Longitudinal Ambient Sensor Monitoring for Functional Health Assessments: A Case Study

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Abstract

Ambient monitoring systems offer great possibilities for health trend analysis in addition to anomaly detection. Health trend analysis helps care professionals to evaluate someones functional health and direct or evaluate the choice of interventions. This paper presents one case study of a person that was followed with an ambient monitoring system for almost three years and another of a person that was followed for over a year. A simple algorithm is applied to make a location based data representation. This data is visualized for care professionals, and used for inspecting the regularity of the pattern with means of principal component analysis (PCA). This paper provides a set of tools for analyzing longitudinal behavioral data for health assessments. We advocate a standardized data collection procedure, particularly the health metrics that could be used to validate health focused sensor data analyses.

Author Keywords

Activity Monitoring; Ambient Intelligence; Health Care; Sensor Networks; Trend Analysis; Aging in Place; Assessment

ACM Classification Keywords

H.4.2 [Information systems applications]: Decision support

Introduction

An increasing number of homes of independent living elderly are equipped with environmental (ambient) sensors for supporting safety and independent living. The data from such systems are used for health monitoring [2][10], where most work is in activity recognition [3] or anomaly detection. These surveys show that other sensing modalities such as wearables or cameras can be useful as well, but in our study we only focus on simple ambient sensors. For the use of sensor data in clinical practice most solutions are not mature enough yet [9]. Most health monitoring systems aim at detecting anomalies in the behavioral pattern by applying predefined (or learned) thresholds on features derived from sensor data (e.g. [11]). However, setting a threshold to find the optimal trade-off between generating too much false alarms or missing relevant events is difficult. For example, [12] present both a time-slot based model and a duration-based model for learning normal behavior of a resident, that can be used to detect anomalies. In their field trial no actual alarming situation occurred, which make it even impossible to find the optimal threshold.

In addition to detecting incidents, we think that 'slow' changes in health are of particular interest. Our goal is to develop an instrument that can automatically assess someone's functional health from sensor data, which makes it possible to detect health trends. Current functional health assessment instruments such as the Katz Activities of Daily Living (ADL) [6] or Timed Up and Go [8] are only used incidentally, whereas sensor monitoring systems can monitor health continuously. Several systems provide a visual trend inspection for individual activities, but assessing the whole pattern at once is more efficient. Related approaches are [15], who determine changes in activity patterns by calculating the dissimilarity of two

months based on textural features in activity density maps and [14], who analyze the circadian rhythms of a resident. Focused on trend modeling is [13], who report trends and forecasting based on activities, detected with a very simple object usage based detection algorithm. Interesting approaches for making direct health assessments with ambient sensors are [7], who focus on continuous walking speed assessments and relate this to the status of the participants and [4], who focus on making cognitive health assessments.

It is our aim to compare longitudinal sensor data with trends in functional health. Already, we collected data in the context of a larger study, but new methods are required to analyze such multidimensional longitudinal data. To get some insight into the domain and challenges that lie ahead, it is useful to zoom into a few cases. This paper uses two case studies to present methods for inspecting trends in health from longitudinal sensor data. First, the methods and cases are introduced, then results are presented.

Methods

The data of these persons were collected in a pilot of a prospective cohort study, where a total of 23 independently living elderly were included. Ambient sensor monitoring systems were installed in the homes of all the participants and in addition their functional health was assessed every three months. This section describes the health metrics and the sensor system.

Health metrics
The health metrics comprise self reported data such as demographic data, comorbidities, physical functioning ((I)ADL), self perceived health status, psychological and social functioning (Rand-36), health related quality of life

(EuroQual) and health care utilization data. The questions of the self reported data are part of a Dutch national database [1]. In addition, objective metrics were included such as walking speed, grip strength and the Assessment of Motor and Process Skills (AMPS) [5].

