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EMERGENCY DETECTION BASED ON PROBABILISTIC MODELING IN AAL-ENVIRONMENTS

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ABSTRACT

The actual demographic trend predicts a significant increasing percentage of elderly people in the German society until 2050. According to this trend, it must be assumed that the number of elderly persons who wants to live self-sufficiently in their habitual environment will rise as well. In this paper a human centered assistance system is tightly described and proposed as a resolve for the coherent challenges of this structural, societal changes which relate to home care and geriatrics; thereby the focus of consideration lies on the statistical analysis of gathered process data in order to derive an intelligent emergency detection based on probabilistic modeling. Using room automation states and events to design and train Hidden Markov Models for position tracking, complemented with the stochastic evaluation of telemedical devices and contactless sensor networks, the main issue is to achieve a solid, robust situation recognition mechanism. Due to the knowledge of the hidden user states or i.e. situations, this approach offers the opportunity to detect emergency situations instantly and to prevent harmful aftermath for the user through interventions like emergency calls. This paper illustrates the architectural concept of the assistance system with its implemented techniques and demonstrates the approximation of user situations through a clear example. Simulation results are discussed and finally, a first conclusion with an outlook on further progress of research closures this article.

KEYWORDS

Probabilistic, situation recognition, Hidden Markov Models, distributed sensor networks, assistance systems

1. INTRODUCTION TO THE FIELD OF RESEARCH

Due to the demographic change in most of the highly industrialized western countries, modern societies are confronted with an enormous growing group of seniors. Nowadays in Germany, 21% of the population are older than 65 years, but it is expected that this age group will grow up to 34% until 2060 (refer to figure 1). Some reasons for the alteration of the age pyramid are the aging of baby boomer generation, the overall increasing life expectancy due to high economic standards, decreasing birth rates and an improved health care system. Due to this trend the growing number of elderly people living alone at their home behaves diametric to the number of kin persons like children who cares for them. The demographic change will have a dramatic impact on the society, on financial aspects as well as on organizational aspects if we care only about health care institutions such as hospitals, nursery homes, health insurance funds or social facilities, welfare services and retirement funds. In addition, in shrinkage regions medical or custodial maintenance will be insufficient. Keeping this conceivable progress in mind, the *Bundesministerium für Bildung und Forschung – BMBF* initiated a program for research institutions and enterprises in order to aid groundbreaking developments for geriatric care solutions under the term *Ambient Assisted Living – AAL*. Relating to the BMBF-definition, this acronym comprehends technical concepts, products and services for the non-stigmatizing, situation dependent support of people with special demands in their daily life under consideration of their informal self-determination. The integration of an AAL-solution is provided, if constructive, completely technology-focused approaches fail due to their lack of consideration of human preferences and human environments.

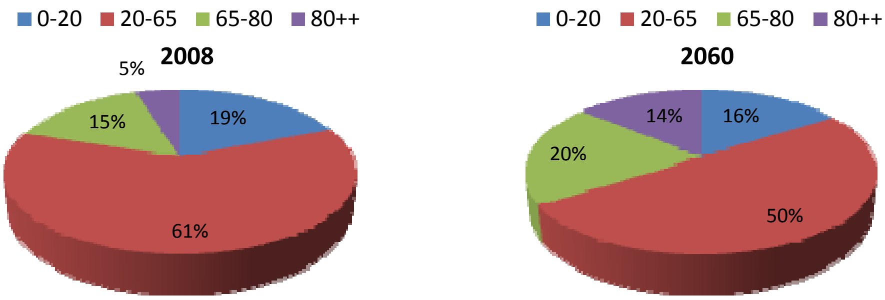

Figure 1. Demographic change in Germany until 2060 [DESTATIS, 2010]

In this context, alternative approaches for human centered assistance systems deal with camera-based techniques to identify *Activities of Daily Life - ADL*, utilize energy consumption of electronic devices for user situation modeling or combine established methods by the evaluation of distributed sensor networks for providing situation dependent services. Our approach to enable elderly people to live further in their familiar environment in a secured and comfortable manner focuses on the fusion of many techniques of data processing with the appropriate principles of stochastic automata. The evaluation of ambient technologies benefits, in relation to sensor density, a high degree of situation recognition if probabilistic modeling adapts to environmental properties. This is the key part of the research project *AAL@Home*, which is designated to the development of an adaptive, generic human centered assistance system. This paper proposes the ideas behind the approach and contributes through experimental results an outlook for the upcoming vicissitude in the area of geriatric home care.

2. CHALLENGES

Considering the special demands of the potential customer, many restrictions and traits have to be regarded. Geriatric care includes also the requirement for a continuous medical monitoring system and the option to control therapy compliance of the patient in the future. Due to limited amount of space this papers addresses only a separated area of the implemented medical diagnosis system with the focus on cardiac diseases which is detailed in the first section below. The second section studies the established modern telemedical devices and their restrictions.

