Generalized Virtual Stochastic Sensors - Training and Reconstruction in Various Single Resident Apartments

Claudia Krull*, Vishwajeet Karumuri

Fakultät für Informatik, Otto-von-Guericke-Universität, Postfach 4120, 39016 Magdeburg, Germany
*claudia.krull@ovgu.de

SNE 36(2), 2026, 87-94, DOI: 10.11128/sne.36.tn.10774
Selected ASIM GMMS/STS 2025 Postconf. Publ.: 2025-10-22
Rec. Full English: 2026-03-30; Accepted: 2026-05-10
SNE - Simulation Notes Europe, ARGESIM Publisher Vienna
ISSN Print 2305-9974, Online 2306-0271, www.sne-journal.org

Abstract. The advancements in Ambient Assisted Living (AAL) have been prompted by the growing population of elderly individuals facing diagnoses such as Dementia or Alzheimer's, aiming to enhance their overall quality of life. To provide support it is important to know their daily activities and aid them when needed. A large portion of research in the field of Human Activity Recognition uses black box learning approaches such as deep learning, but there are cases where model based methods, such as Virtual Stochastic Sensors (VSSs) are competitive. This is possible because the model based methods can include system structure in the modeling process if it is known. VSS's are derived from Hidden Markov Models (HMM) and applied to single resident datasets, which are collected in apartments fitted with different types of ambient sensors. For future applications a generalization of behavior, sensors or models is necessary so that models are not just trained and used for one specific apartment and setup. In this paper we test different model and activity setups while training and testing on different apartments. The results show that a model trained on a set of similar apartments can be used for behavior reconstruction on an apartment outside of that training set.

Introduction

Advancements in the medical field led to long and healthier lives, roughly around 20% of the world population will be aged above 60 by 2050 [1], seeking to explore effective solutions that empower elderly individuals to maintain independent living.

Studies of Counsel and Care in UK showed that elderly people have a preference to stay in their apartments rather than nursing homes [2]. Researchers have shown that having clinical therapy at home has no negative effect on the process [3]. There are multiple ways to make this happen, one way is Ambient Assisted Living, where some ambient sensors are installed, e.g. motion sensors, to monitor the behavior of elderly residents, a model is used to guess the behavior using the sensor readings, then, this is used to identify if everything aligns with the usual behavior, and if not, assistance can be provided. This ensures a safer living space without unduly intruding on the privacy of the residents.

For replicating human behavior [4], [5] and [6] successfully implemented machine and deep learning algorithms for this task. In [7] Virtual Stochastic Sensors (VSSs) are used, which are designed to facilitate the reconstruction of partially observable stochastic systems and enable solving backward problems in the realm of stochastic modeling and simulation. The model is based on the ideas of Hidden Markovian Models (HMM) but extends these by arbitrary non-Markovian distribution functions for multiple concurrent processes and symbol outputs at arbitrary points in time [8]. VSS discretize the time domain and use a simple iterative algorithm to discover the reachable state space of a model, therefore being very flexible. However, they cannot be applied in real-world scenarios on a large scale yet, because model parametrization is not automated, and the model needs to be trained for a specific system to be used for reconstruction. The application of pre-trained models is tested in this paper for the first time, where previously the training and testing data were taken from the same apartment.

This research aims to test different model setups and activity granularities for the task of using a pre-trained model on the behavior reconstruction for a different apartment, comparing different performance measures.

The datasets contain activities performed by the residents and the corresponding active sensors for the activities performed. The rest of the paper is structured as follows, Section 1 contains the details of related research, Section 2 underlines the details of the datasets, Section 3 explains the conceptual model and the algorithm design, Section 4 shows the outcome of the research.

1 Related Work

This section explores different approaches for reconstructing human behavior in the field of ambient assisted living that are similar in approach or goal to this research. Additionally, it presents relevant information for Virtual Stochastic Sensors (VSSs).

[9] has mainly emphasized the duration of the activity to find the abnormality in human behavior using Explicit State Duration Hidden Markov Model (ESD-HMM). They checked the deformity of current activity which might be shorter or longer than the usual routine, the dataset used for this research was limited to the kitchen.

[10] introduced a new observation probabilistic model to recognize daily activities, incorporating temporal data which had information regarding 77 sensors.

