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Analyzing GPS and Accelerometer Data in the Study of the Mobility, Activity and Social Interaction of Older Adults

Pia Bereuter[1], Michelle Fillekes[1], Robert Weibel[2]
[1]URPP "Dynamics of Healthy Aging" & Department of Geography, University of Zurich, Winterthurerstrasse 190, Zurich
{pia.bereuter | michelle.fillekes}@geo.uzh.ch
[2]Department of Geography, University of Zurich, Winterthurerstrasse 190, Zurich
robert.weibel@geo.uzh.ch

1. Introduction

How we maintain our health in older age in everyday life becomes increasingly important as the proportion of elderly people rises. Physical activity, real-world space use, and a stimulating environment are predictors for maintaining good physical and mental health (Mollenkopf et al. 2004, Wahl et al. 2007, Reed and Buck 2009, Eskes et al. 2010, Voelcker-Rehage et al. 2011). The overwhelming majority of research in the health sciences and particularly in psychology has been conducted in controlled laboratory settings, typically focusing on a particular health condition to identify its causes and how to improve it. In order to validate findings in *real-life*, however, research is required that investigates the correlation between space use, social and physical activity, and the cognitive well-being in a *real-world* research setting.

Contextual factors affect behavior and show that findings from laboratory research are only partially applicable to dynamic and real-world situations (Reis 2012). Also, older adults, despite showing a drop in cognitive ability, cope well with the challenges of everyday life (Verhaeghen et al. 2012). Hence, affordances imposed by contextual factors play a key role. *In situ* measurements in everyday life, known as ambulatory assessment, have been widely advocated to study dynamic health stabilization models in their real life context (Hoppmann and Riediger 2009, Reis 2012, Scholz et al. 2015, Brose and Ebner-Priemer 2015). Means of ambulatory assessment include the collection of physiological and biological data, observed behavior and self-reports over predefined periods of time (Ram and Gerstorf 2012, Trull and Ebner-Priemer 2013). Measurements such as the collection of physiological data require established methods to derive meaning and allow for interpretation. Self-reports provide contextual meaning and additional semantics, but are of a subjective and usually of a retrospective nature and therefore risk being biased (Schwarz 2012, Do and Gatica-Perez 2014).

This paper reports about the design and some initial results of MOASIS, a project jointly pursued by researchers of the URPP "Dynamics of Healthy Aging" Department of Psychology and the Department of Geography of UZH. In particular, it highlights some practical considerations in conducting ambulatory assessment using mobile sensors within the context of a daily-life study setting.

2. MOASIS - Mobility, Activity and Social Interaction Study

The Mobility, Activity and Social Interaction Study (MOASIS) collects individualized everyday-life health 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. In order to provide access to real-life health outcome measurement tools, the study aims to detect and model intraindividual changes and interindividual differences in movement trajectories and social activities of older adults, indexed by repeated measures of movement, space use and social context parameters.

2.1. Data collection with a mobile sensor

The small mobile sensor *uTrail* is used for the data collection, assuming no prior technical knowledgeby the participants. uTrail (Fig. 1), 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 et al. 2001). The sampling rates (Fig. 1) reflect the scale of analysis for the three different sensors including taking account of practical considerations regarding battery life and internal storage.

	Sensor	Variable	Sampling rate
Spatial mobility	GPS	timestamp, latitude, longitude	1 / sec
Physical activity	IMU	timestamp, Acceleration (x,y,z)	3 / sec
Social interaction	EAR	timestamp, sound samle (30 secs)	1 / 12.5 min

Figure 1: uTrail mobile sensor used in the MOASIS study

2.2. MOASIS study design

The study design of MOASIS includes baseline tests, self-reports, an evening diary, complemented by the ambulatory assessment of the physical, spatial and social activity with uTrail. Figure 2 shows the timeline of the study with baseline tests, intermediate session(s) for data download and intermediate tests, and a post-test session at the end of the study. On a daily basis the participants carry the uTrail to assess their activity, while in the evening they keep track of their activity with an evening diary.

