

Automated Assistance Services

Experience from the SmartSenior Project

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Abstract— Ambient Assisted Living (AAL) addresses the drastic demographic change of today’s modern world and motivates further research on the necessary technological steps for offering sufficiently sensitive and appropriately responsive smart environments in the near future. Thus, enhancements and permanent improvements of technology in the AAL domain result in the sustainable development of new software and hardware platforms for suitable automated assistance services, bound to relevant business models. In this paper, an innovative, practicable technological approach for a future automated assistance service is presented, covering several currently open issues: (1) incomplete sensing, (2) insufficient communication techniques among human beings and smart environments, and (3) lack of situation-awareness of assistance services. To solve these problems, we propose the following: usage of gas sensors in smart environments, an intelligent wristwatch for people in smart environments, and the implementation of new software algorithms for improved automated situation understanding and further assistance support. These components will be offered together with currently existing products for a qualitatively new technical automated assistance system.

AAL, Situation Understanding, Gas Sensor, Intelligent Watch, Complex Event Processing, Abductive and Temporal Reasoning, SmartSenior Project

I. INTRODUCTION

In response to the dramatic growth of the elderly population in Germany, the nationally funded project SmartSenior [1] aims at developing and evaluating near-future systems to provide the elderly with a safe and comfortable everyday life, including just staying at home and driving somewhere else. The system is designed to work for both relatively healthy individuals as well as those having some physical disabilities or medical liabilities. The diversity and breadth of these scenarios and the proximity to real life make the target challenging, assuming the use of various medical devices, different home and mobile systems, heterogeneous and data-rich (i.e. smart) environments. Technological enhancements and permanent improvements in the domain of Ambient Assisted Living (AAL) result in the sustainable development of new software and hardware platforms for appropriate automated assistance services, bound to relevant business models. This paper aims at

the description of our derived experience from the project SmartSenior, combining new sensor systems and software algorithms with existing related products to implement qualitatively new technical systems for automated assistance services.

A. Critical Issues of Automated Assistance Services

As asserted in [2], one of the core functionalities of any AAL system is the conclusion of knowledge about the user activities and the current situation in the environment from low-level sensor data in order to plan appropriate short-term and long-term reactions. It is especially necessary when assisting elderly people, where prevention from possible dangerous situations and prediction about health-related conditions is still an open and serious issue. Reactions on situations and activities to be recognized are based on situational scenarios that have to keep reasoning systems within automated assistance services safe for users and preserve the relevancy of reactions to recognized situations respectively. Using this kind of “situation understanding” allows the conclusions on reactions to be performed mostly automatically, taking into account the whole range of available information. In automated assistance services, it is generally done either on a home automation platform or on a user specific smart phone, where available information from smart environments is continuously collected in real time.

However, in reality, any perception about situations without video cameras due to ethical norms is quite restricted and does not usually meet appropriate expectations. Likewise, very often it is required that the user be allowed to decide for himself about whether an interpretation about his activity or proposed reaction is correct and to give some relevant feedback to the responsible automated system about the quality of recognition and proposed reaction. Another issue concerns a software module responsible for the intelligent interpretation of raw sensor data and correlation among different heterogeneous sources of information. It is usually not very flexible for the introduction of new situation scenarios and applications and requires a lot of time for appropriate calibration under specific conditions. Besides, when it comes to product implementation, data privacy and security issues have to be carefully examined.

We thank the German Federal Ministry of Education and Research (BMBF) for funding the project SmartSenior and for giving us the opportunity research and develop AAL systems.

