Formal Representation for Sensor Data in Smart Home Environment

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Abstract

During the last decade we have been witnessing fast development in the area of sensor technologies and communications that have enabled applications within the Internet of Things (IoT). Subsequently implementations of systems for continuous monitoring of human´s vital parameters and daily activities started to appear. Since the ageing population is constantly increasing, the development of such applications is necessary. The growing number of sensor types and their producers introduces a problem concerning data formats and data representation. Sensor data representation is an important issue since we do not want to lose any useful information. Additional issue is the design of detection and evaluation algorithms. In the article we present briefly the considered types of sensors, proposed systems architecture, and experimental setup installed in a real apartment.

Keywords

Data representation; Sensors; Behavior informatics; Ambient assisted living

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1. Introduction

Fast recent developments in sensors, information and communication technologies resulting in applications of Internet of Things (IoT) enable implementation of various systems for continuous monitoring of health state and daily activities, especially in home environment. Statistical data in Europe show that in 2016 there were 98 million people in the European Union (EU) aged 65 years or older, compared with 80 million children aged 16 or younger [1]. Prospects show that this trend is currently only halfway through and will reach its peak around 2040-2050. Across the member states of the EU, the highest share of young people in the total population in 2017 was observed in Ireland (21.1%), while the lowest share was recorded in Germany (13.4%). Regarding the share of persons aged 65 and over in the total population, Italy (22.3%), Greece (21.5%) and Germany (21.2%) had the highest shares, while Ireland had the lowest share (13.5%). As accompanying phenomenon we observe increasing number of seniors living by themselves in their homes. It is estimated that more than one elder in four (27.1% of the over 65-year olds) is living alone. More than a decade ago (in 2008), ambient assisted living (AAL) appeared as an EU funding program and subsequently the AAL as term started to be used for topics focused on better care for frail individuals (elderly, chronic and disabled patients), in particular in a home care setting. To improve this kind of care means to allow the citizens to stay at home where they are used to live as long as possible, delaying the institutionalization of people, possibly avoiding it for a high percentage of them. Institutionalized elderly citizens are at high risk of cognitive impairment, functional loss, social isolation, or death. To stay at home means to keep independence, self-sufficiency, social network role.

Continuous monitoring generates large volumes of data that are of heterogeneous character and are multidimensional. The task is to extract useful information from the data. Data mining and knowledge discovery techniques are used with the aim to propose medical and social actions. These actions are to be appropriately performed with reliable information, to improve the quality of life of patients and caregivers.

This article is an extension of work originally presented in pHealth 2019: 16th International Conference on Wearable, Micro & Nano technologies for Personalized Health [2]. In Section 2 we discuss principal differences in data acquisition from ambient sensors and wearables and connected issues. Section 3 focuses on system architecture, formal model of data representation, and designed algorithms for sensor data processing. In Section 4, the experimental setup is presented and representation of the apartment topology is proposed and discussed. Section 5 concludes the paper.

2. Ambient Sensors and Wearables

Seniors are used to living in a certain way, and most of the times, they suffer from an unwillingness to accept anything new. For instance, if they were not used to wearing watches for their whole lives, they are doubtful to wear them right now in the era of smart technologies and wearables. Further, if we suppose to monitor a particular individual in the environment where one is used to living, naturally at home, we cannot expect him or her to wear the watches either. In general, the use of wearables can be very convenient in exterior spaces (cellular phones, GPS trackers, pedometers, smartwatches…). On the other hand, if we want to monitor people at home, we cannot rely on them. Wearables can be taken off, or deliberately, but also inadvertently, be put aside. In such cases, we are losing the expected data. The age of a person, eventually various cognitive impairments, starting dementia, Alzheimer disease, or memory loss, may affect such situations.

These facts bring common questions what systems and approaches to use to monitor an individual's daily living activities. We propose to focus on non-invasive data acquisition methods, which have minimal impact on the way of life. Ambient sensors placed explicitly in certain places in the apartment can be one of the approaches.

