Technical Approaches to Unobtrusive Geriatric Assessments in Domestic Environments

Thomas FRENKEN [a,1], Olaf WILKEN [a] and Andreas HEIN [a]
[a] *OFFIS - Institute for Information Technology, Escherweg 2, D-26121 Oldenburg*

Abstract. Two novel approaches to implementing unobtrusive and and non-stigmatizing geriatric assessments in domestic environments are presented. Mobility regarding self-selected gait velocity is assessed using light barriers and a two dimensional laser range scanner. A single power sensor installed into the fuse box helps determining self-care ability by detecting appliance usage. The described assessment approaches are meant to enable early detection of disabilities and thus prevention and provision of individual support directly in peoples' homes. They overcome the disadvantages of classical geriatric assessments. The technical assessments contribute to the concept of Ambient Assisted Living (AAL) which targets at fostering a self-determined lifestyle in peoples' personal homes by providing a technical infrastructure and supporting services. The assessments do not require any direct interaction with the inhabitants. Two experiments conducted in a living lab and a residential care facility in Oldenburg, Germany demonstrate the general feasibility of the approaches.

Keywords. assessments, mobility, laser range scanner, power sensor, activity recognition

1. Introduction

The so called double aging of the society which can be observed in many European and industrial countries poses many problems. While on the one hand less young people are born, peoples' general life life expectancy constantly increases. The resulting increase of the old-age dependency ratio means that in the future there will be less young people having to pay and care for more and older elderly people [7]. This trend also means that, considering that many diseases' prevalence increases with old age, in the future there will be more multimorbid patients i.e. more patients suffering from more than one disease. In Germany, nearly 40% of all people aged 40-54 years suffer from more than one diseases, 4% of those people are diagnoses to have at least five diseases. These figures tremendously increase with age. Nearly 60% of people aged 55-69 years have more than one, 12% have more than five diseases. For people aged 70-85 years these figures increase to over 70%, respectively 24% [14].
The branch of medicine concerned with the diagnosis, treatment, and prevention of dis-

[1]Corresponding Author: Thomas Frenken, E-mail: thomas.frenken@offis.de.

eases in older people and the problems specific to aging is called geriatrics. In this context the term "older" often refers to people being older than 80 years or being multimorbid and older than 70 years. The aim of each geriatric treatment is to recover and maintain an independent lifestyle of patients. In difference to other branches of medicine a detailed diagnosis of diseases is not that important and sometimes even not possible due to the interference of diseases in multimorbid patients. The so called geriatric assessment is a "multidimensional process designed to assess an elderly person's functional ability, physical health, cognitive and mental health, and socio-environmental situation" [2]. Within the assessment process standardizes assessment tools like the Timed-Up-And-Go [27] are used.

In today's health care systems assessments are only applied in hospitals most often after acute incidents took place. This is mainly because domestic environments are only fractionally integrated into health care systems. By assessing elderly peoples' abilities directly in their home environments many acute incidents may be prevented and care or rehabilitation means may be provided according to individual needs. This may increase concerned peoples' perceived quality of life while saving costs.

Within this paper two technical approaches to implementing unobtrusive geriatric assessments in domestic environments are presented. The approaches are exclusively based on ambient sensors and require no interaction with the patients monitored. A laser range scanner is used to assess peoples' self-selected gait velocity. A power sensor integrated into the fuse box monitors peoples' appliance usage in order to deduce their self-care ability. Experiments have been conducted in a living lab and a residential care facility.

2. Medical Motivation

The aim of each geriatric treatment is to recover and maintain an independent lifestyle of patients. Therefore, instead of focusing on a detailed diagnosis, the geriatric assessment concentrates on assessing an elderly person's functional ability, physical health, cognitive and mental health, and socio-environmental situation. This can not be done by a single physicians but it is a multidimensional and multidisciplinary process in which standardized tests, so called geriatric assessment tools, are utilized.

Although providing a good insight into peoples' abilities in rather short time, there are several drawbacks about geriatric assessments in today's health care systems:

Place of Execution Today, geriatric assessments are only used in professional care facilities like hospitals or doctors' practices most often after an acute incident already took place. Their potential for prevention or surveillance of rehabilitation advances within the domestic environment is not exploited. Additionally, professional care facilities are free of environmental obstacles which leads to test results not reflecting the performance of people in their domestic environments.

Test Awareness Geriatric assessments in professional care facilities are often perceived as test situations which leads to people performing at their best. Again the assessment results do not reflect the performance of people within everyday life.

Subjective Execution Despite providing standardized descriptions and guidance for execution, geriatric assessment are often executed subjectively by caretakers. Small differences in execution make comparison of results between people and between several executions difficult.

