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Continuous Preventive Diagnosis for Cardiovascular Diseases Based on Stochastic Modeling

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***Abstract*: Ambient assisted living (AAL) gained much more importance as a self-contained field of research and yields appropriate, promising concepts for the assignments following from the actually observable demographic change in Germany. Against this background, this paper proposes a human centered assistance system for the unobtrusive support of elderly people with special demands in their daily life. Keeping in mind the designated user group, the proposal has to care about the implementation of a medical monitoring mechanism for continuous compliance control, preventive diagnosis and early detection of crucial states of health. Thereby, the focus lies on the surveillance and prevention of cost-intensive cardiovascular diseases such as heart arrhythmia or heart insufficiency. However, actual telemedical devices — implemented as body attached sensor networks — fail due to numerous reasons in the context of home care scenarios. Hence, it is essential to combine innovative contactless measurement methods with distributed sensor-, actuator- and communicator-networks consisting of standardized components which are evaluated under consideration of user preferences in order to derive higher knowledge about the inner system states, respectively user- and environmental-situations for the offer of adequate services. With the focus on atrial fibrillation as one predisposing influence for appoplexia, this paper explains the architectural and functional concept of the mentioned assistance system and grants an insight view to the implemented methods through a vivid modeling example.**

Keywords: atrial fibrillation, preventive diagnosis, HMM, medical monitoring, contactless measurement, probabilistic networks

I. Introduction

The demographic vicissitude confronts the saturated societies in most of the highly industrialized countries like Japan or in particular, in Germany, with enormous challenges and threats exacerbated by the coherent structural demise (refer to figure 1). Due to this trend, the growing number of elderly people who want to live independently in their familiar environment behaves diametrically to the number of kin persons who cares for them. The demographic change will have a critical 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*.

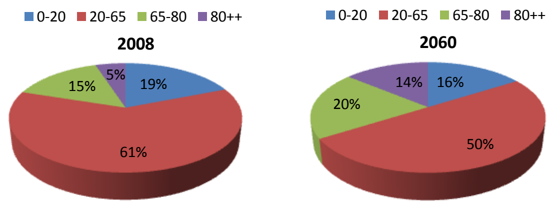

Figure 1. Demographic change Germany [1]

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 informational self-determination. Therefore, this paper recommends the implementation of a human centered assistance system consisting of context-free and context-sensitive software agents. These agents facilitate the everyday life of elderly people and ensure also their physical and mental infirmity by regulatory interventions, which occur autonomous, proactive, or reactive or optionally due to the non-intermittent interpretation of a continually growing knowledge base. Atrial fibrillation as one distinctive predisposing factor for the incidence of cerebral insults is used as an appropriate case study to explain the thoughts behind the architecture of our assistance system and is evaluated by first experiments.

II. Background of research

A. *Cardiovascular diseases – atrial fibrillation*

Atrial fibrillation is the most common heart arrhythmia in western industrialized countries (refer to table 1); with nearly 2.3 million concerned persons just in the USA [2], but it must be assumed that there is a much higher prevalence and incidence [3]. Furthermore, the results of the Framingham heart study suggest a significant increase of the AF prevalence due to the decreased lethality after critical heart event like infarctions through improved medical engineering.

Almost one third of AF cases occur idiopathic — without any identifiable primary structural coronary disease, at which patients with paroxysmal AF (45%) are more often represented than patients with permanent or chronic AF (25%). According to randomized studies, approximately 25-33% of diagnoses of permanent AF change to chronic AF [3]. The consequences of AF can be severe. As a disease itself, it serves not only as a marker for serious cardiac complaints but is also associated with an increased morbidity and mortality.

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

Table 1. Most common reasons for hospital stay [4].

Among the most fatal consequences of AF are thromboembolisms, esp. cerebral insults, induced by thrombi forming in the left atrium of the heart. In accordance to the Framingham Heart Study, it can be emphasized that there is a fivefold increased RR of ischemic insults relating to AF, the lethality of these insults are twice as high compared to insults with a differing anamnesis. Therefore, an early detection of AF is a key feature for a prospective assistance system which enables preventive interventions such as the application of anticoagulants. This is the main reason, why telemedical devices and infrastructures (refer to figure 2) were improved in the recent years, but actual solutions lack applicableness in the area of domestic care as elucidated the following section.

