Towards Proactive Health-enabling Living Environments: Simulation-based Study and Research Challenges

Sven Tomforde*, Tobias Dehling†, Reinhold Haux‡, Denis Huseljic*, Daniel Kottke*,
Jonas Scheerbaum*, Bernhard Sick*, Ali Sunyaev†, and Klaus-Hendrik Wolf‡
*Intelligent Embedded Systems, University of Kassel, Germany
Email: {dkottke|bsick|stomforde}@uni-kassel.de
†Information Systems and Systems Engineering, University of Kassel, Germany
Email: {tdehling|sunyaev}@uni-kassel.de
‡Medical Informatics, TU Braunschweig and Hannover Med. School, Germany
Email: {reinhold.haux|klaus-hendrik.wolf}@plri.de

***Abstract*—Nowadays, information and communication technology (ICT) has become a key driver for future health-enabling and ambient assisted living technologies. These future health-enabling living environments proactively anticipate the inhabitants' needs and adapt their behaviour accordingly. They further continuously monitor the behaviour of the inhabitants and may call in support in suspicious cases. In this article, we present an architectural blueprint for such a proactive living environment and highlight the corresponding challenges for research in the field. Afterwards, we present a simulation as experimental platform for learning the daily routine of inhabitants of a flat-sharing community of senior citizens. The experimental evaluation highlights that probably unusual behaviour of persons can be detected using a probabilistic approach, which may serve as an indicator for external support.**

I. Introduction

Digitalisation has become a priority for governments and societies [1] as well as one of the United Nation's Sustainable Development Goals [2]. Correspondingly, Information and Communication Technology (ICT) is increasingly becoming a key driver for future health care processes [3], [4], [5].

According to the World Health Organisation, ICT for health, often addressed under the term eHealth, are "recognised as one of the most rapidly growing areas in health today" [6]. Health-enabling and ambient assisted technologies play an important role in this context, in particular for smart homes for senior citizens [7]. In 2060, every third person in Germany, will be 65 years old or older [8]. Whereas in 2013 in Germany 4.4 million citizens have been 80 years old or older, this number is expected to increase to close to 10 million in 2050 [8].

We can observe massive ICT-driven progress in health-enabling and ambient assisted technologies in the last decade [9], [10]. As a result, living environments are transformed into smart homes with the potential of becoming an additional "institution for health care" [11], [12]. Especially senior citizens benefit from this development since health information systems [13], [14] support self-determined living even if persons suffer due to health detriment and need assistance. However, this trend has not come to an end. In contrast, massive research and development effort is needed to allow for diagnostic relevance and therapeutic efficacy based on a living environment that proactively takes care of its inhabitants [7].

We envision future living environments that (a) seamlessly integrate with people's living routines, (b) leverage current technologies, (c) are future-proof and easy to use, (d) strengthen participation and integration of caregivers, relatives, and inhabitants in care processes, (e) work as well in rural as in municipal areas, (f) contribute to the creation of reliable digital personal health records, and (g) are evidence-based. In short, proactive health-enabling living environments will improve access to health care, educate inhabitants about their health, support inhabitants in managing their health, and empower inhabitants to take a more active role in their health care with less effort due to supportive health information technology [15].

In this article, we present an architectural blueprint for future proactive health-enabling living environments: A redefined variant of the Observer/Controller tandem [16] as known from the Organic Computing domain [17]. We further describe a first simulation-based study for such environments and demonstrate the feasibility of learning models for inhabitant activities. These models are used to determine unexpected behaviour of inhabitants which may serve as an indicator for the need of external support.

The remainder of this article is organised as follows: Section II describes relevant contributions from the state of the art. Section III presents the vision of future proactive health-enabling living environments in more detail. Afterwards, Section IV discusses an experimental platform for learning behavioural models of inhabitants in such a living environment and highlights the benefit of determining probably unusual activities. The experimental results are analysed and evaluated in Section V. Finally, Section VI summarises this article and gives an outlook to future work.

II. State of the Art

The concept of proactive health-enabling living environments combines techniques and methods from several fields of research. In the following section, we initially discuss relevant contributions in the field, followed by a discussion of promising technology for achieving the overall vision as outlined above.

Originally based in the area of "smart homes", a variety of assistive systems have been proposed in recent years, typically under the term "ambient intelligence". Ambient intelligence is a field in ICT that aims at empowering people's capabilities by the means of digital environments that are sensitive, adaptive, and responsive to human needs, see e.g. [18], [19]. The basic idea is that ubiquitous, unobtrusive, and anticipatory communication is available via human-machine interfaces that provides the basis for proactively supporting the inhabitant in its daily routine and simultaneously monitoring its behaviour to identify situations where assistance or emergency is needed. Environments equipped with such a technology are called "ambient assisted living" (AAL) environments. In general, AAL technology is intended to be able to prevent, cure, and improve wellness and health conditions, especially of older adults. For instance, part of the scope are medication management tools that remind inhabitants to take control of their health conditions [20], [21], [22]. Other possible benefits include mobile emergency response systems [23], fall detection systems [24], or video surveillance systems [25], [26]. Furthermore, researchers focused on technologies that support daily activities by monitoring the behaviour and providing reminders [27], [28] as well as by means of automation [29]. Another example is the CARE project [30] that aims at combining digital image frames with an active recommender mode, where recommendations cover possible activities for the elderly living in the environment and are derived from a (generalised, pre-defined) "well-being model".

In contrast to the vision presented in this article, these systems have several drawbacks: they do not adapt their behaviour to changing preferences, they do not learn at runtime, they do not incorporate the knowledge of humans, or they do not incorporate detection of suspicious behaviour.