Required Effort At the moment there is only very little technical support for geriatric assessments. Assessments need to be repeated several times during the treatment in order to provide reliable results. This makes assessments, although being rather simple tests, time- and personnel-intensive.

Two central aspects of each geriatric assessement are a patient's mobility and self-care ability. A person's mobility, i.e. being able to move around and to get into and keep up certain body positions, is a fundamental requirement for an independent lifestyle [9] and is closely connected to his or her perceived quality of life. Starting at the age of 60 years, elderly people expose a slower gait velocity [13]. This age-related change in mobility is not pathological. Nevertheless, many pathologic diagnoses can be directly deduced from an impaired mobility [3]. Gait and balance disorders have shown being related to a higher risk of falling. The most obvious impairment visible even to layman is a reduced self-selected gait velocity which has been found being related to an increased risk for falls, admission to hospital, and need of care [20]. The most frequently used assessment from the field of mobility is the Timed-Up & Go [27]. Despite being able to move around taking care of oneself requires various cognitive and physical capabilities for executing certain activities. Therefore, a person's self-care ability is often assessed in terms of the ability to execute various (instrumental) activities of daily living (ADL).

3. State of the Art

Currently, there is only very limited technical support for executing geriatric assessments and nearly no support is used in daily clinical practice. However, due to the potential of assessing people in their domestic environments research has investigated various approaches utilizing different sensor technologies.

3.1. Mobility Assessments

Within hospitals, especially in case problems with prostheses or implants, laboratories equipped with camera-based systems for cinematic gait analysis based on marker tracking, fluoroscopy systems, systems for cinetic gait analysis of ground reaction forces utilizing force platforms, and dynamic electromyography are used.
Recent research investigated mobility telemonitoring directly in the home of affected people using either wearable sensors or sensors installed into the environment [30]. Wearable sensors may be placed either on one or many positions directly on the body or in cloth and objects worn. Several wearable sensors are also referred to as body area networks (BAN). Accelerometers and gyroscopes have been applied to gait phase detection [33] and measurement of various parameters of gait like walking velocity, cadence, average step length, and step timing variability [17,35]. Pressure sensors under or integrated into the sole of shoes, later combined with accelerometers and gyroscopes, have been used to measure pressure distribution on certain points of the feet in order to infer gait phases or events [22,15] or to detect abnormal gait patterns [34,6].
Ambient sensors are integrated into the environment or in objects used by the person monitored. Environments equipped with such sensors are also referred to as health smart homes [30]. Very few systems for detailed mobility analysis based on ambient sensors

have been described so far. Most approaches rely on home automation technology like motion sensors, light barriers, or reed contacts placed in door frames or on the ceiling in order to determine a person's walking direction or velocity [4,24]. The iWalker [31] is a mobile assessment instrument. It is equipped with optical sensors for measuring wheel rotation and moving direction, a six-dimensional gyroscope and accelerometer measuring speed and distance, several load cells in the handles and on the frame measuring weight distribution and propulsion forces, and a portable camera for recording the environment while walking.
In summary, miniaturized wearables can provide detailed biomechanical information about the person wearing the device, ideally in any environment. Nevertheless, most wearable sensors are not suitable for unsupervised use by layman. Wearables require direct interaction, not or incorrectly donning the device heavily influences the measurements. Studies indicate that simply being aware of wearing a sensor may influence the measurement results [16]. Mobility monitoring utilizing ambient sensors has been rather imprecise so far. Nevertheless, ambient sensors are totally unobtrusive and suited even for layman. Ideally, monitored persons do not recognize present sensors in their everyday life, thus measurements might be more reliable. Ambient sensors may monitor several persons in their coverage at the same time. However, identifying the monitored persons is often difficult. Installation of sensors may be costly.

3.2. Activity Recognition

Early approaches to activity recognition utilized mainly home automation sensors such as motion sensors [19], temperature sensors, light sensors [1], and binary-state sensors [32]. More complex sensors like RFID-tags [26], vision sensors [18], body-worn accelerometers [29], or microphones [5] can be used as well. Recognition of interleaved and concurrent activities, and the unsupervised learning of activities are still open research questions since the collection of good training data is difficult. In [11] skip-chain conditional random fields (SCCRF) are applied to the recognition of interleaved activities. Detection of concurrent activities was realized using correlation graphs. Detection accuracy was up to $90\,\%$. In [12] unsupervised learning was used for activity recognition. With the use of k-means cluster and Latent Dirichlet Allocation (LDA) various activities like dinner, commuting, lunch and office work were recognized with an accuracy of $76.9\,\%$.
The application of power sensors to activity recognition is currently investigated. The idea is to map appliance usage to activity execution e.g. the usage of a coffee machine in the morning to preparing breakfast. In the area of NALM (non-intrusive load monitoring), i.e. the process of analyzing the properties of the electrical energy consumption of a house in order to identify the electrical appliances used and their energy consumption, two different types of power sensors are used. The first type are proprietary sensors e.g. described in [10,21,23] that have a very high sampling rate. The second type are smart meters [28] that are produced in large quantities and are installed by energy providers in households. This type has a low sampling rate. In [10] only devices consuming more than $100\,\mathrm{W}$ were detected with a sampling rate of $1\,\mathrm{Hz}$. It could not be distinguished between different states of a device. In [21] the authors describe how the different states of a washing machine can be identified by a directly connected power sensor. In [23] a proprietary high resolution sensor $5\,\mathrm{kHz}$ was used, resulting in a correct identification rate of $90\,\%$. In [28] devices could be identified with a smart meter using neural networks.