B. *Limitations of actual telemedical solutions*

As aforesaid, atrial fibrillation one of the main predisposing factors for cerebral insults, but it is also a very intricate parameter to observe. 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. Even observations through long-term ECGs are incomplete and do not capture every episode of AF [5]. However, studies with telemedical devices prove an increased rate of detection. Over an examination period of 40 days, episodes of heart arrhythmia could be detected and analyzed at 94% of patients with palpitations [6]. In addition to the analysis of ambiguous palpitations, telemedical surveillance is relevant for the control of therapies after the treatment of heart arrhythmia. The PAFAC-study points out, that patients after a successful electronic cardioversion and the prophylactic application of physics could be monitored through telemedical devices such as 1-channel ECGs. The study proved that nearly 30% of AF-episodes occur asymptomatic [7][8]. Another study demonstrates that ECG-monitoring shares a high rate of detection considering the relapse of AF at 27% of the test subjects after a successful catheter ablation [9]. Considering health safety aspects, the occurrence of ventricular arrhythmias caused by medicaments may be an indicator for the sudden cardiac death (SCD). Therefore, an early detection through telemedical devices is indispensible as [10][11][12] show. Actually, the use of telemedical devices is restricted to the ECG-recording for the diagnosis of palpitations, presyncopes and syncopes in the context of therapy control after treatment of heart arrhythmias and implantations of cardiac pacemakers. Used technologies are ICDs, event-recorders and pacemakers [13][14][15]. They reached a high degree of recording quality by now [16]. But telemedical devices reveal a lot of weaknesses if they are preferred for vital sign acquisition at home; they are subject of numerous restrictions as listed below:

- the patient has to use them autonomous at deterministic points of time – uncomfortable and untrustworthy for critical vital signs
- restriction of user's mobility and autonomy, if body attached sensor-networks are applied
- stigmatization of the user
- user may reject or have reservation towards the system, because camera-based systems imply an impression of observation to the user

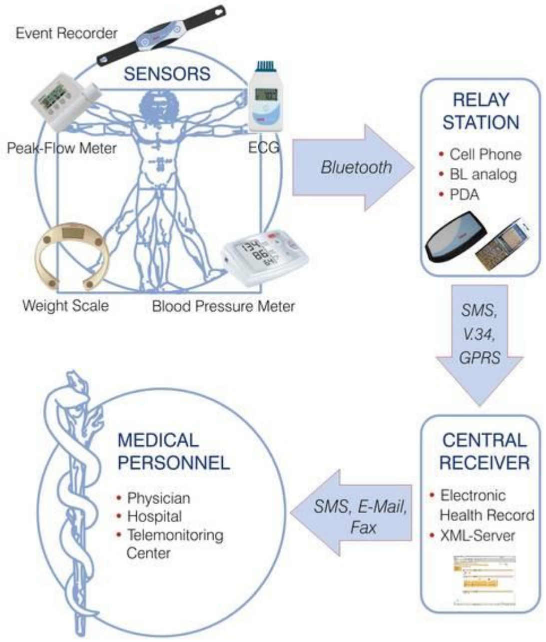

Figure 2. Telemedical devices [17]

In addition, the detection of paroxysmal or the first occurrence of AF is even more difficult, because telemedical devices are usually installed in relation to the anamneses.

Therefore and considering the aspects listed above, we decided to implement contactless, unobtrusive and non-invasive measurement devices as described in section III.D. Telemedical devices as depicted in figure 2 are an extension enhancing continuous vital sign monitoring implemented within the assistance system.

III. Related Work

A. *Assistance systems in the context of AAL*

Many research projects were launched, which address the domain of ambient assistance with totally different concepts and scopes for the recognition of life patterns or respectively, *ADLs – Activities of Daily Life*.

For example, the multinational research project *AMIGO* picked out the design and the development of a scalable, open and interoperable middleware for the fusion of diverse data sources like home automation components, consumer electronics, mobile devices and personal computing in a kind of a home networking infrastructure to gain information and obtain context data for user's benefit [18]. An alternative approach combines information and communication infrastructures of smart buildings and telemedicine devices in order to provide social and medical services within the familiar environment of the user [19]. Closed meshed maintenance servicing through ambient technologies, linked communication services to external institutions such as hospitals and a tight supervision by medical or custodial attendants is the purpose. The project *SmartSenior* is also focused on the demands of elderly people and the facilitation of their daily tasks. But this approach is not only restricted to home care scenarios but deals also with mobile, ubiquitous services just such as emergency detection within a car including vital sign transmission. Expanded automatic location services are used to increase the impartial and subjective safety of the user [20]. The project Ambience [21] is focused on the development of system architectures for context aware environments relating to home and professional indoor domains under inclusion of natural interaction, adaptivity to user behavioral, identification and tracking.

Our proposal, the research project *AAL@Home* is engaged with the design and implementation of a user centered assistance system, which originates from the mergence of signal processing and time series analysis of environmental process data, gathered by distributed sensor networks, as the precondition for probabilistic modeling of user situations [22].