Health-enabling and ambient assistive technologies can also be viewed as components of *health information systems* (HIS), which support health care processes [31]. In HIS terminology, these tools are computer-based application systems, which are installed on physical subsystems such as computer systems and support specific services. As such application systems on the physical layer include sensors, HIS using such tools are called sensor-enhanced health information systems [32], [33]. Since a person's (smart) home is typically also included, such HIS are also denoted as transinstitutional HIS [31], [33]. Data from such health-enabling and ambient assistive technology tools and findings based on these data (which may be derived automatically, semi-automatically, or manually) may or perhaps should become part of a person's electronic health record [14]. The applications must be understood as informatics diagnostics and informatics therapeutics tools [34].

We will approach the goal of proactive health-enabling living environments on the basis of technology from the fields of Organic Computing, Active Learning, and Online Learning. The following paragraphs briefly summarise the basic concepts and relevant contributions in these fields.

Organic Computing (OC) is a recent paradigm of designing and developing self-adapting and self-organising technical systems acting in the real world [17]. OC proposes to master the increasing complexity of technical systems (e.g. in terms of openness and interconnection, see [35], [36]) by moving traditional design-time decisions to the runtime and from system engineers to the systems themselves. Thus, OC systems are designed to process so-called self-* properties that allow them to be self-adaptive and self-organising at runtime. In this article, we aim at proactive health-enabling living environments that self-adapt to the anticipated inhabitant demands and their behaviour, which require a system design allowing for internal adaptation. OC and related initiatives (such as Autonomic Computing, AC [37]) have proposed a variety of architectural blueprints. For instance, the generalised observer/controller (O/C) framework [16] is a popular representative from the OC domain. Closely related is the Monitor-Analyse-Plan-Execute(-Knowledge) cycle from the AC domain, typically referred to as MAPE(-k) [37]. For both concepts (i.e. O/C and MAPE-k), multi-layered extensions have been proposed as well as system-of-systems concepts [38]. We will adapt the general multi-layered O/C blueprint for the purpose of this article.

Active Learning (AL) provides powerful approaches to create flexible systems that are able to adapt themselves to a changing environment [39]. These methods interact with their target system to investigate which information might optimise their model best, and they actively acquire this information. In classification (also in regression) problems, AL algorithms actively request the target value of an instance (feature vector) [40]. Three basic AL approaches exist: 1) query synthesis (the query instance is generated), 2) pool-based AL (the query is an instance from a pool of unlabelled instances), and 3) stream-based AL (instances successively appear and the AL algorithm decides if the label should be acquired) [40]. One of the main challenges is to balance the exploration of new regions in the feature space and the exploitation of the existing knowledge to refine the trained model [39]. Especially when applied to activity recognition problems, a further relevant aspect of AL is the ability to efficiently generate training data, since labelling is an expensive task [41]. Here, AL methods have been combined with traditional semi-supervised learning techniques, such as self-training and co-training. AL has also been applied to reduce labelling costs in a smart-home environment [42] and in health applications on mobile devices [43].

Online or stream learning [44] is a machine learning paradigm developed to work in time-variant (also called non-stationary, or evolving) environments. Thereby, it delivers real-time predictions, efficiently built on large data streams (e.g.

sensor inputs). One of the most important components is the ability to detect drift (gradual change) or shift (abrupt change). Here, change detection mechanisms are of great importance [45]. Online learning has also been used in smart home environments for activity recognition [46] or to detect lighting behaviour [47]. In the field of preference learning [48], the goal of a classifier is to predict the preferences of humans. Therefore, it is necessary to identify so-called perennial objects, e.g. in form of inhabitant profiles [49].

III. Proactive Health Enabling Environments

The overall vision of this article is to integrate existing knowledge in the domains of sensor infrastructures, active learning, and user-centred design into a solid scientific foundation for design of effective, IT-supported living environments for proactive health enablement. We focus on ordinary living environments inhabited by multiple persons with diverse demographic backgrounds. The main challenge to be resolved is that different inhabitants will have different expectations for how their living environments should behave [15]. Accordingly, smart devices must identify with which person they are interacting and have to learn how inhabitants' requirements and perceived preferences evolve over time.

	a) living as couple ('normal case')	**b) living with assistance**
1.) self-sufficient living ('normal case')	_1.a)_ Erich Edam, 75 years old, and Elfriede Edam, 72 years old, are living for more than 20 years on the 3rd floor of a multi-family house in their ca. 100 m^2 apartment in Ploetzberg. Both senior citizens are physically and mentally fit. Despite of some minor but increasing age-related deficits, they clearly want to remain in their apartment for a variety of reasons. Moving to an assisted-living facility or even to a nursing home is neither considered nor intended. Erich and Elfriede have two daughters who live with their families about 50 and 200 km away, respectively. *Continue, if applicable, with 1.b or 2.a.* *"To fulfill their desire ..." (see below)*	_1.b)_ As housekeeping and shopping became more difficult, Mr. and Ms. Edam decided to engage a company for senior citizen services, in particular, for cleaning and for shopping of heavy items. Since then a staff member of the company is coming to their apartment twice a week. Mr. and Mrs. Edam are satisfied, especially since the staff member, coming to them, is very sympathetic. Other services, for instance, meals on wheels or nursing services, can also be booked through this company, if needed. *Continue, if applicable, with 2.2.* *"To fulfill their desire ..." (see below)*
2) one partner is not at home due to illness	_2.a_ Three weeks ago, Elfriede Edam unfortunately had a fall while cleaning windows, causing a fracture of her left femoral neck. Luckily, her husband, who was shopping at this time, came back home few minutes after her fall. He called emergency services, who Elfriede could no longer have informed herself. An ambulance took Ms. Edam to the Department of Trauma Surgery at Ploetzberg Medical Center, where she was successfully operated. After about one week, she was transferred to a rehabilitation hospital for further treatment, where she is currently staying. The discharge examinations in the Medical Center resulted in a predominantly positive prognosis. Mr. Edam now has to take care for himself alone. So far this works out, especially, since his daughters visit at weekends to support him. After Elfriede's fall, it remains however uncertain whether the couple will be able to completely manage their daily activities themselves. According to their daughters, moving to an assisted-living facility would be a good choice. However, Mr. and Mrs. Edam still insist on staying in their apartment. *Continue, if applicable, with 2.2.* *"To fulfill their desire ..." (see below)*	_2.b (from 1.b)_ Due to a femoral neck fracture, caused by a fall, Elfriede Edam currently stays at a rehabilitation hospital (details at 2.a). Erich Edam was very glad to have the senior citizen services already in place. It is also reassuring for him to know about the option of booking additional services, although they are currently not needed. *"In their objective ...": see below.* _2.b (from 2.a)_ As housekeeping and shopping became more and more difficult for him, Erich Edam had to recognize that he cannot accomplish his daily-living activities on his own. Together with their daughters it was decided to engage a company for senior citizen services, in particular, for cleaning and shopping of heavy items. Since then a staff member of the company is coming to Mr. and Ms. Edam's apartment twice a week. Erich is very satisfied, especially since the staff is sympathetic and since she also takes time to talk to him. It is also reassuring for him to know about the option of booking additional services, for instance, meals on wheels or nursing services, although they are currently not needed. *"To fulfill their desire ..." (see below)*
For all four scenarios: To fulfill their desire to live as long as possible self-determined and self-dependent (autonomous) as senior citizens, they use existing assistive technologies. They would be willing to transform their apartment into a proactive health-enabling living environment.		