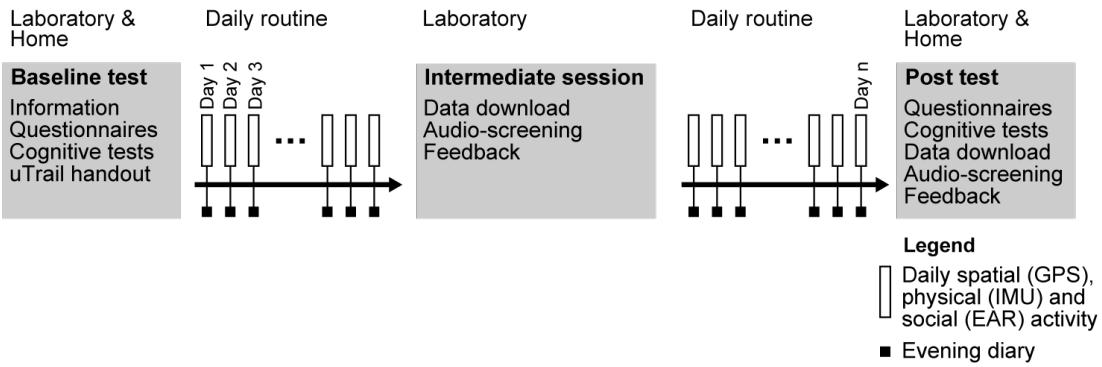

Figure 2: MOASIS study design

The inclusion criteria for the participants of the MOASIS study are: aged 65 - 80 years, fluency in German and a score above 26 in the Mini Mental State Examination MMSE (Folstein et al. 1975) to set the minimum required cognitive ability (i.e. good mental and cognitive health.

The main MOASIS study will run in late summer 2016, but is preceeded by two pilot studies testing the uTrail sensor, improving the measurement protocols and conducting the first two data collection campaigns (Table 1).

The first feasibility study took place at the end of 2015 with a sample size 6 participants during a 2 week period, collecting about 0.80 per participant, the bulk of which consists of the EAR audio samples (75.82%).

Table 1 Timetable and organization of the MOASIS study

Phase	Date	Description
Initialization	November 2015	Sensor tests and ethics approval
Feasibility Study I (N = 6, 14 days)	December 2015	First data collection, test and improvements of the sensor device
Feasibility Study 2 (N = 30, 30 days)	March - April 2016	Second data collection, testing of sensor specification, sampling rates, observation duration and data quality. Compilation of the psychological tests and measurement protocols.
Main Study (N = 150, 30 days)	Summer 2016	Main study with optimized measurement protocols.

3. Preprocessing

3.1. Temporal coverage

Aside from the analysis of the different sensor data providing insights on the participants' every-day life, the analysis of the temporal sensor coverage reveals when the sensor has been used. The temporal coverage investigates the time interval during which the sensor is actively *recording*, *charging* (sensors switched off) or completely *offline* during the study period. It shows that the temporal coverage of the sensor varies between participants including completely missing days, with up to 3 missing days for one participant and a median of 1 per participant (in a 14-day period).
Days with some non-recording periods occured for all participants, with an average of 20.61% of the 24h-day missing. Those periods with the device switched off also include the download periods or moments where the participants switched the device off consciously or unconsciously.

3.2. Day-night and charging patterns

The variations in acceleration reveal the day-night pattern of the participants and its regularity. Table 2 presents the summary of active periods per day for each user excluding days with any missing data. On days without any missing data, participants' average day length is 12:45:26. They show fairly stable times of starting their day with a median standard deviation of 43.29 minutes, though one participant shows a high standard deviation. Cross-checking with the acceleration pattern revealed that the participant forgot the device overnight at home and did not move it until the next evening. The standard deviation for the end of the day shows a higher variation than for the day start.

Table: 2 Summary of active periods per day for each user (complete days only).

Participant	Average day start	Standard deviation day start	Average day end	Standard deviation day end	Average day length [h]	Complete days	Active day ratio
# 1	07:44:21	00:25:25	22:01:26	00:07:16	14:17:00	4	0.60
# 2	08:21:10	00:59:25	19:34:29	01:07:49	13:53:20	9	0.58
# 3	10:03:41	00:43:56	14:11:59	04:17:56	12:08:20	9	0.51
# 4	07:58:32	00:30:34	21:40:34	01:57:28	13:42:00	11	0.57
# 5	08:13:36	00:42:39	12:09:52	03:46:08	14:36:20	9	0.61
# 6	11:24:51	06:43:01	19:20:35	04:11:44	07:55:40	4	0.33

The participants received the instruction to charge the device overnight. The overnight charging pattern reveals how consistently participants charge the device and if periods of missing data are due to low battery power. A closer look at the charging patterns indicates that no missing data were caused by running low on battery power. The maximum number of individual days without charging was 1 and the uTrail charging duration lasted on average 8.94 hours.

Figure 3 visualizes an exemplary day of one participant during the study with no missing data periods. For each sensor it presents on the temporal axis their activity during the day. For the GPS data, it shows when the device was *charging*, had *GPS reception* or *no GPS reception* and what the *speed* of the device was. Additionally it shows the participants' activity based on the accelerometer and the sampling of the audio recording. This *'barcoding'* (Paraschiv-Ionescu et al. 2012) of the different sensor states allows to quickly identify whether the device worked properly and to infer the participants' daily pattern.