B. *Description Logic*

We are using Description Logic in order to represent knowledge in general. This includes the transfer of gathered higher knowledge about the addressed domain between the sedentary assistance system and mobile knowledge bases integrated in handhelds for synchronization (refer to figure 3).

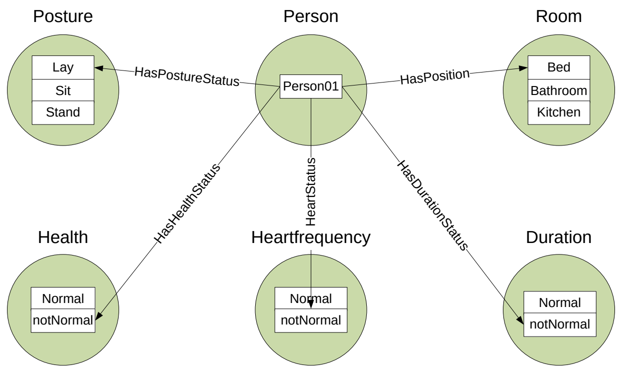

Figure 3. Ontology example

Additionally, parametric information such as system configuration files and preference data related to the user like the digital health record or other a priori knowledge is represented by OWL ontologies. In 2004 the OWL recommendation [23] has been released by the World Wide Web Consortium W3C. The acronym OWL stands for Web Ontology Language. OWL pursues as an enlargement of RDFS (RDF Vocabulary Description Language [24]) the goal to allow for complex ontologies offering a good compromise between computational complexity and decidability. The W3C offers three dialects supporting modeling of knowledge representations with different expressional capabilities. We use OWL DL which is a subset of OWL Full. OWL DL is based on Description Logic and represents a decidable subset of predicate logic for this reason [25]. Description Logics forms a family concept of sublanguages. The OWL DL semantics bases on the expressive Description Logic *SHOIN(D)* subsuming *ALC* (Attributive Language with Complement) and transitive roles (r^+); $ALCr^+$ is abbreviated by *S*. Further elements are *H* (role hierarchy), *O* (nominals), *I* (inverse roles), *N* (unqualified number restrictions) and *D* (data types).

C. *Unobtrusive vital sign acquisition*

Contactless measurement procedures for the acquisition of health parameters are essential for user acceptance as mentioned in section II.B. Hence, we prefer a m-sequence ultra-wideband radar for the discreet measurement of respiratory rate, heart rate and the detection of position and composure (refer to figure 4).

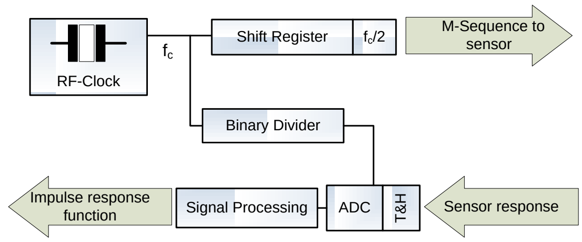

Figure 4. Scheme of baseband m-sequence radar [28]

Helbig and his colleagues broached the issue of UWB-radar for the analysis of organic tissues through the evaluation of the characteristic material-specific dielectric contrast [26]. Another approach deals with the usage of an UWB-radar for the robust indoor-tracking [27], which enables the localization of mobile and static objects through massive walls. Vital signs like breath rate are detected through UWB-radar components described by [28]. One approach deals with the combination of ultrawideband radar with magnetic resonance imaging as a new concept for multimodal biomedical imaging, a nice idea for our approach to generate context for the detection of periodic signals [29].

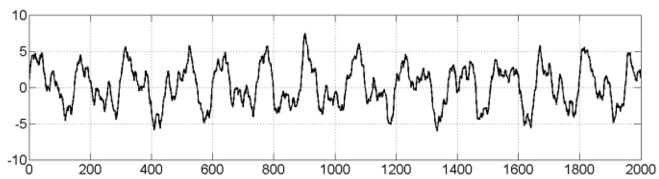

Figure 5. Extracted UWB-signal relating to signal propagation time

Actually, we are using an UWB-radar device with a bandwidth of 3.9 GHz, one transmitting antenna and two receiving aerials for heart rate detection. This sensor network is integrated within an armchair and additionally within a test bed. For the measurement of respiratory signals over a distance of nine meters, the mounting of antennas within the habitat at walls is sufficient. The measurement of oscillatory vital signs relates to the mapping of bioelectrical values to the superposition of mechanical quantities, caused by the expansion of the heart muscle and the upheaval of the thorax through the expanding lung. An example of a sum-signal of the UWB-radar, relating to the time domain and scaled in fractional, is described in figure 5.