Fig. 1. Schematic description of four possible scenarios in proactive health-enabling living environments highlighting different requirements for the underlying observation and actuator control system.

For illustration purposes, consider four scenarios focusing on senior citizens as outlined in Figure 1. The scenarios describe varying living conditions of an elderly couple that introduce different aspects and corresponding needs: i) normal behaviour (i.e. support through smart home technology), ii) assisted living (i.e. automatically distinguish between inhabitants and housekeeping), iii) surveillance of normal behaviour (i.e. detect unexpected behaviour of inhabitants for emergency or entertainment requirements). In future work, we will investigate these four scenarios with senior citizens in apartments equipped with corresponding ICT.

In contrast to current systems from the state of art, proactive health-enabling living environments (PHELE) as outlined above provide novel benefits:

1) PHELE learn user preferences, behaviour, and corresponding context from direct and indirect user interaction.
2) This learning mechanism adapts over time to cover concept drift and shift, e.g. if one of the persons is temporarily absent or housekeeping is introduced.
3) PHELE improve the actuator control in the sense of a smart home concept over time.
4) The system supports the inhabitants in their daily routine, especially in the context of health, e.g. by reminding about medication.
5) PHELE use the behaviour models to detect suspicious conditions, e.g. if persons grow lonely or loose control of their daily routine.
6) Based on such detected events, they autonomously trigger support mechanisms, e.g. inform relatives or raise an alarm.

We envision future living environments that seamlessly integrate with people's living routines, leverage current technologies, are future proof and easy to use, strengthen participation and integration of caregivers, relatives, and inhabitants in care processes, work as well in rural as in municipal areas, contribute to creation of reliable digital personal health records, and are evidence-based. In short, proactive health-enabling living environments will improve access to health care, educate inhabitants about their health, support inhabitants in managing their health, and empower inhabitants to take a more active role in their health care with less effort due to supportive health information technology. We claim that future successful PHELE require fundamental input from several research domains including OC and AL. Therefore, we outline an architectural blueprint for these environments in the following and highlight the resulting major research challenges.

A. Architectural concept for proactive health-enabling living environments

Figure 2 illustrates the technical realisation of the proactive health-enabling living environment. The apartment is equipped with sensors (to perceive the current conditions) and actuators (to control devices such as light and heating). This constitutes the "System under Observation and Control" (SuOC) in OC terms, see [16].

On-top of this SuOC, a control loop is established that consists of an observer and a controller unit. The observer

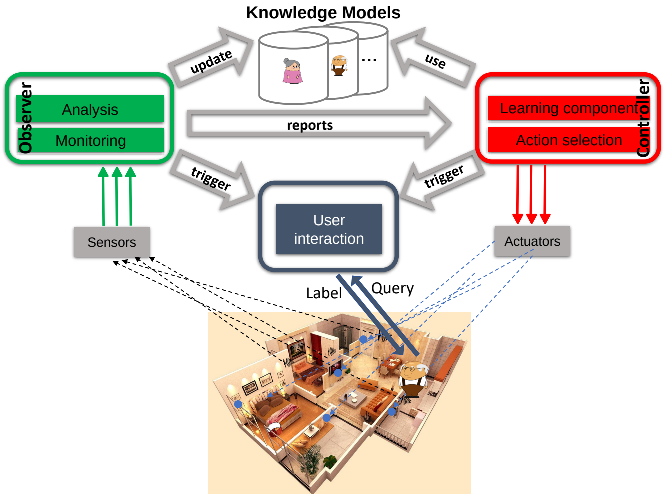

Fig. 2. Schematic illustration of the proactive control loop based on the architectural Observer/Controller blueprint from the Organic Computing domain [16].

is responsible for analysing the sensor information, maintaining user models, and finally passing an aggregated situation description to the controller unit. The controller decides about necessary interventions (i.e. control of actuators) and learns from feedback. Furthermore, a user interaction module may be triggered from both units, which is responsible for efficiently querying the particular inhabitants for preferences and labels.

The observer component gathers raw data from the sensors and analyses the data. Based on this information, it maintains models for all inhabitants including the expected daily behaviour (in terms of expected sequences of activities), the preferences (e.g. temperature and light), and the corresponding context information. The former model is a result of a generative approach using the probability distribution of the observations and may be realised using techniques such as Hidden Markov Models [50]. The preferences and context models may also be derived from observations – however, this process can be realised efficiently by using the inhabitant as source of information. Here, mechanisms from the active learning [39] domain are used to efficiently ask the inhabitant: a) about his/her preferences in a certain context, b) to distinguish between normal and probably unusual behaviour, c) to get labels for activities, and d) to verify detected events, locations, and interactions with devices (e.g. coffee machine, TV, or shower).