The AMPS instrument differentiates between motor and process skills. The skills are observed in two standardized daily activities and linked to a continuous scale of ability in motor or process functioning (range from -3 to 4). The process score contributes to functioning as it is related to cognitive skills, while the motor skills are related to the ability to perform goal directed actions. The Modified Katz-15 consists of the 6 basic Katz ADL and the instrumental ADL. Each person scores an '1' when assistance is required with the activity, '0' otherwise. This results in a theoretical range of 0-15. The measure for walking speed is the number of seconds to walk 3 meters. The cut-off point for a decreased walking speed is when it takes a person more than 3.6 seconds. The number of comorbidities is based on self report and ranges from 0 to 18 as the person is asked to indicate from a list of 18 diseases which apply to their situation.

Sensor data
Collection   The selection and installment of sensors are based on requirements from the health domain. A house is equipped with approximately 16 sensors such that the main areas of the house are covered with presence sensors and for some activities more detailed information is available. The basic sensors are: passive infrared motion sensors for presence, contact switches (reed) on doors and cabinets and a float sensor for the toilet. In addition some houses are equipped with bed mats to detect sleeping, others use sensitive motion sensors.

When the behavior of the resident triggers the sensors, events are generated and stored in a remote database as triples $(label, timestamp, value)$, where 'label' is the sensor ID for which also some meta data is known (e.g. type, location) and value $= \{0, 1\}$. Small pets generally do not trigger these sensors. On a daily basis a contact switch typically generates less then two dozens of events, while a motion sensor can generate up to hundreds of events.

Analysis   A location extraction algorithm is applied to the data, including five major areas in the domestic environment: bedroom, living room, kitchen, bathroom and outside of the home. Based on the sensor events we can continuously infer the location of the resident, where it is assumed that the resident is within a location until a sensor in another area is triggered. Subsequently, the time spent in a location is calculated for each hour, resulting in a 5*24-dimensional feature vector for each day. The complete data matrix has dimensions of #days by 120 and can be used for visualizing the daily pattern of the resident and for further trend analysis.

Two methods are presented that both analyze trends in the data on a daily basis. The first is simply plotting the time spent in a location per day as a function of time, therefore losing information on the daily structure. The second is reducing the dimension of the feature vector by performing principal component analysis (PCA) on the complete data matrix. PCA transforms the original (normalized) data to a space of orthogonal axes (vectors). The first axis is the axis which accounts for the most variance in the data, and this can be plotted as a function of time. The argument for applying this to the whole data matrix is that it is possible to detect deviations in the whole pattern at once. Not only trends like time spent on individual activities, but also shifts in time cause

deviations.

Case 1

The participant in this case study has been followed for almost three years, though the sensor data from the first months have to be discarded due to hardware failure in critical areas such as the living and bedroom area. The women lives independently in an assisted living facility, where she mostly eat simple meals from the microwave. Indoor she walks without aid, but outside she uses a walker or scooter. She reports being lonely and does not feel like doing activities anymore. She used to have a dog with which she went out a lot, and after the death of the dog (spring 2012) she goes outside less than before. This is the start of a trend that continues long after the dog died.

Possibly there is a relation between inactivity, staying indoors and loneliness with a decrease in functioning. The number of self reported comorbidities is also provided, which is quite high for this participant.

Figure 1 provide the details of the health assessments that are taken every three months. The participant is relatively stable, still living independent, but showing a slight decrease in functioning on the AMPS motor scores. Over the years she had two periods of more comorbidities including suffering from a form of cancer, stroke and depression.
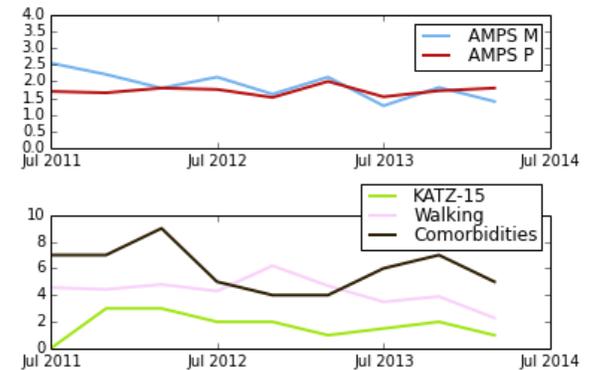

Figure 1: Case 1: Health report. The upper figure shows the AMPS motor and processing scores, the lower figure Katz-15, number of comorbidities and walking speed (seconds to walk 3 meters) over time.

