Motion Pattern Generation and Recognition for Mobility Assessments in Domestic Environments

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Abstract. A novel approach to continuous and unobtrusive detection of motion patterns in domestic environments is presented. Motion patterns refer to motion primitives which can be detected via presence events emitted by ambient sensors. The approach enables adaption of the system to heterogeneous environments by building upon two pieces of information: a 2D/3D floor plan of the environment and a definition of available sensors. Using this input the system is capable of generating all information required for the monitoring. This minimizes effort for adaption of the system to other environments. A path-planning algorithm is used to automatically detect possible motion patterns and their length within the environment. A generated sensor-graph and finite state machines enable effective processing of sensor events on a common set-top-box. An experiment with 15 participants was conducted. The system is especially suitable for unobtrusive long-term trend analysis in self-selected gait velocity and does not require direct interaction with people monitored.

1 Introduction

The demographic change poses many problems e.g. due to the decline of the care ratio. In the near future there will be less people paying taxes for financing the health care system while there will be more people requiring health services. Costs due to the high need of care of demented people [1] and by their high fall risk [2] are two of the major factors influencing the proportionally higher costs to the health care system caused by elderly people.

In order to meet the increased challenges on the health systems, new approaches for delaying the need of care and for prevention of acute incidents like falls need to be developed. Long-term monitoring of mobility may provide the required means for supporting more early diagnosis and thus for initiating early prevention. This may help saving costs while increasing perceived quality of life for people concerned. Mobility impairments also have a high prevalence in dementia [3] and are an early indicator [4]. However, today's health systems often can not exploit the possibilities of early diagnosis through mobility assessment. Today, health care professionals do most often only get in contact with people concerned after an acute incident took place or after evidence for a disease is already obvious to layman. Additionally, they can only assess a person's health state in a proportionally small time frame while long-term assessment may provide more reliable and even more detailed insights. This is mainly due to missing remote assessment possibilities in domestic environments of people. Therefore, various

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approaches to mobility telemonitoring or remote assessment have been developed utilizing either wearable sensors or ambient sensors [5]. Nevertheless, existing approaches have serious limitations especially regarding the monitoring of demented people and are most often special-purpose applications which can not be used for wide-spread application.
Within this paper we present our first work towards a system for continuous and unobtrusive mobility assessment in smart domestic environments. A novel approach to configuring the system for wide-spread application in various environments with different sensor configurations is presented. The system was implemented to work effectively on a common set-top-box. An experiment with 15 health participants was conducted in a living lab.

2 Medical Motivation

A person's mobility is closely connected to his or her perceived quality of life and a fundamental requirement for an independent lifestyle. Starting at the age of 60 years, elderly peoples' mobility characteristics change [6] i.e. self-selected gait velocity decreases each decade by 12%-16% during self-imposed activities. However, these age-realted changes in mobility are not pathological [7]. A recent clinical study with more than 700 healthy participants aged between 20 and 90+ years has found an average gait velocity during a six meter walk of 1.1 m/s for people aged between 75-79 years, decreasing by 0.1 m/s every five years [6]. Impairments of mobility due to pathological reasons lead to more significant changes in parameters of gait than age-related changes [7]. Therefore, significant long-time changes in mobility may point to pathological causes and may thus be utilized for early diagnosis [8]. Gait and balance disorders have shown being related to a higher risk of falling. Especially slow self-selected gait velocity has found being related to an increased risk for falls and need of care [9].
One of the most frequent pathological reasons for mobility impairments are neurological diseases, especially dementia. Severity of gait and balance disorders increases with severity of neurological disorders [10]. Mobility impairments are also an early indicator in dementia [4]. Step-to-step variability in gait parameters of demented people seems to be more specific and sensitive than changes in mean values of gait parameters [8]. Due to their often severe gait and balance disorders dementia patients have an increased risk of falling [2]. From a clinical perspective long-term monitoring of changes in mobility has a high-potential for early diagnosis of various diseases and for assessment of fall risk [8]. In today's health systems this potential is most often not exploited because technical capabilities for large-scale remote assessments don't exist in domestic environments.