[4] tried to identify the critical features from the sensor data, these features are used to classify overlapped activities. Unsupervised K nearest neighbor (KNN) was applied to day-to-day activities but with a small set of activities.

[5] implemented long short-term memory (LSTM) recurrent neural network (RNN) to perform activity recognition from wearable sensors, this implementation was not tested for activities of daily living.

[11] suggested another approach using RNN on three different datasets, this approach outperformed similar approaches concerning accuracy and speed, but the dataset is not publicly available.

[6] proposed an unobtrusive activity recognition classifier using deep convolutional neural network (DCNN) and publicly available CASAS Aruba dataset.

[12] used a knowledge-driven approach, including a Partially Observable Markov Decision Process (POMDP) and exploited the task information, while the location is combined with the sensor events in the smart home, but the series of conditions are used to classify activity.

This shows that AAL is a current research field with several approaches all with their individual features.

1.1 Virtual Stochastic Sensors

Virtual Stochastic Sensors represent a framework for analyzing partially observable stochastic systems, including different modeling paradigms and solution methods [13]. VSS can compete with some black box models when the hidden system structure information is available [7], and can incorporate such information to accurately represent dynamic system behavior and its relationship with the observable output. VSS use augmented stochastic Petri nets (ASPN) as user models that contain multiple concurrent non-Markovian transitions [14]. ASPNs generate observable output by the firing of transitions depending on the discrete system state, the discrete system output is collected in a protocol with associated time stamps, since in contrast to the Hidden Markovian Model (HMM), the model is defined in continuous time and can produce output at arbitrary points in time [7].

[7] has applied VSS on CASAS Aruba 2010 dataset and produced a very promising result, based on this VSS is considered to be a viable option for activity classification. However, the previous implementations were all trained and tested on the same use case, which is not a feasible approach for broad scale applicability. Therefore we are examining different methods of generalization to eventually enable generalized models to be applied on systems not used for the training.

2 CASAS Dataset and VSS Model

In this paper we are using data from the CASAS Research Project of Washington State University [15]. There are different types of datasets, one contains the daily activities of 20 participants, few other datasets include pets for single or multiple residents, and finally, HH datasets are mostly single residents but a small portion of them are two-resident apartments. In this research, the HH101 to HH105 single resident apartment datasets are considered because they are multivariate, sequential, and time series. The data is collected using different kinds of sensors, like motion, door/temperature, and light switch sensors placed throughout the apartment, while the residents perform their normal routines. The dataset format is Date, Time, Sensor, Room, Furniture, Activity, and Sensor Type (Table 1). In this research we will concentrate on the motion sensors, omitting all other sensor types.

The time frame of the datasets is for all roughly two summer months in the years 2011 and 2012.

Date	Time	Sensor	Room	Furniture	Activity	Type
08/01/2012	00:00:06	M008	LivingRoom	Chair	Watch_TV	Control4Motion
08/01/2012	00:00:07	M008	LivingRoom	Chair	Watch_TV	Control4Motion
08/01/2012	00:00:09	M008	LivingRoom	Chair	Watch_TV	Control4Motion
		....				
08/01/2012	01:12:51	M012	Bedroom	Bed	Sleep	Control4Motion
08/01/2012	01:12:54	M012	Bedroom	Bed	Sleep	Control4Motion
08/01/2012	01:12:55	M012	Bedroom	Bed	Sleep	Control4Motion
		....				

Table 1: Sample extract from single resident HH101 dataset.

To ensure balance, one full month is selected from each dataset, for details check [16]. The remainder of the section will outline the generalization steps that were performed on the sensors and the activities, in preparation for the experiments.

2.1 Generalization of Sensors

Different types of sensors are installed across the apartments to record the resident's behavior, such as motion sensors for specific locations or broader areas. Based on these sensor readings the activity that the person is performing is recorded.

There are three levels of sensor descriptions in the datasets, one field (*Sensor*) contains the actual sensor ID that is active. The second one (*Room*) contains room-level reading, specifying on which room the sensor is located.

The third (*Furniture*) contains a specification of the place or area the sensor is monitoring, which can be a specific piece of furniture (e.g. *Chair* or *Bed*), or the room which the area sensor is monitoring.

