

Behavioural Data Modeling: A Case Study in IoT

Jiri Petnik¹, Lenka Lhotska², Jaromir Dolezal² and Jindrich Adolf²

¹Faculty of Information Technology, Czech Technical University in Prague, Thákurova 9, 160 00 Prague 6, Czech Republic

²Czech Institute of Informatics, Robotics, and Cybernetics, Czech Technical University in Prague, Jugoslávských partyzanu 1580/3, 160 00 Prague 6, Czech Republic

Keywords: Behaviour Informatics, Behaviour, Sensor, Topology, Internet of Things, Smart Home, Elderly Care.

Abstract: Modeling and analysis of behaviour by using data extracted from Internet of Things (IoT) sensors is an open area. We take Behaviour Informatics (BI) as a formal representation into account and describe the case study of the apartment monitored by IoT sensors. The case study targets persons who live home alone (e.g., elderly people) without assistants (nurses), or any roommates. We present the apartment as a directed multigraph and propose the model to deal with the conversion of transactional data coming from IoT sensors into behavioural feature space represented by behavioural vectors. Further, the article describes a few use cases which can occur in the apartment with installed sensors and explains how behavioural vectors are created. Last but not least, we present the high-level overview of the complex system for detection and evaluation of behaviour identified from data of IoT sensors.

1 INTRODUCTION

European Union countries are facing unprecedented and extraordinary challenges linked to the progressive aging of their population. Research is focused on novel medical solutions on one side and on technologies that might support independence, self-management of elderly persons (those living alone in particular) on the other side. In addition, these technologies allow long-term monitoring of physiological parameters and changes in behaviour. One of the enabling technologies in this area is the Internet of Things (IoT). The IoT as a paradigm deals with the connection of physical devices, vehicles, buildings, and other items – embedded with electronics, software, sensors, actuators, and network connectivity that enable these objects to collect and exchange data. The collected data represent different events, phenomena, etc. The most frequently analyzed data are physiological parameters, for example, heart activity (heart rate, electrocardiogram), breathing rate. They are represented as time series derived from measured analog signals. Besides this kind of data, it is currently possible to acquire data from sensors placed in buildings, apartments. Usually, this data has the binary form (yes/no, logical 0/logical 1). A single item does not provide information. To be able to interpret a sequence of data from more sensors placed in the rooms it is necessary to know the topology of

the space, types of sensors, possible actions, etc. It is evident that these items cannot be represented in the same form as physiological signals. We found a formalism that enables efficient representation and manipulation of data – Behaviour Informatics (BI).

The paper is structured as follows. Section 2 describes the basic features of BI and defines behaviour model, vector and sequence. Section 3 presents a case study, describes the apartment as a directed multigraph, and proposes the model how to convert transactional data coming from IoT sensors into behavioural feature space represented by behavioural vectors. In Section 4, illustrative use cases are shown. Section 5 discusses the proposed model and its use in a complex system for detection of behaviour. Section 6 concludes the paper.

2 BEHAVIOUR INFORMATICS

One of the critical IoT application within the smart healthcare area is called behavioural detection, behavioural analysis, or BI (Sheriff et al., 2015). BI can be used for initial problem description and formalism.

2.1 Definition

BI is a scientific field which aims to develop methodologies, techniques and practical tools for representing, modeling, analyzing, understanding and/or utilizing symbolic and/or mapped behaviour, behavioural interaction and networking, behavioural patterns, behavioural impacts, the formation of behaviour-oriented groups and collective intelligence, and behavioural intelligence emergence (Cao and Yu, 2009).

Within healthcare, the IoT system with the analytical layer may help specialists to detect severe illnesses at their early stages and subsequently prevent the loss of life (Ahmed et al., 2017). Nowadays, we use several IoT devices to monitor the human body. The wearables are employed for direct monitoring; while the sensors installed in the ambient environment monitor the human body indirectly. In combination with clinical data, all of these can be used to model the particular behaviour of specific individuals or precision cohorts.

