on the rate of steps per minute [11]. This objective measurement, however, can go beyond the simple assessment of levels of PA. Smart environments allow rich context information to be collected which is not

---

*This research has received funding under the ACROSSING project Marie Sklodowska-Curie EU Framework for Research and Innovation Horizon 2020, under Grant Agreement No. 676157.

$^1$F. Cruciani, C. Nugent, I. Cleland and P. McCullagh are with Ulster University, School of Computing and Mathematics.
limited to the level of energy expenditure corresponding to an activity. For example some studies have focused on measuring time spent out of the home and the analysis of the relationship between loneliness and levels of PA [12]. Indeed, social aspects play a key role in behavior change interventions. The main factors behind behavior change (e.g. users’ motivation in Fogg’s Behavior Model [13]) are constantly affected by the socioemotional state of the person [10]. Smart technologies can therefore help to develop dynamic behavior models considering socioemotional parameters for Just-In-Time Adaptive Intervention (JITAI), providing real-time information useful to assess the emotional state [10]. Similar studies using the smartphone as a mood sensor have been conducted [14].

A behavior change intervention aimed to promote PA can benefit from the solid research background on activity recognition in pervasive systems, that can provide rich context information for behavior change purposes. Even though, it has been shown that these approaches perform well in controlled environments, their application in the real world on a large scale still represents an issue [9]. *Data-driven* approaches are quite robust to deal with data uncertainty, however, they suffer the cold-start problem for a set-up/learning phase and require a large quantity of labelled data [9]. On the other hand, *knowledge-driven* approaches, even if more generic and more easily applicable in large scale studies, do not evolve through time and are not robust to data uncertainty [9]. Here we propose a combined approach for providing rich context information in behavior change interventions. developing a personalized unobtrusive system, easily applicable in large scale studies without the need for any adaptation or configuration by end users.

### III. Description of the Context Model

The use of smart technologies and their application for behavior change purposes can produce an enormous quantity of valuable information. Technology can provide data to objectively assess levels of PA and can further contextualize data with information related to other physiological parameters or the emotional state of the person. The model presented in this work aims to define rich context information that can be coupled to a behavior change model. Following a fully unobtrusive approach, our proposal uses the smartphone as the main information source. Nevertheless, additional information sources (e.g. fitness wearables for users who already own them, or information from home installed sensors where available) may be included in an opportunistic sensing paradigm. Wearables as an additional piece of information can provide real-time information on a range of physiological parameters that may be useful in a behavior change model, particularly in monitoring physiological response. Our model for rich context information (Fig. 1) can be viewed as being composed of five essential dimensions:

1. **Temporal** i.e. time interval in which an activity occurs, its relations to diary information, drug prescription or appointments.
2. **Spatial** taking advantage of ubiquitous localization that smart technologies can provide including both outdoor and indoor localization.
3. **Physiological** including body measurements and physiological parameters that can help to contextualize data.
4. **Physical activity** assessment enriching the model on how the activity can be classified (i.e. sitting, walking, running), its intensity and the estimated energy expenditure.
5. **Socioemotional** provides rich contextual information that can be used for dynamic models for behavior change based on JITAI.

![Fig. 1. Rich context information for behavior change, leading to physical activity assessment, and potential behavior change, mediated by a virtual coach.](image)

These five dimensions and their role in providing meaningful information for behavior change will be described in the following sections.

#### A. Temporal dimension

Time dimension is essential for the assessment of PA. It provides information on the duration of sedentary or active periods, and their frequency. This is the basis for computing the ratio of active time compared with sedentary or inactive periods. Existing guidelines define target objectives for levels of PA in terms of minimum amount of time spent undertaking moderate and intense physical activity. These guidelines also highlight that these exercising sessions must not be divided into exercise bouts less than 10 minutes in duration [11]. The time dimension is also relevant in combination with other dimensions, specifically the spatial dimension, providing for example information on current weather or ongoing events nearby that can be used as motivational leverage to promote time spent outside the home. In a smart technology context, however, the temporal dimension is not limited to information on time intervals. Scheduled appointments, diary and medical prescriptions to name but a few, also provide valuable semantic information that can play a role in the
combined use of knowledge and data-driven approaches for data mining.

B. Spatial dimension

The smartphone and its on-board sensors can provide ubiquitous localization through the combined use of GPS for outdoor tracking and RSSI-based localization for indoor environments. The combined use of unsupervised data-driven techniques, by means of clustering and statistical analysis of the most frequently visited locations can provide identification of relevant locations detecting locations where more time is spent. This, in combination with a knowledge-driven approach to labeling these locations based on time patterns spent in each environment can produce ubiquitous localization. Most frequent GPS locations can be used to automatically identify important places and this information can be easily labeled automatically using knowledge-driven methods based on time pattern analysis of occurrences of the same location (e.g. 'home' at night time or the 'office' at working hours). GPS locations can be used to label automatically generated indoor maps linking vectors of RSSI to their correspondent GPS location. Detected vectors of RSSI values can then be clustered to identify different spaces within the same location. Coupling this with information, relating to the usual time spent there and duration, provides automatic detection and labeling of spaces as rooms (e.g. kitchen, bedroom). This results in labeled clusters of indoor locations identifying spaces in the same map that are finally grouped to their correspondent GPS location, realizing in this way an unsupervised ubiquitous localization that can enrich the analysis of behavioral patterns in combination with users’ localization. Finally, the identification of repeating transportation routines can be used to suggest alternative routes increasing PA levels.