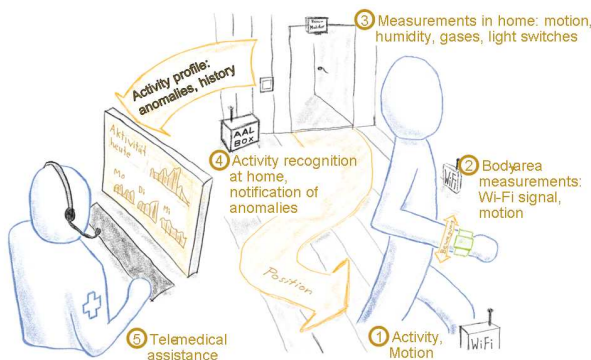


Figure 1. Remote Activity Monitoring Scenario (from [13])

Therefore, in order to provide a feasible, but comprehensive solution for automated assistance services, we address the following questions in this paper:

- What are the benefits of the utilization of gas sensors in smart home environments?
- Is the use of an intelligent wristband to be used by users in not only reactive, but also interactive intelligent environments?
- What are the new challenges for software algorithms providing situation understanding?

B. Use Cases from the SmartSenior Project

The objective of the SmartSenior project is to ensure that the growing number of senior citizens could live longer and independently, while receiving optimal care. The project has three central focuses:

- Remaining safe and allowing for mobility;
- Staying healthy / quick recovery;
- Achieving independent life in a home environment.

Therefore, the idea of automated assistance services becomes of the most importance to be implemented for smart environments. The main expectations about such functionalities are quite obvious: (1) to correctly detect situations, (2) to be able to offer possible assistance to users in a broad meaning of this term, and (3) in case of uncertainty about the decision to be made, it should be possible to interact with the user in a low-key manner.

Here we present some of the most current scenarios discussed in the project:

- Automated management of household appliances, e.g. by switching on/off various devices;
- Intelligent monitoring of household appliances, e.g. by a reactive notification about possible failures;
- Proactive nursing service, e.g. by an automated call to a remote assistance center when necessary;

- Proactive medical service, e.g. by an automated call to a remote telemedical center if a heart attack is recognized;
- Preventive/predictive telemedical assistance, e.g. by an indication about a possible health deterioration.

Thus, the key functionality of an automated assistance service is the remote monitoring of the activities of daily life, including a detection of anomalies (e.g. in human behavior or even in some properties of a smart home environment). The proposed general scenario for an automated assistance service as discussed in this paper is shown in Fig. 1.

Presence/absence in a car, in an apartment, or in a particular room, drinking liquids or preparing meal, pushing an emergency button, or sudden downfalls are only some of the activity examples which may be recognized. Detected activities will not just be evaluated temporarily, but also cached by the automated assistance service for further recognition of temporal or sequentially dependent activities. Besides that, stored information about detected activities is also needed for statistical purposes. Those statistical data are especially useful in the evaluation of so called “Activities of Daily Living” (ADLs) [3]. Information about ADLs is then exploited by evaluation tools such as the Katz ADL scale [4] or the Lawton IADL scale [5]. To learn more about this subject, please refer to [6] and [7]. To determine how independent an elderly person can perform in his everyday living, the Barthel scale (also called Barthel ADL index) is used, which is a scale used to measure performance in basic ADLs [8]. It uses some certain variables to rate the performance of an individual. A higher score is associated with a greater likelihood of being able to live at home with a degree of independence, allowing, for instance, a discharge from a hospital. The activities captured by our system will be used for achieving independent life in a home environment, referring to the scenario of preventive/predictive telemedical assistance.

II. AUTOMATED ASSISTANCE SERVICE APPROACH OVERVIEW

Automated assistance services are one of the key components of a comprehensive complex technical infrastructure for smart environments. They have to deal with both humans and their environment, persisting information and providing appropriate reactions either to environment, to a human being or to other additional services as mentioned above (e.g. telemedical assistance). Obviously, a way of interaction between a human and her environment, so that uncertain issues could be clarified without any external help, is also desired.

In order to overcome typical daily obstacles for a real deployment of such kind of automated assisted services, we follow the following approach (see Fig. 2):

- Besides deployment of typical house sensing techniques, such as temperature, humidity, pressure and contact sensors, we also use gas sensors as necessary components of smart environments and most “productive” sources of perception. Thus, the analysis of gas sensor data should be computationally coupled to usual sensors for situation understanding purposes;

- An intelligent wristwatch performs both roles of additional sensing about human activities (e.g. deploying an accelerometer there) and an additional communication interface functionality with an automated assistance service (i.e. messaging and feedback functionality), therefore providing an effective interactive mechanism among humans and their environment;
- Specific model-based reasoning methods are implemented: rule-based temporal reasoning and ontology-based abduction for further automated hypothetical analysis and “easy” calibration during technical maintenance of an automated assisted service in specific environments.