2.2 Abstract Behaviour Model

A behaviour \mathbb{B} is described as a four-ingredient tuple (Cao, 2013):

$$\mathbb{B} = (\mathcal{E}, \mathcal{O}, \mathcal{C}, \mathcal{R}) \quad (1)$$

It indicates:

- Actor $\mathcal{E} = \langle \mathcal{SE}, \mathcal{OE} \rangle$ is the entity that issues a behaviour (subject, \mathcal{SE}) or on which a behaviour is imposed (object, \mathcal{OE}).
- Operation $\mathcal{O} = \langle \mathcal{OA}, \mathcal{SA} \rangle$ is what an actor conducts in order to achieve certain goals; both objective (\mathcal{OA}) and subjective (\mathcal{SA}) attributes are associated with an operation. Objective attribute may include time, place, status, and restraint; while subjective aspects may refer to action and its actor's belief and goal of the behaviour, and the behaviour impact on business.
- Context \mathcal{C} is the environment in which a behaviour takes place.
- Relationship $\mathcal{R} = \langle \theta(\cdot), \eta(\cdot) \rangle$ is a tuple which reveals complex interactions within an actor's behaviours (namely intra-coupled behaviours, represented by function $\theta(\cdot)$) and that between multiple behaviours of different actors (inter-coupled behaviours by relationship function $\eta(\cdot)$).

2.3 Behaviour Vector

Behaviour can also be represented as a behavioural vector $\vec{\gamma}$ which consists of behavioural attributes

(basic properties) including social and organizational factors. When deploying this abstract model into different domains, some attributes and properties may not be present, and thus a simplified behavioural model $\vec{\gamma}'$ can be defined, e.g., as follows (Cao, 2010):

$$\vec{\gamma}' = (s, o, a, f, t) \quad (2)$$

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

2.4 Behaviour Sequence

Further, a behaviour sequence Γ' of an actor can be represented in terms of a vector sequence $\vec{\Gamma}'$, which consists of the behaviour instances represented in vectors (Cao, 2010):

$$\vec{\Gamma}' = \{ \vec{\gamma}'_1, \vec{\gamma}'_2, \dots, \vec{\gamma}'_n \} \quad (3)$$

3 CASE STUDY

Basic task of BI is the preparation of behavioural data. Usually, we deal with transactional data which are not relevant for further behavioural analysis, and thus a data conversion from transactional space to behavioural feature space is necessary (Cao, 2010). In the behavioural feature space, behavioural elements are presented in behavioural itemsets.

The movement of a person in the environment of his/her apartment can be considered as one of the primary activities, which can be monitored. It is evident that possible movement is given and constrained at the same time by the actual structure of the apartment, its topology. The topology clearly defines the organization of individual rooms and mutual interconnections. We can differentiate the movement either within the particular room or movement (transition) between the rooms.

Assuming we can detect the movement itself, we can further infer the activity of the individual – whether he or she is active during the day, or rather stays in a single room, whether he or she has some problems with sleeping, how often he or she visits the restroom which can inform us about some urinary problems, etc.

This case study targets persons who live home alone (e.g., elderly persons), without assistants (nurses), or any roommates. Thus we consider a single actor model. The movement is detected in an indirect way by using sensors, so we talk about so-called

Mapped behaviour. The main focus is to detect and be able to describe transitions between each room.

3.1 Floor Plan and Sensors Placement

The apartment floor plan is depicted in Figure 1. This is a common 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 labeled with a letter mentioned in parenthesis.

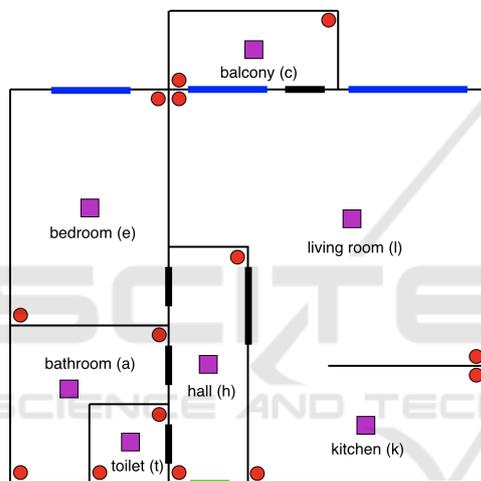


Figure 1: The floor plan of the apartment with sensors (PIR sensors as red dots, Grid-EYE sensors as purple squares, magnetic sensors on all windows and doors are not highlighted). Windows are marked in blue, the main door in green, the rest of the doors in bold black.