The character of data we can acquire from ambient sensors is very variable due to the type of measured physical quantity. Let us consider the basic types of sensors that might be installed in the home environment. The PIR motion sensors give only two values: 1 and 0 (motion detected/motion not detected). The speed of change is relatively high. The Grid-EYE thermal sensor sends 2D data (a matrix) representing larger viewed space; the values represent the temperature at the given spot. Several types of other sensors send the measured values every two seconds. Magnetic sensors are frequently used for the detection of open doors and windows, and again we get binary values. Similar to PIR sensors if there is a moving person, the changes are relatively fast. We can use a pressure sensor detecting the presence of the person, for example, sitting on a chair or lying in a bed. Again, we get two discrete values: yes/no (1, 0). A more advanced version of such a detector can be used in a bed for heart rate and breath detection at night. This sensor type generates a continuous signal that requires a completely different algorithm for processing. In addition to these sensors, we can measure the quality of the home environment, for example, temperature, humidity, carbon dioxide, sound noise, light. Sound noise and light can change abruptly, while temperature, humidity and carbon dioxide change more slowly. These properties must be respected when designing the evaluating algorithms.

We believe that in particular these sensors can provide sufficient information to be able to assess particular activities and states of individuals in their household. On the other hand, such an approach brings new challenges which must be considered and solved in a specific way.

However, there are cases, in which wearables are almost inevitable. Usually, these persons are used to a specific regime. Among them, there are diabetic or cardiac patients who have to measure defined physiological parameters regularly. For them, wearables might represent certain help and more straightforward data acquisition. Since many parameters can be measured continuously, the trends can be indicated easily. This is actually the core of the concept of the quantified self. The original idea of the quantimetric self-tracking began in the 1970s. However, technology has made it easier and simpler to gather and analyze personal data. Since these technologies have become smaller and cheaper to be put in smartphones or tablets, it is easier to take the quantitative methods used in science and business and apply them to the personal sphere.

A significant application of quantified self has been in health and wellness improvement. Many devices and services help with tracking physical activity, caloric intake, sleep quality, posture, and other factors involved in personal well-being. Corporate wellness programs, for example, often encourage some form of tracking. If we want to get an objective picture, the measurement must be synchronized. For example, if we monitor heart rate, we have to know the context, namely whether the person is at rest or walking or performing more demanding physical activity. Therefore, additional data from accelerometers must be provided.

The trend in current medicine is towards personalized treatment because each individual is different, and the interpersonal variability is very high. Therefore, it is necessary to adjust the personal model (patient state) by his or her personal parameters and compare the future development of the health state with the

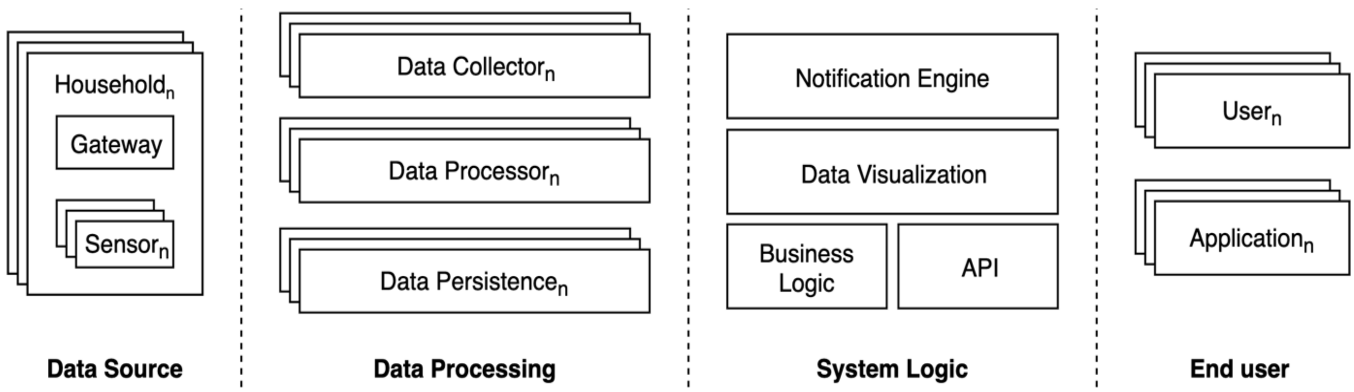

Figure 1: Brief architecture overview.