Only appliances with a major energetic impact on the daily load shape were detected. In an evaluation the appliances were detected with an accuracy of $90\,\%$.

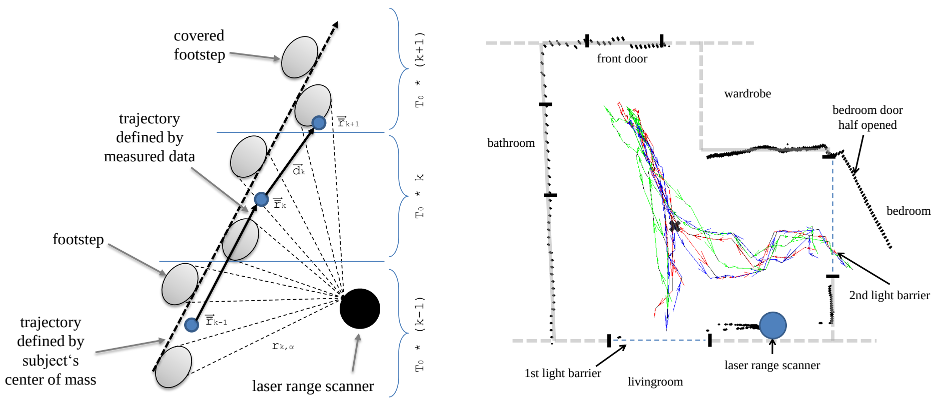
4. Approach to Unobtrusive Assessments

The concept of Ambient Assisted Living (AAL) targets at fostering a self-determined lifestyle in peoples' personal homes. It combines a technical infrastructure within the home environment, consisting of sensors, actuators, and communication technologies, with supporting services often provided by third-parties. Support within the domestic environment may be provided in various domains like communication, mobility, self-care, or domestic life (according to the International Classification of Functioning, Disability and Health (ICF) from the World Health Organization (WHO)). Support provided should be as unobtrusive, individual, and non-stigmatizing as possible and should be usable with only little technical precognition. However, in order to provide support existing impairments, activity limitations, or participation restrictions (summarized as disabilities within the ICF) first need to be detected, ideally in peoples' homes and as early as possible. We have developed two novel approaches to detecting disabilities in the field of mobility and self-care ability in domestic environments. The approaches are designed to meet the aforementioned requirements of supporting services within the AAL concept.

4.1. Mobility Assessments

Our novel approach to mobility monitoring combines two types of ambient sensors: Light barriers for measurement of general trends in mobility mainly in the home environment and a very precise ambient sensor, a two dimensional laser range scanner for detailed gait analysis. We hypothesize that laser range scanners are applicable for precise measurement of capacity regarding mobility in an environment mainly free of environmental influences like a hospital as well as for measuring performance in a domestic environment. Gathered information should be sufficient for analyzing various spatio-temporal parameters of gait. Additionally, there is no need for the patients to interact with the sensor which may lead to more reliable results and makes the sensor even suitable for measuring mobility of cognitively impaired people. As a first step towards realizing the desired assessment system, we have designed an algorithm for reliably and precisely computing self-selected gait velocity in domestic environments [8]. The approach does not require a priori knowledge about the environment.
Figure 1(a) shows the principle of computing a person's movement trajectory from measurements taken by a laser range scanner at the height of the subject's legs. The process of computing an approximated self-selected gait velocity from those measurements involves three steps: environment recognition, dynamic object measurement, and gait velocity computation:

Environment Recognition Prerequisite for measuring the movement trajectory of a subject is the ability to distinguish moving objects like humans from stationary objects. This is achieved by computing a histogram of measurements for each measurement angle α in the measurement sector $[start_\alpha, end_\alpha]$ over a given number k^c of measurement sets including only the static environment.