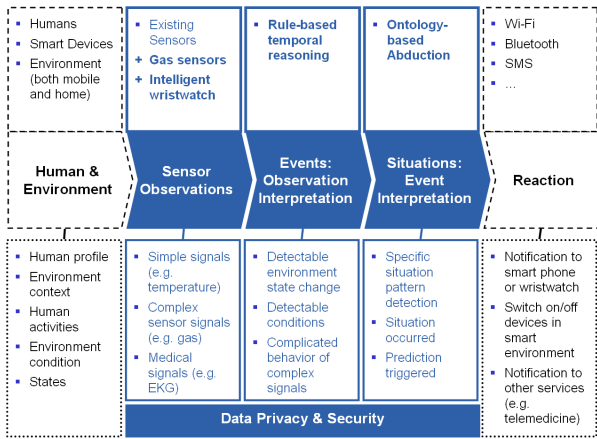


Figure 2. Approach for Automated Assistance Services

Details on the proposed enhancements and improvements of this new approach are presented in the following chapters.

III. ENHANCED PERCEPTION FUNCTIONALITY

A. Usage of Gas Sensors in Smart Environments

Gas sensors are already widely used for the detection of events and activities on more technical levels like leak alarms or fire detection [9]. The ability to recognize human activities with the help of gas sensors has also been shown with different sensor technologies and signal evaluation approaches [10, 11]. For our approach we combine a metal oxide gas sensor, which shows excellent response to human induced Volatile Organic Compounds (VOCs) [12] with both rule-based temporal reasoning and ontology-based abduction algorithms for data evaluation (see below).

Commercial micromachined metal oxide based gas sensors (AppliedSensor type AS MLC) have been investigated for their usability in the field of detection of human activity. The principle of these classical semiconductor gas sensors is depicted in Fig. 3: a suitable metal oxide based gas-sensitive layer is heated to temperatures of several hundred degrees Celsius to become semiconducting. Due to gas interactions, the electronic conductivity changes reversibly with the partial pressure of reactive gases P_{gas} in the ambient. The sensor

signal is represented by the electrical resistance between the sensor electrodes $R(T, P_{gas})$. Metal oxide gas sensors react to a large variety of gases and show limited selectivity to single components. Depending on the chosen sensing layer and the operation temperature, the sensitivity and selectivity of can be adapted. Since the nature of the chemical components, which have to be detected in the context of human activity monitoring is not well defined, a temperature modulated operation is used to separate different chemical classes.

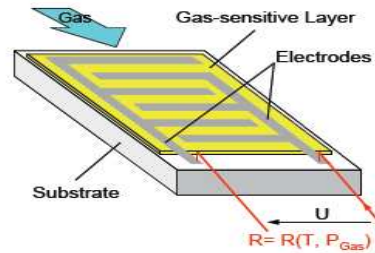


Figure 3. Schematic depiction of a metal oxide gas sensor as used in this work

This sensor type has to be heated up to temperatures from 200°C to 350°C and suffers therefore from relatively high heating power consumption in the range of 30mW. Therefore, a new operation mode for this type of sensor has been developed, which enables an operation with a reduced overall heating power below 1mW. To achieve this extreme reduction in power consumption, the sensor heater is activated only periodically. In addition, the sensor data recorded in this way allows a significantly more stable and reliable detection of activities. For the use in real life environments, a microcontroller-based sensor module for the temperature modulated operation has been designed (see Fig. 4). The gas sensor module features one micro machined tin-oxide gas sensor (see Fig. 4 left). It is equipped with a MSP430 (Texas Instruments) microcontroller and a GainSpan GS1011 low power Wi-Fi module transmitting data within an automated assistance service and further as results of an intelligent analysis sent to further services as appropriate and relevant situation to various services respectively. An additional passive infrared motion detector is used to indicate movement of persons (see Fig. 4 right).



