A study design for physical activity reference data collection using GPS and accelerometer

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Abstract: A physically active lifestyle is a key component of promoting health and well-being particularly for healthy ageing. Most sensor-based studies are focused on measuring the level (or intensity) of physical activity and use data collected using a specific study protocol under a controlled laboratory condition and are thus hardly comparable to each other and difficult to use as training or validation data for real-life studies. Therefore, it is important to have available a reference dataset for physical activity type classification especially in real-life environments. The main aim of this study is to provide a study design for collecting a reference dataset that can maximize both internal and ecological validity of measuring physical activity types. To that end, we designed study protocols in three different conditions, namely: laboratory/controlled, semi-structured and real life. To collect data, a sample of 40 healthy participants (30 younger adults and 10 older adults) will participate to perform activities including: lying, sitting, standing, walking on level ground, running, cycling, walking uphill, walking downhill, walking downstairs and walking upstairs both indoors and outdoors. The activity walking on level ground will be performed at three different speeds. Additionally, GPS and GIS methods (e.g. information about slope or dominant land use) will be used to enrich the detailed information about accelerometry-based activity types and to provide the environmental information of the place where the activities will take place. The proposed reference dataset can be useful for future validation and comparison studies and for the development of new physical activity type classifications algorithms particularly under real-life conditions.

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A Study Design for Physical Activity Reference Data Collection Using GPS and Accelerometer

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Abstract

A physically active lifestyle is a key component of promoting health and well-being particularly for healthy ageing. Most sensor-based studies are focused on measuring the level (or intensity) of physical activity and use data collected using a specific study protocol under a controlled laboratory condition and are thus hardly comparable to each other and difficult to use as training or validation data for real-life studies. Therefore, it is important to have available a reference dataset for physical activity type classification especially in real-life environments. The main aim of this study is to provide a study design for collecting a reference dataset that can maximize both internal and ecological validity of measuring physical activity types. To that end, we designed study protocols in three different conditions, namely: laboratory/controlled, semi-structured and real life. To collect data, a sample of 40 healthy participants (30 younger adults and 10 older adults) will participate to perform activities including: lying, sitting, standing, walking on level ground, running, cycling, walking uphill, walking downhill, walking downstairs and walking upstairs both indoors and outdoors. The activity walking on level ground will be performed at three different speeds. Additionally, GPS and GIS methods (e.g. information about slope or dominant land use) will be used to enrich the detailed information about accelerometry-based activity types and to provide the environmental information of the place where the activities will take place. The proposed reference dataset can be useful for future validation and comparison studies and for the development of new physical activity type classifications algorithms particularly under real-life conditions.

Keywords: physical activity type, accelerometer, global positioning system, reference dataset

1 Introduction

Active modes of transport such as walking, bicycling, and jogging contribute to reduced risk of physical and mental health problems (Physical Activity Guidelines Advisory Committee 2008). A physically active lifestyle is particularly paramount for healthy aging, as it is associated with higher levels of functional health, a lower risk of falling, and better cognitive function (Voss et al. 2016). Physical activity (PA) is defined as any bodily movement produced by skeletal muscles that results in energy expenditure (Caspersen et al. 1985). PA is a complex behaviour with four main measures, which can be abbreviated as FITT: Frequency, Intensity, Time and Type of activity (Cavill et al. 2006) .

Most of the sensor-based methods for PA rely on the level (also called intensity) of the activity. The exclusive focus on PA level can be problematic (Rosenberg et al. 2017). Being able to recommend that people and particularly older adults increase the time they spend walking is much easier to control individually than recommending a certain level of activity intensity, a concept that most laypersons are likely unable to clearly understand. Moreover, once the type of activity is classified other features such as the time duration of activity and its frequency over the day or week can be estimated (Lindemann et al. 2014). Accurate measurement of the physical activity behaviour type during everyday living independently of, and in addition to, other PA measures is therefore important.

Existing sensor-based studies of PA are somehow incomparable with each other, particularly due to considerable variation in environmental and conceptual factors under which the studies were conducted. Using different study designs and training data collection protocols is one of the examples of this problem. Most of the sensor-based methods for PA recognition are based on accelerometer data from a limited number of laboratory activities (controlled condition) performed by young participants. Using this approach, participants are asked to follow a standardized protocol with a fixed order of instructions. Therefore, it is questionable whether laboratory-derived algorithms and models can be reproducible in real-life situations (De Vries et al. 2011) and for other age groups. Haché et al. indicate that monitoring the mobility outside a clinical setting is important because mobility in the real world typically differs from the mobility measured in the clinic (Haché et al. 2011). Studies of real-life activity are then needed to improve the ecological validity of lab-based methods.