The controller uses the situation description and the models as basis to decide about actuator control. This can be realised by means of a rule-based reinforcement learning approach, e.g. in terms of variants of the Extended Classifier System as introduced by Wilson [51] that are especially developed for controller tasks in OC systems [52], [53]. In order to be able to learn from feedback, two basic mechanisms are used: 1) indirect feedback (i.e. the inhabitant does not revoke actions of the controller) and 2) direct feedback (i.e. asking the inhabitant if decisions correspond to preferences using an active learning mechanism again).

B. Technological challenges

As outlined above, the proactive living environment constitutes a control loop that requires models for preferences and context of inhabitants. The underlying challenge is to learn the models of inhabitants' preferences and context – as a mixture of efficient explicit labelling of preference information, implicit recognition of conclusive behaviour, and assessment of expected behaviour from sensor information. In the next section, we present a first approach to determine the expected sequences of user activities. However, this is just a first step in the process towards proactive health-enabling living environments. For a fully fledged system, research has to address several challenges and develop novel techniques to fill the gap. The following list names and explains the most relevant challenges in this context:

1) Modelling of context and user preferences based on probabilistic techniques: In order to act appropriately and proactively, the PHELE has to be aware of the underlying user preferences. Since a universally applicable model for all possible inhabitants is not available, the proactive home has to be able to learn such an individual model per inhabitant from observations – which also includes the challenge to distinguish between inhabitants and to identify them. We therefore need novel techniques from generative, probabilistic modelling for a multi-levelled modelling of context information and preferences of different inhabitants. Context includes information such as time, location, user status, etc.

2) Self-assessment of context and preferences: In order to proactively assist the inhabitants, the modelling techniques have to be able to adapt their behaviour to changing conditions and preferences. This includes mechanisms for a detection of concept drift (for both, preferences and context), an ageing of knowledge in the sense of being able to forget outdated model information, and a prediction mechanism for preferences, i.e. to answer the question what the inhabitant wants to do next and anticipate the corresponding actuator control actions. This is accompanied by mechanisms to assess normal and unexpected behaviour [54], which could be used as a basis for analysing the inhabitants' conditions.

3) Interaction-based continuous self-improvement of context and preference models: The necessary knowledge about preferences is seldom available in advance and the only person that is able to provide the corresponding information are the inhabitants themselves. Consequently, the inhabitant has to be efficiently included into the self-learning process of the control system without annoying him. Therefore, we have to investigate novel techniques from the active learning (AL) [39] domain, especially novel selection strategies for uncertain and time-variant environments. In order to keep the querying of the inhabitant as low as possible, we have to further develop novel mechanisms to consider and assess other feedback sources, including indirect feedback (i.e. conclusive behaviour of the inhabitant), which may be further improved by taking reinforcement mechanisms into account. Finally, this has to be included in the proactive control strategies of the proactive home.

IV. A Simulation as Experimental Platform for Learning User Behaviour

In the following, we present a first step towards such proactive health-enabling living environments. Since using real apartments will be subject of future work, we developed a simulation of a senior citizen flat sharing community in Unity 3D [55]. Conceptually, this simulation is modular and can be extended for containing several inhabitants – in the current version, one male and two female persons are contained.

Fig. 3. The simulated apartment in UNITY3D.

Figure 3 depicts the simulation in Unity3D, which consists of ten rooms: three individual rooms (i.e. private sleeping rooms) with three bathrooms, a common kitchen/eating room, a utility room, a living room, and two corridors. The rooms are equipped with sensors (presence detection, light, temperature, and status detection for devices) and actuators. All rooms contain different devices that come with actuators: a) the kitchen contains fridge, cooker, oven, coffee machine, table, and chairs, b) the bathrooms contain shower, toilet, and basin, c) the living room contains armchair, floor lamp, radio, and TV, d) the utility room contains washing machine and desk, and e) all rooms contain shutters, light and heating with actuators.

As a result, several different activities are possible: movements (walking, sitting, running, standing, and laying), basic activities (e.g. sleeping, washing, preparation of coffee/food, eating, laundry, dishes), and leisure (e.g. TV, reading, music). Furthermore, interaction with devices refers to user preferences, e.g. the control of shutters, temperature, or light are a result of a context-dependent preference of an inhabitant for a certain temperature or light conditions.

We used RainAI [56] to simulate the behaviour of the inhabitants. This includes a parametrable course of a day (containing sequences of activities and their duration with variations) and a path selection routine that considers the shortest path to the closest point for the currently simulated activity.

V. Evaluation

For evaluation purposes, we simulated six consecutive days in the simulation environment as described above. From these simulations, we modelled the expected course of a day of one individual character by training a Hidden Markov Model (HMM). An HMM is a statistical Markov model in which the observed system is assumed to be a Markov process with unobserved states, see [50] for an introduction. In contrast to simple Markov Models such as Markov Chains, where the state is directly visible to the observer (i.e. the parameters are only the probabilities for state transitions), the state is not visible in HMM – but the output (i.e. the observation) depends on the state and allows to draw conclusions about the (hidden) states. More precisely, each hidden state is characterised by a probability distribution over the possible observable outputs. Consequently, the sequence of outputs generated by an HMM allows for conclusions about the sequence of states that have been passed while generating these outputs.

The goal of the evaluation is to demonstrate the general feasibility of learning the "normal" course of the day. More specifically, the goal is to show that a trained HMM is able to explain the sequence of user activities that are observed – and, in turn, signalise a deviation from the explainable behaviour pattern.