(a) Principle of computing gait velocity from laser range scanner's measurements

(b) Laser range scanner's measurements for three measurement sets of the second experiment displayed into the living lab's floor plan

Figure 1. Utilizing a Laser Range Scanner for Computing Self-selected Gait Velocity and for Visualizing Movement Trajectories

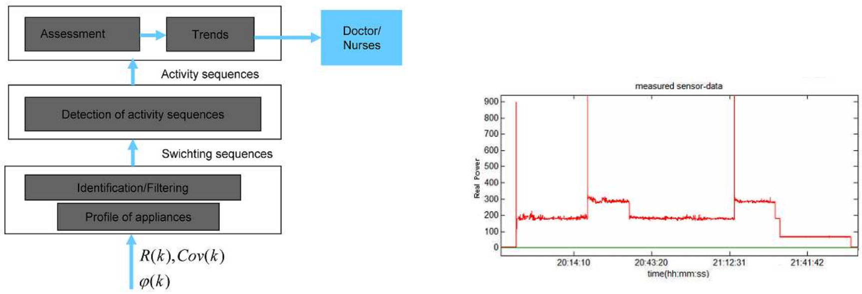
Dynamic Object Measurement During the measurements the mean range $\bar{r}^c(\alpha)$ and standard deviation $\sigma^c(\alpha)$ for each measurement angle stored within the histogram are used to subtract measurements representing background from the foreground i.e. the legs of a moving person. All range measurements $r_{k,\alpha}$ outside the histogram's interval $[\bar{r}^c(\alpha) - \sigma^c(\alpha), \bar{r}^c(\alpha) + \sigma^c(\alpha)]$ represent a dynamic objects and thus a person's legs.

Gait Velocity Computation For each measurement set k the mean range vector $\vec{\bar{r}}_k$ is computed from all foreground measurements. The computed mean range vector represents the approximated center of mass of the measured person. The distance walked d_k between two measurement sets k and $k-1$ is approximately the length of the vector $\vec{d}_k$ between two consecutive mean range vectors $\vec{\bar{r}}_k$ and $\vec{\bar{r}}_{k-1}$. d_k by the time elapsed $T_0 * k - T_0 * (k-1) = T_0$ between the two corresponding measurement sets k and $k-1$ gives approximately the self-selected gait velocity v_k for point in time $T_0 * k$. Applying an additional mean filter to all computed velocity values v_k within one second gives the approximated gait velocity per second.

4.2. Activity Recognition

Our novel approach to activity recognition utilizes a single power sensor installed into the fuse box of a house or flat (one for each power circuit). Activities are detected by mapping these to sequences of appliance usage which are detected by the power sensor. Based on the measurement of electrical parameters by the power load sensor the on- and off-switches of electrical appliances can be identified. The electrical parameters voltage $u(t)$, current $i(t)$ are measured and sampled at a frequency of 17 Hz. Devices are identified by their characteristic switching operations. An example of a characteristic signal of devices is shown in figure 2(b). The overall principle of the approach is shown in figure 2(a). It consists of three levels:

Identification/Filtering First, running appliances are identified. Concurrently running appliances have a different voltage drop compared to a single one since each



(a) Principle of activity recognition using electrical parameters

(b) Current curve measured by the power load sensor

Figure 2. Utilizing a Power Sensor for Activity Recognition

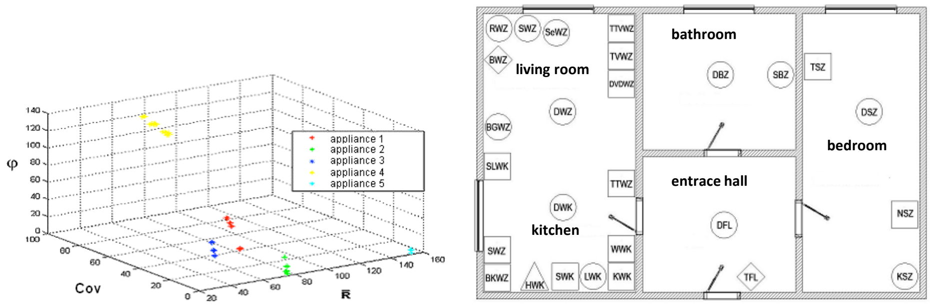
switch-on of an appliance produces a small voltage drop. Therefore, electrical parameters such as the real power, which is dependent on the voltage, is not a well-defined feature. Resistances are the basis for extracting features of each appliance since they remain constant for concurrently running appliances. The features mean (R), covariance (Cov) and phase φ are extracted from the switched-on devices. For switch-off, only the features' mean values are extracted. For the correct identification of concurrently running appliances these have to be switched on one after another with a delay of at least 1.5 seconds. Currently, a supervised learning technique is applied for learning the appliances' characteristic features (profiling). After the classification (nearest neighbor method, example in figure 3(a)) the states of appliances with user interaction have to be separated from those without interaction (e.g. turn on/off of the refrigerator is a interaction without a user).