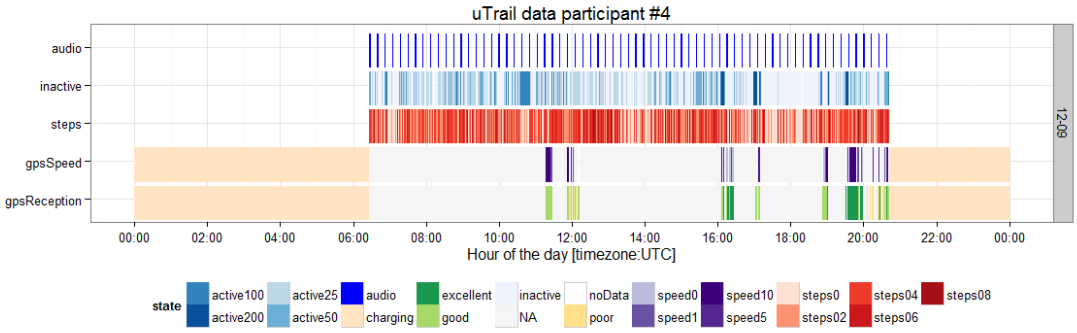

Figure 3: uTrail sensor data recorded during one day

4. (Re)construction of daily spatio-temporal timeline

To reconstruct lifelines of participants in order to infer the participants' mobility patterns and their activity or social interaction, the different states of the sensor readings need to be taken into account. Because of the real-world study setup, the device 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 in indoor locations or trains, or missing data due to the device being switched off, interrupting the regular sampling rate of the different sensors.

For all three sensors, time is used as a unique identifier (uid) to merge the datasets based on the recorded timestamps. The merge enables insights on various topics, including how active a person is according to where they are, in which places the person is socially active, and the frequency and intensity of paths or locations visited. Combining accelerometer with GPS data provides more solid estimates of GPS location when the participant moves slowly or is stationary (Montoliu and Gatica-Perez 2010), and helps to detect the mode of transport (Reddy et al. 2009, Shen and Stopher 2014).

Handling different sequences based on data availability allows us to work with partial data, and build inferences to reconstruct timelines. Table 3 summarizes how temporal gaps may be addressed from a trajectory segmentation point of view.

Table 3 Trajectory classification including sequences of missing GPS readings and offline periods (ND = no-date segments).

Categories	GPS	Acceleration	Description
Move-GPS	available	available	Move based on GPS segmentation methods (w/o acceleration)
Stop-GPS	available	available	Stop based on GPS segmentation methods reduction of pseudo movement with accelerometer classification
Move-ND	ND	ND, available	Move inferred from last/next known location based on a minimum distance threshold (w/o acceleration)
Stop-ND	ND	ND, available	Stop inferred from last/next known location based on a minimum distance threshold (w/o acceleration)
Stop-NDS	ND	ND	Stop inferred from last/next known location with semantic annotation (e.g. charging)

In this work, temporal gaps are defined by a preset temporal threshold and are used to split the segments into subsegments. These subsegments 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 4 shows conceptually for a sample day the different types of moves and stops. The duration of a no-data segment increases the uncertainty in guessing the participants whereabouts. Given accelerometer data, inferences of activity intensities and classification provide additional data to no-data segments. No-data segments also effect data merging; in this study they affect how well the audio data are mappable to the closest known GPS position (shown in Figure 4 with the audio symbol on a gray circle.)

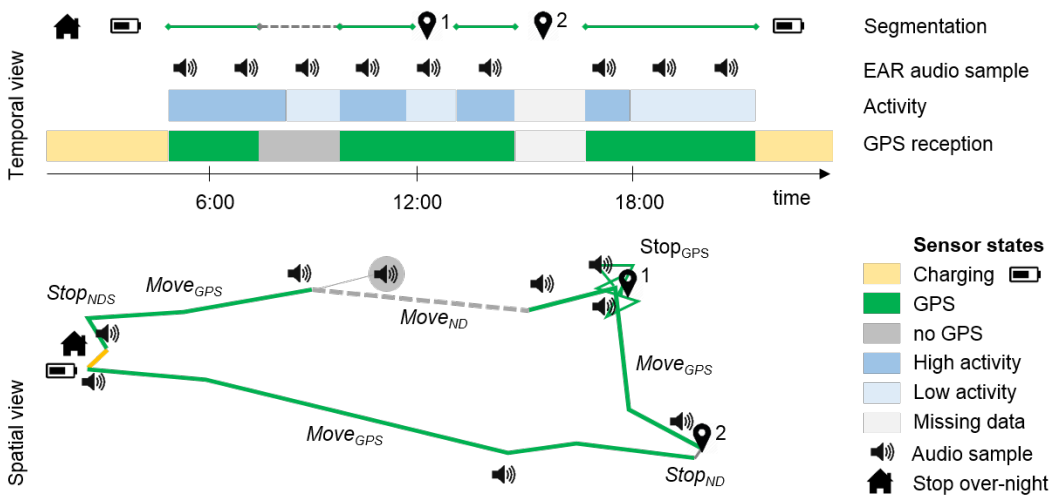

Figure 4: Conceptual illustration of a spatio-temporal trajectory and timeline taking into account gaps in GPS data and offline periods