A. Data creation

As mentioned above, the simulation was used to generate observation data for five days following the idea of covering a week by analysing a sequence of "normal" weekdays, i.e., without the weekend. These five days serve as training data for our models. In addition, a sixth day was generated for testing purposes. Each day was created by using a daily routine template, but we added variations and uncertain activities to simulate a real-world environment. For instance, we introduced routines such as eating breakfast, lunch, dinner, or watching TV shows which were considered in the routine of each day. In addition, uncertain activities such as reading a new book or doing the laundry were implemented randomly. For instance, the use of the toilet was mostly triggered randomly, but it was also added as a regular daily activity as well (e.g. after drinking a coffee in the morning). Figure 4 shows an example for the daily routine used in the simulations.

The recorded data was gathered for one person in the apartment shown in Figure 3. Rooms that were used in our simulations are the bathroom, bedroom, kitchen, lavatory, and living room. Activities included dressing, cooking, making coffee, food, reading, sleeping, using the fridge, the shower, the toilet, walking through rooms, washing clothes, dishes, hands, and watching TV.

B. Hidden Markov Model

After gathering data through our simulations, we made comparisons between sequences to investigate if it is likely that a specific sequence was created by the model. Therefore, we initially had to prepare the data of a day to an appropriate encoding. Notice that we ignored the time aspect and only focused on the order of activities in a certain room. For instance, an encoding of a day starts in the bedroom with activity "sleeping" and could be followed by opening the

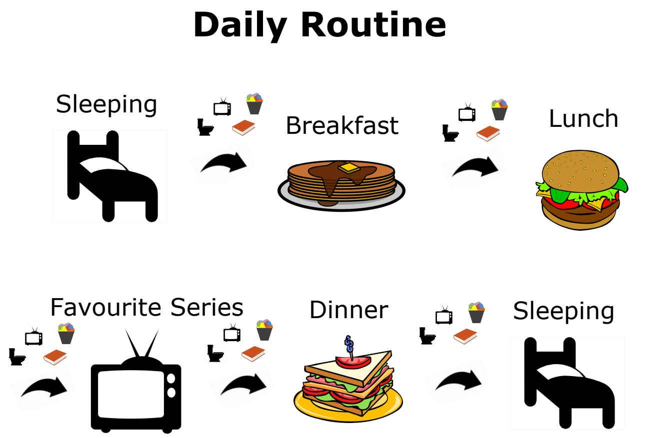

Fig. 4. Example for the daily routine: Sleeping, breakfast, lunch, favourite series, and dinner are included in every day. The symbols on the arrows denote the randomised activities.

shutters and going to the toilet. This ends when the person is going to sleep again. Hence, one day is encoded as a sequence of activities with their corresponding locations. As an alternative – and as subject of future work – an encoding approach may consider the time aspect which may contain significantly more information.

We trained two multi-nomial HMMs. The first one was trained with only the location sequences as input. We set the emission matrix to the identity matrix and did not modify it during the training process of the HMM. This is equivalent to a standard Markov chain since our hidden states correspond to the ouputs. Afterwards, the transition matrix was computed by the model. Following this, the second HMM included the current activities as output data and rooms as hidden states. Additionally, we set the transition matrix of our second model to the one computed in the first HMM above. The emission matrix was computed as the relative frequency of an activity in a room.

Figure 7 illustrates the complete HMM, which was responsible for the room prediction of the training process with the data generated during simulations. The circles depict the states and the arrows highlight the corresponding transition probabilities derived from the training data. The trained HMM then serves as basis to quantify how probable it is that the observed behaviour has been generated through this HMM – and, consequently, if the behaviour of the inhabitants of the apartment differs significantly from the expected behaviour.

C. Experimental results

After training the HMMs, we tested our models with random sequences to see how similar they are in comparison to our encoding of the sixth day. Hence, we created $5,000$ randomly generated sample days (generated from a uniform distribution for every activity and location) and compared their scores to the one that was computed from the test day. We noticed that the probabilities that were computed on the random samples were significantly smaller in comparison to our test day.

Figure 5 shows the probability distribution of the first model that only used locations for training. The model computed the log likelihood probability of our location sequences that were randomly generated. We used a kernel density estimation with a Gaussian kernel to estimate the distribution of the results. The red line shows the threshold that was created by our test day.

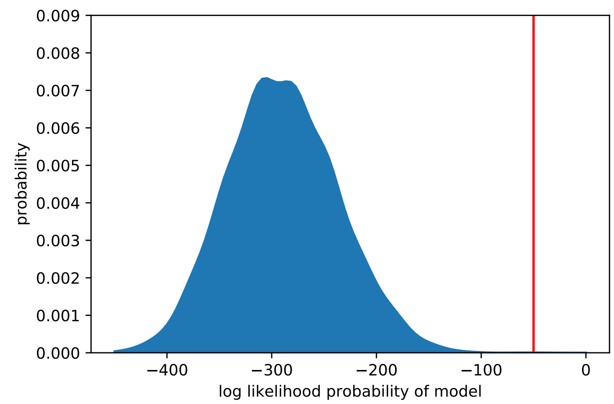

Fig. 5. Probability distribution of our first model.

We see that the randomly generated samples have a much smaller log likelihood probability which implies that their probability is significantly higher than the one from our test day.

Our second model, which considered the activities as outputs and the locations as hidden states, had similar results. In Figure 6, we can see the probability distribution for the second model. The results are almost the same as the ones we see in the first model – but the threshold of our test day is closer to our samples which is due to the complexity of the second model. The probability distribution was estimated the same way as the first model.

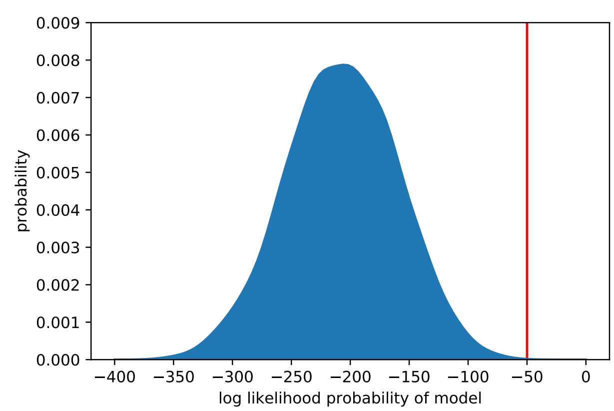

Fig. 6. Probability distribution of our second model.