D. Probabilistic Modeling

The work of [30] seizes the idea of developing software agents for spatial and temporal environments. Thereby models for spatial and temporal states are described with Hidden Markov Models (HMM) and relational state descriptions in order to recognize and interpret situations. The decoding of several sequences of system states [31] by using Markov Networks follows the aim to detect activities by the evaluation of sensor networks; inference processes are referring to a MCMC-algorithm. A successful approach is the hierarchical expansion of dynamic Bayesian networks as proposed in [32] and [33]. The theoretical aspects of Hidden Markov Models (HMM) and its application to a selected area are based on [34]. A framework for tracking and predicting attack int–entions based on HMMs is proposed by [35] and [36]. Methods for the initialization of HMMs in the context of human activity recognition are subject of the research of [36]. The recognition of residential persons within a mock habitat based on the probabilistic evaluation of sensor by HMMs is part of the work of [37]. The approximation of composure, motion and activity through HMMs is proposed by [38]. Our approach for situation recognition is described in detail in section IV.C.

IV. Methods and techniques

A. Main objectives when designing assistance systems

Human centered assistance systems offer situation dependent, possibly little or no perceptible services for comfort, health safety and security.

Our concept of an assistance system regards some additional essential tasks considering the integration of the user and his preferences:

- *Perception assistance*: The assistance enables the selective perception and individual visualization of complex user-/environmental situations.
- *Access assistance:* The assistance system supports the interaction between the user and his technical environment; the user can access cooperative, adaptive 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.

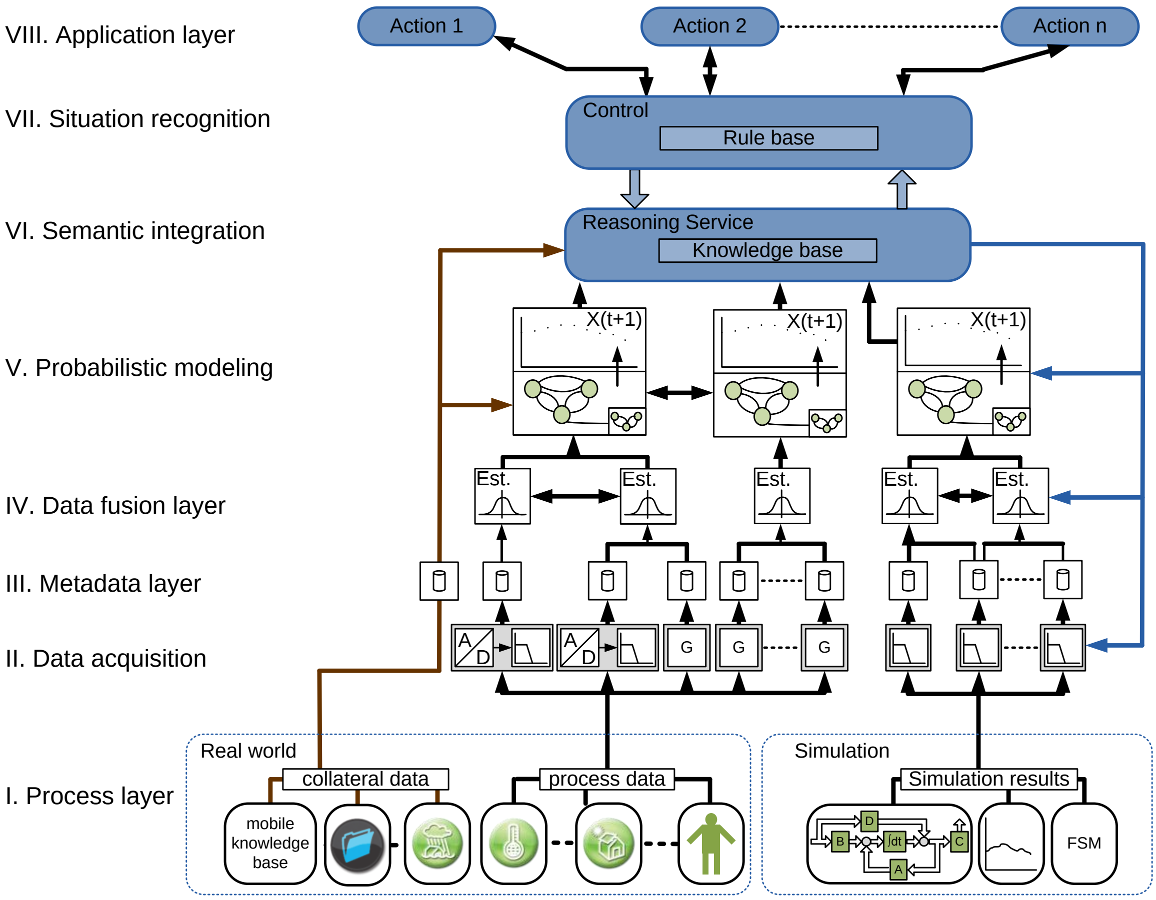

Figure 6. Architecture of the assistance system

B. Architectural approach 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 this propagated design is generic, adaptive to different use cases and may be gradually expanded when it's needed. The architecture is consisting of different layers reflecting the different degrees of gathered information and functionality (refer to figure 6).