initial state. The most important part of the evaluation is trend evaluation. In any case, the model is a certain simplification and represents more or less system level, not the organ or cell level. Any disease contributes to variations, usually changes in trends, e.g. influenza-change of body temperature, possibly change of heart rate, change of behavior (less movement, staying in bed).

The aim of using both ambient sensors and wearables is to support the individual's self-sufficiency and feeling of safety in the first place and also the option of getting help in case of emergency, even without actively calling for help (e.g. due to unconsciousness).

3. System Architecture

In this section, the system architecture is briefly introduced in the top-down approach starting from the high-level components and then focusing more on essential details. The description follows with selected pain points which the system should deal with, especially in the area of data processing and data representation.

3.1 Architecture Overview

The whole proposed system can be divided into four distinct blocks, each with a different intention and functionality (Figure 1). Each block is described in the following subsections.

Data Source: Indirect monitoring using ambient sensors opens challenges in data representation and data processing. Why? When we monitor vital parameters with wearables, we receive continuous signals, for example, ECG, breathing, motion. However, ambient sensors frequently send only binary data (yes/no interpretation of a particular state) as shown in examples in the previous section. That means we need to add contextual information to such simple data to follow the trajectory of the person, to derive activity performed.

The most widely used sensors for human motion detection are passive infrared (PIR) motion sensors. They can support the long-term continuous observation. Zhaoyuan et al. [3] proposed a geometric algebra (GA)-based approach to generate all possible human trajectories from the PIR sensor network data. Firstly, the representation of the geographical network, sensor activation response sequences and the human motion are represented as algebraic elements using GA. The human motion status of each sensor activation is labelled using GA-based trajectory tracking. Then, a matrix multiplication approach is developed to dynamically generate the human trajectories according to the sensor activation log and the spatiotemporal constraints.

It is necessary to mention that the PIR sensor network cannot provide enough information to recover the complete trajectory of an individual. Therefore, we decided to consider additional types of sensors to make the picture of a person´s activities more complete. The Grid-EYE thermal sensor, presence detectors (pressure sensors) and magnetic sensors represent additional valuable sources of information about the person´s actions. This approach requires to analyze the data representation formalisms to be able to apply one formalism to data from different sensor types. Our final decision is to use the framework defined in behavior informatics. In our case, the target application is also very close to the detection of a person's suspicious behavior, as described in [4].

In the case of a home environment, the temporal pattern detecting an unusually long period of stay in a given area may represent a fall of the person or a collapse. The repetitive pattern detecting repetitive accesses within a given period can indicate problems with orientation and memory of the person, for example, the unintentional repetitive opening of wardrobe or cupboard within a short time interval (one of the symptoms of some neurodegenerative diseases). The out-of-sequence pattern described as consecutive accesses in an undefined sequence may also indicate problems with orientation and memory. An example may be a complete changeover of the previously standard sequence of daily activities.

The ambient sensors (eventually the actuators too) are placed in a particular household [5] in order to sense different metrics in the environment. These can be environmental characteristics themselves, for instance, temperature, humidity, pressure or level of CO2. There have been published studies which prove that by using some of these environmental characteristics, we can infer about the number of people in the room [6-8].

We assume to use and connect more devices as a data source. Most of them belong to the category of Internet of Things (IoT) that might be, in principle, mutually interconnect able. This interconnection is usually realized via the Internet above TCP/IP stack, in case the device is directly capable of this connection. If this is not possible, mainly due to any restriction or insufficient resources, such as limited CPU, memory space, battery capacity, use of short-distance personal area networks (PAN), etc., the connection is mediated. This mediator is usually called a gateway. The gateway can be either physical or application-based. It can serve as an integration point for a subset of further devices allowing multiple interfaces and executing protocol conversion. It can perform data processing (pre-processing), compression, or encryption. It can even dynamically discover and automatically register new devices into the system.