3 State of the Art

Several approaches to mobility telemonitoring or remote assessment have been developed utilizing either wearable sensors or ambient sensors [5]. However, most wearable sensors are not suitable for unsupervised use by layman or demented people. Wearables require direct interaction, therefore attaching, charging, or operating the device every

day. Not or incorrectly donning the device heavily influences the measurements. Our research is explicitly targeting elderly with reduced cognitive capabilities i.e. especially demented people. Therefore, within the state of the art we focus on research whose resulting systems do not require user interaction for mobility assessment.
Ambient sensors e.g. belonging to home automation or security technology systems seem to be most suitable for long-term unobtrusive mobility assessment in domestic environments. An approach presented by Cameron et al. [11] employs optical and ultrasonic sensors placed in door frames to determine the walking speed and direction of a person passing. Pavel et al. [12] developed a system based on passive motion sensors covering various rooms of a flat. Gait velocity could be computed by dividing known distance between coverages by measured transition times. Placing three passive motion sensors in a sufficient long corridor makes those computations more reliable [13]. However, if using only ambient sensors in a domestic environment with more than one person it is often difficult to correlate a sensor-event to a person triggering it. Various approaches to solve this problem have been presented [13, 14]. Large arrangements of pressure sensors can be used to locate a person and to monitor gait when placed under the floor. Steinhage et al. [15] introduced a system based on a smart underlay with capacitive proximity sensors consisting of conductive textiles. Since the spatial arrangement of sensor is known, a person walking over the surface can be located. Recently, more precise sensors have been employed for gait analysis in domestic environments. Pallejà et al. [16] and Frenken et al. [17] use laser range scanners to determine mobility parameters.
Most existing approaches have in common that they are single-purpose solutions working only in predefined environments with static sensor configurations. This is mainly caused by huge and changing environmental information in domestic environments not being properly defined and externalized and thus by missing capabilities to automatically adjust a system to changed circumstances.

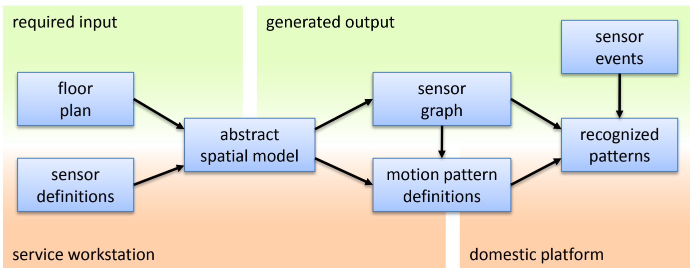

Fig. 1. Overall Concept of the System.

4 Approach

We present a new approach to continuous and unobtrusive detection of motion patterns in domestic environments. The term *motion pattern* refers to a motion primitive such as walking around or taking certain body positions which can be detected via presence events emitted by ambient sensors. The approach enables adaption of the system to different environments by building upon two pieces of information: a 2D/3D floor plan of

the environment and a definition of available sensors. All other required information for motion pattern detection is generated automatically. Recognized motion patterns can be used to estimate the mobility of persons monitored e.g. by computing the self-selected gait velocity.
The overall concept of the system is shown in figure 1. Building upon the required information the system generates an abstract 2D spatial model of the given environment including only obstacles for a person's motion. Within the abstract model a coverage area for each available sensor is defined. Hence, recognizing a sensor-event caused by the person monitored gives us the location (associated coverage area) of this person at a particular time. Via a path-finding algorithm from the field of robotics, the abstract spatial model is used to generate a sensor-graph which consists of the sensors as nodes and the adjacency relations between these nodes as edges. Motion pattern definitions between adjacent sensors are generated automatically. In addition, more complex motion patterns can be defined manually for available adjacency relations. Both, the abstract spatial model and the sensor-graph as well as the motion pattern definitions are generated on a service workstation. The sensor-graph and the pattern definitions are transferred to a platform in the domestic environment. The platform records sensor events and validates these via the sensor-graph. Pattern definitions are used to detect motion patterns in a sequence of valid sensor events. Recognized motion patterns can be used for further analysis and can be combined to create more complex motion patterns. If sensor events violate the sensor-graph, this may indicate additional persons inside the environment or defective sensors.

4.1 Abstract Spatial Model Generation

In order to generate the abstract spatial model, a floor plan of the domestic environment is analyzed. A parser for the Drawing Interchange Format (DXF) format was implemented. Objects recognized within the floor plan are classified into walls, openings, considered and unconsidered spatial objects. However, the generated abstract spatial model contains relevant objects only with their paraxial bounding boxes and relative positions. Definitions of available sensors, which are ideally generated directly on the domestic platform, are used to manually draw sensor coverage areas into the abstract spatial model. The whole process is supported by a GUI. The abstract spatial model is visualized in figure 2 which also contains explaining annotations which are not stored within the model.