The selection and placement of the sensors is based on the study and the experimental verification how to deal with its data as discussed in (Lhotska et al., 2018). We propose to use:

- *Passive Infrared (PIR) Sensor* – is a standard motion detection sensor used in security technology solutions. Since it works in an infrared portion 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 the 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 with the combination of 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, e.g., not by a robotic vacuum cleaner which is cleaning the apartment.

To collect data from the sensors a Programmable Logic Controller (PLC) is used which fulfills regular data acquisition (Lhotska et al., 2018). 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 (Petnik and Vanus, 2018). 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 behavioural data.

3.2 Topology

The apartment can be represented as a directed multi-graph:

$$G = (V, E, f) \quad (4)$$

which consists of a set V of vertices (or nodes), a set E of edges, and a function $f : E \rightarrow V \times V$ 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:

$$R \cup EV \cup UV = V \tag{5}$$

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:

$$DE \cup WE = E \tag{6}$$

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 unsymmetrical vertex-edge incidence matrix of a graph G , denoted \mathbf{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.

3.2.1 Model Description

The apartment in Figure 1 can be represented by the topology in Figure 2 where $R = \{a, c, e, h, k, l, t\}$ is the set of rooms with balcony. $EV = \{s\}$ is the set with the single item representing the shared hall of an assisted living facility (ALF). 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 7.

$$\mathbf{VE}(G) = \begin{matrix} & \begin{matrix} h-a & a-h & \dots & o-k & k-o \end{matrix} \\ \begin{matrix} a \\ c \\ e \\ h \\ k \\ l \\ t \\ s \\ o \end{matrix} & \begin{bmatrix} -1 & 1 & \dots & 0 & 0 \\ 0 & 0 & \dots & 0 & 0 \\ 0 & 0 & \dots & 0 & 0 \\ 1 & -1 & \dots & 0 & 0 \\ 0 & 0 & \dots & -1 & 1 \\ 0 & 0 & \dots & 0 & 0 \\ 0 & 0 & \dots & 0 & 0 \\ 0 & 0 & \dots & 0 & 0 \\ 0 & 0 & \dots & 1 & -1 \end{bmatrix} \end{matrix} \tag{7}$$

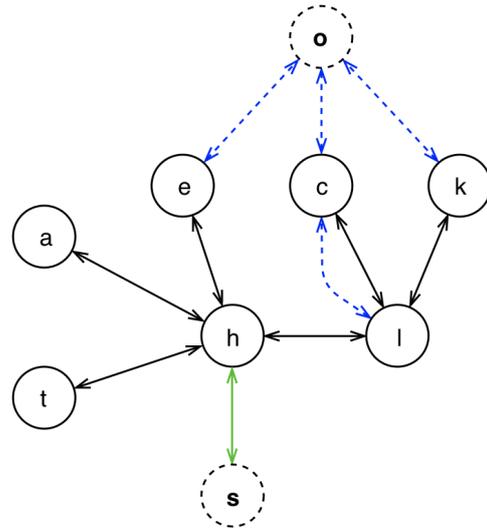


Figure 2: The topology of the apartment (virtual nodes are dashed, entrance transition via the main door is marked in green, unusual transition via windows are highlighted with dashed blue).

3.3 Behavioural Walk

Let's define a Behavioural walk BW as an alternation sequence of nodes and edges:

$$BW = \langle v_0, e_1, v_1, \dots, v_{n-1}, e_n, v_n \rangle \tag{8}$$

where $(\forall v; v \in V)$ and $(\forall e; e \in E)$, which represents sequential behavioural activity (movement) of a person in an apartment from the room v_0 to the final room v_n . BW can be used for description of person's translations between apartment rooms for the relevant period (i.e., an hour, a day, a week or so). The length of a BW is the number m of its edges.

$$m = len(BW) \tag{9}$$

3.4 From Behavioural Walk to Behavioural Vector

The definition of BW is based on a *walk* from graph theory and its usage here is suitable for the formalization mapping of a topology describing the structure of the apartment itself into the behavioural vector $\vec{\gamma}$ which forms a cornerstone of further behavioural pattern analyses.