2.1 Medical Challenges – Cardiac Diseases and their Impact for the Society

As mentioned before typical use case scenarios of the proposed assistance system in the field of geriatric care call for medical monitoring mechanisms in relation to the patient's compliance, for postoperative therapy control or for the preventive detection of critical states of health. The decrease of the hospitalization rate is one goal of this approach. Due to their role as a cost driver in the health care sector (refer to figure 2), cardiovascular diseases like myocardial infarction, cerebral insults and heart arrhythmia or heart insufficiency are in the focus of further considerations. The prevalence and incidence of these diseases increased significantly in the recent years and caused additional stresses and strains for the health insurance funds [Klauber et al, 2010]. Therefore it is one important requirement to implement reliable diagnosis functionality within the assistance system in order to reduce the costs by preventive detection of cardiac diseases. One essential problem in the context of many cardiac diseases like atrial fibrillation follows from the asymptomatic aetiopathology in many illness cases – the patient is apparently free of any disorders.

Rank	ICD-Pos.	Main diagnosis	Patients	Ø hospital stay	Ø age at committal
1	Z38	Neonates referred to birthplace	245838	3.8	0
2	F10	Behavioral disorder by alcohol	233278	8.6	44
3	I20	Angina pectoris	177595	5.2	65
4	I50	Heart insufficiency	156893	11.5	73
5	K40	Hernia inguinalis	148363	3.7	56
6	I25	Chronic ischemic heart disease	144579	6.1	66
7	I21	Myocardial infarction	134721	8.8	66
8	C34	Virulent neoplasm of bronchia	131461	8.2	66
9	S06	Intracranial harm	123417	4.3	33
10	J18	Pneumonia	112508	9.9	56
11	I48	Atrial fibrillation	107623	5.6	65
12	I63	Cerebral insult	101254	12.9	70

Figure 2. Most common diagnoses in Germany 2007 [QUELLE]

Therefore a discreet continuous monitoring of vital signs like heart frequency for the identification of extrasystoles or tachycardia provides a great chance to apply necessary interventions to avoid serious aftermath before the patient recognizes any illness [Busch et al a), 2010]. Atrial fibrillation may be classified into a set of states which allude to the aspects of occurrence and duration [Gerhard 2005]:

- First occurrence of atrial fibrillation – a special case which is seldom noticed
- Paroxysmal atrial fibrillation – atrial fibrillation occurs and lasts for nearly 7 days
- Persistent atrial fibrillation – after 7 days atrial fibrillation switches to a persistent state
- Permanent atrial fibrillation – if cardioversion fails atrial fibrillation is called permanent

The first occurrence of atrial fibrillation is unaccounted for the probabilistic modeling through hidden Markov models because it is usually not detectable. In the model we use paroxysmal AF to cover this event.

2.2 Technical Challenges – Limitations of Actual Telemedical Solutions

Human centered assistance systems, which implement a continuous vital sign monitoring, are subjects of numerous restrictions:

- Users may reject or have reservation towards the system, because camera-based systems imply an impression of observation to the user.
- Restrictions of user's mobility and autonomy, if body attached sensor-networks are applied.
- Concerns towards data privacy, if external service providers are connected to the system.

An essential problem in the context of AF follows from the asymptomatic aetiopathology in many illness cases – the patient is apparently free of any disorders. In addition, long-term ECGs do usually not cover all episodes. Even more difficult is the detection of paroxysmal or the first occurrence of AF. Different studies have shown that the detection rate can be increased through telemonitoring devices [Hördt M. et al, 2003]. Telemedical monitoring gets also more importance in the therapy control, as the PAFAC study points out [Patten M. et al, 2006].

Another aspect addresses the recognition of life-threatening, medication coherent arrhythmias, which are considered as indicators of sudden cardiac death (SDC) [Anderson JL. et al. 1999]. However, up to now applications of telemedicine ECG recordings focus on the diagnosis of palpitations, presyncope and syncope in order to control medical rehabilitation measures according to cardiac treatment or after the implantation of pacemaker, ICDs and event-recorders [Kouidi E. et al, 2006].

3. METHODS AND TECHNIQUES

3.1 Major Tasks of Assistance Systems

Human-centered assistance systems are subsumed with other technology-concepts, products or services which serve the situation-dependent, possibly little or no perceptible support of people classified under the term Ambient Assistant Living, abbreviated as AAL.