Where the sensor ID is unique to a particular apartments sensor setup, both the room level and furniture level sensor descriptions are shared across apartments. The superset of rooms contains six rooms: *Bathroom*, *Bedroom*, *Kitchen*, *Livingroom*, wich are present in all five apartments and *Diningroom* and *Work_area*, which are present in three out of five apartments each.
Similarly, some furniture is present in all apartments (e.g. *Bed*, *Chair*) while others is only shared in some (e.g. *Desk*).

These three different levels of sensor descriptions already provide two levels of generalization, where in the current research we will use the room level sensors and the furniture level sensor descriptions, as only these allow a generalization across apartments.

2.2 Generalization of Activities

Each of the five datasets contains around 30 labeled activities that were recorded, describing the daily routine of a person living in this residence. Before grouping similar activities, some were removed from the datasets, specifically activities with very short durations or very rare occurrences. Very short activities (e.g. Step_Out) are hard to detect using the given sensor setups. Modeling infrequent activities, such as *Work_At_Table*, do not have enough data to model properly, and are also not relevant for regular behavioral patterns.

In the first step, a combined set of activities for all five apartments is created. Some activities like e.g. *Go_To_Sleep* or *Wake_Up* also have very low occurrence, but can be combined with *Sleep*, and will therefore not be omitted. Furthermore, functionally similar activities, such as *Cook_Breakfast*, *Cook_Lunch*, *Cook_Dinner*, and *Cook* are grouped to *Cook*, even though these activities occur during different times of the day. Similar to cook, we can combine all eat, wash dishes and sleep activities into *Eat*, *Wash_Dishes* and *Sleep* respectively. The resulting combined set of activities is depicted in Table 2, with the activities present in all five highlighted in bold.

To obtain the first level of generalization, the five activities with the lowest duration overall were omitted, as they do not contribute significantly to the overall behavior. For the second level of generalization, meal related activities were grouped together, as well as leisure related activities and personal hygiene, resulting in six very general activity categories. Table 3 shows the two groupings.

2.3 Data preparation

After cleaning the data, the next step is to modify the data into distributions and probabilities so that it can be used as input in the model.

Activity	Percentage %
Sleep	47.2%
Watch_TV	14.4%
Relax	13.9%
Work	4.6%
Eat	4.1%
Cook	3.5%
Personal_Hygiene	3.2%
Read	3.2%
Toilet	1.7%
Dress	1.4%
Wash_Dishes	1.2%
Entertain_Guests	0.7%
Phone	0.6%
Medicine	0.2%
Drink	0.2%
Step_Out	0.1%

Table 2: All 16 activities from the combined set and their total share in occurence time the five CASAS HH datasets, activities common to all datasets in bold

All Activities	11 Activities	6 Activities
Sleep	Sleep	Sleep
Watch_TV	Watch_TV	Personal_Activity
Relax	Relax	
Read	Read	
Eat	Eat	Meal
Cook	Cook	
Wash_Dishes	Wash_Dishes	
Personal_Hygiene	Personal_Hygiene	Personal_Hygiene
Toilet	Toilet	
Work	Work	Work
Dress	Dress	Dress
Entertain_Guests		
Phone		
Medicine		
Drink		
Step_Out		

Table 3: Activity grouping, separated by dashed lines.

Each activity has breaks, which can be characterized as short breaks or long breaks.

Distributions for all the breaks and activities are based on their duration in minutes. Distributions are estimated with the help of the MATLAB distribution fitter app. Probabilities for an activity to go to breaks are needed to be calculated.

If a break is less than or equal to 60 minutes it is considered a short break and anything longer is a long break. Depending on this probability for an activity to go to short or long break is obtained.

Once all the distributions and state transition probabilities are determined, probabilities for output symbols are calculated.

This is the final input required to run the model, and this is achieved with Equation (1).

$$P(S_i|A_i) = \frac{(\Delta t|\forall S = S_i \cap A = A_i)}{(\Delta t|\forall A = A_i)} \tag{1}$$

- S_i the sensor
- A_i the activity
- $P(S_i|A_i)$ is the probability of sensor given activity

The distributions and sensor descriptions can now be used to create ASPN for the VSS reconstruction task, which will be discribed in the next section.