C. Physiological dimension

The Physiological dimension includes all physiological information and body measurements that can contextualize information, both on the PA dimension and in the socioemotional dimension. BMI and age are fundamental data to better target users according to the group they belong. Even though the approach proposed here is mainly unobtrusive and based on the smartphone, the semantic model cannot exclude data that can come from wearable devices where available. Fitness wristbands and similar devices are becoming increasingly common and sophisticated. Therefore, the proposed model also includes these data sources for physiological data, such as the heart-rate. Physiological data as in the case of heart-rate can contextualize not only the intensity of PA, but also can provide measures on the stress level that can be derived from heart rate variability analysis and can be used for JITAI purposes.

D. Physical activity

Assessing levels of PA is undoubtedly the main feature in a behavior change intervention aimed to reduce SBs or promoting PA. Guidelines regarding recommended levels of PA explicitly refer to the recommended amount in terms of moderate (≥30 minutes, 5 times per week) and intense physical exercise (≥20 minutes, 3 times a week) [11]. Smartphones and their on-board sensors can provide a refined information source useful to assess the level of PA. Inertial sensors can be used to unobtrusively monitor activities and the step count. Data mining can be performed on the data gleaned from inertial sensors, labeling data based on activity recognition performed through knowledge-driven activity classification based on GPS information distinguishing between walking speed (≈1.4m/s), running (≈6m/s) and transportation (>20 m/s). Finally, the step rate per minute in relation to the duration of the time segment of exercise can be used to evaluate intensity and duration of physical exercise according to the PA guidelines.

E. Socioemotional dimension

The key factors behind behavior change, such as a users motivation to perform a task, are deeply affected by their emotional state. Depressing events during the day can reduce levels of perceived competence and self-regulation [10]. This is the main principle behind JITAI, i.e. being able to detect these changes and consider them in a behavior model detecting when levels reduce and there is the subsequent need to intervene. This feature of operation provides essential information to a virtual coach to improve the timing of feedback to the user. Some information related to the emotional state can be analyzed also through physiological signals, as in the case of heart rate variability analysis to detect occurrence of stressful situations.

IV. Assessing physical activity

This Section presents data recordings gathered for two active adults based only on a smartphone as an information source, thereby demonstrating how the model can be applied to extract rich contextual information and to perform a refined assessment of levels of PA. As in other studies, we consider the step count and cadence (steps/minute) as a basic level of assessment. Fig.2 shows the average daily distribution of steps per minute rates. This vector provides a basic metric to evaluate how PA levels are distributed in terms of moderate activity (90-110 steps/minute) and intense activity (160-180 steps/minute).

![Fig. 2. Average daily distribution of steps/minute rates.](image)

As defined in the guidelines, it is important not to split physical exercise in time epochs smaller than 10 minutes in duration. Fig.3 presents the distribution in terms of rate of steps per minute of the exercise in relation to the overall duration of the activity.
As previously mentioned, ubiquitous localization plays an important role in multiple aspects. It provides in the first instance an easy way to measure time spent out of the home. Fig. 4 presents a user’s location in a bubble chart where the point radius is proportional to the time spent at that location. This, combined with knowledge-driven analysis of time patterns, allows the detection of home location and consequently to measure time spent out of home. Finally, Fig. 5 presents the overall assessment over the period of a week period showing total number of steps, how PA levels are distributed in terms of rate of steps per minute and the total amount of active time compared with the sedentary periods and time spent out of home. The lowest level of PA and the worst ratio active/inactive time corresponds to the lowest time spent out of the home.

V. CONCLUSION

This paper has shown how it is possible to provide rich contextual information to promote behavior change, following an unobtrusive approach utilizing only smartphone as data source. The next step will be an investigation and evaluation of applying behavior change techniques through virtual coaching and the exploration of dynamic models for JITAI using the smartphone as a social sensor in order to identify decision points for intervention through virtual coaching. This flexible and unobtrusive approach will facilitate delivery of interventions in large pilot studies that will serve to evaluate the effectiveness of different strategies for behavior change. In addition, it will serve to evaluate if smart technologies can provide sufficient information to automatically select the best strategies for the specific user.

ACKNOWLEDGMENT

This work has been funded by the European Union Horizon 2020 MSCA ITN ACROSSING project, GA no. 616757.

REFERENCES

[2] Physical Activity and Lifestyle announced as a clinical priority by the RCGP. Royal College of General Practitioners.