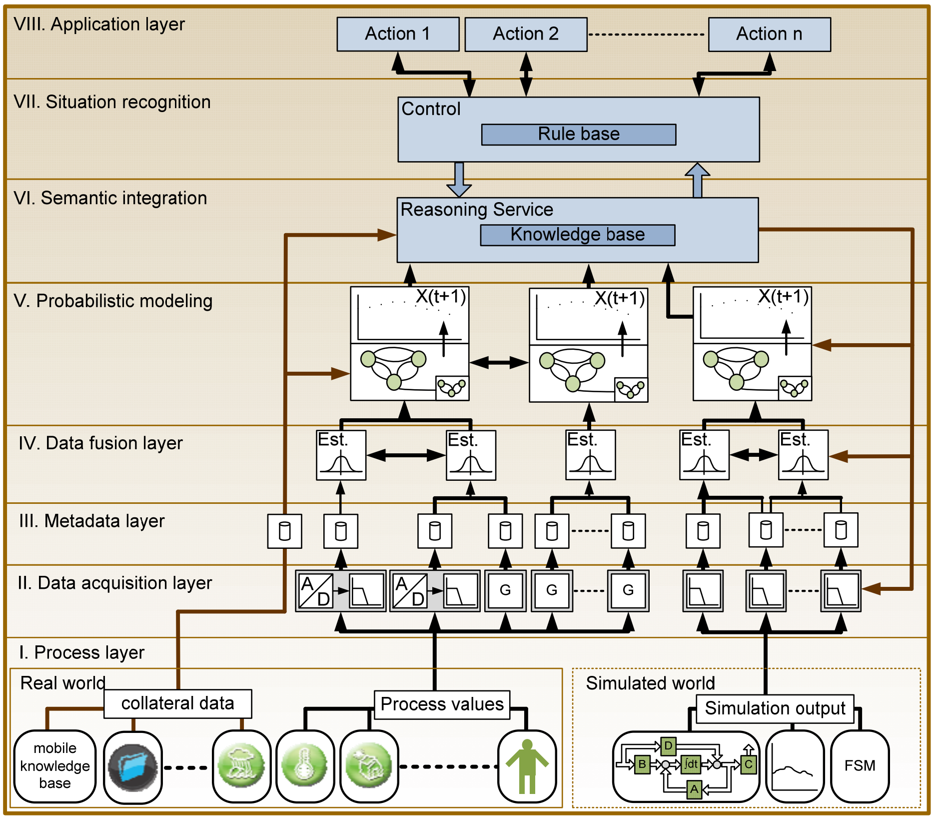

Figure 3. Layer concept of the assistance system

Our concept of an assistance system regards some essential tasks considering the integration of the user:

- *Perception assistance*: The assistance contributes to the selective perception and individual visualization of complex environmental situations.
- *Access assistance:* The assistance system supports the interaction between the user and his technical environment; the user can access cooperative interfaces.
- *Communication assistance:* It promotes the interaction of users with each other in the sense of 'community buildings' to form user groups by defining common objectives.

- *Cooperation assistance:* It offers remote, maybe only indirectly, communicating user decision-based or semi-autonomous behavior in order to support collaboration for common objectives.

The assistance system supports the user at the accomplishment of their daily tasks by the delivery of decentralized technical services and their adaption to these tasks. The detection of individual user situations under inclusion of their preferences is essential for the ubiquitous providing of appropriate cooperative services for comfort, safety, energy management and security.

3.2 Architecture of the Assistance System

The kernel of the architecture for the proposed assistance system relies to the hierarchical arrangement of techniques based on probabilistic functions and description logic. The topology of the design is generic and adaptive to different use cases (refer to figure 3). The *process layer* comprehends all accessible information about the observed area of the specific use case. The process data covers all information about the user's environment which can be obtained e.g. by distributed embedded sensor networks (for detail refer to section 3.3). The *data acquisition layer* contains proceedings and filter operations, which are needed to gain and transform the essential measurement signal. The *metadata layer* handles the mapping of the acquired process data and the unspecified part of the collateral information to a generic data structure.

The *data fusion layer* offers a conglomerate of methods and techniques to derive higher knowledge for a superior grade of integration from the basic information extracted in the lower layers or to increase the quality of these values. The estimation of situations, esp. of the internal hidden states of the system, depends on uncertain process data and incomplete knowledge. In this layer the extracted emission data and the a priori knowledge form the basement for the modeling of the discrete event systems (DES) according to the spatial and temporal environments of our assistance system using the advantages of HMMs. The *probabilistic modeling* for this specific scenario is discussed is in the following sections.

The layer of the *semantic integration* deals with the transfer of the explicit and implicit knowledge about the structure and the identified states of the addressed domain into a representation of description logic. The implemented reasoning service gathers higher knowledge for the situation recognition attending to the associated knowledge base by cyclic queries and using appropriate description logical interferential mechanisms. Application-specific rules follow within the corresponding applications, which are running within the context of the assistance system and are assigned to the *application layer*. The *situation recognition* accesses the reasoning service in a cyclic query to analyze the different events and states due to the probabilistic modeling. The retrieved conclusions about the inner states are used for the completion of the application rules, e.g. emergency assistants, which decide about appropriate actions relating to the recognized situations [Busch et al b), 2010].