Activity Recognition In the second level the switch on/off sequences of appliances are assigned to activities. For the sequence analysis algorithms from the field of bioinformatics are applied. In figure 5 an example of a sequence pattern is shown. The letters represent the states of different appliances. For example the letter "P" stands for a switched on cooker. Patterns may change throughout different days (e.g. weekdays/weekends) and time of day.

Assessment and Detection of Behavioral Change In the third level the identified activities are qualitatively analyzed and mapped to geriatric assessments. Furthermore, changes in activity patterns are detected over time and are transfered. Deficiencies in certain activities are detected and allow to assess a inhabitants self-care ability respectively his or her requirement for supporting services.

5. Experiments

Approaches are still within an experimental state. Initial experiments to proof the feasibility of the developed approaches have been conducted in a living lab and in an apartment located in a residential care facility in Oldenburg, Germany.



(a) Feature space and clusters of five different appliances during a switchon operation

(b) Floor plan of the apartment with available appliances used for the experiment with the power sensor

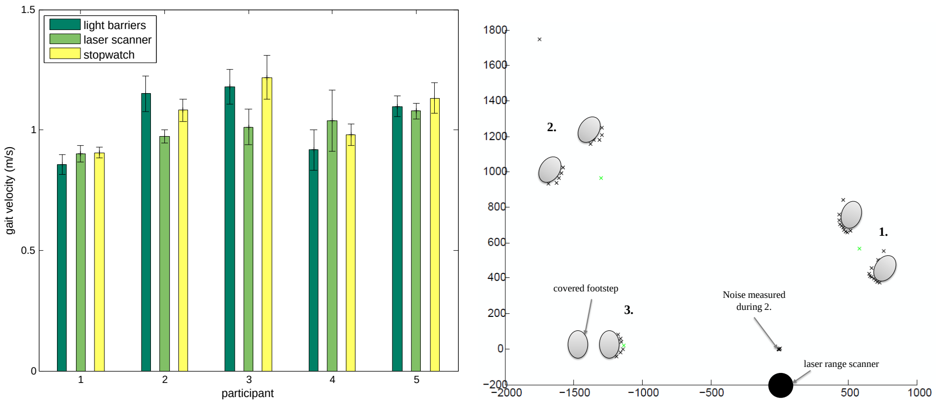
Figure 3. Clustering of Appliances and Floor Plan of the Apartment for the Conducted Experiment

5.1. Mobility Assessments

An experiment for comparing feasibility and precision of measuring self-selected gait velocity using light barriers and a laser range scanner was conducted. Five healthy people aged 25-39 years participated in the experiment. The laser range scanner was placed at a height of 38cm in the entrance hall of the flat. The light barriers were mounted to the door frames in the living room and the bedroom. Doors to living room and bedroom were open, front door and bathroom door were closed. On- and off-states of the light barriers were wirelessly transmitted to an FHZ1000PC FS20 base station. The FHZ1000PC and the Hokuyo URG-04LX-UG01 laser range scanner were connected to a PC using the USB port.

For each participant ten measurement sets were recorded while walking along two paths within the flat's entrance hall (figure 1(b)). For the first part of the experiment participants were asked to walk directly from the living room to the bedroom and vice versa. For the second part, participants had to walk from the living room to the front door, lock the front door, and then walk to the bedroom. On their way back they were asked to reopen the front door before entering the living room. Participants were instructed to walk at their normal speed. The time to walk the paths was recorded directly by the laser range scanner, by computing the time between reception of "on" states of the light barriers, and manually using a stopwatch. The manual measurement is thought to be the gold standard since it is commonly used in clinical environments. The distance walked was again measured by the laser range scanner and thought to be apriori knowledge for the computations based on the time measurements of the light barriers and the stopwatch.

Results show (figure 4(a)) that during the first part of the experiment (walking straightly from living room to bedroom and vice versa) self-selected gait velocity could be precisely computed from measurements of light barriers as well as from those of the laser range scanner compared to the stopwatch measurements. Mean difference compared to the gold standard was only 0.023m/s for the light barriers and 0.063m/s for the laser range scanner. Standard deviations were 0.05m/s respectively 0.10m/s. Mean self-selected gait velocity across all participants was 0.99m/s, ranging only from 0.90m/s for the first participant to 1.1m/s for the third participant. The second part of the experiment was conducted in order to demonstrate the advantages of using a laser range scanner's measurements for computing self-selected gait velocity. Computations based on the time mea-