Figure 4. Gas sensor (left), gas sensor module board (middle), and housing (right) as implemented in the SmartSenior project

The sensor response in temperature modulated operation results in a set of 90 data points recorded at different sensor temperatures with a time interval of 10 ms each (see Fig. 5). Each data point corresponds to the sensor resistance at a specific sensor temperature with a specific gas response. In this

way, a virtual sensor array is created, allowing the distinction of different gaseous substances.

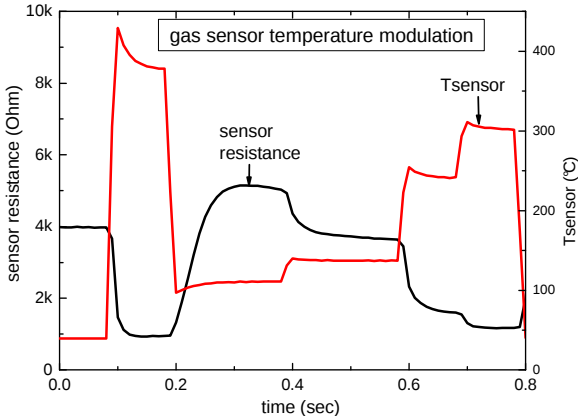


Figure 5. Gas sensor signal example: response in temperature modulated operation.

The responses of several temperature modulated gas sensors in a test apartment are shown in Fig. 5. The sensors respond clearly to the number of people in the room, if windows are opened or by cooking.

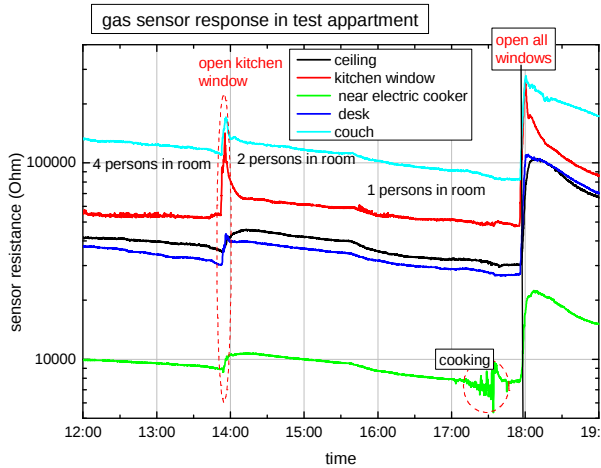


Figure 6. Examples of gas sensor signals analysis in a test apartment related to different human activities

As mentioned already, data from gas sensors should be coupled computationally to the other sensors used for situation understanding purposes, as later discussed in Section IV.

Within the SmartSenior project, gas sensors have proven to deliver the most appropriate information in the following daily activities: absence/presence of a person, drinking/eating, cooking, ventilation, sleeping, and the number of people within a specific space (i.e. in a room).

B. Intelligent Wristwatch for Users of Smart Environments

In addition to sensors in the environment, the user can be equipped with a body-area sensor and interaction device. An intelligent wristwatch is a necessary element in smart environments, providing the following: (1) additional sensing about human activities (e.g. by deploying an accelerometer there), (2) possible aggregation of healthcare information from medical devices (e.g. ECG), and (3) an additional communication interface functionality with the automated assistance service (i.e. messaging and feedback functionality);

This is all in the form of an intelligent Wi-Fi wristwatch, shown below in Fig. 7, first described in [13], from which an excerpt follows. Further applications are described in [14].



Figure 7. User interface design study of wristwatch

This intelligent wristwatch is the size of a normal wristwatch and is designed to look non-stigmatizing, so it can be worn as an everyday watch by healthy users as well. The main visual difference to a classical wristwatch is a large color OLED (Organic LED) display, which can show short text messages and four buttons, allowing simple menu navigation. Two additional side buttons, when squeezed simultaneously, signal a call for help.