3 Conceptual Model and Algorithm Design

3.1 Conceptual Model

There are different ways to model the daily activities of a resident. In this research, we compared two different model designs. The first design was also used in previous research [17], where each activity has is represented as an individual Augmented Stochastic Petri net (ASPN) with places representing three tangible system states, *Activity* where the person is currently engaged in said activity, *Short_Break* and *Long_Break*, which represent the period in between different instances of the same activity. (see Figure 1) As most activities show a distinct differentiation of the time between activity instances, two timed transitions represent the duration of long breaks and short breaks. Each ASPN is independent of the other activities ASPNs.

The second model design contains one ASPN per room. Here the places represent the tangible system states of performing a certain activity (e.g. *Work* or *Eat*) or of not performing an activity in the room *Break*, which can either mean being in between tagged activities, or performing an activity in another room of the apartment. Figure 2 shows the SPN, without the augmented symbol emissions, for better readability.

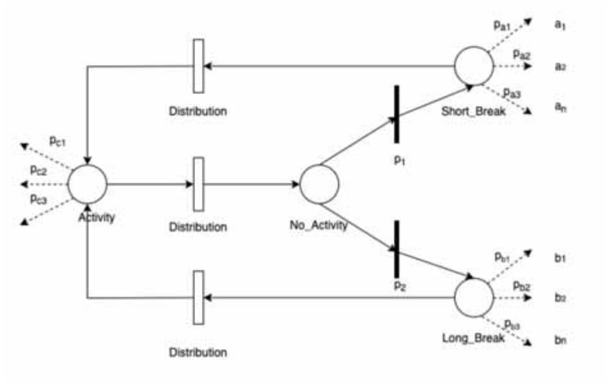

Figure 1: Augmented stochastic Petri net for one activity.

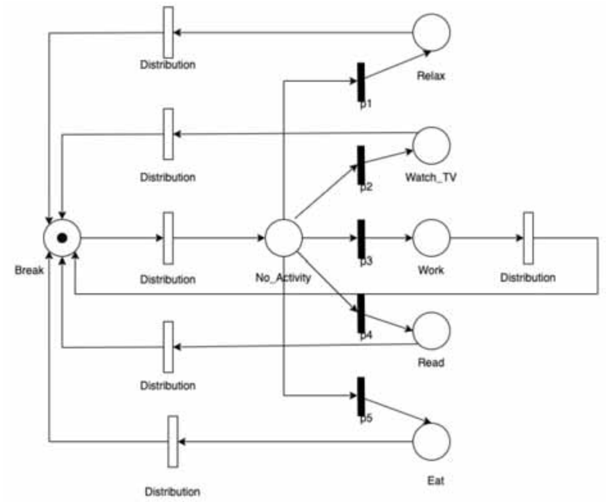

Figure 2: Stochastic Petri net for a room.

Once the structure of the Petri net is finalized, the output symbol emissions for the behavior reconstruction algorithm are added. These output symbols are linked with the Petri net places [8], as they occur, when an activity is being performed rather then when a state change occurs. From Figure 1 and 2 the output symbols are connected to all places except *No_Activity*. The p_k denote transition probabilities of the immediate transitions, p_{ak} denotes the output probability of symbol a_k.

The two different model designs will be augmented with the two different sensor level descriptions. The activity-based model can be augmented with both room level sensors as well as furniture level sensors. The room-based model is only augmented with the furniture level sensors, as the room level sensors would not enable differentiation between different activities within the room.

This results in three distinct model layouts: room-based model with furniture level sensors, activity-based model with furniture level sensors and activity-based model with room level sensors.

3.2 Algorithm Design

To reconstruct the unobserved system behavior, here the residents activities, the Proxel algorithm is used. The Proxel algorithm determines possible development paths of the system and their probability [18, 19, 8]. A Proxel is a 5-tuple, which represents one point in the expanded system state space, this tuple consists of the state of a system, age intensity, current point in simulation time, route through the state space and probability. All individual models are executed independently and determine output paths for all activities. This output path contains the probability of an activity occurring at a certain point in time.

The final reconstruction step has a different structure for the two model layouts. For the activity model, first the probabilities for each activity ASPN are computed and then the activities need to be classified. For classification a simple decision system is incorporated. This system outputs the activity which has the highest probability for all individual models for their activity state at that point in time. For every timestep of the protocol, this decision system results an activity. This type of system works because all the activities have individual ASPNs independent of each other. If for a particular timestep the probability of all activities is zero then the model returns *Other_Activity*.

