Activity-monitoring in Private Households for Emergency Detection: A Survey of Common Methods and Existing Disaggregable Data Sources

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Abstract: Ambient-Assisted Living (AAL) technologies can enable the elderly people to live a self-determined life in their own home environment instead of hospitals and retirement homes for a longer period of time. Hence, AAL systems are not only used for everyday support but also for the detection of potential emergency situations and for triggering notification chains. For this purpose the people are usually continuously monitored within their residents by ambient or wearable sensors to detect deviations in their daily behavior.

This work surveys common used technologies for Human Activity Recognition (HAR) / Human Presence Detection (HPD), which is the basis for emergency detection. Furthermore, by examining various home automation software, existing data sources from the residential infrastructure, are identified that would be suitable for detecting personal activities.

1 INTRODUCTION

Due to the demographic change – which means a rising life expectancy and a decrease in the birth rate – the German society is aging increasingly, so elderly care is one of the major challenges for society in the near future (Hoffmann, 2016; Fischer and Krämer, 2016; Paulus, 2015). *Parra et al.* (Parra et al., 2015) noted that elderly people usually have several health afflictions. 85% of the elderly have at least one chronic disease, 65% even two or more. Furthermore, it is important to know that most of elderly people (61% of men and 75% of women) live alone or with his/her partner. The ones who live alone generally have more accidents. In fact, 30% of them have one fall per year and the 50% of them even suffer more than one fall. (Parra et al., 2015). Therefore, it is essential to monitor the health status – i.e., the activity of the individual – in order to recognize possible emergency situations in the home environment (Hoffmann, 2016; Munstermann, 2015).

There are already various market solutions and research projects for supporting elderly in their everyday life and monitoring people in their home environment to detect possible emergency situations in the households which are denoted as Ambient-Assisted Living (AAL) systems (Uddin et al., 2018). This work focuses on AAL systems for emergency detection. In contrast to common emergency call systems, where the resident himself or herself has to actively request help, AAL systems are supposed to recognize automatically when a potential emergency situation exists.

Therefore, most common AAL systems use data from various sensors, which are installed specially for this purpose within the residence or are worn on the body of the person to be monitored (Munstermann, 2015).

In the scope of our work within the research project *BLADL* an alternative approach to monitor residents inside their home environment by reusing existing data sources from the residential infrastructure instead of installing additional sensors is investigated. This allows AAL technologies to be integrated even more unobtrusively into the everyday lives of elderly people.

In private households there are already numerous data sources such as smart meters, digital water meters, weather stations, routers, mobile phones or voice assistants available. Intelligent algorithms (e.g., Machine Learning (Alpaydin, 2020), Deep Learning (LeCun et al., 2015)) can be used to disaggregate this data and conclude on personal activities. This, in turn, allows the creation of comprehensive activity profiles

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of the residents. Deviations from the typical activity profile can in turn indicate possible emergency situations (Floeck and Litz, 2009; Clement et al., 2013; Reyes-Ortiz et al., 2016; Parra et al., 2015).

The main contribution of this paper is to survey which data sources are currently used for HAR / HPD and which further data sources are available in the infrastructure of private households, that can potentially be used for HAR / HPD.

The remaining of the paper is structured as follows: common methods for HAR / HPD are presented in Section 2. With Section 3 existing data sources from the residential infrastructure, are identified which are potentially suitable for detecting human activities. In addition different software for home automation were examined. Finally, the paper is concluded in Section 4.

2 COMMON METHODS

Most of the current available AAL systems for emergency detection use sensor data to monitor the activities of the residents. In practice, motion detectors, fall detectors, fall mats or window/door contact sensors are used for such applications. They are often called *ambient sensors* because they can be integrated into the home environment. *Vital sensors* are another type of sensor that can be used for emergency detection. These are worn directly on the body by the person to be monitored. This enables even more detailed monitoring of the person and emergencies can be detected even faster (Munstermann, 2015).