Combining laboratory and real-life data to develop classification models and considering the concepts of “real life” and “controlled condition” on a relative scale are proposed as potential solutions for improving classifiers in real-life data (Vincent Hees et al. 2013; Gyllensten & Bonomi 2011). Activities can be carried also out in a semi-structured protocol. Using this protocol to simulate real life, participants are free to perform required activities in their own way, for example at their comfortable speed or in an outdoor area.

Data gathered solely with an accelerometer do not provide information about mobility in different environments. For example, without additional information it is impossible to determine where the activities were undertaken (e.g., indoors or outdoors). Ecological approaches to health and behavior have long held that place matters for health (Jankowska et al. 2015).Outdoor physical activity can have important benefits for health, particularly in older adults and in children. Thus, to improve health outcomes it is critical to accurately measure physical activity and sedentary time spent in- and outdoors (Rosli et al. 2013).

Many studies have examined the relationship between PA and characteristics of the built environment, such as green spaces or walkability based on neighborhood areas using GIS. Using Global Positioning System (GPS) and advanced GIS methods has the potential for enhancing our understanding of the association between sensor-based measured PA and physical and social environments (Lee & Kwan 2018). A valuable tool for improving the assessment of physical activity utilizes GPS (Maddison & Ni Mhurchu 2009). The addition of GPS data to accelerometer monitoring can provide more detailed information about activity types under real-life conditions, particularly in detecting activities e.g. with similar accelerometer profiles, but different speed profiles (Troped et al. 2008) or in determining elevation changes (Nguyen et al. 2013). Using GPS particularly in real-life protocols provides greater insight into the nature of activity with both location and activity information available.

Recently, researchers tried to provide a framework for standardizing the study of sensor-based activity monitoring in older persons (Lindemann et al. 2014) or produce a reference dataset for that purpose (Bourke et al. 2017). In this following study, by considering different age groups, the aim is to provide a preliminary design for collecting a reference dataset for PA type classification that can maximize both internal and ecological validity. To do so, we introduce activity protocols in three different conditions: laboratory, semi-structured and real life and in both indoor and outdoor environment. We also propose using GPS to provide more detailed information about activity types and the place they are taken. We believe that this dataset will be useful for validation of existing activity classifiers and the training and development of new PA type classification algorithms, particularly under real-life conditions.

2 Method

We aim to provide a reference data set for classifying PA types in real life considering different age group and different environment. To maximize both internal and ecological validity, we designed protocols in three different conditions, namely: laboratory, semi-structured and real life.

2.1 Participants

To cover different age groups in the study, a sample of 40 participants including 30 young adults ranging in age from 20 to 35 and 10 older adults above 65 years old (20 male, 20 female) will be recruited. As inclusion criteria, participants are required to be healthy and be able to walk and run without walking aids, be able to cycle and accept the instructions of the study protocol. Approval by the appropriate ethics committee is pending; participants will also have to provide written informed consent.

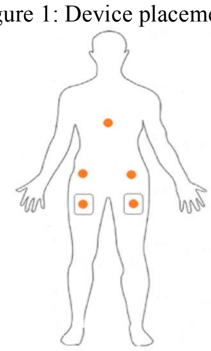
2.2 Device description

To collect data, we use a smartphone (Motorola Moto E, 2nd gen) and a wearable customized device called uTrail (Bereuter et al. 2016). The smartphone includes a GPS and an accelerometer with 1 Hz and 200 Hz maximum sampling rates, respectively. The uTrail device includes an audio sensor, a GPS (uBlox UC530M) and an accelerometer (ST Microelectronics LSM303D) that includes 3 magnetic field channels and 3 acceleration channels. The GPS can record data at 1 Hz and has the ability of concurrent reception of up to 3 GNSS (GPS, Galileo, GLONASS, and BeiDou). The accelerometer of both devices will be set to 50 Hz continuous sampling rate.

2.3 Device placement

The most popular sensor device placement is on the waist because it is near the center of the trunk and can better represent human movement (Liao et al. 2015). Findings shows that wearing the device on the thigh and chest can help to discriminate between sedentary PA types such as sitting and standing (Skotte et al. 2014) and sitting/standing vs. lying (el Achkar et al. 2016), respectively. The participants will be asked to wear the smartphone in their right pocket and to wear the uTrail device at different body placements including: right and left hip, left pocket and chest, (Fig. 1).