(a) Computed gait velocity for first experiment

(b) Noise and occlusion in laser range scanner measurements

Figure 4. Results and Problems of Computing Self-selected Gait Velocity From Range Measurements

sured by the light barriers and the stopwatch for the second part were very imprecise due to the participants not walking directly from the living room to the bedroom but standing still in between while opening or locking the front door. There is no possibility to compensate for this using only light barriers on room doors and in a real setup there would even be no chance to detect the longer walking distance. However, using the measurements of the laser range scanner, self-selected gait velocity could be computed precisely even for the second part of the experiment. This was achieved by removing all distance measurements from the computation whose difference vectors were smaller than a defined threshold and did thus represent rest. By filtering those measurements computed self-selected gait velocity for the second experiment had a mean error of only 0.01m/s and a standard deviation of 0.22m/s compared to the computation for the first experiment based on the laser range scanner's measurements.
Depending on the position of the laser range scanner relative to the subject measured, trajectory and gait velocity computed based on the measurements may differ from the trajectory defined by the subject's center of mass and the actual gait velocity due to two reasons. First, the laser range scanner measures only the surface of legs facing the scanner (figure 4(b), case 1). The scanner is not capable of measuring the depth of an object. Therefore, the computed mean distance vector will point to a position slightly more into the direction of the laser range scanner than the vector pointing to the real center of mass. The difference in these two vectors depends on the depth of the object measured. Second, looking from the position of the laser range scanner one leg may be covered by the other while walking (figure 4(b), case 3), especially during the gait phases mid stance and initial swing of the human gait cycle [25]. The computed mean distance for such measurements differs from those including both legs resulting in either a longer or shorter mean distance depending on the leg covered. Intermittent noise (figure 4(b), case 2) does not heavily influence the measurement results.

5.2. Activity Recognition

Within a field study over a period of six months the system was installed in an apartment (floor plan in figure 3(b)) inhabited by an elderly person. A total of about 30 appliances

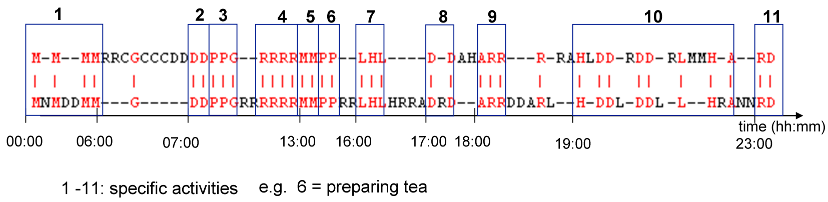


Figure 5. Recorded Appliance Sequence and Identified Activities From the Experiment

were available in the apartment. In the course of data collection some problems occurred in contrast to laboratory studies like signal noise of appliances and replacement of electrical appliances the system was unaware of. The accuracy in the detection of devices was about 80 %. For the unsupervised learning of activities it is important to filter as much noise as possible like visiting hours and absences times of the inhabitant. Finite state machines have been applied for filtering. The absences have been detected with 78 % and the visiting hours with 67 %. In figure 5 the result of unsupervised learning activities over a period of four days is shown. The individual sequences are different activities.

6. Conclusion

In the near future health systems will have to cope with more elderly and thus multimorbid patients. The medical branch of geriatrics deals with these patients respectively with diseases and problems specific to aging. The aim of each geriatric treatment is to recover and maintain an independent lifestyle as long as possible. Required support or compensation is determined within the geriatric assessment respectively by utilizing various geriatric assessment tests. The concept of Ambient Assisted Living (AAL) targets at fostering a self-determined lifestyle in peoples' personal homes. It combines a technical infrastructure within the home environment with supporting services. Therefore, bringing geriatric assessments to the home environment seems to be reasonable in order to provide prevention and to determine existing disabilities and thus required support. Support provided should be as unobtrusive, individual, non-stigmatizing as possible and should be usable with only little technical precognition.

Within this paper we have presented two novel approaches to implementing unobtrusive and non-stigmatizing assessments in the domestic environment. Light barriers and a laser range scanner have been used to reliably and precisely compute self-selected gait velocity. The conducted experiment suggests that light barriers shall be used for measuring general trends in mobility covering a whole flat while the laser range scanner provides detailed measurements in a smaller area and in professional care facilities. The computation works without a priori knowledge of the environment. A power sensor installed into the fuse box of homes helps detecting appliance usage of inhabitants. By determining activities carried out and anomalies regarding learned normal behavior self-care abilities may be assesses. The experiment has revealed problems during the measurements like signal noise of appliances and replacement of electrical appliances the system was unaware of. The technically supported assessments overcome the disadvantages of classical assessments. They may be utilized directly in the home environment enabling prevention and surveillance of rehabilitation advance. Since the used technology is totally unobtru-

