Ambient Activity Monitoring for Medical Applications in Multi-Person Households

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ABSTRACT
This paper outlines doctoral research towards automated activity monitoring in the home, including past results and future plans. The aim of this research is to understand the possibilities and limitations of automated, or "unsupervised", approaches to ambient activity monitoring. Numerous applications of ambient activity monitoring, from care assessments to rehabilitation monitoring, have been developed in the past, but most approaches require complex calibration routines or are limited to single-person households. Furthermore, the requirements and theoretical limits of these approaches, such as sensor density and inhabitant-sensor-ratio, have not been studied.

Categories and Subject Descriptors
J.3 [**Computer Applications**]: Life and Medical Sciences – *Health, Medical information systems.*

General Terms
Algorithms.

Keywords
multi target tracking, multi hypothesis tracking, ambient assisted living, activity monitoring, ambient sensors.

1. BACKGROUND
Thanks to advances in modern health care, the share of the elderly population – and with it the number of people requiring assistance – is growing rapidly. At the same time, health care institutions are overburdened and strive to shorten in-patient time, while the demand and availability of ambulant care teams is increasing. One proposed solution to this problem is to use automatic health monitoring by installing ambient sensors, which help care patients and elders live safely in their own homes and collect medically relevant data. Such systems, however, are currently limited either by complex setup procedures, or use in single-person households: Wilson [7] describes an algorithm to track people and their activity status in a binary sensor network. In this work, subsequent sensor events create a graph weighted by frequency. By keeping track of the identity of people present, personal motion models emerge. Unlike our approach, the setup requires an initialization, for which a person walks through the living space to trigger all sensors. This way, no training period is required; the system starts tracking immediately. However, this process would have to be repeated each time a new sensor is placed in the area, or a sensor is relocated.

Steen et al. use data from binary sensors to calculate average room residence time and frequency. It is shown that "some items from assessment tests may be assessable by using only recordings from light barriers and reed contacts" [5]. It is argued, however, that using light barriers alone do not constitute sufficient evidence of a person entering a room, because people may change directions between rooms. The authors further suggest combining light barriers with sensors covering larger areas. In their evaluation, the authors calculate room residence times by manually labeling the sensors constituting a room using a floor plan and knowledge of the sensors' placements.

The possibility of deriving sensor graph topologies from recorded data is largely discussed outside the application area of medical assessments: Oh and Sastry [1] present a set of algorithms for tracking in binary sensor networks. Like our approach, this concept does not require network localization. Instead, passage connectivity graphs are calculated from transition probability matrices. Then a tracking algorithm, derived from the Viterbi algorithm, pruning strategies and multiple target tracking extensions are presented. We use these authors' definition of sensor node graphs to formulate our approach later on.

Wren and Rao [2] show that movement in a motion sensor network is sufficient to derive neighborhood relations between sensors and information on their sensing region overlap and relative distance. Inter-sensor transitions are represented as co-occurrence matrices. Using cameras to collect ground truth data and converting the data to binary presence information shows 99% correct overlap detection. It is also shown that the noise caused by movement of an unrestricted number of people in the sensor area is low compared to the signal.

Marinakis et al. [3, 4] derive transition times and probabilities between sensors from recorded data. Expectation maximization is used to assign activity to agents in order to build a graph of the sensor network. 95% of the topology of simulated node graphs is recovered correctly. However, the algorithm requires the expected number of people present as input, and it is shown that this is "a critical parameter" [4].

1.1 Motivation
A small set (7-12) of simple sensors (passive infrared sensors, reed switches, and light barriers) is sufficient to model a person's activity, including sleeping habits and mobility [5]. It has also been shown that it is possible to track multiple people on a topological graph of such sensors. Use of these sensor technologies – instead of complex ones like cameras or microphones – guarantees a minimal protection of privacy, as the localization and identification capabilities are limited. Given the sensors' locations, we collect just enough information to approximate a person's location and deduce information on his or her mobility and activities. Furthermore, the sensors are small and consume little power, causing a reduction in installation complexity and acquisition and operating costs.

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All ambient monitoring approaches to date require preliminary information: Steen et al. [5, 6] rely on the availability of the living space's layout (floor plan), knowledge of the sensor placement and the sensors to remain static; Wilson [7] uses an initialization process in which a person must trigger all sensors in succession by walking through the monitored area.

Removing the requirements of an initialization process and information on the localization of sensors offers two main advantages: First, sensor hardware failure can be accommodated by automatically recalculating sensor arrangements from recorded data, thus improving reliability and accuracy of the system and data. In the field of ambulant care support, where patients and care professionals might use such information to circumstantiate medical decisions, these are important factors. Second, although removing, relocating or replacing sensors invalidates the information gathered previously, it is not necessary to manually update the information or to repeat the initialization, further reducing maintenance costs.