Figure 1: Device placement



2.4 Physical activity selection

The International Classification of Functioning, Disability and Health (ICF) is a framework for describing and organizing information on functioning and disability (World Health Organization 2001).The target PAs in this study including: lying, sitting, standing, walking on level ground, running, cycling, walking uphill, walking downhill, walking downstairs and walking upstairs were chosen by considering a subset of: 1) simple physical activities classified by (Spinsante et al. 2016), 2) mobility-related activities of the ICF, 3) global body motion activities classified by (Cornacchia et al. 2017) , 4) activities that are commonly performed in everyday life (Skotte et al. 2014) and 5) activities that can cover different levels/intensities of PA.

2.5 Laboratory scenario

The study protocol will be performed in a sports centre and at a six-floor building at the University.

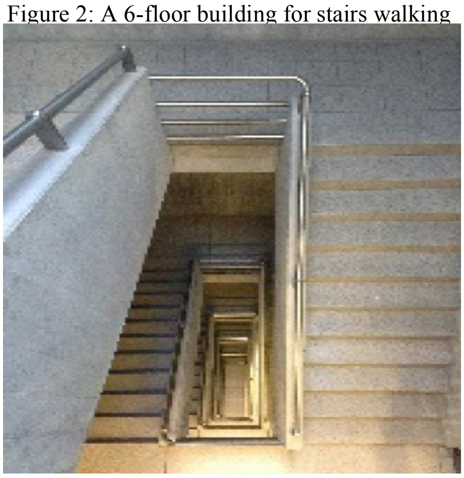
The activities for laboratory/controlled condition protocol is described in Table 1. First, participants will lie on a bed. It means staying in a lying position (face down or face upwards or side-lying) for at least 1 minute (min). Then, they will sit and will stay in a seated position for 1 min, on a seat or the floor, such as when sitting at a desk or table with straight legs or cross-legged, with feet supported or unsupported. After that, they will stay in a standing position for 1 min, such as when standing in a queue. For walking and running, the participants will be asked to move along a treadmill on foot. The cycling activity will be performed on a cycle ergometer. Walking on level ground should be performed at three different speeds including slow (less than 3 km/h), normal (4 km/h) and fast speed (6 km/h). Walking uphill and walking downhill will be performed on 7 % to 9% slope and –7% to –9% slope, at normal speed, respectively.

Table 1: Laboratory protocol

Activity	Time (in minute) Total time:21 mins
Lying	1
Sitting	1
Standing	1
Walking, level ground (3 speeds)	6
Walking uphill (normal speed)	2
Walking downhill (normal speed)	2
Running, level ground	2
Cycling, level ground	2
Walking downstairs	2
Walking upstairs	2

For stairs walking, a 6-floor building with stairs will be used, (Fig. 2). A short break of 30 seconds to 1 minute is inserted in the data collection protocol after each of the activities, so that activities would not be affected by the previously performed activities. The numbers for the speeds and slopes are adopted from (Nguyen et al. 2013; Reiss & Stricker 2011).

Figure 2: A 6-floor building for stairs walking



The activity tasks will be labelled by direct observation and video recording. An observer will monitor each participant during the study protocol and record the start and end time of each activity using a stopwatch. A video camera will record each participant's performance.

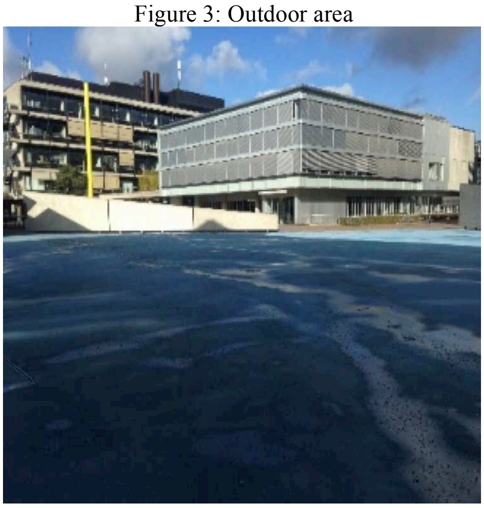
2.6 Semi-structured scenario

The activity tasks described in Table 2 will be used for the semi-structured scenario. A total of 15 mins of data will be collected for each person. Participants will be asked to perform the activities outdoors. A large flat area of the University campus will be used for outdoor walking, running and cycling, (Fig. 3).