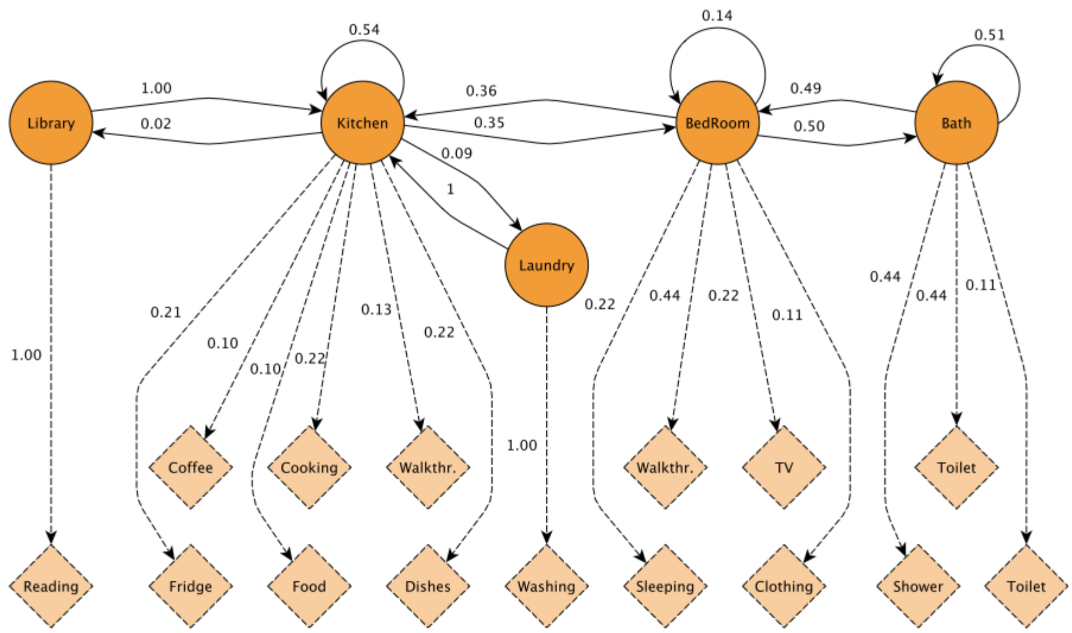

Fig. 7. Resulting HMM after training.

VI. Conclusion

This article discussed future proactive health-enabling living environments as a fundamental challenge for research in the Organic Computing domain. We introduced the vision of these environments and highlighted how health-support can be achieved. Based on an architectural blueprint for such environments, we derived the gap in research that needs to be addressed.

As a first step towards such environments, we presented a simulation-based experimental platform of a senior citizen flat sharing community. In this simulation, we demonstrated how the daily routine of inhabitants can be learned as a behaviour model encoding expected behaviour. We illustrated this model realised as a Hidden Markov Model and further showed that unexpected behaviour can be detected – which may be used as an indicator for triggering support from relatives or professional care givers.

In future work, we will focus on the research challenges outlined in the article: Initially, we will focus on efficiently maintaining the knowledge models included in the architecture. This mainly addresses research in the field of active learning, namely novel selection techniques. Afterwards, we shift the focus to mechanisms for anomaly detection and utilising different feedback sources (i.e. implicit feedback from inhabitant conclusive behaviour and direct feedback from user interaction). In addition, we will use real apartments with elderly people as basis for our investigations and analyse the implications of real-world sensor data instead of simulation results.

References

[1] The Federal Government of Germany, “Digital agenda 2014 – 2017,” https://www.digitale-agenda.de (last access: 08-12-2017), 2017.

[2] UN General Assembly, “Transforming our world: the 2030 agenda for sustainable development. resolution 70/1 adopted by the united nation‘s general assembly on 25 september 2015,” http://www.un.org/en/development/desa/population/migration/ (last access: 08-12-2017), September 2015.

[3] F. J. Martin-Sanchez, G. H. Lopez-Campos *et al.*, “The new role of biomedical informatics in the age of digital medicine,” *Methods of information in medicine*, vol. 55, no. 5, pp. 392–402, 2016.

[4] E. H. Shortliffe *et al.*, “Digital medicine and biomedical informatics: What’s in a name?” *Methods of information in medicine*, vol. 55, no. 5, pp. 389–391, 2016.

[5] N. Al-Shorbaji, R. Bellazzi, F. G. B. de Quiros, S. Koch, C. A. Kulikowski, N. H. Lovell, V. Maojo, H.-A. Park, F. Sanz, I. N. Sarkar *et al.*, “Discussion of “the new role of biomedical informatics in the age of digital medicine”,” *Methods of information in medicine*, vol. 55, no. 5, pp. 403–421, 2016.

[6] World Health Organisation, “Global Observatory for eHealth,” http://www.who.int/goe/en/ (last access: 08-12-2017), 2017.

[7] R. Haux, S. Koch, N. Lovell, M. Marschollek, N. Nakashima, K. Wolf *et al.*, “Health-enabling and ambient assistive technologies: Past, present, future,” *IMIA Yearbook*, 2016.

[8] Federal Statistical Office of Germany, “Population of Germany until 2060. 13. Coordinated Population Projection (in German),” https://www.destatis.de (last access: 08-12-2017), 2015.

[9] G. Demiris, H. Thompson *et al.*, “Smart homes and ambient assisted living applications: from data to knowledge-empowering or overwhelming older adults?” *IMIA Yearbook*, vol. 6, no. 1, pp. 51–57, 2011.