For the second model setup with one model per room, the actual Proxel simulation is followed up by a reconstruction step, where the most likely path for each room is determined. Then these paths are combined over the different rooms and the most likely sequence of activities is the reconstruction result. Details of both the solution and post-processing methods can be found in [16]. The results obtained using the activity models and the room models are presented and reviewed in the following section.

4 Experiments and Results

In this section, the performance of the three different models on the three different generalization levels of activities is evaluated. These results are classified correctly if at a given time the reconstructed activity corresponds to the trace's ground truth.

The metrics precision, recall and F1 score are calculated for individual activities, and then they are averaged in two different ways one by averaging for all the activities (*Average*) and the other by adding weights depending on the overall activity duration (*Weighted Average*). The average recall is also often used as an overall accuracy measure. The above-discussed metrics are evaluated for weekdays and weekends separately, to account for differing behavioral patterns.

In a baseline experiment, the three models are applied to the reconstruction of the full set of 16 activities for model HH101. In k-fold cross validation, three weeks are used for training and one week for testing each. For all other experiments the k-fold cross validation is used for the five different datasets, training with four and testing on the fifth for each in turn.

4.1 Baseline Experiment

The results of the baseline experiments are shown in Table 4, the three different model designs are room-based model with furniture level sensors (*RoomM/-FurnS*), the activity-based model with room level sensors (*ActM/RoomS*) and the activity based model with furniture level sensors (*ActM/FurnS*). This experiment shows, that the accuracy per activity is less than the time weighted accuracy, as longer activities are detected more reliably. For the time weighted F1 score and accuracy, the room based model with furniture level sensors performed best.

4.2 Generalization Experiment

In the main experiment, we tested all three model setups and three different activity granularities, when using four apartments for training the model and the fifth as test set. This is a more realistic use case than using training and testing data from the same apartment. Having a small set of fully annotated apartments for training can be the basis of reconstruction models for apartments with a similar sensor setup, but without annotated training data.

Table 5 shows the full set of relevant performance measures, again separated by weekends and weekdays. Combining the data by averaging weekends and weekdays for the accuracy by activity results in the data shown in Figure 3. Similarly Figure 4 shows the weighted accuracy for all three models.

Compared to the basline data, the accuracy by activity seems to be improved for both models with furniture level sensors, whereas the activity-based model with room level sensors shows better performance only with the 11 activity set. This improvement in the per activity accuracy is most likely due to an increase in training data when using 4 apartments instead of just one. The improvement in performance for the furniture level sensors with more generalized activities is due to a grouping of activities with similar semantics, and therefore similar sensor activations.

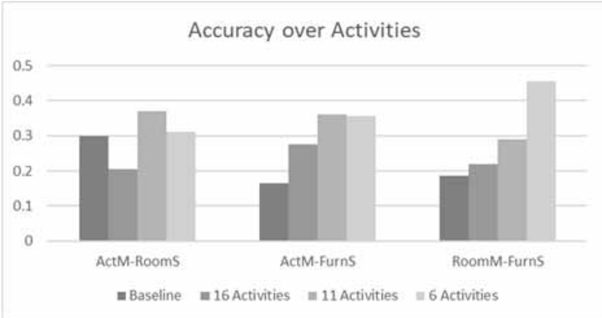

Figure 3: Accuracy per activity for all three models comparing baseline with different activity granularities.

The weighted accuracy performs better than in the baseline for the two activity based models, where in the room-based model, the baseline performance is better. The improvement in the activity based models is most likely due also to an increase in training data.

The decrease in performance for the room based model can be due to the larger differences between the apartments in the locations where activities are performed, and therefore more overlap in the models for the different rooms, which in turn results in worse reconstruction results.

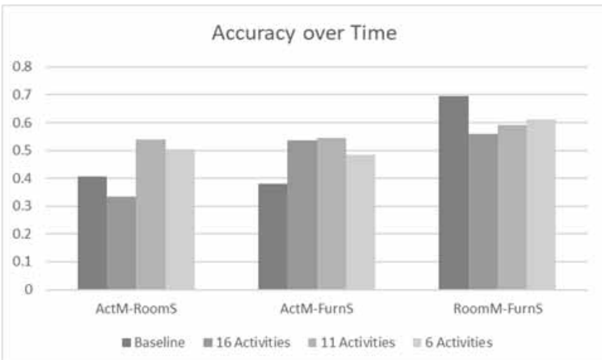

Figure 4: Time-weighted accuracy per activity for all three models comparing baseline with different activity granularities.