The undermost layer of the middleware, the *process layer*, comprehends the real world or respectively the target environment and the simulated world, which consists of sensor emulators (if devices are not available), behavioral-, activity- and situation models for testing and validation. The information about the real world is differentiated by the character of the acquisition; the collateral data subsumes the a-priori knowledge about the process environment, configurations and parameter sets, user preferences stored within mobiles devices like Mobile Smart Nodes (MSN) and in addition, information from external service providers and communication links. This includes medical services for advice also. The process data consists obviously of representative physical values, collected through distributed embedded sensor devices such as UWB-radar components, telemedical devices like , home automation components and HCI-events (refer to table 2) and includes equi-spaced values as well as irregular measurement data.

Sensor devices	Extracted features
UWB-radar (integrated in a test bed and an armchair)	Respiratory rate, tidal volume, heart rate, extrasystole
UWB-radar (attached at walls in the mock habitat	Respiratory rate, posture, position, degree of activity
Telemedical devices	Weight, systolic and diastolic blood pressure, temperature, blood glucose
Home automation	Door and window events, room temperature, moisture, illumination level
HCI	User adjustments, fuzzy symptoms like dizziness, abdominal pain etc., alerts

Table 2. Process values and their features

The *data acquisition layer* contains proceedings and filter operations, which are needed to gain and transform the essential measurement signals obtained by discretization process without feedback effects like alteration or any loss of information. Additionally, we implemented reconstruction filters and interpolation methods for the evaluation of irregular samples. The *metadata layer* handles the mapping of the acquired process data and the unspecified part of the collateral information to a generic data structure, expanded with ad–herent metadata considering the characteristics of the selected system parameters like air moisture e.g. or other descriptive information. The *data fusion layer* offers a conglomerate of methods and techniques to derive higher knowledge for a higher level of integration from the basic information extracted in the lower layers or to increase the quality of these values. The estimation is based on proven practices such as Kalman filter or Bayesian estimators in order to gain more accurate and meaningful data for the following, restrictive cognitive procedures of the overlying layer or to extract additional features respectively information which cannot be represented by a single entity. Time series analysis (TSA) is utilized to detect trends in measurement campaigns of vital signs. Finally, emissions for the probabilistic modeling are the results of the data fusion layer.

The estimation of situations respectively of the internal hidden states of the system depends on uncertain process data and incomplete knowledge. Therefore, the layer of probabilistic modeling cares about the extracted emissions, a priori knowledge and configuration adjustments in order to estimate the inner states of the system. Considering the mock habitat, representing a typical dwelling of a senior, we use stochastic automatons for the localization of the user. We utilize adapted Hidden Markov Models for the estimation of the activity of the user for an optimal parameter selection (refer to V.A) and we use these Models for the preventive, continuous diagnosis by the evaluation of vital signs and trend data. In summary, we adopt discrete event systems (DES) according to the spatial and temporal environment of our assistance system (user and mock habitat) to approximate the most likely situation.

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. The situation recognition accomplishes the mechanisms of inference with complex control structures as an interface between the hierarchical, knowledge processing system and the ride-on applications. These structures are part of the rule base and defined either systemic or application specific. Systemic rules are static and depend on the characteristics of the process environment. 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 or diagnosis assistants, which decide about appropriate actions relating to the recognized situations.

V. Modeling scenario – CI-risk approximation

A. Activity dependent threshold selection

In respect to the detected user situation, vital sign threshold values are selected (refer to figure 7).

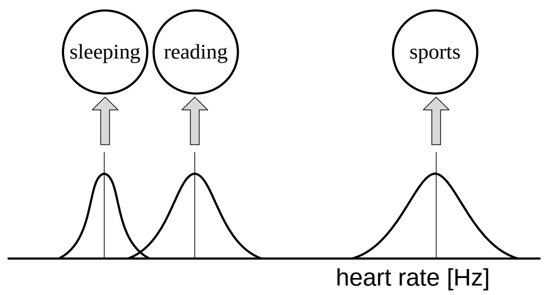

Figure 7. Parameter shift due to exposure

The boundary values relate to an anthropometric survey of the user resp. the subject who evaluates the mock environment for testing.