[10] S. Koch, M. Marschollek, K. Wolf, M. Plischke, R. Haux *et al.*, “On health-enabling and ambient-assistive technologies,” *Methods Inf Med*, vol. 48, no. 1, pp. 29–37, 2009.

[11] R. Haux, “My home is my hospital: on recent research on health-enabling technologies,” *Stud Health Technol Inform*, vol. 226, no. 1, pp. 3–8, 2016.

[12] R. Haux, J. Howe, M. Marschollek, M. Plischke, and K.-H. Wolf, “Health-enabling technologies for pervasive health care: on services and ict architecture paradigms,” *Informatics for Health and Social Care*, vol. 33, no. 2, pp. 77–89, 2008.

[13] B. Reeder, J. Chung, T. Le, H. Thompson, and G. Demiris, "Assessing older adults' perceptions of sensor data and designing visual displays for ambient assisted living environments: An exploratory study," *Methods of information in medicine*, vol. 53, no. 3, p. 152, 2014.

[14] P. Knaup, L. Schöpe *et al.*, "Using data from ambient assisted living and smart homes in electronic health records," *Methods Inf Med*, vol. 53, no. 3, pp. 149–151, 2014.

[15] K.-H. Wolf, T. Dehling, R. Haux, B. Sick, A. Sunyaev, and S. Tomforde, "On Methodological and Technological Challenges for Proactive Health Management in Smart Homes," in *Informatics Empowers Healthcare Transformation - Proc. of 15th Int. Conf. on Informatics, Management, and Technology in Health Care*, 2017, pp. 209 – 212.

[16] S. Tomforde, H. Prothmann, J. Branke, J. Hähner, M. Mnif, C. Müller-Schloer, U. Richter, and H. Schmeck, "Observation and Control of Organic Systems," in *Organic Computing - A Paradigm Shift for Complex Systems*, ser. Autonomic Systems, C. Müller-Schloer, H. Schmeck, and T. Ungerer, Eds. Birkhäuser Verlag, 2011, pp. 325 – 338.

[17] C. Müller-Schloer and S. Tomforde, *Organic Computing – Technical Systems for Survival in the Real World*, ser. Autonomic Systems. Birkhäuser Verlag, October 2017, iSBN: 978-3-319-68476-5.

[18] F. Sadri, "Ambient intelligence: A survey," *ACM Computing Surveys (CSUR)*, vol. 43, no. 4, p. 36, 2011.

[19] H. Bouma, "True visions–The emergence of ambient intelligence," *Gerontechnology*, vol. 6, no. 1, pp. 58–60, 2007.

[20] I. Qudah, P. Leijdekkers, and V. Gay, "Using mobile phones to improve medication compliance and awareness for cardiac patients," in *Proceedings of the 3rd International Conference on PErvasive Technologies Related to Assistive Environments*. ACM, 2010, p. 36.

[21] D. U. Khan, K. A. Siek, J. Meyers, L. M. Haverhals, S. Cali, and S. E. Ross, "Designing a personal health application for older adults to manage medications," in *Proceedings of the 1st ACM International Health Informatics Symposium*. ACM, 2010, pp. 849–858.

[22] A. Grube, T. Dehling, and A. Sunyaev, *How Do Patients Expect Apps to Provide Drug Information?* IEEE, 2017, p. 3577–3586.

[23] J. M. Eklund, J. Sprinkle, S. Sastry, and T. Hansen, "Information technology for assisted living at home: building a wireless infrastructure for assisted living," in *Proc. of 27th IEEE Int. Conf. on Eng. in Med. and Bio. Soc. (EMBS'05)*. IEEE, 2006, pp. 3931–3934.

[24] H. Aghajan, J. Augusto, C. Wu, P. McCullagh, and J.-A. Walkden, "Distributed vision-based accident management for assisted living," *Perv. Comp. for Qu. of Life Enhancement*, pp. 196–205, 2007.

[25] S. Fleck and W. Straßer, "Smart camera based monitoring system and its application to assisted living," *Proceedings of the IEEE*, vol. 96, no. 10, pp. 1698–1714, 2008.

[26] S. Tomforde, U. Jänen, J. Hähner, and M. Hoffmann, "SmaCCS: Smart Camera Cloud Services – Towards an Intelligent Cloud-based Surveillance System," in *Proc. of ICINCO13 – Int. Conf. on Informatics in Control, Automation and Robotics*, 2013, pp. 288–293.

[27] M. E. Pollack, L. Brown, D. Colbry, C. E. McCarthy, C. Orosz, B. Peintner, S. Ramakrishnan, and I. Tsamardinos, "Autominder: An intelligent cognitive orthotic system for people with memory impairment," *Robotics and Autonomous Systems*, vol. 44, no. 3, pp. 273–282, 2003.

[28] A. Sunyaev and D. Chornyi, "Supporting Chronic Disease Care Quality: Design and Implementation of a Health Service and its Integration with Electronic Health Records," *ACM Journal of Data and Information Quality*, vol. 3, no. 2, pp. 3:1–3:21, 2012.

[29] S. Dubowsky, F. Genot, S. Godding, H. Kozono, A. Skwersky, H. Yu, and L. S. Yu, "Pamm-a robotic aid to the elderly for mobility assistance and monitoring: a" helping-hand" for the elderly," in *Robotics and Automation, 2000. Proceedings. ICRA'00. IEEE International Conference on*, vol. 1. IEEE, 2000, pp. 570–576.

[30] A. Seiderer, S. Hammer, E. Andre, M. Mayr, and T. Rist, "Exploring digital image frames for lifestyle intervention to improve well-being of older adults," in *Proceedings of the 5th International Conference on Digital Health 2015*. ACM, 2015, pp. 71–78.

[31] A. Winter, R. Haux, E. Ammenwerth, B. Brigl, N. Hellrung, and F. Jahn, *Health information systems - architectures and strategies*. Springer, London/UK, 2011.