3.3 Process Data Acquisition

There are three different kinds of technical devices which are utilized for the acquisition of the process $\{y_n(t)\}, n \in N, t \in R_+$ values relating to the inner states of the observed system.

Considering the sampling time Ts and discretization effects like distortion by noise the process data can be expressed by $\{y_d(nT_s)\}$ with $d,n \in N, T_s \in R_+$. This data results from these three essential procedures:

- Evaluation of telemedical devices such as sphygmomanometer, mobile ECG recordings etc.
- Evaluation of the home automation components
- Evaluation of contactless sensor networks particularly UWB-radar

The telemedical equipment will be used by the patients themselves after stipulated intervals which relate to the anamnesis stored in the digital health record (DHR). Partially this information is gathered at deterministic points of time nT_s via standardized communication interfaces like Bluetooth, stored and expanded through a specific data structure and conveyed to the data fusion layer as described in section 3.2. Another source of system information refers to the examination of the home automation components including features like system states or events just such as the opening/closing of a door for example. The preferred home automation system is accessible through the established interface BACnet and is evaluated in a cyclic query. Contactless measurement takes an exposed tank in the context of assistance systems implementing medical monitoring functionality as described in section 2.2. One promising concept is based on the work of [Helbig et al, 2007] and deals with the detection of heart rate and breath frequency through UWB-sensor components. Another approach proposes the appraisal of composure and position with the aid of UWB-sensor networks [Thomä et al, 2007]. In summary, the relevant process values gained in the data acquisition layer can be expressed by these following terms:

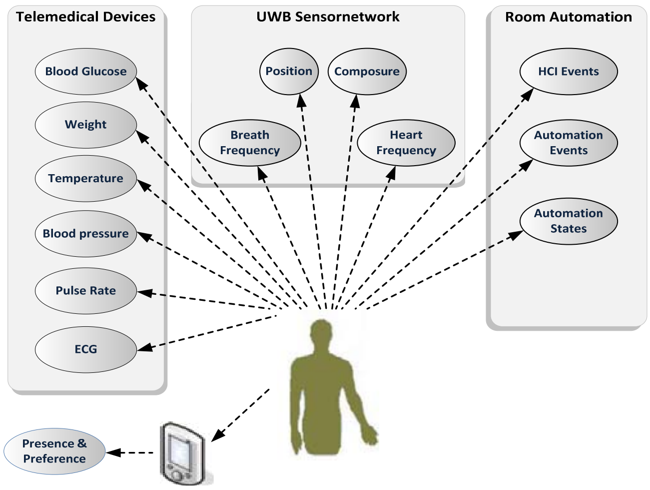

Figure 4. Sources of process data and a priori knowledge

$$\{y_{AssistanceSystem}\} = \{\{y_{TelemedicalDevices}\}, \{y_{UWB}\}, \{y_{Automation}\}\} \quad (1)$$

with

$$\{y_{Automation}\} = \{e_{HCI}, e_{BASC}, x_{BASC}\}, \quad (2)$$

$$\{y_{UWB}\} = \{f_{Heart}, f_{Respiratory}, xyz_{Position}, x_{composure}, X_{respiratory} \ldots\}, \quad (3)$$

and

$$\{y_{TelemedicalDevices}\} = \{\theta_{Body}, f_{HeartECG}, m_{Body}, (mmHg)_{systolicBloodPressure}, \ldots\} \quad (4)$$

These properties are individually evaluated due to specified parameters which relate to system inherent characteristics including the patient’s characteristic traits.

3.4 Probabilistic Modeling with Hidden Markov Models

Hidden Markov Models (HMM) combined with Relational State Descriptions are a successful approach to design software agents addressed to temporal and spatial environments [Meyer-Delius et al, 2007]. An alternative approach deals with the sensor based activity recognition utilizing Relational Markov Network (RMN) under inclusion of the MCMC-algorithm for inference [Liao et al, 2005]. The works of [Taskar et al, 2002 and Pearl, 1997] deal with the implementation of RMNs with the aid of undirected graphic models i.e. Markov Nets. Furthermore the hierarchical expansion of dynamic Bayesian Networks is a probate resolve for probabilistic modeling [Subramanya et al, 2006]. The work of [Rabiner, 1989] reinforced the theoretical aspects of HMMs and their benefit for technical solutions in the context of statistical modeling. A Hidden Markov Model, representing a stochastic process like a time corresponding motion pattern, may be described by the quintuple $\lambda = \{X,A,Y,B,\pi\}$ with the state space X, the alphabet Y, the relating characteristic emission and transition matrices B and A, and finally the initialization vector π. The behavior of the probabilistic model refers to the relationship expressed by the equation $P(X_{t+1}=x_j|X_t=x_i)$, which is drawn for every state transition by the matrix A. As sketched in figure 5 every hidden state emits an element of the subset *Y* due to distribution specified by the matrix B. For further detail refer to the following sections.