4.2 Sensor Graph Generation

Adjacency relations between sensors respectively between their coverage areas are needed to generate the sensor-graph. Two sensors are adjacent if there is a path between the corresponding coverage areas that does not contain a coverage area of another sensor. In addition, a sensor is adjacent to itself. A path-planning algorithm is used to automatically find these relations between all available sensors within the abstract spatial model. For this purpose, the system currently employs a discrete version of the potential field method, described in [18]. While analyzing relations between two sensors all other sensors' coverage areas are regarded as obstacles. The abstract spatial

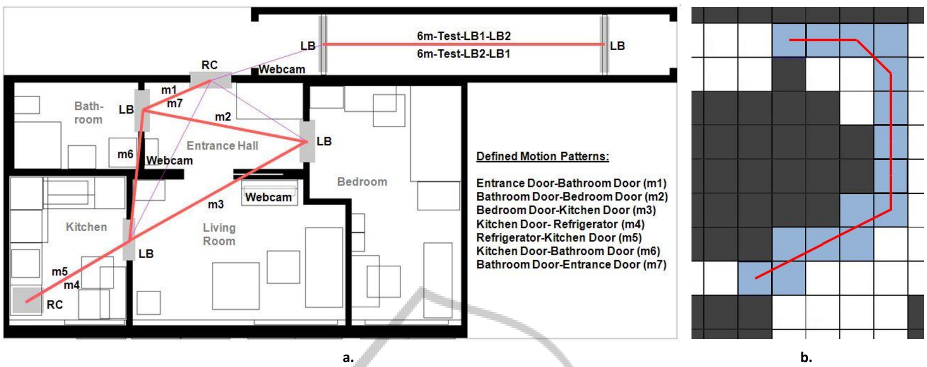

Fig. 2. a) Visualization of the Abstract Spatial Model for the Conducted Experiment, b) Detected Path for m6 (Brighter Fields) and Path After Smoothing Step (Line).

model is evenly divided by a grid. Each field of the grid is assigned a potential that is the result of superposition of the attractive goal potential and the repulsive potentials caused by existing obstacles. The attractive potential of a field is determined by computing its Manhattan distance metric from the goal. The Best First Algorithm is used to find a path.

4.3 Motion Pattern Recognition

Each motion pattern is transformed into a finite state machine. A motion pattern consists of a start-event and an end-event. In a sequence of homogeneous events either the first or the last occurrence of the start-event (or end-event) can be selected. Hence, there are four different models of state machines which are parametrized. As soon as an event has been detected on the home platform it is validated by means of the sensor-graph. A sensor event is valid if there is an adjacency relation between the related sensor and the sensor of the previous sensor event. Subsequently, a valid sensor event is forwarded to every state machine instance. In case a state machine instance detects a motion pattern, an instance of this motion pattern is created and stored for further analysis.

5 Experiment

The system was evaluated in a living lab in Oldenburg, Germany. The main objective of the conducted experiment was to check the general applicability of the system to gait velocity analysis in a domestic environment and to evaluate the automatic computation of the sensor-graph and motion patterns.

A common set-top-box was employed as a platform in the domestic environment. Software i.e. detection of available sensors, sensor event registration, sensor event validation, and motion pattern detection was implemented in Java and deployed into an OSGi framework. A common PC was used as service workstation in order to generate and manage the abstract spatial model, create the sensor-graph, enable the definition of motion patterns, and to visualize recognized motion patterns. A floor plan of the living

Table 1. Lengths of Paths Corresponding to Motion Patterns.

Motion Pattern	Meas. Length [m]	Comp. Length [m]
6 m-Test	6.00	5.60 (- 6.7 %)
Bathroom Door - Bedroom Door (m2)	3.61	3.39 (- 6.1 %)
Bedroom Door - Kitchen Door (m3)	4.73	4.75 (+ 0.4 %)
Kitchen Door - Refrigerator (m4, m5)	2.23	2.33 (+ 4.5 %)
Kitchen Door - Bathroom Door (m6)	4.45	4.75 (+ 6.7 %)