Evaluation Metric	RoomM/FurnS Weekday	RoomM/FurnS Weekend	ActM/RoomS Weekday	ActM/RoomS Weekend	ActM/FurnS Weekday	ActM/FurnS Weekend
Average_Recall	0.18	0.19	0.27	0.33	0.16	0.17
Weighted_Average_Recall	0.68	0.71	0.35	0.46	0.45	0.31
Average_F1	0.66	0.64	0.36	0.62	0.55	0.38
Weighted_Average_F1	0.53	0.55	0.32	0.50	0.35	0.29

Table 4: Baseline experiment performance of different models.

Evaluation Metric	RoomM/FurnS Weekday	RoomM/FurnS Weekend	ActM/RoomS Weekday	ActM/RoomS Weekend	ActM/FurnS Weekday	ActM/FurnS Weekend
Average_Recall	0.20	0.24	0.22	0.19	0.25	0.30
Weighted_Average_Recall	0.58	0.54	0.36	0.31	0.56	0.51
Average_F1	0.56	0.52	0.33	0.27	0.46	0.45
Weighted_Average_F1	0.54	0.48	0.34	0.28	0.54	0.47
Average_Recall	0.30	0.28	0.35	0.39	0.38	0.34
Weighted_Average_Recall	0.62	0.56	0.53	0.55	0.58	0.51
Average_F1	0.53	0.49	0.46	0.47	0.58	0.54
Weighted_Average_F1	0.54	0.51	0.49	0.49	0.51	0.47
Average_Recall	0.49	0.42	0.32	0.30	0.37	0.34
Weighted_Average_Recall	0.60	0.62	0.50	0.51	0.51	0.46
Average_F1	0.49	0.49	0.49	0.48	0.48	0.45
Weighted_Average_F1	0.56	0.55	0.46	0.46	0.51	0.45

Table 5: Experiment performance of different models for full activity set (top), 11 activites set (middle), and 6 activites set (bottom).

4.3 Experiment Discussion

Overall the experiment shows that models trained on a set of apartments can be used for behavior reconstruction on a different apartment with similar sensor setup and resident behavior. Sometimes the performance even improves due to a larger amount of available training data when using multiple apartments for training, also avoiding overfitting. However, the selection of a fitting activity granularity and good model setup is crucial. The combination performing best overall and at the same time yielding still useful results in this experiment was the activity-based models and the furniture level sensors.

A semantic grouping of activities by similar time of day and living area, which corresponds to a similar sensor footprint, leads to an improvement in accuracy. However, the information content of the reconstruction is considerably less, when more activities are combined under the same label.

It has to be investigated with the help of domain experts at which point the generalized set of activities with better performance measures still holds enough information to assess the residents status.

Ultimately the goal is to use this ambient sensor observation to decide, whether the residents behavior is still within normal bounds, or whether outside assistance or intervention is necessary.

5 Conclusion

This research used the CASAS datasets for several single-resident apartments. Three different model setups and three different activity granularities are tested on the behavior reconstruction of the residents when the apartment reconstructed was not part of the training set. Virtual Stochastic Sensors (VSS) are used to reconstruct resident activities. Using activity-based models and furniture level sensors resulted in the overall best performance.

5.1 Future Work

The analysis presented in this paper is only part of the research aiming at providing generalized models to be pre-trained and then applied for the reconstruction of previously unknown apartments, or systems in general.

In order to validate the results, the experiments need to be conducted on larger datasets and discussed with domain experts.

The paper shows that the approach is feasible in general, but also needs some more automation steps. An automatic adaption of the trained model to an apartment not in the trainings set can also be of interest, as well as the transfer of the idea to different domains such as non-intrusive appliance load monitoring.

Publication Remark. This contribution is the English full version of the German abstract version published in ASIM Workshop GMMS/STS 2025 Tagungsband ARGESIM Report 48, e-ISBN 978-3-903347-66-3, Volume DOI 10.11128/arep.48, p 77.

References

[1] Rashidi P, Mihailidis A. A survey on ambient-assisted living tools for older adults. *IEEE journal of biomedical and health informatics*. 2012;17(3):579–590.