Data Processing:

Data collectors can realize data acquisition. One of the examples can be IoT platforms which are usually hosted by cloud providers. Further, we can mention open-source components like Apache NiFi, Node-RED, Extract-Transform-Load (ETL) engines. Any of these create data pipelines which consolidate data from multiple sources. In this form, the data are available for further analysis or direct visualization.

Data processors can use message queueing engine (MQ) as the core. Data processing, as such, depends heavily on data character and place where we want the data to be processed. Usually, we talk about three main approaches: cloud-centric data processing, device-centric data processing, and edge-centric data processing. Each approach has its advantages and disadvantages, which means that the decision about utilizing any of these is application dependent. Cloud-centric approach benefits from the fact that all data are in one place at a particular time. Thus, we can apply robust analytical methods that can combine several aspects, visualize trends or heatmaps, and much more. The condition is stable connectivity and reasonable bandwidth for communication. Device-centric data processing approach natively leads to distributed analytical systems. Primary data processing is executed at the level of the device and only aggregated information, e.g. about unusual event or values, is reported to a higher level. This approach significantly reduces the demand for ingress bandwidth and volumes of data sent into the cloud and helps to minimize the complexities in IoT systems. Edge-centric data processing deals with both approaches mentioned above. It is a trade-off between strictly centralized and strictly distributed data processing.

Data persistence is essential for any system because we usually need to store different types of data for a particular time when they are relevant (so-called live data), or we want to archive permanently (so-called cold data). This usual split allows us to efficiently govern requirements, meet eventual compliance, simplify data management and last but not least, reduce overall storage costs.

In addition to measured data collected by sensors, we need to store and aggregate information that serves us as metadata like semantic ontologies, household topology information, location and types of the installed sensors. Further, the storage is used for partial results of data processors, results of analytical models and the models itself.

System Logic:

The System Logic module comprises of four main building blocks, namely Notification Engine, Data Visualization, Business Logic and API.

Notification engine is in principal an event server that informs the users about their environment through notification service. The service offers notifications tailored to the user's preference and current content. The basic pattern is event-condition-action that can be represented by rules which are easily interpretable. Notification service makes applications aware of context changes by notifying them. Applications do not have to care about managing and monitoring context data. They have to register monitoring rules that specify what changes in what context should be notified to them.

Data Visualization is tightly related to visual perception, which is the most important means of knowing and understanding the world. Our ability to see patterns in things and pull together parts into a meaningful whole is the key to perception and thought. This ability is very closely linked with experience: the more experienced we are, the more complex tasks of deriving meaning out of essentially separate and disparate sensory elements we are able to perform. Seeing and understanding together enable humans to discover new knowledge from large amounts of data with more in-depth insight. The visualization approach integrates the human mind's exploratory abilities with the enormous processing power of computers. Sometimes, this is one of the first approaches we try to explore if we want to understand and see a potential relationship among unknown data. Having a quick view on pipelined data for a certain period or seeing basic aggregations might (sometimes might not) help us to choose the right way of subsequent data analysis.

IoT systems generate vast amounts of data, but at the same time, there are often lacking explicit relations among these data and data understanding. Orientation in this amount of data is not always easy and unambiguous. Computation, based on these large data sets, creates content. Visualization makes data, computation and mining results more accessible to humans, allowing comparison and verification of results. Visualization techniques are applied to both physical data and abstract non-physical data such as text, hierarchies, and statistical data.

I propose following formulation: Business Logic means in our context application (system) components that manage communication between end-user interfaces, databases, application modules and libraries. This part makes the system more consistent, and integral combining, at first glance, disparate elements which were discussed above. The main components of business logic are business rules and workflows. A business rule describes a specific procedure. A workflow consists of the tasks, procedural steps, required input and output information, and tools needed for each step of that procedure. Business logic describes the sequence of operations associated with data to carry out the business rule.