The wristwatch has a 3-axis inertial sensor, used for activity detection, and can measure Wi-Fi signal strengths for rudimentary simple indoor positioning.

As shown in Fig. 8, the wristwatch functions are partitioned into two blocks, with a separate microprocessor for each.

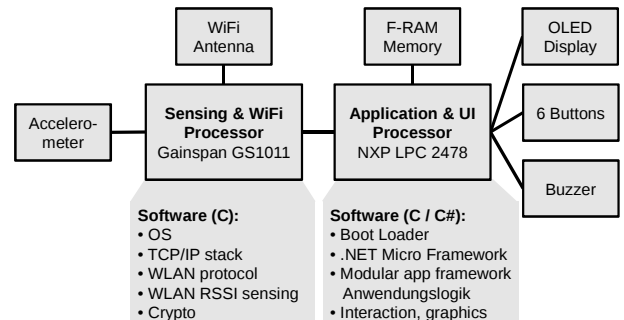


Figure 8. Functional blocks of the wristwatch

1) Sensing & Wi-Fi Processor

The first block is for sensing and Wi-Fi. It receives data from the inertial sensors and Wi-Fi signal strength measurements, and transmits them via Wi-Fi. This block, by

itself, already allows basic sensing and monitoring functionality, even without interaction, and can be used to build other, smaller devices. It uses a GainSpan-SoC with two ARM7 cores and is programmed in embedded C.

2) Application & User Interaction Processor

The second block is for applications and interaction. It controls the OLED display, responds to buttons and executes complex applications. It uses a second ARM7 processor running the .NET Micro Framework and a custom framework for loading and running customer-specific Apps written in C#. For example, a rehab clinic could develop their own custom application combining a reminder service for scheduled treatments and a recommender for value-added services on site.

3) Interaction

A crucial success factor for the wristwatch is a simple and pleasing interaction, suitable for users of different ability levels. Some features, such as the emergency button and of course time display, are designed to be usable by all users, even with slight motor or visual impairments. Other features, such as complex apps, are also possible.

Fig. 9 gives an example for such an interaction logic designed for privacy issues: a privacy mode without sensor activity can be activated and the status of privacy mode can be displayed for more transparency.

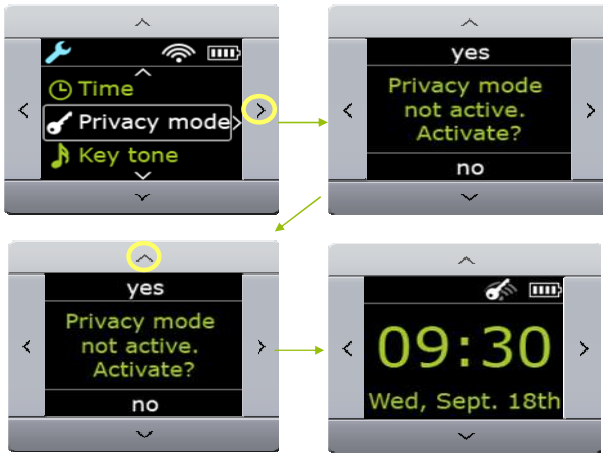


Figure 9. Interaction logic for privacy mode

IV. NECESSARY REASONING ALGORITHMS

Some efforts for situation understanding without using video recognition systems have already been performed based on various reasoning algorithms. For instance, both [15] and [16] give a comprehensive overview of existing techniques and of specific probability-based methods as well. In [17] another technique can be found, where the usage of ontology-based algorithms is exploited. The major disadvantage of all previously proposed methods is in applying them. It is focused not on their benefits, but on the attempt to cover all necessary steps and functions of a situation understanding with a single technique. We assert that any usage of reasoning algorithms have to be defined precisely by using either appropriate model-based logic formalisms for knowledge representation and/or

data-driven techniques for mathematical functions implementation. A variety of math and logic families has emerged; each of these languages/algorithms is designed to solve particular aspects of reasoning. Very often the focus is primarily on the expressivity of modeling languages for appropriate algorithms and methods, thereby neglecting the impact that expressivity has on the performance of reasoning algorithms and the facility to integrate these formalisms into industrial applications. Due to these problems, very few applications of situation understanding techniques have been successful in real environments.

