Using multi-sensor tracking data to analyze the mobility and activity behavior of older adults

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The increase in the older adult population has been occurring at unprecedented and accelerating rates in recent decades.Healthy ageing as the process of maintaining the functional mobility is therefore important. In order to understand how functional mobility in daily life is associated with health in older adults, such behaviour needs to be studied in real-life conditions, which can be done using sensor-based ambulatory assessment methods. The aim of this study is to contribute to developing a full, individualized description of human mobility behavior considering different spatio-temporal patterns, and link such personal mobility profiles to psychological resources available to an individual. The participants are healthy older adults above 65 years old from MOASIS study, who will collect the data during 4 weeks of their everyday life. The multi-sensor data will be used for the movement analysis. Pattern recognition and classification algorithms are proposed methodologies to achieve the aim of this study. This paper is quite useful for understanding of individual movement through the use of new sensing devices.

Keywords: movement analysis, ambulatory assessment, real-life, older adults

1 Introduction

Projections indicate that by 2050 the elderly population will reach 2 billion people worldwide (Toledo & Barela, 2010) Along with these demographic changes, medical conditions associated with aging will represent a burden to society, for example by an increase in demand for health services. Because older adults demand more from the health service infrastructure, efforts have been made to understand the factors that contribute to healthy aging (Toledo & Barela, 2010). The WHO, in its "World Report on Ageing and Health", defines healthy aging as the process of maintaining the "functional ability" of individuals through a dynamic interplay between an individual's biological and physiological endowments, abilities, skills, diseases, subjective evaluations, traits, environments, and real-life activities (Sugawara & Nikaido, 2014).

To describe and analyse functional mobility, then, one needs to measure all mobility-related biological and physiological endowments, mobility-related abilities, skills, diseases, subjective evaluations, traits, contexts, and activities, as potentially these are all equally relevant parts of an individual's functional mobility profile, uniquely characterizing an individual. Research on some of these elements of a mobility profile has been carried out in mobility laboratories or in clinical and experimental studies. The advantages of laboratory experimentation have a price, however, as the laboratory setting by definition isolates research participants from their everyday concerns and activities and subjects them to an artificial environment in which nearly all contextual factors – for example physical features, goals, or other persons involved – are determined by the experimenter (Mehl & Conner, 2012).

In field settings (i.e. real-life contexts), in contrast, the physical and social environment is substantially cluttered, people must choose for themselves which tasks to pursue and how to engage them and the option of changing the setting and tasks is usually available. All of these can, of course, alter the results of the research (Mehl & Conner, 2012). In essence, we find the inverse of the laboratory situation, that is, a high ecological validity of the results at the price of reduced internal validity.

There is some flexibility in what counts as a method for studying daily life. Among the terms used for studying daily life we find, among others, the term ambulatory assessment (AA). Alternative labels for this methodology are ecological momentary assessment and experience sampling methodology (Brose & Ebner-Priemer, 2015).

The aim of this study is by utilizing ambulatory assessment methods to contribute to developing a full, individualized description of human mobility behavior considering different spatio-temporal patterns, and link such personal mobility profiles to psychological resources available to an individual. To do so, we aim to address the following research questions:

1. What are the main movement behaviors expressed in people's movement using multi-sensor data?

2. What types of movement patterns do the individuals show considering different temporal granularities (daily, weekdays, weekends, and particular days, weekly)?

3. To what extent does context/environment play a role in the human movement behavior at the micro and macro level? And can we find patterns that match certain psychological trait.

2 Background

The WHO in its "World Report on Ageing and Health" defines healthy aging as the process of maintaining the "functional ability" of individuals through a dynamic interplay between an individual's biological and physiological endowment (Sugawara & Nikaido, 2014). Therefore, on the one hand, to describe and analyse functional mobility, one needs to measure all mobility-related biological and physiological endowments, and on the other hand, to achieve the ecologically valid measurements needs considering real-life contexts, which can be realized using ambulatory assessment methods. Most existing examples of ambulatory assessment fall into one of the two broad categories below:

The first and most common category includes self-reports. Self-reports provide information that no one but the respondent knows including goals, emotions, thoughts etc., which is why many theories about human behavior and interventions focus on them (Brose et al. 2015; Ebner-Priemer et al., 2013a; Ebner-Priemer et al., 2013b; Niermann et al., 2016).

The second and newer category includes more technically oriented methods for capturing diverse, non-self-reported aspects of everyday experience, such as the auditory environment, physiological status, the physical location or proximity to particular other persons etc., all of which can be provided by using different sensors including Bluetooth, RFID, GPS, accelerometer, heart rate sensors, audio sensors, etc. These instruments provide extensively detailed data that can be used to examine the operation of social, psychological, and physiological processes within their natural contexts (Verlaan et al., 2015; Zisko et al., 2015; Reichert et al., 2016).

There is much research that shows that two of the most frequent sensors used in movement analysis are GPS and accelerometer (Kaghyan 2013; Spink et al. 2013). In addition to sensing different aspects of a person's life (GPS = position, spatial activity; accelerometer = physical activity), each of these two sensors also provides us information about different scales of movement. For example, by extracting information from an accelerometer we may explore human activity at the micro-scale (e.g. physical activity mode, body motion, number of steps, gesture change, intensity, duration, etc.), while by analyzing GPS data we get to know about the macro-scale of human movement (e.g. point of interest, transportation modes, displacement, speed, etc.).