The boundary values are relative to the user's average characteristics which can be described by ordinary statistic parameters like mean and sigma. These parameters are activity dependent and shift obviously with the physical abilities and actual exposures. Concerning our introductory background of cardiovascular diseases, we have to model the risk of an acute heart insufficiency by a stochastic automaton. In addition to the stochastic automaton, we use the results of the time series analysis to control our probabilistic prediction mechanisms for security aspects.

B. Simulation model for atrial fibrillation

In this modeling scenario, we do not care about the loca-li–zation and activity recognition based on the probabilistic procedures in detail. The estimated activities are a result from a hierarchical HMM whose partial models address each room with a specified subset of corresponding activities marked by one or more asterisks (refer to figure 8).

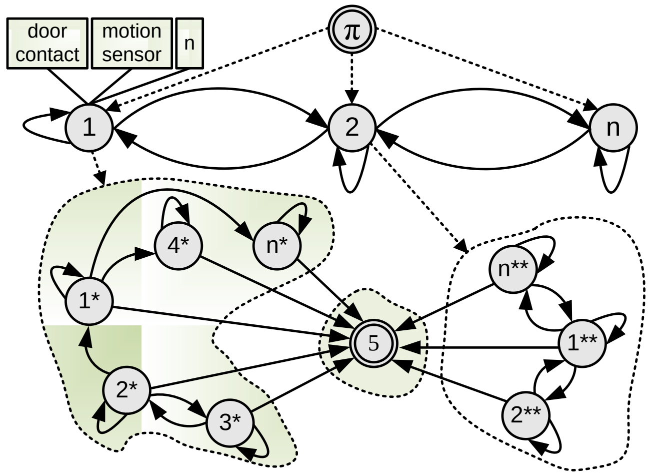

Figure 8. Concept of activity recognition

The bedroom, for example, is represented by a state in the localization model and holds a number of characteristic activities like sleeping or dressing. Of course, the transition and emission probability distributions for each model vary during daytime. Knowing the actual activity allows us to interpret the vital signs correctly as mentioned in the section before. The preventive diagnosis consists of a subset of partial HMMs which relate on the anamnesis of the particular patient: actual diseases and most likely diagnosis models are implemented.

For the sake of clarity, we developed a model consisting of four states in order to estimate the stages of AF (refer to figure 9). Atrial fibrillation can be classified by four different states, which relate on the duration and the instant of time of their occurrence. The HMM

$$\lambda_{AF} = \{A, B, X, Y, \pi\}, A = \{a_{ij}\}, B = \{b_j(k)\} \quad (1)$$

with the state space

$$X = \{NoAF, ParoxAF, PersAF, PermAF\} \quad (2)$$

prescinds the aetiopathology of AF in a comfortable and adequate manner. The state '$ParoxAF$' represents occurrences of AF which last for a maximum of seven days. If atrial fibrillation takes more than seven days, we assume persistent atrial fibrillation embodied through the state '$PersAF$'. If a cardioversion fails, we call the stadium permanent atrial fibrillation – '$PermAF$'. The initial probability distribution π for the model depends on the anamnesis stored within the digital health record and defines the starting state clearly without any ambiguity. The transition and emission matrices A and B contain coefficients which trace back to medical studies. Due to the fact that the actual estimation of a state might be an error, the emissions resulting from the feature extraction process gain much importance contrary to the emissions induced by the state duration.

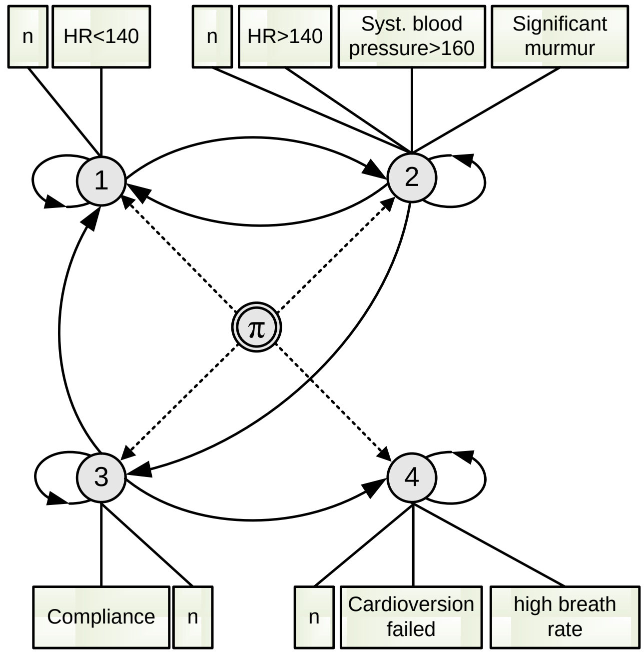

Figure 9. Partial HMM for the detection of AF

The alphabet Y containing single observables and their interconnections considers user input through HCI- components like the utterance of dizziness, headache or significant heart murmur as well as examined vital signs as high blood pressure and others:

$$Y = \{\mathrm{HR} > 140, Syst.\mathrm{bloodpressure}{>}160, \ldots\} \quad (3)$$