Therefore, our approach of necessary reasoning algorithms for situation understanding is based on the idea of the “Logic-on-Demand”, presented already in [18]. It is supposed to overcome the typical problems of application of reasoning techniques, by accommodating the expressivity of the appropriate logic languages to the varying needs and requirements, in particular with respect to decidability (i.e. whether an algorithm terminates on any input and yields always correct positive and negative answers). Here we address only the utilization of model-based reasoning techniques for situation understanding as the only most preferred way to overcome both problems: (1) with the software system calibration at the beginning of the automated assistance service maintenance and (2) with an “easy” modification of situation scenarios during system lifetime in operational mode.

To achieve this for our purposes, we distinguish between the following components:

- Model-based implementation of threshold and trend analysis for simple and complex sensor data, where rule-based temporal reasoning can be efficiently used for the pre-analysis, taking into account time constraints and temporal dependencies. Output is a set of events, about activities of a human and situations in a smart environment;
- Model-based implementation of hypothetical analysis of various sensor sources correlation, where ontology-based abduction used as additional reasoning mechanism for the first component. As input it receives recognized activities and situations (i.e. events) from the first threshold and trend analysis. As output it provides results of automated interpretation about possibly incomplete and uncertain information due to the situational scenarios definition.

Both components express their knowledge in a declarative way, using formal logic representation formats: rule-based and ontology-based. This model-based nature has the following advantages in comparison to classical data-driven methods: (1) the possibility to use generic problem solvers, which are independent of a specific functionality of the situation understanding; (2) the explicit representation of situational scenario definitions and additional constraints in a formal model and their easy modification even by a non-programmer; (3) if changes or modifications are necessary, only models (i.e. situational scenario definitions) need to be changed. Nevertheless before providing discrete logical structures as model-based approach we have to apply some arithmetic calculation to the raw sensor data as well, known as sensor data

processing. Very roughly, the architecture of the provided software system for situation understanding is represented in Fig. 10.

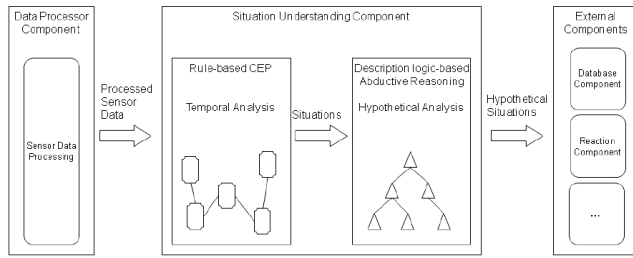


Figure 10. Architectural Blueprinting of the Situation Understanding Component

A. Sensor Data Processing

Basically, there is no difference whether a simple sensor (e.g. contact sensor or motion detector) or, as in our case, a complex one (such as the accelerometer in the intelligent wristwatch or a gas sensor) is used to collect the data. In both cases the sensor is required to process the raw data so that the reasonable interpretation would be possible. The difference is the way to provide normalization step, which is here called as sensor data processing.

The raw values of both an accelerometer and a gas sensor are not self-explained as temperature or humidity and require some mathematics to be performed.

1) Accelerometer

3-axis inertial sensor provides three values, where X axis responsible for left and right side from the display, Y – for top and low part, and Z – for perpendicular movements about the wristwatch. In quiescent mode the signals look as presented in the Fig. 11 (upper part), where the graphic is only for one possible state of a display responsible – being lying on a straight surface, display is above. If there is any movement of a wristwatch, then both gravitation and external impact would be measured and represented as deviation to a normal state, i.e. a quiescent mode.