Using GPS devices and accelerometers together provides the most complete information about human mobility in community environments. Although combined GPS and accelerometer technologies have been used successfully to gather detailed information about discrete bouts of outdoor activity (physical endeavors, as well as driving), the same success has not been realized in studies that have attempted to monitor functional everyday human movement over an extended period of time. These technologies, however, would offer the potential to accurately monitor mobility patterns in older adults (Webber & Porter, 2009).

In order to study the movement behavior of moving objects, it is important to understand what types of movement patterns can be identified from their movement (Dodge et al. 2008). Among different movement pattern detection methods, periodic pattern mining (PPM) can be used for discovering the intrinsic behavior of moving objects, compressing movement data (Agrawal & Srikant, 1995), predicting future movements of objects (Jeung et al. 2008), and detecting abnormal events. Mining periodic behaviors can bridge the gap between raw data and semantic understanding of the data (Li et al., 2010).

It is difficult to study human mobility without considering its temporal nature. It has been shown that both the ordering of visits and the timing of visits (Song et al. 2010) contains information that can be used to build powerful predictors of future behavior. Furthermore, human behavior is driven by daily and weekly routines ((Williams et al., 2012; Scellato et al., 2010). Although this form of temporal structure is a rich source of information about individual behavior, there has been little work to examine the regularity in individual visiting patterns. Factors such as wealth, profession, lifestyle, and health affect an individual's routine, and therefore his or her mobility patterns. This is likely to give rise to diversity in the population's visiting patterns and regularity (Williams et al. 2012).

The literatures show that there is still little research on using real-life datasets for movement analysis and compared to self-reported ambulatory assessment using sensor-based ambulatory assessment in mobility and activity analysis is limited. Considering temporal information in human movement pattern is also a topic that requires further studies.

3 Dataset

The Mobility, Activity and Social Interaction Study (MOASIS) collects individualized everyday-life health-related data in older adults. MOASIS started in August 2015 and ultimately aims to develop computational models to measure, analyze, and improve health behaviors and health outcomes in the everyday life of aging individuals (Bereuter et al., 2016). The mobile sensor *uTrail* is used for the data collection, assuming no prior technical knowledge by the participants. uTrail, a tracker specifically developed for this study, measures the mobility (spatial activity) with GPS, physical activity with a 3-axis accelerometer and social interaction with a microphone using the electronically activated recorder (EAR) method (Mehl & Conner, 2012).

The MOASIS initialization phase started in November 2015 including initial device testing and ethical approval. After that

a first pilot study with 5 participants during 14 days took place in December 2015, focusing primarily on testing and improving the sensor device.
The second pilot study ran from March to April 2016 with 27 participants during 30 days. Further testing and refinement of the device, as well as the data collection protocol sampling rates, and observation length were included in this stage. The main data collection with 150 participants during 30 days will take place in the first half of 2018.

4 Proposed methodology and discussion

To address the research questions, the methodologies below are proposed:

1. What are the main movement behaviors expressed in regular patterns of people's movement using multi-sensor data and how do they interrelate with each other?

Travel behavior and physical activity (PA) are two important movement behaviors in older adults' daily routine. To figure out how variable or predictable older adults are in their routines, one way is to investigate their movement patterns by answering the questions of when, how and where they go during the day (travel behavior) and what they do meanwhile (physical activity). Having this, the association between movement patterns and the way it affects older adults' physical and mental well-being can be distinguished.

2. What types of regular or irregular patterns do the individuals show considering different temporal granularities (daily, weekdays, weekends, and particular days, weekly)?

In order to study the movement behaviors of moving objects, it is important to understand what types of movement patterns can be identified from their movement. A considerable number of works have shown that human mobility is regular, predictable and unique in both the temporal and spatial domains (De Montjoye et al., 2013; Kim et al. 2007; Wang et al. 2011). Observable regular movements among a few frequented locations, such as home and work (Eagle & Pentland, 2009; Li et al., 2010) embody the regularity and predictability of human mobility.

It is claimed that human trajectories show a high degree of temporal and spatial regularity, each individual being characterized by a time independent characteristic travel distance and a significant probability to return to a few highly frequented locations (Liang et al. 2012; González et al., 2008). Even older adults without cognitive problems feel safer and less anxious when they do not have to worry about 'the unknown' or what is coming next (Lythgoe, 2016) in their mobility. It is easier to cope with memory and cognitive issues when as many activities as possible are predictable. Even though a person with cognitive problems might not be aware of the routine or even of the time passing, having a routine helps them feel more grounded and secure (Lythgoe, 2016), and consequently maintain their mental health. The one way to address this research question is to apply human movement pattern recognition methods and see what types of patterns could be derived from the dataset considering temporal information.

3. To what extent does context/environment play a role in the human movement behavior at the micro and macro level? And can we find patterns that match certain psychological traits?

The impact of context on behavior is fundamental. To understand behavior, one had to first understand what sorts of behavior the setting – its context – was likely to evoke. Thus, there is a need to identify regularities in the properties of behavior setting (e.g. home, social activity places, medical offices or roadways) and the behavioral patterns that they evoke (Mehl & Conner, 2012).

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