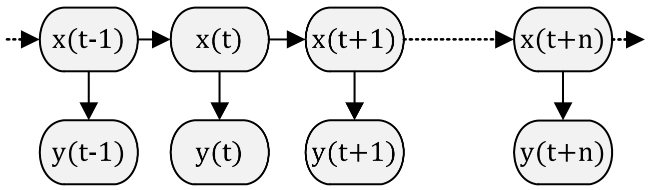

Figure 5. State – Emission sequence of a HMM

4. IMPLEMENTATION EXAMPLE

4.1 Subgraph for Position Recognition

The assistance system evaluates distributed sensor networks which are embedded within the home of the patient. One problem to solve is the recognition of the place where the patient dwells. The position is one indicator for the recognition of the person's activity and essential for the estimation of the user situation. Therefore one subgraph was drawn to reflect the position tracking through the habitat by the evaluation of the home automation events. The positions are considered by the state space:

$$X_{Home} = \{x_1 \dots x_n\} = \{bedroom, study, floor, storage\ room, bathroom, living\ room, kitchen\} \quad (5)$$

with

$$\{1,2,3 \dots |X_{Home}|\} \rightarrow X_{Home} \quad (6)$$

Every room is equipped with automation devices such as motion sensors m_x, door contacts d_x and window contact w_x (refer figure 6). The evaluation of these devices implies an alphabet

Y_{Room} = {w_{11}...w_{72}, m_3, d_3, d_{76}, ε} under consideration of situations without notice of any emission through the surrogating symbol *ε*. If a person uses a door or opens a window, a significant emission is registered and used to approximate the most likely location of the person.

The relationship between the stochastic process model and inhabitation is illustrated by the Markov graph (refer to figure 6).

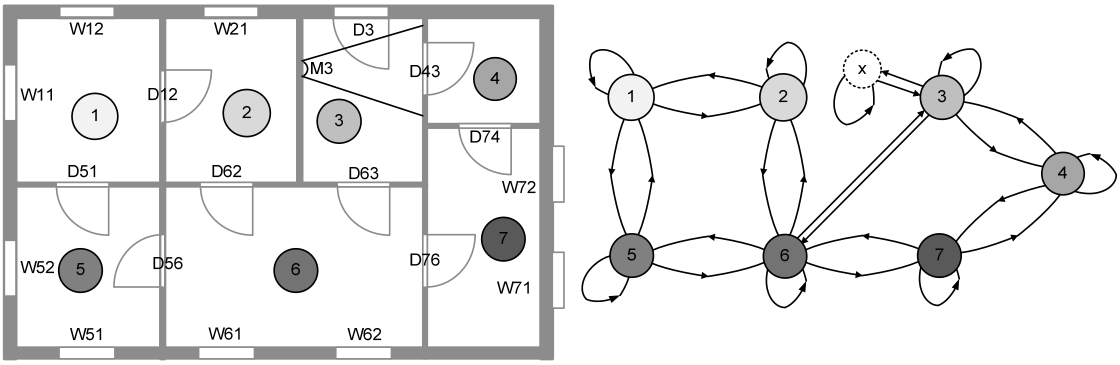

Figure 6. Mock habitat and corresponding HMM

Relating to the motion track drawn in figure 7 we get a state sequence

$$Q_T = \{1,1,1,1,1,1,1,5,5,5,5,6,6,7,4,7,7,7,6,3,3,3,3,3\} \tag{7}$$

for an evaluation interval $T_{eval} = nT_s$ with $0 \leq n \leq 24$. We obtain a corresponding emission sequence formally expressed by $O_T = \{o_1, o_2,\ldots, o_T\}$, $o_t \in Y_{Home}$ in order to determine the hidden states:

$$O_T = \{\varepsilon, \varepsilon, \varepsilon, \varepsilon, w11, w12, d51, \varepsilon, \varepsilon, w52, d56 \ldots\} \tag{8}$$

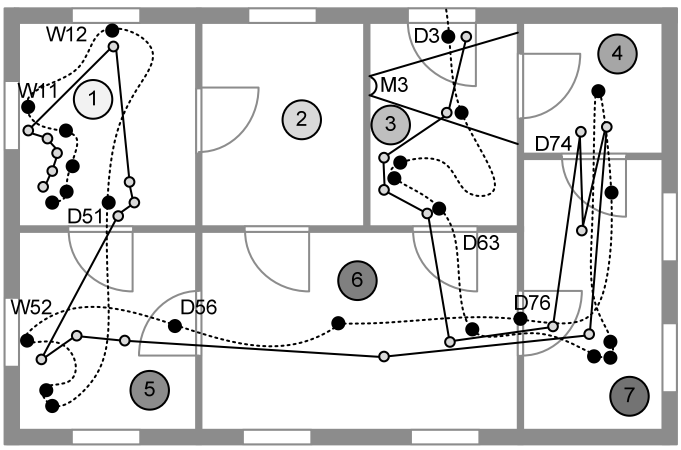

Figure 7. Example track through the mock habitat

The relationship between emission sequence and the state sequence follows from the equation:

$$P(O_{T0} | Q_{T0}, \lambda) = \sum_{for\ all\ Q}^{1} [X_t, X_{t+1} \dots X_{T0} = i, O_t \dots O_{T0} | \lambda], \tag{9}$$