The lower part in Fig. 11 is an example of the specific event “drinking” which could be easy detected using only an accelerometer sensor. The way to describe any movement could be quite comprehensive using advanced methods from clustering, Markov-chains etc. For our purposes in the project we used very simple approach by providing a regression analysis.

If the regression line for the acceleration of the x-axis over a given time period (e.g. 2 seconds) below a given threshold value and is situated shortly above a given threshold value, based on a further period (here, the same 2 seconds), then the acceleration in the direction of the x-axis the observed, which is typical for the “drinking event” as assumed. The same is applied Z-axis as well. So, based on a signal processing we can generate various activity events and use them further for more complex situational analysis.

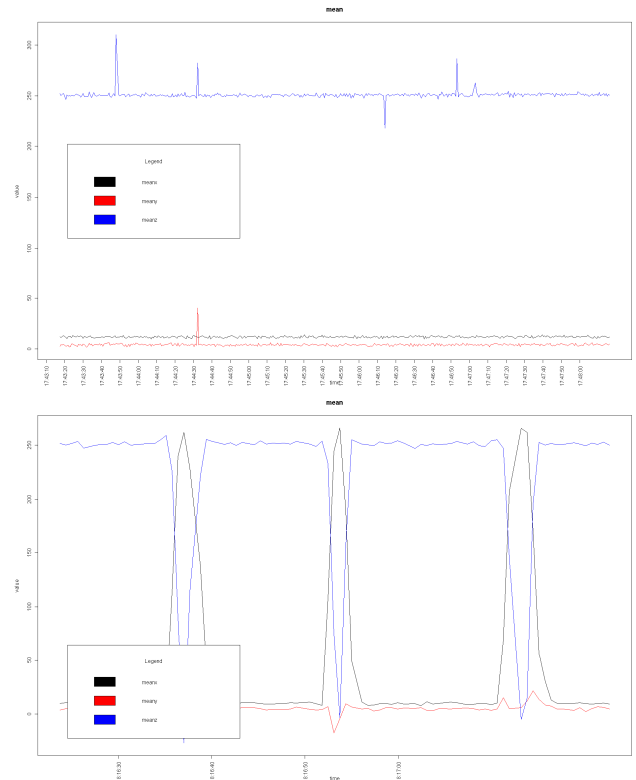


Figure 11. Signal behavior of an accelerometer in a quiescent mode and by drinking event

2) Gas Sensor

The gas sensor used in the project provides 90 values, which are mostly for further analysis redundant. The idea is to have three points in the fourth measurement point map. So we use regression analysis again using the "Least Squares Fitting". By dividing the chosen three values by the last one, we obtain a value close to 1. To improve the approximation to 1 further, we run another regression with a trial function of the temperature and humidity, as we suspect a correlation among measurements of gas sensors with temperature and humidity conditions. The results of a processing could be seen in Fig. 6.

B. Rule-based Temporal Reasoning

The usage of rule-based temporal reasoning for threshold and trend analysis of simple and complex sensor data for situation understanding is founded on its rich expressivity and declarative nature.

From [19] we know that rules correspond to Horn clauses in classical logics. They can be defined as follows:

- A literal is either an atomic proposition (such as `situation_presence_from_motion_detector`) or the negation of an atomic proposition (such as `NOT situation_presence_from_motion_detector`).
- A clause is a literal or a disjunction of literals, e.g., `situation_presence_from_motion_detector OR (NOT movement_kitchen) OR (NOT movement_bathroom)`

A Horn clause is a clause in which at most one of the literals is positive, as in the example above for `situation_absence`. In essence, by converting the disjunction into implications, we see that in a Horn clause a conjunction of zero or more literals implies either a non-literal or a single literal (the one that was negative). For the above example, this would be:

```
situation_presence_from_motion_detector ←
(movement_kitchen AND movement_bathroom)
```

Recall that a conjunction of non-literals is true. If there is no positive literal, then the conjunction of literals is false.