In order to automate the installation and evaluation process, we have developed a set of algorithms which derive the topology of the living space (i.e. the sensors' relative locations and relation through concurrent or consecutive activations) and a person's location in this space. From this, we can *a)* infer information on the functional segmentation of the living space, and *b)* create a basis for a multi-person tracking algorithm. The functional segmentation of the living space enables us to derive data on activities from the person's location information suitable for care assessment tests, and the tracking algorithm enables us to utilize the approach in multi-person households, which has been a major limitation of other works.

2. SPECIFIC PROBLEMS ADDRESSED

At the heart of this research, two distinct, but intertwined problems are being addressed: Multi-target tracking with low resolution sensors and the lack of safety and usability of ambient sensors in medical and care support.

Activity monitoring using ambient sensors has been the subject of numerous research projects, and even commercial products[1], in recent years. Due to privacy concerns, they forego the use of complex sensors like cameras and microphones. Consequently, much, if not all, of the sensor activity is anonymous, meaning that the sensors are unable to distinguish multiple sources of activity.

Through the assignment of activity to anonymous sources ("tracking"), it is possible to transport any potentially existing identifying information across data which, on its own, would be anonymous. In order to achieve this, information on the placement of the sensors is necessary. Using a blueprint, we can create a graph connecting the sensors by their proximity [6]. Alternatively, this graph can be created by a "calibration" procedure, in which a single person triggers all sensors in the order they are accessible [7].

The existing approaches both cause *a)* extra work during installation, and *b)* rigid data, that does not honor the changes and failures that occur in daily life. For example, each time a sensor is removed, re- or displaced, manual recalibration is necessary. Therefore, my studies are based on a graph recorded from data in-situ. This removes the need for a calibration procedure during setup and enables us to automatically recalculate the graph whenever changes in the setup occur.

In a single-person household, the recorded data, which is used to generate the graph, is the same as the data recorded during the calibration suggested by Wilson [7]. In a multi-person household, the sensors do not necessarily trigger in the order of topological proximity. Without a proper understanding of the arrangement of sensors, the tracking is prone to errors.

The major part of the work proposed here, is to separate the anonymous data from multiple sources, so as to be able to minimize the error on the graph which is introduced by the lifting the limitation of a single person in the monitored space.

3. APPROACH

3.1 Sensor Network Graph

A sensor graph is defined as a graph of sensors $s_1, \ldots, s_N$ as a weighted, directed graph $G = (V, E)$, where $V = \{1, \ldots, N\}$ is the set of nodes in the graph representing the sensors, and E contains all edges (u, v) for which there is a direct passage from the sensing region of sensor u to the sensing region of v which does not intersect any other sensing regions. Informally, two sensors u, v are connected if it is possible for a person to walk from the sensing region of u to the sensing region of v without activating any other sensor. Due to sensor noise and presence of multiple persons, the recordings also show the subsequent activation of sensors which are not topologically close.

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3.2 Multi-Hypothesis Tracking

Due to sensor noise and presence of multiple persons, the recordings of activity data show the subsequent activation of sensors which are not topologically close. It is this data that prevents simple tracking algorithms to fail regularly. Therefore, we use multi-hypothesis tracking to keep track of possible data associations in a window of updates and accept the hypotheses only if they prove to be plausible over time.

An update to the tracking hypotheses happens each time a sensor provides new data. This data could be bundled into larger updates within reasonable time frames, but in our case an update occurs for each new datum.

There are three possible interpretations for each datum: *a)* it is an update to an existing path, *b)* it is considered noise and discarded, or *c)* it spawns a new path. Because the number of possible hypotheses follows *Bell's numbers*, it becomes intractably large after only a few update steps. We must apply a range of filters to maintain only the most likely hypotheses.

4. WORK DONE TO DATE

4.1 Study One

In this work [9], we have shown that networks of binary sensors can be useful tools in care assessments and rehabilitation. Reliability is a major factor in medical applications and the choice of sensor technologies for such systems is limited by practical reasons. We have shown that it is possible to derive information on the topology of living spaces and placement of binary sensors from recorded sensor data alone. Graphs, generated from data recorded on site, representing movement between sensors, depict

[1] http://www.locatesolution.de/produktloesungen/my.sens.html

neighborhood relations of the sensors. Modularity optimization is used to successfully recreate functional sensor clusters within households. As a measurement of the quality of the clustering and the underlying graph, we compare the clusters and their associated sensor nodes with the floor plan of the living space and the sensor placement.