Figure 5 shows a combination of screenshots of a day map of Participant #4 (see Fig. 3 for the timeline of the same day) presenting the segmented trajectory as a sequence of various stops and moves combining visualization methods and analysis (Demšar et al.

2015). For stop and move segmentation the method by Gschwend 2015 has been applied. DBSCAN (Ester et al. 1996) was used to find distinct spatial clusters spanning the whole study period. *Charging* and *over-night* stops and *no-GPS segments* implement the last-next known location logic, to locate these segments on the map. The audio samples are merged based on the closest temporal valid GPS location logic.

Figure 5: uTrail day of Participant #4

5. 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. 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 (Fig. 6).

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 sequence analysis with a variety of methods and measures. Furthermore, we will develop improved, probability-based methods of estimating activity spaces and deriving exposures (going beyond current buffer-based methods).

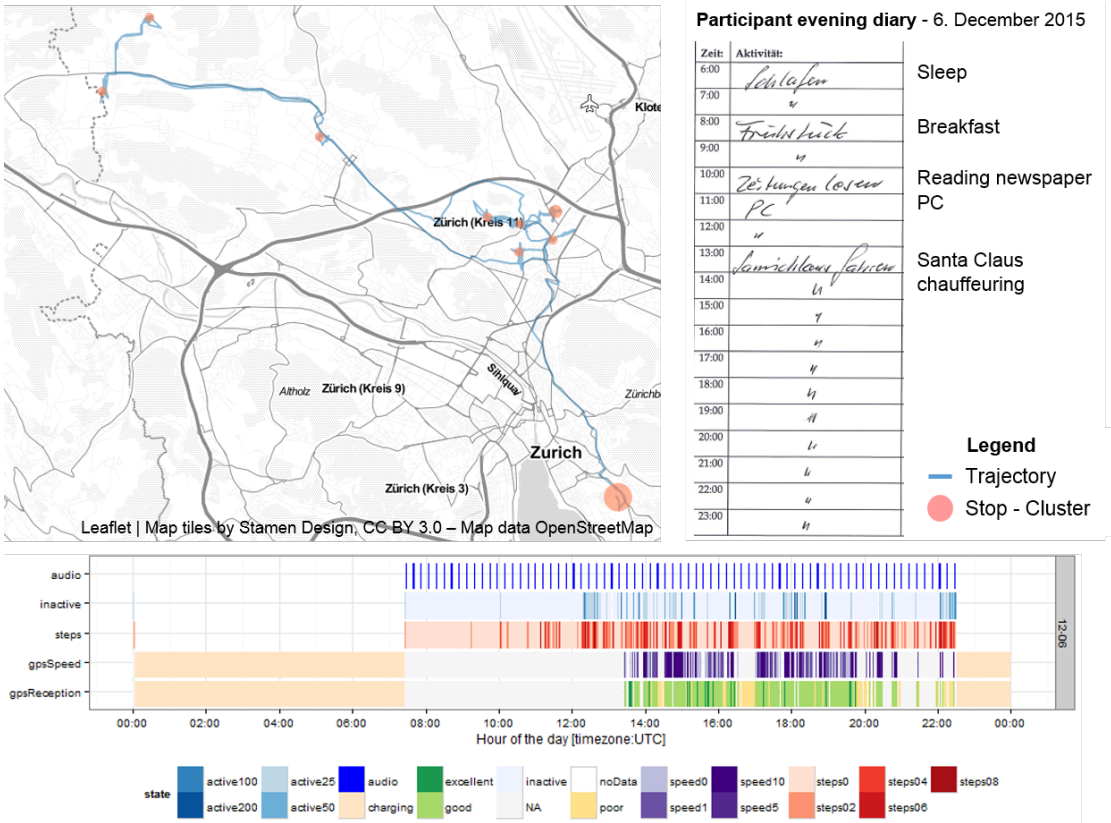

Figure 6: This uTrail day and timeline of Participant #5 on December 6th, 2015 exemplifies that context and cultural situation play a role in finding a meaning why the participant would visit 8 different places (Santa Claus visits in different households; December 6th is Santa Claus day in Switzerland).

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