As it can be seen from the example above, this kind of a model is not complete, and requires an explicit reference either to concrete time points related to the events `movement_kitchen` and `movement_bathroom` or temporal relation among these events for an identification of an event ordered sequence. As well there is a need to define duration of the situation `situation_presence`: if there are no movements in the next e.g. 20 minutes, then an automated assisted service should guess that there is nobody at home, and previous sensor signals (e.g. from motion detector were simply uncertain). That is why our situational model extended with temporal constraints looks as follows:

```
situation_presence [20 minutes] ←
(movement_kitchen AFTER movement_bathroom)
```

Of course, the presented example is very simplified and in reality may involve: (1) various references to concrete sensor signals in form of their measurements; (2) mathematical functions as threshold (i.e. for simple sensors) and trend analysis (i.e. for complex sensors, see Fig. 4) for an appropriate interpretation of these measurements; (3) additional variable context information, as for instance, specific medical conditions or even patient acts.

C. Ontology-based Abduction

The example presented above would only work in an ideal situation, when all sensors provide correct and complete information, and situational models are properly defined. Unfortunately, this is not the case for real world applications where sensor failures happen regularly, or the connection to the server part is broken, and information is simply missing. Human factors play an important role: performing specific situational analysis and further relevant modeling of identified situation definitions is very time consuming and error-prone. The use of some well-known probabilistic methods (e.g. Support Vector Machines) is data-driven without declarative knowledge formalization. Therefore, we have chosen a so-called ontology-based abduction approach (i.e. abductive reasoning for description logics [20]), already described in [21] and [22].

Abduction is well known as a method for tentative diagnostic reasoning, where it provides automatically possible explanations for some observations according to inverse modus ponens rule:

$$\frac{A \rightarrow B \quad B}{A}$$

where in mathematical logic the major premise $A \rightarrow B$ is typically understood as an implication from A to B. Since there may be multiple alternatives and potentially contradictory explanations A_i for a given B, automated abductive reasoning aims at selection of optimal solutions among A_i based on some predefined preference function.

Let us consider an extended example from the above:

```
situation_presence_from_motion_detector [20 minutes] ←
(movement_kitchen AFTER movement_bathroom)

situation_presence_from_gas_sensor [20 minutes] ←
(person_number_kitchen > 1)
```

Both definitions can be considered as redundant, as they always define the same situation “presence” from either a motion detector or a gas sensor. An ontological model (additional to the above rule-based definitions) may look as follows:

```
situation_presence SubClassOf
(hasEvent some situation_presence_from_motion_detector
AND
hasEvent some situation_presence_from_gas_sensor)
```

When the situation “presence” is confirmed from both sensor sources, then the situation is recognized. But when only one sensor has given the information about “presence”, and another has not, then an automated assistance service provides an answer about possible situation “presence” and automatically explains the reason for the uncertainty. Thus, it can always be easily proven that a situational definition has been correctly provided (i.e. situational definitions debugging functionality) or that the reason why some situation is only probable (e.g. sensor failure, which sensor).

CONCLUSION

Already available automated assistance systems still face several open issue: (1) incomplete sensing, (2) insufficient communication techniques among human beings and smart environments, and (3) lack of situation-awareness of assistance services. In this paper, we have proposed a comprehensive solution for automated assistance services addressing these issues on the basis of complementary components:

- Gas sensors, which have shown very useful in smart home environments;
- An intelligent wristband to be used in smart home environments;
- Innovative software algorithms providing situation understanding.

The presented approaches still require further research and implementation in the following areas:

- Recognition of compound situations based on gas sensor data (e.g. sport activities, sleeping, parties, number of people);
- Complicated apps for wristwatch (e.g. local situation understanding app);
- Complexity issues of reasoning algorithms approached here (i.e. NP-hard in worst case).

We also would like to point out data privacy and IT security issues which need to be solved prior to the deployment of automated assistance services, which is one of the most important results in the SmartSenior project. A secure handling of personal data is not only a legal issue, but is also crucial for the acceptance of AAL solutions. This is especially important for home assistance services like the ones described in this paper, monitoring daily-life activities since this requires the collection and processing of large quantities of personal data, intruding hereby into people's privacy (see [24]).

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