[2] Sun H, Florio VD, Gui N, Blondia C. Promises and Challenges of Ambient Assisted Living Systems. In: *2009 Sixth International Conference on Information Technology: New Generations*. 2009; pp. 1201–1207. URL `https://ieeexplore.ieee.org/abstract/document/5070788`

[3] Deutsch JE, Lewis JA, Burdea G. Technical and patient performance using a virtual reality-integrated telerehabilitation system: preliminary finding. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2007;15(1):30–35.

[4] Fahad LG, Tahir SF, Rajarajan M. Feature selection and data balancing for activity recognition in smart homes. In: *2015 IEEE International Conference on Communications (ICC)*. IEEE. 2015; pp. 512–517.

[5] Ordóñez FJ, Roggen D. Deep convolutional and lstm recurrent neural networks for multimodal wearable activity recognition. *Sensors*. 2016;16(1):115.

[6] Gochoo M, Tan TH, Liu SH, Jean FR, Alnajjar FS, Huang SC. Unobtrusive activity recognition of elderly people living alone using anonymous binary sensors and DCNN. *IEEE journal of biomedical and health informatics*. 2018;23(2):693–702.

[7] Mueller LF. Feasibility and Applicability of Virtual Stochastic Sensors for Human Activity Recognition in the Context of Ambient Assisted Living. Master's thesis, Otto-von-Guericke-University Magdeburg. 2021.

[8] Krull C. Virtual Stochastic Sensors: Formal Background and Example Applications Reconstructing the Behavior of Partially Observable Discrete and Hybrid Stochastic Systems. Habilitation thesis, Otto-von-Guericke-University Magdeburg. 2021.

[9] Lühr S, Venkatesh S, West G, Bui HH. Explicit state duration HMM for abnormality detection in sequences of human activity. In: *PRICAI 2004: Trends in Artificial Intelligence: 8th Pacific Rim International Conference on Artificial Intelligence, Auckland, New Zealand, August 9-13, 2004. Proceedings 8*. Springer. 2004; pp. 983–984.

[10] van Kasteren T, Kroese B. Bayesian Activity Recognition in Residence for Elders. In: *3rd IET International Conference on Intelligent Environments*. 2007; pp. 209–212.

[11] Singh D, Merdivan E, Psychoula I, Kropf J, Hanke S, Geist M, Holzinger A. Human activity recognition using recurrent neural networks. In: *Machine Learning and Knowledge Extraction: First IFIP TC 5, WG 8.4, 8.9, 12.9 International Cross-Domain Conference, CD-MAKE 2017, Reggio, Italy, August 29–September 1, 2017, Proceedings 1*. Springer. 2017; pp. 267–274.

[12] Chen L, Nugent CD, Wang H. A knowledge-driven approach to activity recognition in smart homes. *IEEE Transactions on Knowledge and Data Engineering*. 2011;24(6):961–974.

[13] Krull C, Horton G. Hidden Non-Markovian Models: Formalization and Solution Approaches. In: *Proceedings of 6th Vienna Conference on Mathematical Modelling, Vienna, Austria*. 2009; pp. 682–693.

[14] Krull C. A Hybrid User Model for Virtual Stochastic Sensors. *Simulation Notes Europe SNE33*. 2023; 33(1):35–43.

[15] Cook DJ, Crandall AS, Thomas BL, Krishnan NC. CASAS: A smart home in a box. *IEEE Computer*. 2013;46(6):26–33.

[16] Karumuri V. Generalization of Virtual StochasticSensors in the Field of AmbientAssisted Living for MultipleSingle-Resident Apartments. Master's thesis.

[17] Karumuri V, Krull C. Virtual Stochastic Sensors for Ambient Assisted Living - Analyzing the Effect of Generalized Resident Behavior. In: *Tagungsband Langbeitraege ASIM SST 2024*. 2024; .

[18] Horton G. A New Paradigm for the Numerical Simulation of Stochastic Petri Nets with General Firing Times. In: *Proceedings of the European Simulation Symposium 2002*. SCS European Publishing House. 2002; pp. 129–136.

[19] Lazarova-Molnar S. The Proxel-Based Method: Formalisation, Analysis and Applications. Ph.D. thesis, Otto-von-Guericke-University Magdeburg. 2005.