The Viterbi-algorithm expressed by the term

$$\delta t(i) = \max_{q1, q2, \dots qt+1} [X_t, X_{t+1}, \dots, X_{T0} = i, O_t \dots X_{T0} | \lambda] \tag{10}$$

offers the opportunity to approximate the most likely state of the system. With an explicit state assignment for the model with $\pi_{eval} = \{1, 0, 0, 0, 0, 0, 0)$ and previous initializations $\delta_1(i) = \pi_i b_i(k = o_i), 1 \leq I \leq |X|$, $\psi_1(i) = 0$, we use the recursive equations

$$\delta t(i) = \max_{1 \leq i \leq |X|} [\delta_{t-1}(i) a_{ij}] \, b_j(O_t) \tag{11}$$

$$\psi t(j) = \operatorname*{argmax}_{1 \leq i \leq |X|} [\delta_{t-1}(i) a_{ij}] \tag{12}$$

$$X_t^* = \psi_{t-1}(X_{t+1}^*), t = T-1, T-2, \dots 1 \tag{13}$$

Through backtracking it is possible to identify the most likely path through the trellis structure. Referring to figure 7 the black dots mark the real positions of the example motion sequence, the grey dots mark the estimated positions. Untrained models, recognizing only the geometry of the mock apartment, permit only a rate of cognition of 36%, which is a logic consequence due to random behavior. Models, trained with real recorded emissions and plotted state sequences with approved techniques like Baum-Welch, offer an optimized average detection rate of approximately 85%.

4.2 Activity Recognition for Feature Extraction Adjustment

The knowledge of the most likely activity of the patient is essential to choose the best fitting parameter set to obtain the emissions for the probabilistic modeling. The estimated position is one criterion for calling the adaptive activity HMM-graph.

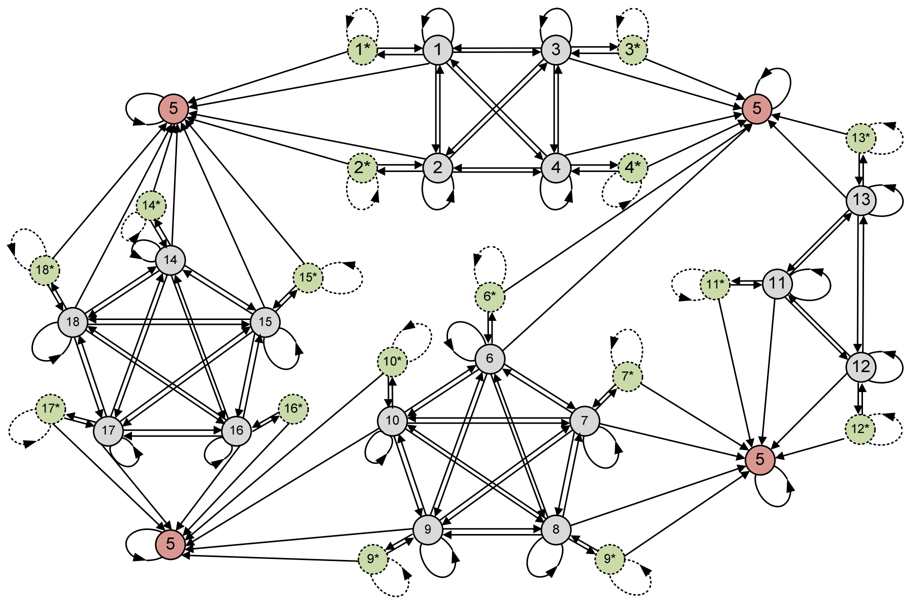

Figure 8. Exemplary activity model

For example, if the person resides in the bedroom, a graph with a state space

$$X_{bedroom} = \{Sleeping, Dressing, Reading, Yoga, Resting, Emergency\} \tag{14}$$

is selected.
Or if the person's location changes to the bathroom, a model with the state space

$$X_{bathroom} = \{Showering, UsingToilette, TeethBrushing, Bathing, Shaving \ldots\} \tag{15}$$

is active and responsible for choosing the correct parameter structure (refer to figure 8). The training and evaluation of these stochastic activity models is done in the same manner as the position tracking. The process data, gathered and filtered in the data acquisition layer is used to gain significant emissions (refer 3.2-3.3). For example, the repeated measurement of the body temperature is obviously used for the detection of the indicator fever:

$$\Theta_{Body}(nTs) > \Theta_{Body}(Parameterset) \rightarrow O_{t=nTs} = Fever \tag{16}$$