[32] M. Marschollek, "Recent progress in sensor-enhanced health information systems–slowly but sustainably," *Informatics for health and social care*, vol. 34, no. 4, pp. 225–230, 2009.

[33] W. Ludwig, K.-H. Wolf, C. Duwenkamp, N. Gusew, N. Hellrung, M. Marschollek, T. V. Bargen, M. Wagner, and R. Haux, "Health information systems for home telehealth services–a nomenclature for sensor-enhanced transinstitutional information system architectures," *Informatics for Health and Social Care*, vol. 35, no. 3-4, pp. 211–225, 2010.

[34] R. Haux, "Medical informatics: past, present, future," *International journal of medical informatics*, vol. 79, no. 9, pp. 599–610, 2010.

[35] S. Tomforde, J. Hähner, and B. Sick, "Interwoven Systems," *Informatik-Spektrum*, vol. 37, no. 5, pp. 483–487, 2014, Aktuelles Schlagwort.

[36] S. Tomforde, S. Rudolph, K. Bellman, and R. Würtz, "An Organic Computing Perspective on Self-Improving System Interweaving at Runtime," in *Proceedings of the 13th IEEE International Conference on Autonomic Computing, held in Würzburg, Germany*. IEEE, 2016, pp. 276 – 284.

[37] J. Kephart and D. Chess, "The Vision of Autonomic Computing," *IEEE Computer*, vol. 36, no. 1, pp. 41–50, 2003.

[38] S. Tomforde and C. Müller-Schloer, "Incremental Design of Adaptive Systems," *Journal of Ambient Intelligence and Smart Environments*, vol. 6, pp. 179 – 198, 2014.

[39] B. Settles, "Active learning," *Synthesis Lectures on Artificial Intelligence and Machine Learning*, vol. 6, no. 1, pp. 1–114, 2012.

[40] C. C. Aggarwal, X. Kong, Q. Gu, J. Han, and P. S. Yu, "Active learning: A survey," *Data Classification: Algorithms and Applications*, vol. 21, no. 1, pp. 571 – 605, 2014.

[41] M. Stikic, K. Van Laerhoven, and B. Schiele, "Exploring semi-supervised and active learning for activity recognition," in *Wearable computers, 2008. ISWC 2008. 12th IEEE international symposium on*. IEEE, 2008, pp. 81–88.

[42] C.-H. Lu, Y.-C. Ho, Y.-H. Chen, and L.-C. Fu, "Hybrid user-assisted incremental model adaptation for activity recognition in a dynamic smart-home environment," *IEEE Transactions on Human-Machine Systems*, vol. 43, no. 5, pp. 421–436, 2013.

[43] B. Longstaff, S. Reddy, and D. Estrin, "Improving activity classification for health applications on mobile devices using active and semi-supervised learning," in *Proc. of 4th PervasiveHealth Conf.* IEEE, 2010, pp. 1–7.

[44] J. Gama, *Knowledge discovery from data streams*. CRC Press, 2010.

[45] R. Elwell and R. Polikar, "Incremental learning of concept drift in nonstationary environments," *IEEE Transactions on Neural Networks*, vol. 22, no. 10, pp. 1517–1531, 2011.

[46] N. C. Krishnan and D. J. Cook, "Activity recognition on streaming sensor data," *Pervasive and mobile computing*, vol. 10, pp. 138–154, 2014.

[47] I. B. Dinata and B. Hardian, "Predicting smart home lighting behavior from sensors and user input using very fast decision tree with kernel density estimation and improved laplace correction," in *Proc. of Int. Conf. on Adv. Comp. Sc. and Inf. Sys. (ICACSIS)*. IEEE, 2014, pp. 171–175.

[48] J. Fürnkranz and E. Hüllermeier, "Preference learning: An introduction," in *Preference learning*. Springer, 2010, pp. 1–17.

[49] Z. F. Siddiqui, E. Tiakas, P. Symeonidis, M. Spiliopoulou, and Y. Manolopoulos, "Learning relational user profiles and recommending items as their preferences change," *International Journal on Artificial Intelligence Tools*, vol. 24, no. 2, p. 1540009, 2015.

[50] L. Rabiner and B. Juang, "An introduction to hidden markov models," *ieee assp magazine*, vol. 3, no. 1, pp. 4–16, 1986.

[51] S. Wilson, "Get Real! XCS with Continuous-Valued Inputs," in *Learning Classifier Systems*, P. Lanzi, W. Stolzmann, and S. Wilson, Eds. Springer Berlin / Heidelberg, 2000, pp. 209–219.

[52] A. Stein, S. Tomforde, D. Rauh, and J. Hähner, "Dealing with Unforeseen Situations in the Context of Self-Adaptive Urban Traffic Control: How to Bridge the Gap," in *Proc. of 13th IEEE Int. Conf. on Autonomic Computing (ICAC'16)*, 2016, pp. 167 – 172.

[53] A. Stein, D. Rauh, S. Tomforde, and J. Hähner, "Augmenting the Algorithmic Structure of XCS by Means of Interpolation," in *Proc. of 29th GI/ITG Int. Conf. on Architecture of Computing Systems (ARCS16)*. VDE, 2016, pp. 348 – 360.

[54] C. Gruhl, B. Sick, A. Wacker, S. Tomforde, and J. Hähner, "A Building Block for Awareness in Technical Systems: Online Novelty Detection and Reaction With an Application in Intrusion Detection," in *Proc. of IEEE 7th Int. Conf. on Awareness Sc. and Tech. (iCAST 2015)*. IEEE, 2015, pp. 194 – 200.

[55] U.-G. Engine, "Unity technologies," *Available: Unity Technologies (https://unity3d.com/)*, 2015.

[56] Rival Theory, "RAIN AI," *Available: Rival Theory (http://unitycoder.com/blog/2013/02/15/rainindie-ai-simple-waypoints-tutorial-1/ / last access 12/12/2017)*, 2017.