Ambulatory Assessment to Study Mobility and Activity Patterns in Healthy Aging Research

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1. Introduction

Research in health science and psychology is focused on particular health conditions and often conducted in controlled laboratory settings. Dynamic real-world situations show that findings from laboratory research are only partially applicable as contextual factors affect behavior (Reis 2012). Older adults, despite showing a drop in cognitive ability, handle well the challenges of every day life (Verhaeghen et al. 2012). *Ambulatory assessment*, *in situ* measurements in everyday life, has recently been advocated to study dynamic health stabilization models in their real-life context (Brose and Ebner-Priemer 2015). Ambulatory assessment includes the collection of various data over predefined periods of time, such as observed behavior and self-reports, and physiological and biological data.

2. MOASIS Study design

The *Mobility, Activity and Social Interaction Study* (MOASIS) collects individualized everyday-life health data in older adults and aims to develop computational models to measure, analyze, and improve health behaviors and health outcomes in the everyday life of aging individuals. It targets to detect and model intra-individual changes and inter-individual differences in

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movement trajectories and social activities of older adults, indexed by repeated measures of movement, space use and social context parameters.

The study employs the custom-built mobile sensor *uTrail* (Fig. 1), which measures the *mobility* with GPS, *physical activity* with a 3-axis accelerometer, and *social interaction* with a microphone using the electronically activated recorder (EAR) method (Mehl et al. 2001).

	Sensor	Variable
Spatial mobility	GPS	timestamp, latitude, longitude
Physical activity	IMU	timestamp, acceleration (x,y,z), step counter
Social interaction	EAR	timestamp, sound sample (30 secs)

Figure 1. Overview of the uTrail mobile sensor

Preceding to the main study, scheduled for early 2017, two pilot studies have been conducted to test the sensors and the overall study protocol. This work in progress reports on the second pilot study conducted between March and Mai 2016 with an observation period of 30 days and 27 participants (aged 65 - 80 years, fluency in German and a score above 26 in the Mini Mental State Examination MMSE; Folstein et al. 1975). The study design includes psychological baseline tests, self-reports, evening diary, complemented by the ambulatory assessment of the physical, spatial and social activity. On a daily basis the participants carry the uTrail to assess their mobility and activity, while in the evening they keep track of their activity with an evening diary.

3. Reconstructing daily spatio-temporal timelines

Due to the real-world study setup, the sensor settings and the participants' daily-life patterns and actions, the analysis must be able to cope with partial data readings. Partial data readings include lack of GPS reception, or missing data due to the device inadvertently being switched off, interrupting the continuous sampling. For all three sensors, time is used as a unique identifier (uid) to merge the different datasets. Merging enables various insights, such as how active a person is according to where they are or in which places the person is socially active. Combining accelerometer with GPS data provides more solid estimates of GPS locations when the participant moves slowly or is stationary, and helps to detect the mode of transport.

Handling different sequences based on data availability allows us to work with partial data, and build inferences to fully reconstruct timelines (Fig. 2). In this work, temporal gaps are defined by a preset temporal threshold and are used to split the segments into sub-segments that require different analysis approaches. Sub-segments with valid GPS readings can then be handled by trajectory segmentation methods (Laube and Purves 2011, Gschwend 2015) based on GPS and acceleration readings (Move-GPS, Stop-GPS). For the temporal gaps, the segment is inferred between the last and next known valid location (Move-ND, Stop-ND) based on a combined distance and acceleration criterion. Figure 2 shows conceptually for a sample day the different types of moves and stops. Given accelerometer data, inferences of activity intensities and classification provide additional hints for segments with no GPS data. No-data segments also affect data merging; here, they affect how well the audio data are mappable to the closest known GPS position (shown in Figure 2 with an audio symbol against a gray circle.)

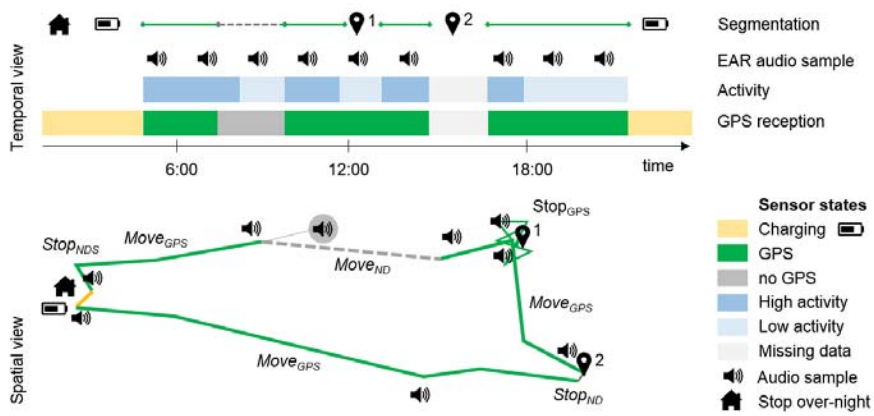

Figure 2. Conceptual illustration of a spatio-temporal trajectory considering gaps in GPS data and offline periods

4. Conclusions

Synchronizing by time allows integration with sensors that are less prone to data reception problems such as accelerometer and EAR, and thus enables (re)constructing the participants' lifelines and computing activity-related measures, while maintaining the spatial perspective (Figure 3). This is especially important as a large part of our daily life is situated indoors, where most of our social and physical interactions occur. By not knowing the semantics of mobility, these mobility patterns nevertheless often remain obscure and require good knowledge of the domain and context.

The next steps of MOASIS will first focus on further semantic annotation of moves, stops and finding further patterns and measures, by including also context data, as well as learning from, and validating with, the self-reporting and diary data. Based on the semantic annotation, we will conduct, among others sequence analysis with a variety of methods and measures.

Figure 3. Visualization of a one-day reconstruction of a participant, with sensor merging, stop and move segmentation and clustering.

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