lab was available in DXF format.
Within the conducted experiment, performance and capacity according to the International Classification of Functioning, Disability and Health (ICF) from the World Health Organization (WHO) with respect to self-selected gait velocity were determined by the system. Capacity was measured on a six meter long, well-lighted, unobstructed, and straight path defined by two light barriers (LB). Performance was determined on several paths in an apartment. Light barriers and reed contacts (RC) were used. The experiment was monitored by video. The corresponding abstract spatial model with explaining annotation generated from the available floor plan is shown in figure 2 a.
15 persons (three women and twelve men aged 20-42 years) participated in the experiment. For this age group we expected neither significant age-related differences nor significant differences between capacity and performance in self-selected gait velocity. A clinical study conducted in 2009 with more than 700 people found an average capacity in gait velocity for people aged 20-39 years of 1.4 m/s on a six-meter walk test [6]. Therefore, we expected similar values, too.

5.1 Methods

Nine motion patterns, two for the six-meter-test path and seven inside the apartment, were defined. These motion patterns are shown in figure 2 a. For measuring capacity in gait velocity, the participants were first asked to walk five times along the six-meter-test path bidirectionally (6m-Test-LB1-LB2 and 6m-Test-LB2-LB1). After that, the experiment was continued in the apartment in order to measure the performance of the participant. Each participant entered the apartment through the entrance door and walked into the bathroom (m1). Then he or she walked from the bathroom to the bedroom (m2) and into the kitchen next to the refrigerator (m3 and m4). Afterwards each participant walked back to the bathroom (m5 and m6). The loop formed by motion patterns m2 to m6 was traversed five times by each participant. While walking, the participant were asked to carry different things (five tissues, five apples, five soaps) from one room to another. Hereby, adherence to paths was supported. The participants left the apartment through the entrance door (m7) after the fifth run was finished. During the experiment, each door inside the apartment was open.

Table 2. Mean Computed Gait Velocity.

Subject	Gait Velocity [m/s]											
	Real Distance						Path-planning Distance					
	6 m	**m2**	**m3**	**m4**	**m5**	**m6**	**6 m**	**m2**	**m3**	**m4**	**m5**	**m6**
Male, 20	1.80	1.85	1.89	1.42	0.90	1.75	1.68	1.74	1.90	1.49	0.94	1.87
Male, 26	2.07	2.28	1.88	1.79	1.03	1.94	1.93	2.14	1.89	1.87	1.08	2.08
Male, 26	1.80	2.15	1.97	1.34	0.92	1.61	1.68	2.02	1.98	1.40	0.96	1.72
Male, 27	1.83	1.56	1.59	1.34	0.92	1.50	1.71	1.46	1.60	1.40	0.96	1.60
Male, 27	1.34	1.46	1.15	1.12	0.80	1.17	1.25	1.37	1.16	1.17	0.83	1.25
Male, 27	1.81	1.98	1.45	1.04	0.57	1.48	1.69	1.86	1.46	1.09	0.60	1.58
Male, 31	1.87	2.15	2.16	1.38	1.26	2.00	1.74	2.02	2.17	1.44	1.31	2.14
Female, 31	1.48	1.87	1.96	1.31	0.98	1.77	1.38	1.75	1.97	1.37	1.03	1.89
Female, 32	1.45	1.76	1.56	1.24	0.88	1.51	1.35	1.66	1.56	1.30	0.92	1.61
Female, 37	1.84	1.96	2.13	1.58	1.13	1.93	1.72	1.84	2.14	1.65	1.18	2.06
Male, 37	1.99	2.01	2.33	1.41	1.01	1.76	1.86	1.89	2.34	1.48	1.06	1.88
Male, 39	2.05	3.01	2.31	1.64	1.35	1.92	1.92	2.83	2.32	1.71	1.41	2.05
Male, 39	1.96	1.90	1.67	1.50	0.98	1.71	1.83	1.78	1.68	1.57	1.03	1.82
Male, 41	1.85	1.82	1.98	1.27	0.99	1.81	1.73	1.71	1.99	1.32	1.03	1.93
Male, 42	1.72	1.60	1.39	1.17	0.56	1.31	1.61	1.50	1.40	1.22	0.58	1.40
Average 1	**1.79**	**1.96**	**1.83**	**1.37**	**0.95**	**1.68**	**1.67**	**1.84**	**1.84**	**1.43**	**1.00**	**1.79**
Average 2	**1.79**	**1.56**					**1.67**	**1.58**				

5.2 Results

In order to compute the self-selected gait velocity $v(p, m)$ of the participant p, the path length $l(m)$ of each defined motion pattern m and the time taken $t(p, m)$ to walk the path is required so that $v(p, m) = \frac{l(m)}{t(p,m)}$. The path length can be directly computed by utilizing the path-planning algorithm, so that the path length between two adjacent sensor is nearly computed by simply adding the size of the grid fields passed. Additionally, the lengths were directly measured in the lab. Table 1 shows a comparison between measured and computed paths for the six-meter path and the paths of the repeated motion patterns m2 to m6.