Table 2: Semi-structured protocol

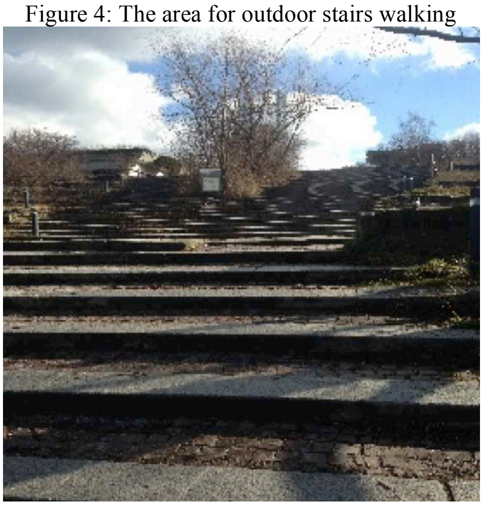
Activity	Time (in minute) Total time:15 mins
Walking, level ground (3 self-speeds)	4
Walking uphill (normal self-speed)	2
Walking downhill (normal self-speed)	2
Running, level ground	2
Cycling, level ground	1
Walking downstairs	2
Walking upstairs	2

Figure 3: Outdoor area



The stairs in a park immediately adjacent to the University campus will be used for outdoors stairs walking, (Fig. 4).

Figure 4: The area for outdoor stairs walking

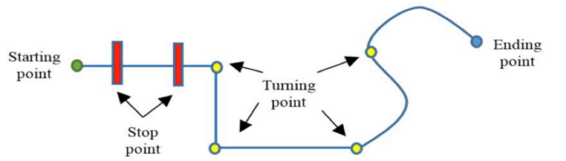


The uphill and downhill activities will be performed at a sloping area near the University campus at participants' normal speed, (Fig. 5).

Figure 5: A sloping area on the University campus

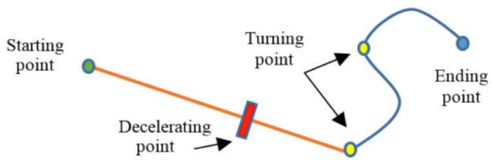
To be able to compare the participants' performance of the activities walking, running and cycling on level ground in a semi-structured protocol with the performance in both lab-based and real-life protocols, there is a need to have a scenario that can simulate human movement in both conditions. In a laboratory, participants are walking/running/cycling on a straight line, while in real-life conditions, more turns and stops may happen. Figure 6 schematically shows the path which is designed for walking and running activities in the semi-structured scenario. The path includes five segments. Participants will start walking straight at their own normal speed for 45 seconds from the starting point while stopping for 2 seconds at each stop point. Then, after passing the first turning point they will continue walking at their own slow speed for 1 minute. Immediately after visiting the second turning point they will change their speed from slow to the normal speed and walk for 45 seconds. They will be asked to walk at their fast speed on the fourth segment for less than 30 seconds. Finally, they will finish the path by walking at their normal speed on the last segment for 45 seconds. The activity running will be performed in the same way but only at the participant's comfortable speed for each segment for 2 mins.

Figure 6: The planned path for the semi-structured protocol, walking and running



As it is difficult to make sharp turns during cycling, another path was designed for the cycling activity in the semi-structured scenario (Fig. 7). The path includes three segments. Participants will start cycling straight at their own normal speed for 20 seconds from the starting point while decelerating their speed at the decelerating point. Then, they will continue cycling on the second and third segments for 40 seconds. Finally, they will stop at the end point to finish the track.

Figure 7: The planned path for the semi-structured protocol, cycling



Direct observation and video tracking will be applied for activity annotation. A GPS sensor will also record the location data of outdoors activities and will be used for activity labelling.

2.7 Real life scenario

Participants will be asked to include the activity tasks described in Table 2 and Section 2.6 in their daily life both indoors (e.g., home, shopping center etc.) and in an outdoors environment for 24 hours in a random order. Each activity task should meet the required minimum time duration described in Table 2.

To label the real-life data, participants are asked to record the start and end time of each activity using an application installed on the smartphone. A wearable camera may be further be used for real-life reference data collection.

3 Discussion and conclusion

Recent technologies are moving toward approaches, which can allow for greater insight and accuracy in exploring relationships between place and health. To be able to begin analyzing specific health behaviors in time and place and to move beyond total PA intensity, incorporating GPS data with accelerometer can help. For PA research, using GPS offers a technological solution to linking accelerometer-based measures of PA to locations. These data can then be represented within a GIS (Jankowska et al. 2015).

In this short paper, we proposed a study design for collecting reference data for PA type classification in three different scenarios. In PA research, using GPS and GIS methods can provide greater insight into the nature of physical activity in different environments, including more realistic settings than are commonly used (i.e. leaving the lab setting). The ongoing data collection can provide a useful dataset for the future validation and comparison studies on using different study designs and applying different classifiers for PA type classification, particularly in real life. Furthermore, we expect to be able to demonstrate that adding GPS (i.e. absolute location) will improve the PA type classification in real-life situations.

As next steps, the proposed study protocol will be tested in a pilot study on 5 participants and potentially optimized. The finalized study protocol will then be administered in the main study on 40 participants, and the detailed study protocol as well as the annotated reference data set will be made available publically.

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