sive, technically supported assessments are ideally not perceived as test situations and do provide a realistic insight in peoples' everyday performance in their natural environment. The sensors measure objectively, continuously, and do not require any direct interaction with the inhabitant. However, it remains to be investigated how to exactly relate measurement results to results of established geriatric assessment.
The conducted experiments have demonstrated the general feasibility of the presented approaches. We are currently planning to evaluate the assessments in a assisted living facility. We are also working on enhancing the gait velocity computation by incorporating background knowledge on human gait and want to compute additional spatio-temporal parameters of gait by applying object identification techniques to the scanner's measurements. These parameters may be used for detection of abnormal gait and may be incorporated into a model of gait. Regarding assessment of self-care ability we are working on models for detection of interleaved and concurrent activities and want to investigate usage of more sophisticated unsupervised learning techniques.

Acknowledgments

This work was funded in part by the German Ministry of Education and Research within the research project "PAGE" (grant 01FCO8044) and in part by the Ministry for Science and Culture of Lower Saxony within the Research Network "Design of Environments for Ageing" (grant VWZN 2420).

References

[1] T.S. Barger, D.E. Brown, and M. Alwan. Health-status monitoring through analysis of behavioral patterns. *Systems, Man and Cybernetics, Part A, IEEE Transactions on*, 35(1):22–27, 2005.

[2] M.H. Beers and R. Berkow, editors. *The Merck Manual of Geriatrics*. Merck & Co., Inc., 2006.

[3] B. G. Celler, T. Hesketh, W. Earnshaw, and E. Ilsar. An instrumentation system for the remote monitoring of changes in functional health status of the elderly at home. In *Proc. 16th Annual International Conference of the IEEE Engineering Advances: New Opportunities for Biomedical Engineers Engineering in Medicine and Biology Society*, pages 908–909, November 3–6, 1994.

[4] M. Chan, C. Hariton, P. Ringeard, and E. Campo. Smart house automation system for the elderly and the disabled. In *Proc. IEEE International Conference on Systems, Man and Cybernetics Intelligent Systems for the 21st Century*, volume 2, pages 1586–1589, October 22–25, 1995.

[5] Jianfeng Chen, Jianmin Zhang, A.H. Kam, and L. Shue. An automatic acoustic bathroom monitoring system. In *Circuits and Systems, 2005. ISCAS 2005. IEEE International Symposium on*, pages 1750–1753 Vol. 2, 2005.

[6] Meng Chen, Bufu Huang, and Yangsheng Xu. Intelligent shoes for abnormal gait detection. In *Proc. IEEE International Conference on Robotics and Automation ICRA 2008*, pages 2019–2024, May 19–23, 2008.

[7] Eurostat. *Key figures on Europe*. Publications Office of the European Union, 2010 edition, 2010. ISBN 978-92-79-14871-2.

[8] T. Frenken, M. Gövercin, S. Mersmann, and A. Hein. Precise Assessment of Self-Selected Gait Velocity in Domestic Environments. In *4th International Conference on Pervasive Computing Technologies for Healthcare 2010*, 2010.

[9] T. M. Gill, C. S. Williams, and M. E. Tinetti. Assessing risk for the onset of functional dependence among older adults: the role of physical performance. *J Am Geriatr Soc*, 43(6):603–609, Jun 1995.

[10] G.W. Hart. Nonintrusive appliance load monitoring. *Proceedings of the IEEE*, 80(12):1870–1891, 1992.

[11] Derek Hao Hu and Qiang Yang. CIGAR: concurrent and interleaving goal and activity recognition. In *AAAI*, pages 1363–1368, 2008.

[12] Tam Huynh, Mario Fritz, and Bernt Schiele. Discovery of activity patterns using topic models. In *Proceedings of the 10th international conference on Ubiquitous computing*. ACM New York, NY, USA, 2008.

[13] F. J. Imms and O. G. Edholm. Studies of gait and mobility in the elderly. *Age Ageing*, 10(3):147–156, Aug 1981.

[14] Robert Koch-Institut. *Gesundheit und Krankheit im Alte*. Deutsches Zentrum für Altersfragen, 2009. ISBN 978-3-89606-196-6.

[15] Kyoungchul Kong and M. Tomizuka. A Gait Monitoring System Based on Air Pressure Sensors Embedded in a Shoe. 14(3):358–370, June 2009.

[16] Pui W Kong and Hendrik De Heer. Wearing the F-Scan mobile in-shoe pressure measurement system alters gait characteristics during running. *Gait Posture*, 29(1):143–145, Jan 2009.