For each of the five tested households, a sensor graph was computed using the algorithm described above (see *3.1 Sensor Network Graph*). Each household contains 11 to 13 sensors spread across kitchen, bedroom, bathrooms, hallways, and living rooms. A sensor node clustering is considered correct if it is part of a cluster which exclusively consists of sensor nodes of a single room. Of the 42 sensors, 40 were clustered correctly.

A preliminary analysis of the presence time of inhabitants to classify the clusters did not prove successful. Further investigation in this regard will be necessary.

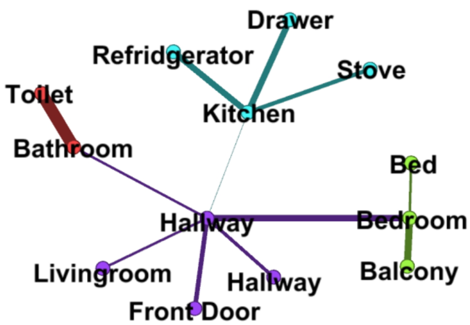

Figure 1. Graph of sensors and their topological relation. Colors represent clusters as per modularity optimization.

The data used for evaluation was collected from single-person households, using comparable sensor setups. Although initial tests show that similar clustering results can be achieved using more (50+) sensors in two-person households, this has yet to be verified.

4.2 Study Two

This study [10] introduces an approach to assign individual sensor events to multiple sources, i.e. people, and to thereby track peoples' activity over periods of time.

The approach is based on the sensor network graph introduced in the first study, and is the first of its kind to show the effectiveness of multi-target tracking on a graph based on historic data alone.

To test the effectiveness of the multi-hypothesis tracking, we use data of two people residing in a living lab, recorded by motion sensors. The data was recorded at the *CASAS* lab at the Washington State University. It is part of a dataset recorded over a period of 8 months while two participants resided in the lab.

Preliminary analysis shows that, despite the error-prone graph as a basis for tracking, most of the activity of two residents in the lab can correctly be separated. Figure 2 shows an evaluation of the number of tracks detected compared to the actual number of participants present. Further analysis has shown that most tracking errors can be attributed to imbalanced activity: when one person is inactive, for example sleeping, his/her track will fade over time, such as it is useful when the same person had left the building.

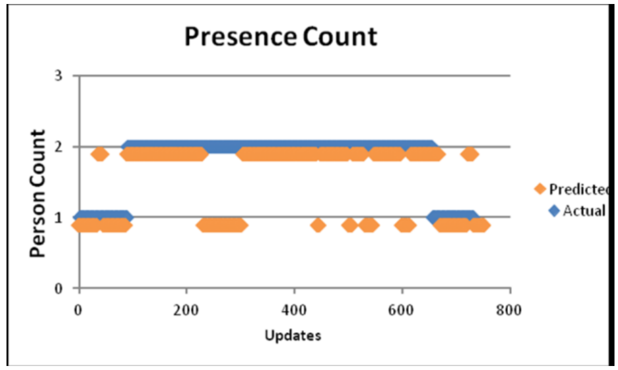

Figure 2. Actual vs. calculated number of people present.

5. FUTURE WORK

While the results of both studies are promising, the reliable generation of topologically correct graphs requires further investigation. The next step will be to use the paths generated from the tracking to create a new graph. The separation of sensor activity by its source potentially limits the error introduced by multiple people.

A field study, starting early 2015, will show if the approach proves reliable.

6. SPECIFIC ISSUES FOR THE DOCTORAL CONSORTIUM

First, the work presented here must face a difficult issue: if and how data generated with the help of probabilistic models can be used in decision making in medical care. Currently, models of medical data containing uncertainty and context information are being developed [8]. With the increase of ambulant care and medical support in the home, such data may play an increasingly important role. Questions that remain to be answered include: What can be done to satisfy reliability and accuracy demands for medical applications? Can algorithms, such as node fault detection, as used in wireless sensor networks, satisfy the strict requirements for medical devices?

Secondly, it would be beneficial for this project to address the societal topic of privacy. While the approach is chosen to protect the users' privacy as far as possible, it has already been shown that much more information can be derived from the data than previously anticipated. Furthermore, while we believe in the benefits of ambient activity monitoring, increasing availability and prevalence of technical systems, especially support systems, commonly brings about a sense of necessity. Most generally, will data-intensive applications such as these be desirable when the integrity of the communication technologies cannot be guaranteed? What, other than offline processing, can be done to protect the privacy of those in need?

7. ACKNOWLEDGEMENTS

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