Application Programming Interface (API) is a computing interface which defines interactions between multiple software intermediaries. It defines the kinds of calls or requests that can be made, how to make them, the data formats that should be used, and the conventions to follow. It can be based on a request-response approach or publish-subscribe approach. It defines standard ways how to communicate with the whole system, which in this particular case is not meant for data sourcing (as discussed separately) but rather as an interface for end-users.

End User: By End User part of the architecture we mean follow-up or related applications and users which can interact with and profit from the whole system by utilizing API calls or the notification engine of the System Logic. For instance, these can be monitoring and surveillance systems, integrations from external systems, mobile applications installed on personal phones or even on wearables (like smartwatches).

3.2 Data and Features

As we already mentioned in Data Source section, data from sensors have different nature. They can be represented by discrete values, signals, or images. In addition to this variability, they can come in various formats, structured or unstructured forms. In such cases, the pre-processing steps must include data conversion and alignment so that the data can be processed further uniformly.

As the data are coming from different and usually completely independent data sources (sensors), they might not be synchronized in time which might (or might not) cause problems in data analysis. Thanks to the hardware configuration which we

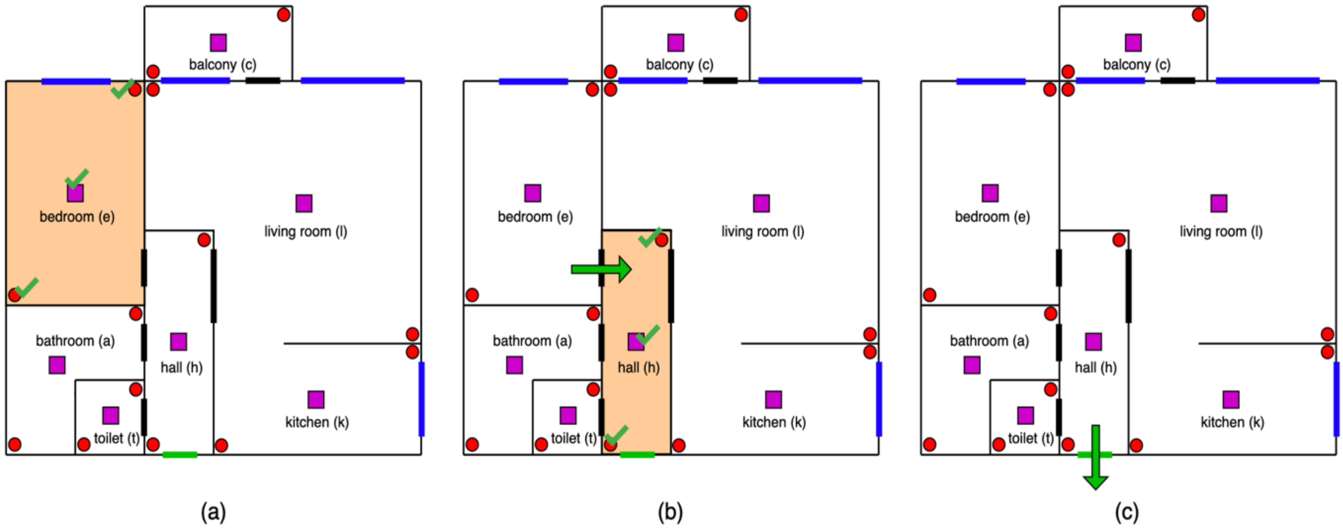

Figure 2: Simple step-by-step (from *(a)* through *(b)* to *(c)*) household walk-through with sensors activations (green check marks). The floor plan with ambient sensors placement (PIR sensors as red dots, Grid-EYE sensors as purple squares, magnetic sensors on all windows and doors are not highlighted). Windows are marked in blue, the main door in green, the rest of the doors in bold black.

use for ambient sensors and the connected control unit, we get regular sequences from PIR sensors and magnetic sensors every second. The thermal Grid-EYE sensor sends the data matrix every two seconds. When using wearables, we do not rely on synchronization with the ambient sensors at all. However, for the evaluation of events occurring in the defined space, the difference in seconds does not play an important role. At the same time, there are cases where the time synchronization matters a lot.