In analogy the detection of overweight works alike:

$$\hat{m}_{Body}(nTs) > \hat{m}_{Body}(Parameterset) \rightarrow O_{t=nTs} = Overweight \tag{17}$$

The boundary values for each type of vital sign classification depend on user's activity at the one hand and on the other hand on information stored in the parameter set. These parameter sets are usually predicated on the anamnesis, the age, gender, fitness and other collateral information stored within the digital health record. According to the estimated activity the interpretation of the vital signs is essential for the recognition of critical situations. Complemented with the criterion of state duration it is a useful approach for emergency detection and prevention of greater harm. For example, if the typical user with an age of 65 dwells in the bedroom at 2:00 AM, it must be assumed, that this person is sleeping. The mechanisms of the assistance system choose the left partial model in figure 9 and select the appropriate parameter set (refer to figure 10). This implies that the average breath frequency and average heart rate should be lower than by day when the person is active. In this example, the permanently monitoring of the heart rate through an embedded UWB-radar component, which is installed in the bed, offers a reliable method for the detection of critical heart events like arrhythmia or other indicators for serious situations. The recognition of emergency cases is the main issue of this assistance system.

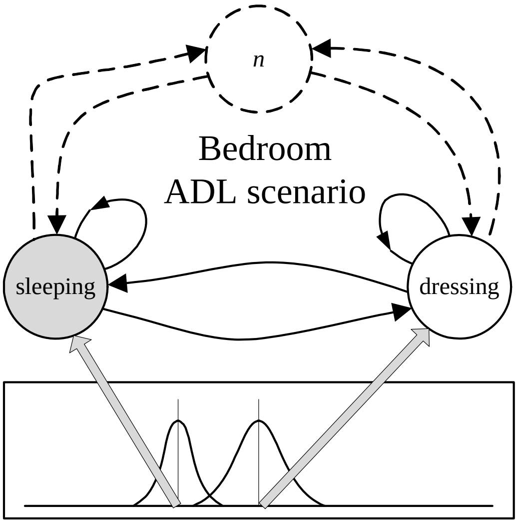

Figure 9. Situation dependent parameter selection

4.3 Emergency Detection

The ability to recognize dangerous situations enables preventive interventions like emergency calls to the hospital, notification of the attending doctor, messages to the members of the patient's family or to take appropriate actions like the dispense of anticoagulants or other advisable medicine in danger. One descriptive example deals with the preventive detection of atrial fibrillation. This cardiac disease is one predisposing factor for cerebral insult and therefore indirectly in charge for a large amount of health costs in Germany (refer to section 2.1). Atrial fibrillation may be drawn by the HMM

$$\lambda_{AF} = \{X_{AF}, A_{AF}, Y_{AF}, A_{AF}, B_{AF}, \pi_{AF}\} \tag{18}$$

with the state space

$$X_{AF} = \{No_{AF}, 1stAF, ParoxysmalAF, PersistentAF, PermanentAF\}. \tag{19}$$

The alphabet

$$Y_{AF} = \{SignificantHeartMurmur, HeartRate > 140, \ldots\}. \tag{20}$$

covers the observables which are symptomatic for the occurrence of atrial fibrillation. The risk for cerebral insult is represented by the state space

$$X_{CI} = \{No\_CI\_Risk, Low\_CI\_Risk, Medium\_CI\_Risk, High\_CI\_Risk\} \tag{21}$$

and the alphabet

$$Y_{CI} = \{\{CheynesStokesRespiratory, Dizziness, \ldots\} \cup X_{AF}\} \tag{22}$$

including the different ranks of AF as an emission itself. According to the introductory described situation with an older person resting in his bedroom and AF as the point of interest, a critical situation may be identified by the repeated detection of a h*eart rate > 140*.