Sensor data
The participant shows a regular daily pattern, a visualization of a location-based monthly pattern is shown in Figure 2, where it can be seen that the participant is in the bedroom between approximately 9pm and 7am, and has few sleep disturbances. She has a fixed morning routine and goes regularly outside for short periods, and some days she leaves the house for several hours. Such visualizations can assist care professionals in assessing the pattern of the resident and in evaluation of their interventions.
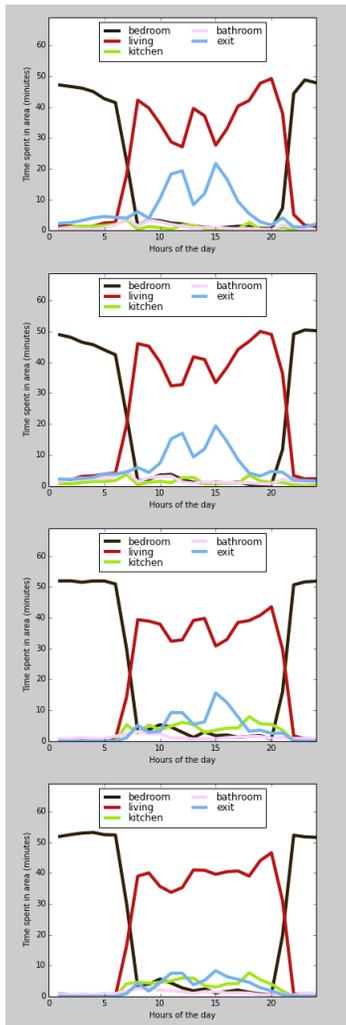
Figure 3: Case 1: Mean time spent in locations of four subsequent semesters.
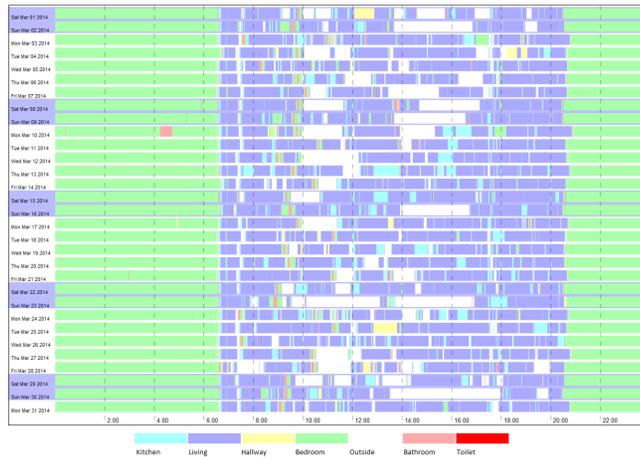

Figure 2: Case 1: Monthly overview. The x-axis indicates the hours of the day and the y-axis the days of the month. Different colors correspond to different locations.