A simple example can be a situation when the person walks through the door between two rooms in the household. We expect the correct ordering of events from PIR sensors placed in both rooms combined with events of a magnetic sensor on the door. In a limited period, we may incorrectly assume a transition from the first to the second room even though it happened the other way around. Nevertheless, in a longer period, we should be able to identify it correctly.

As mentioned at the beginning of this section, signals and images are also among input data. The necessary step in their processing is feature extraction. For example, the set of images (heatmaps) from the thermal Grid-EYE sensor brings information about numbers of persons in the room, about their movement around or sitting in chairs or lying on beds. We need to transform this information from numerical values into one or several descriptive features that are used for successive processing and evaluation of the state or event.

A similar approach must be applied to data acquired from wearables, such as accelerometer data, heart rate frequency, or one channel ECG.

3.3 Events Segmentation

In our context, we understand an event as a sequence of small actions with a particular result. For example, an event is a walk from the kitchen to the living room. Small actions are individual steps; opening/closing door results in being in the living room. Such an event is reflected in a sequence of values from activated sensors: 0/1 from PIR sensors, 0/1 from magnetic sensors and series of images (heat maps) from Grid-EYE sensors in the kitchen and living room. The task of data processing algorithms is to identify individual events from the data sequences and to split data into corresponding segments.

Here, we can leverage machine learning algorithms to be able to learn the typical patterns occurring in data fragments when an individual event happens.

3.4 Events Segmentation

We chose behavior informatics as a way of representing event sequences. Behavior informatics is defined as a scientific field which aims to develop methodologies, techniques and practical tools for representing, modelling, analyzing, and, mainly but not only, understanding of behavior [9].

The core idea of behavior informatics is formed by an abstract model [10]. When this abstract model is turned into practice (used in different domains), we can represent a manifestation of behavior in the form of a behavior vector vector ($\vec{\gamma}'$) with with limited set of attributes and properties, e.g. as follows [10]:

$$\vec{\gamma}\,' = (s, o, a, f, t) \tag{1}$$

It indicates that a subject (s) conducts an action (a) on an object (o) at a time (t) which leads to a certain impact (f).

The instrument which cumulates the actor's manifestations of behavior for a certain period is called a behavior sequence. It can be represented in terms of a vector sequence ($\vec{\Gamma}'$) as follows:

$$\vec{\mathrm{A}}' = \{\vec{\gamma}_1\,', \vec{\gamma}_2\,', \ldots, \vec{\gamma}_n\,'\} \tag{2}$$

As this formalism abstracts partial events and state changes of individual sensors, we talk about so-called Mapped behavior [11] which refers to an indirect mapping of physical behaviors by sensors into computer systems.

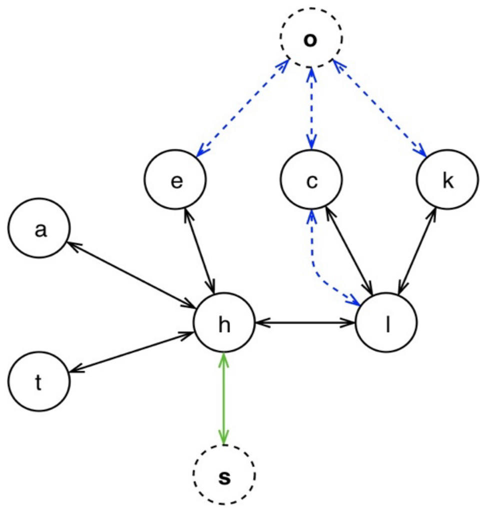

Figure 3: The topology of the apartment (virtual nodes are dashed, entrance transition via the main door is marked in green, and unusual transition via windows are highlighted with dashed blue).