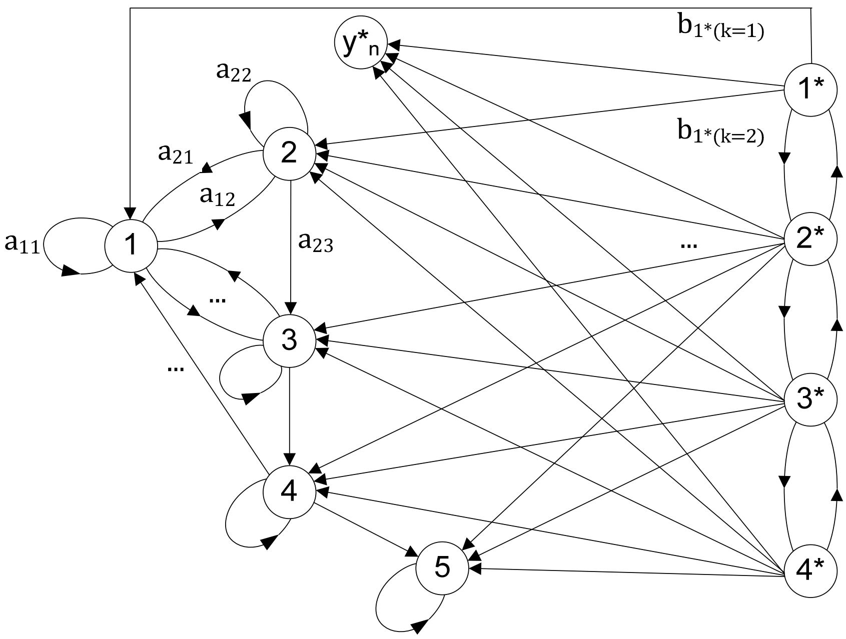

Figure 10. Exemplary model for AF as a CI-risk indicator

The evaluation of this symbol over a deterministic period of time introduces a lot of interventions. The first step is the execution of the diagnosis assistant for the evaluation of the emission sequence to identify the best suitable model for the situation. This diagnosis assistant comprehends partial HMMs similar to the graph in figure 11. According to the decision of the assistant adequate actions will follow.

5. DISCUSSION OF THE RESULTS

The primal model for the position tracking via probabilistic techniques achieved only a detection rate of nearly *35% up to 37%.* After the calibration and adjustment of the transition and the emission matrices coefficients by the use of established algorithms like Baum-Welch the amount of recognized positions rose to an average of 85%. The important feature of self-control by learning is implemented and approved. The system is able to adjust its inference mechanisms with training data gathered from the process environment. The appropriation of the Viterbi-algorithm in the first implementation was very beneficial, referring to the reduction of computational load. In summary, the evaluation of the embedded home automation components based on HMMs is robust and meets the demands of the situation modeling, particularly of the emergency detection module which is a key feature for the proposed human centered assistance system.

The emergency detection module is one complementary part of the situation recognition. Therefore the approach to use the activity recognition like a feedback system for the reconfiguration of the information fusion systems regarding to health parameter threshold is very useful. Relating to this practice the rate of recognized contingency accomplished 72%, if the influence of state duration is considered. Without regarding to state duration, the detection rate dropped to modest 41%, the rate of misapprehension rose from 2 to 15%. The momentary weakness of the contactless measurement system for breath or heart rate detection over distance anticipates a better result, a mechanical feedback system between the assistance system itself and the patient like a biased-off switch is indispensable at the actual status of the research project.

In addition to the room of improvement for the sensor components and the sensor network topology, there is one critical point in respect to the evaluation of non-equidistant measurement data. This is, relating to trend analysis in medical context, an exacerbating threat for the modeling of the patients health status. Due to patient’s behavior there is a temporal inconsistence in the measurement data particularly with regard to criteria like weight, blood-glucose or blood pressure. Coefficients of the emission matrices may be disrupted due to this fact and therefore some retaliatory actions relating to filter algorithms are required.

Unfortunately, time constants of medical or physiological processes are in general too big to determine the dependencies between different health states with learning algorithms at the assistance system. Another challenge is the interdependence between the diverse observables you want to analyze. Considering this fact, further information must follow from clinical randomized studies and must be used to determine appropriate stochastic models to expand the diagnosis assistance topology.

6. CONCLUSION

In this paper it was shown, that classified sequences of system states can be described as a statistical process by the use of Hidden Markov Models. For the use in the assistance systems, the system states are representing human behavior in the evaluation interval. The implemented methods are a useful tool to infer from uncertain knowledge, as long as stochastic independent parameters are being evaluated, the number of system states is kept low and appropriate training algorithms like Baum-Welch are used for the adjustments of the transition matrices.

The integration of this functionality enables the assistance system to regulate systems with known properties as well as to evaluate system with unknown traits. The assistance system is able to make the necessary adjustments of its limited cognitive situation recognition by itself due to the learning process.

For improving the diagnosis system it is necessary to evaluate existing and accessible data sets (Framingham Heart Study) and to obtain valid data sets by the use of randomized, multicentre clinical trials. The integration of time varying matrices for the transition and emission probabilities will be done in the next steps of the research project, so that the probabilistic modeling will be adapted on actual scenarios. Thereby the rhythm of user's life will be integrated in the assistance system also. The implementation of a_{ij} and $b_j(k)$ as $f(t)$ should lead to an dynamic assignment of the coefficients. Another working package is the modeling and implementation of specific *ADL (Activity of Daily Life)* scenarios for different environments, which are based on valid data sets.

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