Therefore the change of the states depends on the relationship

$$P(Oq_t = x_j | q_{t-1} = x_i; \lambda). \quad (4)$$

Observing a sequence of emissions like an increased heart rate or an increased systolic blood pressure or a combination of these indicators, we compute the probability for such a sequence in accordance to

$$P(O|\lambda) = \sum_{n=1}^{|X|^{|Q|}} \prod_{t=1}^{|Q|} P(o_t = y_j | q_t = x_j, \lambda) \cdot P(Q_n|\lambda). \quad (5)$$

While transition and emission coefficients for the localization and activity modeling vary during daytime, the coefficients for modeling AF are constant at the moment and depend only on individual traits of the patient and measurement campaigns. It should be noted that the observation sequence

$$O_{To} = \{o_1, o_2 \ldots o_{To}\} \quad (6)$$

contains not only single observables but also refers to conjunctions of these when they occur simultaneously like

$$O_i = (HR > 140) \cap (Systbloodpressure > 160). \quad (7)$$

Training data like automation events from real data sources is evaluated by established techniques like the Baum-Welch which is a type of EM-algorithm. Real data is used for training and also for evaluation of the models.

The computation of the most likely state sequence – with decimation effects regarding the big time constants of steric processes follows from the Viterbi-algorithm:

$$\delta t_{(j)} = \max_{q_1,q_2 \ldots q_{|Q|}} P(X_t, X_{t+1} \ldots X_{To}, O_t \ldots O_{To}|\lambda) \quad (8)$$

$$\delta_1(i) = \pi_i b_i(k = o_i), 1 \leq i \leq |X|, \psi_1(i) = 0 \quad (9)$$

$$\delta_t(j) = \max_{1 \leq i \leq |X|} [\delta_{t-1}(i) a_{ij}] b_j(o_t), \quad (10)$$

$$\psi_t(j) = \operatorname{argmax}_{1 \leq i \leq |X|} [\delta_{t-1}(i) a_{ij}] \quad (11)$$

The estimation of the actual AF-stage gains the emissions for the Hidden Markov Model for the approximation of the risk for cerebral insults

C. Simulation model for cerebral insult

The partial HMM for the estimation of the risk of cerebral insult is structured as an escalation chain with different degrees and coherent security reactions by the assistance system. Simplifying medical relations we use a reduced model to validate our approach. The HMM-graph shows the abstracted model with an also reduced subset of emissions, abbreviated by "n" with the absorbing state "acute cerebral insult" which induces instantaneous interventions like the application of anticoagulants and the direct emergency call to hospitals and doctors (refer to figure 10).

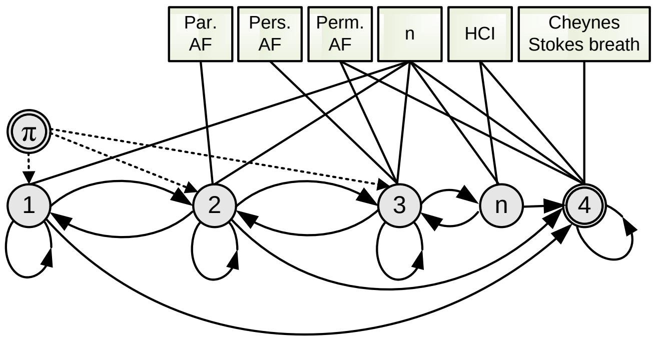

Figure 10. Partial HMM for the detection of CI-risk

The five stage exemplary model for CI-risk consists of

$$\lambda_{CI} = \{A_{CI}, B_{CI}, X_{CI}, Y_{CI}, \pi_{Ci}\}. \quad (12)$$

with the state space

$$X_{CI} = \{No_{Risk}, Low_{Risk}, Med_{Risk}, High_{Risk}, ActCI\}. \quad (13)$$

The estimated stages of AF are treated as emissions and are therefore a subset of the alphabet Y_{CI}.