Let $\vec{\gamma}'$ be a simplified behavioural vector:

$$\vec{\gamma}' = (s, a, p, t) \tag{10}$$

It indicates that a behavioural subject s (a person) conducts an action a (a translation between rooms) in place p at a time t (a timestamp when the translation

was detected). The attribute p can be used to specify a room (both physical and virtual) from which the translation was started, or, e.g., a floor of the house.

Except for the starting node v_0 of Behavioural walk BW , all subsequent adjacent pairs of nodes and edges (e_{k-1}, v_k) where $1 < k \leq n$ can be converted by the process B into the simplified manifestation of behaviour vector as described in Equation 10:

$$B: \{e_{k-1}, v_k\} \rightarrow \vec{\gamma}'_i \quad (11)$$

The final Behaviour vector sequence $\vec{\Gamma}'$:

$$\vec{\Gamma}' = \{\vec{\gamma}'_1, \vec{\gamma}'_2, \dots, \vec{\gamma}'_m\} \quad (12)$$

where $0 < i \leq m$ then contains m behaviour vectors which is equal to the length of initial Behavioural walk BW .

4 USE CASES

We assume that a person's behaviour is partly predictable and that he or she does not try to disguise his or her behaviour intentionally. Following sections describe several typical situations which can occur in the monitored apartment and presents how the behavioural vector sequence $\vec{\Gamma}'$ is gradually created. It is obvious that $\vec{\Gamma}'$ can be created by batch processing or by real-time processing when the system can decide with a certain degree of confidence. For the description, we present the real-time variant.

The person (identified by 's') gets up of his bed in the morning and is moving around the bedroom. PIR sensors detect movement. The Grid-EYE sensor confirms the living person is present. We do not create any behaviour vector that would describe this state. Right now, we understand movement in the room as a standard situation which does not need to be further detailed. The person is opening the bedroom's door, and the magnetic sensor warns that the door is opened. The person is going through to the hall. After a while, PIR sensors in the bedroom do not detect any activity, nor does the Grid-EYE. On the other hand, PIR sensors and the Grid-EYE sensor in the hall detect the presence of the person. Taking the description of defined Behavioural walk (BW) in mind, the person just moved from the starting node v_0 to the node v_1 via the edge e_1 . This transition is therefore described by simplified behavioural vector $\vec{\gamma}'_1 = ('s', 'eh', 'e', t_1)$ where 's' stands for the person, 'eh' is the identification of the movement action from node e to h , and t_1 is the variable representing the timestamp when this behaviour was detected. The system resets (updates, stores, etc.) its

internal state and understands the living person is present in the hall. The person further visits the toilet, has breakfast in the kitchen, and then leaves the apartment. Without the same level of details, the rest of these steps is identified by the following behaviour vectors: $(('s', 'ht', 'h', t_2), ('s', 'th', 't', t_3), ('s', 'hl', 'h', t_4), ('s', 'lk', 'l', t_5), ('s', 'kl', 'k', t_6), ('s', 'lh', 'l', t_7), ('s', 'h-exit', 'h', t_8))$. The last action 'h-exit' expresses that the person left the apartment.

By taking this situation as the initial state, we can imagine that the person has a robotic vacuum cleaner which starts to clean the apartment. Movement is detected by PIR sensors, but the evidence of living person is missing, so the activity is logged, but this has no influence on the overall behaviour of the person.