Differences between measured and computed paths' lengths can be explained by the nature of the path-planning algorithm used. A value computed by the path-planning algorithm is always a multiple of the width of a grid field (40 cm for the experiment). Additionally, the basic path-planning algorithm only examines the 4-connected neighborhood of a grid field which prohibits finding bevel paths. Therefore, in order to further optimize the computed lengths a smoothing step is applied. Within this step 3-corner-fields and 4-corner-fields of the computed paths are transformed into bevel joints (Figure 2 b). Within the smoothing step it may occasionally happen that bevel joints streak (partially) blocked fields.

Table 2 shows the mean gait velocities computed for each participant on the 6-

meter-test path and on all repeated domestic paths (motion patterns m2 to m6). All gait velocities are computed based on the median of the transition times and on the measured and computed path lengths. As expected we found neither significant age-related differences nor significant differences between capacity and performance. The arithmetic mean over all gait velocities for the six-meter-test path is 1.79 m/s (for the measured path length) respectively 1.67 m/s (for the computed path length). Mean gait velocity for all domestic paths is 1.56 m/s, respectively 1.58 m/s. These values are around the estimated gait velocity of 1.4 m/s on a six-meter walk test [6].

5.3 Discussion

One problem of this approach are changes to the environment, e.g. moving a chair, after the abstract room model has been generated. Such changes are hard to detect. Hints may be given by changing transition times over time which may not only point to changes in the inhabitant personal condition but also to changes in the environment. However, such changes would be detected during the trend analysis and might also be a valuable hints for carers since such changes are probably affecting the inhabitants performance and may be dangerous obstacles. Approaches like the housing enabling concept are explicitly targeted at detecting and removing such environmental factors. Due to the nature of the path-planning algorithm used computed path lengths and resulting computed self-selected gait velocity values have slight errors compared to manually measured values. However, mobility assessment in the domestic environment is more intended for a continuous and long-term assessment of mobility parameters. Thus detection of changes over time provide more reliable information to medical professionals than precise single measurements which may be erroneous due to uncertain circumstances. Otherwise, automatic computation of path lengths enables a much broader and time-effective application of remote mobility assessment. Some defined motion patterns within the domestic environment were found being walked in significantly slower speed than others. These patterns e.g. motion pattern m5 (walking from the refrigerator to the kitchen door) required the probands to stand still and to turn around instead of only walking from one to another room. The resulting low values may potentially confuse medical professionals or data analysis tools. Approaches like e.g. described in [17] provide more precise and reliable computations due to their capability to continuously measure a proband and distinguish between times of walking and standing still.

6 Conclusions

A novel approach to continuous and unobtrusive detection of motion patterns in domestic environments was presented. The approach enables adaption to heterogeneous environments by building upon two pieces of information: a 2D/3D floor plan of the environment and a definition of available sensors. All other information required for the monitoring is generated automatically. This may enable large-scale application. A path-planning algorithm is used to automatically compute a sensor-graph and paths' lengths within the environment. The sensor-graph is used to validate sensor events and to generate basic motion patterns. The resulting motion pattern definitions are transformed into

finite state machines and thus enable effective detection of patterns in a series of sensor events. Detected motion pattern instances may be used for further analysis, give hints to or send alarms to medical professionals. The conducted experiment showed that the system may work totally unobtrusive based exclusively on ambient sensors. The system is especially suitable for long-term trend analysis.
Nevertheless, the system currently has some limitations. Precision of computed path lengths may be further optimized. We are currently working on enhanced and additional path-planning algorithms which e.g. use an 8-connected neighborhood of grid fields to directly find bevel paths. Currently, detected motion pattern instances are only stored and transferred in a custom-made format. We are working on the storage of documents according to the Clinical Document Architecture (CDA) and on the integration of rules for automatic alarming. The system will be installed in various flats of community dwelling elderly late 2010.

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