Time spent The time spent in a location can also be plotted over time. Figure 4 shows the mean time spent in an area and the trend for each area. There was a period she spent more time in the bedroom, corresponding to increased number of comorbidities, and it is clear that over time she goes less outside which can be seen better in a separate plot, Figure 5. Figure 3 shows the changing means per period of six months, also revealing that less time is spent outside.
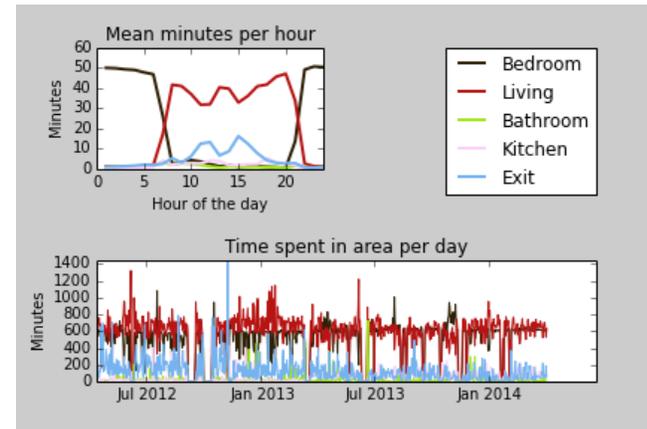

Figure 4: Case 1: Summary. The upper figure displays mean time spent per hour in a location. The lower figure displays the time spent in a location on a daily basis. This can reveal trends in the data, such as a decrease in time spent outside.
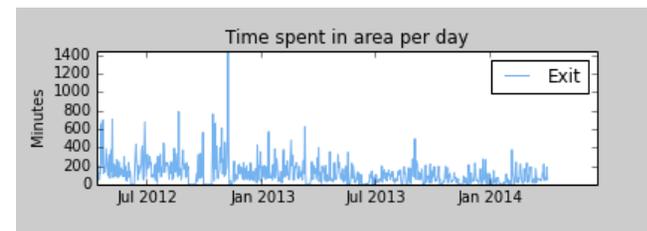

Figure 5: Case 1: Time away from home trend.

Dimensionality Reduction Besides inspecting trends of individual locations, a PCA of the whole data matrix was performed. This revealed trends in the overall pattern. The PCA is calculated over the whole period, and it can be seen that the pattern in the beginning is different that in the later months (Figure 6): the variance in the beginning is larger than the variance at the end. A

possible explanation is that the daily pattern of the person is more regular towards the end. The peaks that appear in the figure may correspond to incidents (that we do not explicitly monitor in this study), but some peaks also correspond to holidays (at least a few are confirmed by the participant).
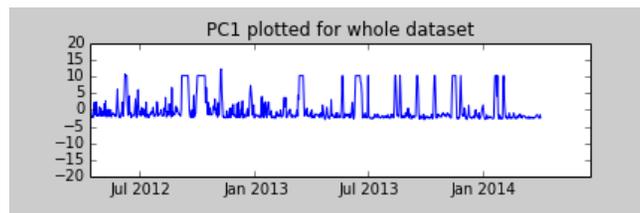

Figure 6: Case 1: First principal component plotted after performing PCA. This reveals trends in the data that are related both to time spent in areas as a shift in time.

Case 2

To illustrate that the tools yield different patterns for different persons, we included another case. This person is an old man with hip problems who has been followed for 16 months, and only shows small fluctuations in health Figure 7. He walks indoor with a walker, but he can still drive a car himself. He does everything himself but receives help for housekeeping. In the morning he performs a lot of small activities in the kitchen for preparing his meal in order to distribute his energy over the day. He has a stairlift, upstairs he walks with a cane. In the morning: goes out of bed, bathroom, downstairs, kitchen, living, etc and then goes back to the bedroom for a short period.
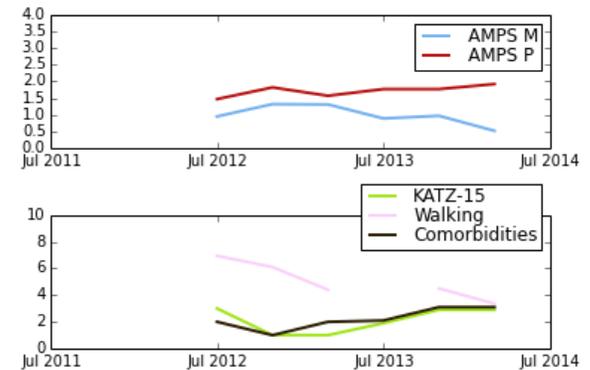

Figure 7: Case 2: Health report. The upper figure shows the AMPS motor and processing scores, the lower figure Katz-15, number of comorbidities and walking speed (seconds to walk 3 meters) over time.