Last but not least, let's imagine an extreme situation. A living person has left the apartment, and suddenly the magnetic sensor of the window in the kitchen detects the window is being opened. This can simply mean the sensor could have been broken and it needs to be repaired, but in combination with the PIR sensors and the Grid-EYE sensor in the kitchen, the presence and movement of a living person are detected. Since this is the transition from the node o to k via the edge 'ok', this behaviour should be described by a behaviour vector, but in this case, the system is missing the context, and the activity is suspicious. This behaviour is logged, but the identifier for an unknown person is used. As can be seen in Figure 2, this particular transition follows dashed line marked in blue. This edge is a part of WE set which can be understood as the set of edges with *warnings*. Any of behaviour vectors which are created by following these types of lines must be reported as unusual and the operator of the system, as same as the user (if it is relevant or possible), should be informed about these events.

5 DISCUSSION

The proposed model deals with the conversion of transactional data coming from IoT sensors into behavioural feature space represented by behavioural vectors. These behavioural vectors can be used further by the processes which try to identify behavioural patterns. It is obvious that the topology of the monitored apartment must be taken into account and it forms an undivided part of the whole system. For instance, the distribution of edges among two separated sets DE , and WE allows immediately distinguish which transition (detected behaviour) is natural and which requires further actions (transitions following edges which are as part of the latter set). Events

in the system must be created as reactions to these situations. As was presented in the previous Section 4, the example can be a housebreaker entering the apartment in case a resident is outside. In extreme case, the similar situation can happen if a resident falls out of the window, etc.

In Figure 3 we present an overview of the complex system where the behavioural data are prepared by using a combination of standard data processing / evaluation and the topology of monitored apartment. Both the events emitted by data processing layer and findings of behaviour pattern analysis should be further processed by an expert system which can decide and act.

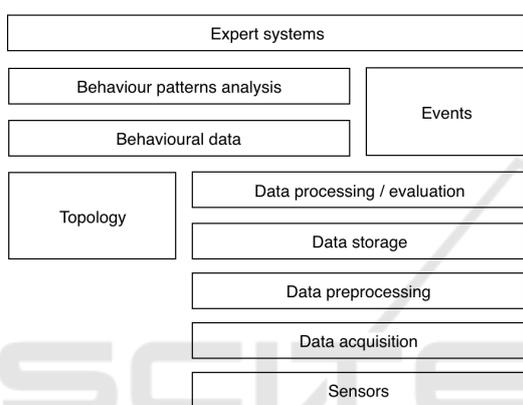


Figure 3: Proposal of the complex system for detection and evaluation of behaviour from data of IoT sensors.

6 CONCLUSIONS

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. Therefore one of the aims of our presented study is 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.

ACKNOWLEDGEMENTS

Research has been supported by the Czech Ministry of Industry and Trade project No. FV-20696 Personal health monitoring and assistive systems.

REFERENCES

Ahmed, E., Yaqoob, I., Hashem, I. A. T., Khan, I., Ahmed, A. I. A., Imran, M., and Vasilakos, A. V. (2017). The role of big data analytics in Internet of Things. *Computer Networks*, 129:459 – 471. Special Issue on 5G Wireless Networks for IoT and Body Sensors.

Cao, L. (2010). In-depth behavior understanding and use: The behavior informatics approach. *Information Sciences*, 180(17):3067 – 3085. Including Special Section on Virtual Agent and Organization Modeling: Theory and Applications.

Cao, L. (2013). Behavior Informatics and Computing. Advanced Analytics Institute, University of Technology Sydney, Australia.

Cao, L. and Yu, P. (2009). Behavior Informatics: An Informatics Perspective for Behavior Studies. *IEEE Intelligent Informatics Bulletin*, 10:6–11.

Lhotska, L., Dolezal, J., Adolf, J., Potucek, J., Krizek, M., and Chbani, B. (2018). Závěrečná zpráva řešerše senzorů a čidel – project No. TRIO FV20696. [Unpublished project report, CTU CIIRC Prague].

Petnik, J. and Vanus, J. (2018). Design of Smart Home Implementation within IoT with Natural Language Interface. *IFAC-PapersOnLine*, 51(6):174 – 179. 15th IFAC Conference on Programmable Devices and Embedded Systems PDeS 2018.

Sheriff, C. I., Naqishbandi, T., and Geetha, A. (2015). Healthcare informatics and analytics framework. In *2015 International Conference on Computer Communication and Informatics (ICCCI)*, pages 1–6.