[17] Hylton B Menz, Stephen R Lord, and Richard C Fitzpatrick. Age-related differences in walking stability. *Age Ageing*, 32(2):137–142, Mar 2003.

[18] Thomas B. Moeslund, Adrian Hilton, and Volker Krueger. A survey of advances in vision-based human motion capture and analysis. *Computer Vision and Image Understanding*, 104(2-3):90–126, 2006.

[19] Dorothy N. Monekosso and Paolo Remagnino. Monitoring behavior with an array of sensors. *Computational Intelligence*, 23(4):420–438, November 2007.

[20] Manuel Montero-Odasso, Marcelo Schapira, Enrique R Soriano, Miguel Varela, Roberto Kaplan, Luis A Camera, and L. Marcelo Mayorga. Gait velocity as a single predictor of adverse events in healthy seniors aged 75 years and older. *J Gerontol A Biol Sci Med Sci*, 60(10):1304–1309, Oct 2005.

[21] Wolfgang Mueller. *Ueberwachung elektrischer Hausgeraete durch Leistungsanalyse*. Pflaum, 2002.

[22] I. P. I. Pappas, T. Keller, S. Mangold, M. R. Popovic, V. Dietz, and M. Morari. A reliable gyroscope-based gait-phase detection sensor embedded in a shoe insole. 4(2):268–274, April 2004.

[23] Shwetak Patel, Thomas Robertson, Julie Kientz, Matthew Reynolds, and Gregory Abowd. At the flick of a switch: Detecting and classifying unique electrical events on the residential power line (Nominated for the best paper award). In *UbiComp 2007: Ubiquitous Computing*, pages 271–288. 2007.

[24] M. Pavel, T. Hayes, I. Tsay, D. Erdogmus, A. Paul, N. Larimer, H. Jimison, and J. Nutt. Continuous Assessment of Gait Velocity in Parkinson's Disease from Unobtrusive Measurements. In *Proc. 3rd International IEEE/EMBS Conference on Neural Engineering CNE '07*, pages 700–703, May 2–5, 2007.

[25] J. Perry. *Gait Analysis: Normal and Pathological Function*. Slack, Inc., 1992.

[26] M. Philipose, K.P. Fishkin, M. Perkowitz, D.J. Patterson, D. Fox, H. Kautz, and D. Hahnel. Inferring activities from interactions with objects. *Pervasive Computing, IEEE*, 3(4):50–57, 2004.

[27] D. Podsiadlo and S. Richardson. The timed "Up & Go": a test of basic functional mobility for frail elderly persons. *J Am Geriatr Soc*, 39(2):142–148, Feb 1991.

[28] A. Prudenzi. A neuron nets based procedure for identifying domestic appliances pattern-of-use from energy recordings at meter panel. In *Power Engineering Society Winter Meeting, 2002. IEEE*, volume 2, pages 941 – 946 vol.2, 2002.

[29] Serge H Roy, M Samuel Cheng, Shey-Sheen Chang, John Moore, Gianluca De Luca, S Hamid Nawab, and Carlo J De Luca. A combined sEMG and accelerometer system for monitoring functional activity in stroke. *IEEE Transactions on Neural Systems and Rehabilitation Engineering: A Publication of the IEEE Engineering in Medicine and Biology Society*, 17(6):585–594, December 2009. PMID: 20051332.

[30] Cliodhna Ní Scanaill, Sheila Carew, Pierre Barralon, Norbert Noury, Declan Lyons, and Gerard M Lyons. A review of approaches to mobility telemonitoring of the elderly in their living environment. *Ann Biomed Eng*, 34(4):547–563, Apr 2006.

[31] J. Tung, W. Gage, K. Zabjek, D. Brooks, D. Maki, A. Mihailidis, G. R. Fernie, and W. E. McIlroy. iWalker: A 'real-world' mobility assessment tool. In *30th Canadian Medical & Biological Engineering Society*, 2007.

[32] Tim van Kasteren, Athanasios Noulas, Gwenn Englebienne, and Ben Kroese. Accurate activity recognition in a home setting. In *Proceedings of the 10th international conference on Ubiquitous computing*, pages 1–9, Seoul, Korea, 2008. ACM.

[33] R. Williamson and B. J. Andrews. Gait event detection for FES using accelerometers and supervised machine learning. 8(3):312–319, September 2000.

[34] H. S. Zhu, J. J. Wertsch, G. F. Harris, J. D. Loftsgaarden, and M. B. Price. Foot pressure distribution during walking and shuffling. *Arch Phys Med Rehabil*, 72(6):390–397, May 1991.

[35] Wiebren Zijlstra. Assessment of spatio-temporal parameters during unconstrained walking. *Eur J Appl Physiol*, 92(1-2):39–44, Jun 2004.