4. Experimental Setup

As experimental setting we used an apartment whose floor plan is shown in Figure 2. The floorplan represents an ordinary apartment with living room, kitchen, bedroom, bathroom, and toilet. The central part is formed by the main hall, which interconnects most of the rooms together. The unfinished wall partially separates the space of the living room and the kitchen. The main entrance door is marked in green. The rest of the doors are marked in bold black (including the door to the balcony). Windows are highlighted with blue. For further description, each room is labelled with a letter mentioned in parenthesis.

The selection and placement of the sensors is based on the study and the experimental verification of how to deal with its data, as discussed in [12]. We proposed to use:

Passive Infrared (PIR) Sensor: is a standard motion detection sensor used in security technology solutions. Since it works in an infrared frequency band of the spectrum, it operates reliably during both day and night. This sensor has two possible states at its output; logic 0 if it does not detect movement, or logic 1.

Grid-EYE Infrared Array Sensor: is a sensor made by Panasonic. The output is an 8 x 8 matrix of temperatures of the scanned area. The built-in lens includes a 60-degree viewing angle which gives us, assuming ceiling height to be 3m, a detection area about (3.48 x 3.48) m.

Magnetic Sensor: consists of two non-connected parts. The first part which contains a magnet is usually placed on movable parts (doors or windows). The second part is formed by a circuit with a switch that is turned on and off by the magnetic field of the first part.

To detect a simple movement inside a room or translation between rooms, PIR sensors in combination with magnetic sensors on the doors should be sufficient. In case we want to refine position within the apartment, the use of Grid-EYE sensor is proposed. Since the Grid-EYE sensor provides complex information about temperature footprint, this can also be used as a confirmation that the motion activity was performed by a living person and not, for example, by a robotic vacuum cleaner which is cleaning the apartment.

To collect data from the sensors, a Programmable Logic Controller (PLC) is used which fulfils regular data acquisition [12]. The sensors are connected via a wired bus or wireless bus. In an ideal case, the wired infrastructure for connecting the sensors is built during the construction of the apartment. Another option is to implement the system with the use of the IoT platform [13]. In any case, we must deal with the data which needs to be processed, evaluated, and put into context. A mix of different sensors and their data can enhance final accuracy.

The algorithms and approaches used for data processing and evaluation depend on the chosen data acquisition method. It can be either regular reading of all sensors at once or event-driven approach where sensors provide data independently to each other. The comparison of possible approaches is out of the scope of this article, and the topic can be a subject of subsequent research.

Further sections deal with the formal description of how a structural arrangement of the apartment can influence and support the acquisition of behavioral data.

4.1 Topology

The apartment can be represented as a directed multigraph:

$$G = (V,E,f) \tag{3}$$

Which consists of a set V of vertices (or nodes), a set E of edges, and a function $f{:}E \to V \times V$ mapping each edge with its incident vertices. The orientation of edges is preserved by order of nodes in the map function f.

Let V be the unification of three sets as follows:

$$R \cup EV \cup UV = V \tag{4}$$

where R is a set of vertices which represent rooms (e.g., living room, kitchen, bedroom), EV is a set of virtual vertices which represent areas directly connected to natural entrances of the apartment (e.g. shared hall, garden), and UV is a set of virtual vertices which represent areas directly connected to possible but non-standard entrances of the apartment (e.g., space outside the window).

Let E be the unification of two sets as follows:

$$DE \cup WE = E \tag{5}$$

where DE is a set of oriented paths through standard building holes (e.g., doors, gateways, some logical arrangement of two spaces shared in one room-living room with shared kitchen), and WE is a set of oriented paths through non-standard entrances (usually windows).

Map function f can be represented by nonsymmetrical vertex-edge incidence matrix of a graph G, denoted VE, which is determined by the incidences of vertices and edges in G. Let's use +1 values for positively incident edges, the -1 values for negatively incident edges, otherwise use 0 values.