$$X_{AF} \subset Y_{CI} \quad (14)$$

Additionally, analogous to the approximation of atrial fibrillation, we evaluate vital signs and much more important, user input via HCI-devices. Dizziness and impaired visions are most significant indicators for an acute insult, an urgent case initiating an immediate reaction. Therefore, this state is modeled as an absorbing state. When acute cerebrovascular accident is detected, immediately life saving measures should be initiated and nursing service, infirmary and emergency physician will be notified. In general, reactions of the system are scaled by the degree of the most likely risk for cerebral insult. Possible actions of the assistance in the case of a successful detected high risk for apoplectic stroke would be a preventive administration of anticoagulants to avoid serious aftermath for the patient. The initiation of emergency calls to connected, medical institutions is another feasible step to protect the patient from greater harm. The notification of the doctor might be an adequate sanction if peculiarities expressed by low or medium risks are identified. The approximation of the most likely state sequence or health situation is also done through established procedures as introduced before. Training data for emission and transition probability distributions results partially from real medical data and medical relationships based on clinical trials and is evaluated through Baum-Welch algorithm. Another part of training data is based on assumptions reinforced by physician's advice.

VI. Discussion of the results

The assistance systems cognitive abilities are based on probabilistic modeling as introduced in the section before. There is a cascade of assumptions for the identification of different situations required. First of all, it is necessary to locate the person within his test environment. We are using a lot of different sensor types with different physical principles under consideration of a varying number of devices respectively a variable sensor density. This regards unequal demands of the prospective user and their financial background. Of course, the highest density of devices provokes the optimal rate of correct localization (refer to table 3).

Sensor density	Average localization rate
Basic (+Actuators & Sensors of the home automation)	71.63 %
Enhanced (+motion sensors)	85.74 %
Premium (+UWB-radar)	99.34 %

Table 3. Partial HMM for the detection of CI-risk

Given that the localization was successful, the situation recognition works robust and reliable enough to select the best fitting parameter set for vital sign analysis. During the daytime, we observe a significant deviation in the recognition rate (refer to table 4).

Detection window	Average activity recognition rate
0:00 – 2:00	99.89 %
2:00 – 4:00	99.82 %
4:00 – 6:00	99.78 %
6:00 – 8:00	87.57%
8:00 – 10:00	85.21%
10:00 – 12:00	84.17%
14:00 – 16:00	82.29%
16:00 – 18:00	84.93%
18:00 – 20:00	84.79%
20:00 – 22:00	97.34%
22:00 – 24:00	98.45%

Table 4. Average activity recognition rate

This is a direct result from the discriminative complexity of the different activity models which are corresponding with each room and time. Obviously, a HMM for activity recognition with coefficients extracted from training data collected over a period from 0:00 – 2:00 do not leave much room for fuzziness; the test person rests usually in his bed. This can be validated through embedded UWB-devices which record vital signs continuously. By day, fuzziness increases due to the fact that there may be gaps in the observation chain; the complexities of the activity models are much higher and measurement techniques like UWB-radar are much vaguer. The measurement of heart rate works only reliable if the person is aligned towards the sender components because we are measuring a mechanical signal e.g. the upheaval of the thorax as substitutional for the lung extent. In addition, the detection of vital parameters of a moving person is very difficult. This is also a fact to concern if vital signs are evaluated for the approximation of diseases or risks for health as described in the section before. If we are validating our models with simulation data based on medical information, we gain a mathematical and methodical accuracy of 32.27% correct detected risk stages regarding an average correct detection rate for AF of 68.03%.

VII. Conclusion and further steps

It was introduced a human centered assistance system for the unobtrusive support of elderly people with special demands in their familiar environment and a first modeling example. This assistance system implements a continuous vital sign monitoring as a basement for a preventive diagnosis mechanism focused on cardiac diseases. Heart insufficiency and in particular in this paper, atrial fibrillation take a central position for further considerations. The generic approach of the system architecture allows a mapping to all the medical problems which can be expressed as stochastic state models.

As a precondition, the activity recognition works reliable due to the high amount of embedded sensor devices and provides adequate parameter set selection. Nevertheless, when activity recognition fails, correct parameters were chosen in the majority of cases because most of the activity patterns are very similar to each other. Therefore, the exposures are almost identical and the selected boundary values are valid. The preventive diagnosis works well if well suited models were selected. Unfortunately, some sensor devices are premature which causes gaps in the vital sign acquisition. Respiratory measurement works over a distance between sensor and subject about 9 meters. Heart rate can be only measured in near of the sensor which is regularly embedded within an armchair or a bed. The detection of heart arrhythmias is difficult at the moment and needs to be improved. In addition to the incomplete state of signal processing and feature extraction we need to calibrate the models through complete medical measurement campaigns and empirical investigations to get a valid set of HMMs for the detection of AF, regarding individual traits of different patients.

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