Time spent   Not enough data (days) were present for performing PCA, but Figure 8 shows the monthly overview and Figure 9 shows the mean of the data and time spent in locations over time. It can be seen that case 2 spends less time outside and is going to bed later than case 1.
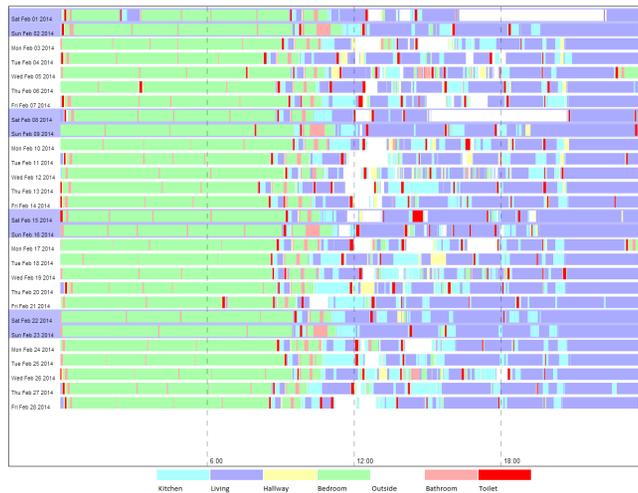
Figure 8: Case 2: Monthly overview. The x-axis indicates the hours of the day and the y-axis the days of the month. Different colors correspond to different locations.
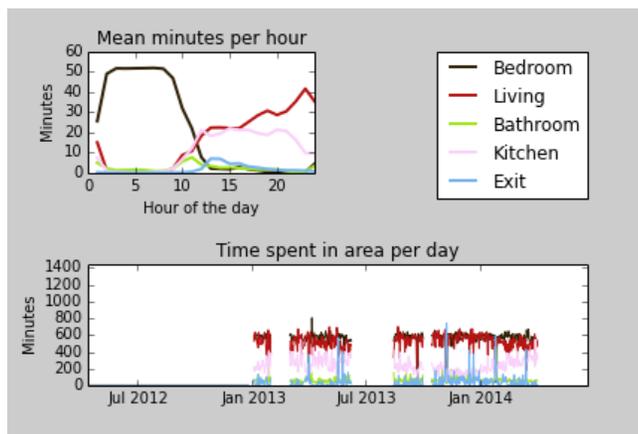

Figure 9: Case 2: Summary. Mean time spent per hour in a location and the time spent in a location on a daily basis.

Discussion and Conclusion

An increasing number of people have monitoring systems in their homes to support them in living independently at home (aging in place). Such systems can increase feelings of safety by detecting alarming situations such as falls. In addition these systems may generate health reports to assist care professionals, because they provide more information on the daily functioning than an incidental self report may reveal. One issue that we continue to face in developing new metrics for these reports is that from the number of people we follow, most remain relatively stable considering health changes. This requires larger scale studies, but assessing functional health is labor-intensive. Legislation in The Netherlands (and probably numerous other countries) prevent linking data from ambient monitoring field trials to official health records, which is why we rely on self report metrics and assessments that are taken by us. The field could advance more quickly if 1) data from sensor monitoring trials is shared and 2) assessment metrics are standardized. The first is quite hard to achieve because of privacy issues, but the second one is feasible and should be discussed. A proposal for this is assessing the self report ADL (KATZ-15) for functional health assessment, Minimental state examination (MMSE) for cognitive health assessment and the timed-up-and-go or walking speed for fall-risk assessment and functional decline indicator. The cases described in this study showed that behavioral data is valuable in making health assessments but the development of metrics can benefit from standardization of metrics.

Acknowledgements

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