4.2 Model Description

The apartment in Figure 2 can be represented by the topology in Figure 3 where $R = \{a, c, e, h, k, l, t\}$ the set of rooms with balcony is. $EV = \{s\}$ is the set with the single item representing the shared hall of an assisted living facility (ALF), i.e., the shared premises of the whole building with particular apartments. Outer space behind all the windows and balcony is described by the single node as part of the $UV = \{o\}$ set. The DE set contains all standard transitions between rooms (see black and green edges), while the WE set includes unusual transitions via windows (see dashed edges marked in blue).

Partial VE incidence matrix of the topology of the apartment can be seen in Equation 6.

$$\mathbf{VE}(G) = \begin{array}{c} \\ a \\ c \\ e \\ h \\ k \\ l \\ t \\ s \\ o \end{array} \begin{array}{c} \begin{array}{ccccc} h-a & a-h & \cdots & o-k & k-o \end{array} \\ \begin{bmatrix} -1 & 1 & \cdots & 0 & 0 \\ 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & \cdots & 0 & 0 \\ 1 & -1 & \cdots & 0 & 0 \\ 0 & 0 & \cdots & -1 & 1 \\ 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & \cdots & 1 & -1 \end{bmatrix} \end{array} \tag{6}$$

As discussed at the beginning of Section 4, in the experimental setting, we currently use PIR sensors (standard motion detection sensors), Grid-EYE infrared array sensors (providing us with an 8 x 8 matrix of temperatures of the scanned area) and magnetic sensors (detecting opened/closed windows and doors). The sensors' placement is shown in Figure 2.

In the next step, pressure sensors have been installed to detect the presence of the person on bed or chair to ease the detection of the person's state and location. A good example is watching TV. In that case, there is no data from PIR sensors. The Grid-EYE sensor indicates a non-moving object with a temperature of 37°C. If the pressure sensor shows the presence of an object (the person) on a chair, then it can be derived that it is a normal situation. Without the pressure sensor, the system could alert that the person lies on the floor, is not moving, and therefore needs help.

The short example also shows how we can further process the data represented by vectors. As a basic reasoning framework, we propose IF-THEN rules. The IF part consists of conditions that must be satisfied to fire the rule. The THEN part describes the action to be performed. The rules can incorporate the topology of the environment and location and type of individual sensors.

5. Conclusions

We tried to analyze the situations arising when performing daily activities at home and data that may be acquired from various ambient sensors at the home setting. We focused on the detection of abnormal situations expressed as abnormal patterns in data. Based on the analysis and purpose, we proposed to use vector representation of data following the framework suggested in behavior informatics. Our target application is the fast detection of accidents and abnormal states that might happen in the home environment. As the next steps we plan more extensive experiments in the experimental apartment and analysis of collected data with proposed algorithms.

Technology may be advantageous when monitoring persons' health state and activities during everyday life in their homes and at work continuously because it helps adjust a personalized health state model, in particular for a person with a chronic disease. We are well aware of the fact that many elderly people prefer not to use wearables, at least in their homes. There- fore one of the aims of our presented study was to find methods and tools for indirect monitoring based on sensors installed in the ambient environment. Next step is then to identify methods that can easily process and evaluate data acquired from such sensors. We showed the basic principles of BI that might be utilized for transparent representation of the environment, sensors, data, and moving persons.

In this study, we also focused on proving the feasibility of our approach. The data is collected using standard communication (either wired or wireless) between sensors and a computer which can behave like a gateway (the edge). The basic assumption of correct integration of data is the synchronization of data transmission. The second approach can be based on event-driven transmission supported by a simple state machine which processes incoming data in real time. The collected data are stored and can be used for evaluation as suggested by clinicians. We plan to design algorithms that will derive aggregated information from the raw data and use it jointly with the patient's medical information stored in Electronic Health Record. Concerning data storage, we follow two options: local server storage with a specific layer of pre-processing logic, and cloud solution storage with centralized processing logic. It can differ case by case, but probably the most relevant database type is a time series database where most of the time-related aggregations can be done by appropriately calling the query, e.g. gathering and averaging over five-minute time intervals. The final decision will always be made depending on the application in a given setting. That has also impact on security and data privacy measures that will be applied accordingly. All data communication must use secure protocols.

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