In the domain of activity recognition the terms 'action' and 'activity' are commonly used. *Chen et al.* (Chen et al., 2012) defined the term 'action' as a simple ambulatory behavior executed by a single person and typically lasting for short duration of time (e.g., opening a door). The term 'activity' refers to complex behaviors consisting of a sequence of actions and/or interleaving or overlapping actions (e.g., making a meal). In most cases, the sensors only detect 'actions'. For further processing in the AAL domain often the information about the specific 'activity' is required. To draw conclusions from 'actions' to 'activities', researchers have created various probabilistic models. The Hidden Markov Model (HMM), Hidden Semi Markov Model (HMM) and the conditional random field (CRF) are among others the most popular modeling techniques (Bakar et al., 2015; Kim et al., 2010; Ghasemi and Pouyan, 2015). Thereby, the main challenges are: (i) recognizing concurrent activities (ii) recognizing interleaved activities (iii) ambiguity of interpretation (iv) multiple residents. (Kim et al., 2010).

Activities are often categorized as Activities of Daily Living (ADLs) or Instrumental Activities of Daily Living (IADLs). ADLs includes the fundamental skills typically needed to manage basic pyhsical need (e.g., personal hygiene, dressing, toileting). IADLs includes more complex activities related to independent living in the community (e.g., managing finances and medications). *Milnac and Feng* (Mlinac and Feng, 2016) noted that the impairment of IADLs can indicate cognitive impairment and mild dementia.

Since our work focuses to the recognition of acute emergency situations – not on the monitoring of the state of help of the residents – it is not necessary to conclude from the detected 'actions' to 'activities' or further categorize them as ADL or IADL.

In their survey papers *Rashidi and Mihailidis* (Rashidi and Mihailidis, 2013) and *Uddin et al.* (Uddin et al., 2018) listed the most common sensors for action detection in the AAL domain.

Table 1 lists ambient sensors used in smart environments, Table 2 shows typical wearable and mobile sensors.

Table 1: Ambient sensors used in smart environments (Rashidi and Mihailidis, 2013; Uddin et al., 2018; Eldib et al., 2016).

Sensor	Measurement
PIR[a]	Motion
Active Infrared	Motion / Identification
RFID[b]	Object Information
Pressure	Pressure on Mat, Chair, etc.
Smart Tiles	Pressure on Floor
Magnetic Switches	Door Opening/Closing
Ultrasonic	Motion
Camera	Activity
Photo Sensor / Visual Sensor	Activity
Microphone	Activity
Temperature Sensor	Temperature of a room
Water flow sensor	Flow of water
Force Sensor	Movements and falls
Smoke Sensor	Smoke in the environment

[a] Passive Infrared Motion Sensor
[b] Radio Frequency Identification

Calvaresi et al. (Calvaresi et al., 2016) and *Uddin et al.* (Uddin et al., 2018) noted that in general these sensors are used independently of each other, although the use of multi-component ambient sensor technologies would increase the quality of the systems. Systems using combined sensor technology most often use a combination of Passive Infrared Motion Sensor (PIR) and video cameras. The next most common combination is a combination of pressure

Table 2: Typical wearable and mobile sensors (Rashidi and Mihailidis, 2013).

Sensor	Measurement
Accelerometer	Acceleration
Gyroscope	Orientation
Glucometer	Blood Glucose
Pressure	Blood Pressure
CO_2 Gas	Respiration
ECG[a]	Cardiac Activity
EEG[b]	Brain Activity
EMG[c]	Muscle Activity
EOG[d]	Eye Movement
Pulse Oximeter	Blood Oxygen Saturation
GSR[e]	Perspiration
Thermal	Body Temperature

[a] Electrocardiography
[b] Electroencephalography
[c] Electromyography
[d] Electrooculography
[e] Galvanic Skin Response

and PIR sensors (Uddin et al., 2018).

Further to the solutions for HAR mentioned in Table 1 and Table 2, investigations are also carried out reusing existing data sources to draw conclusions about user activity, which are listed below:

(i) **WiFi-Signal:**
Several investigates on the extraction of activity-related information from Wireless Local Area Network (WiFi) signals was already made. *Wang et al.* (Wang et al., 2015) and *Pu et. al* (Pu et al., 2013) examined the Channel State Information (CSI) of the WiFi signal for fluctuations caused by the reflection of human bodys. This enables them to detect individual movements of residents (e.g., sitting down, walking, raising an arm). In contrast to examining the CSI *Gu et al.* (Gu et al., 2016) examined the Received Signal Strength Indication (RSSI) due to the simplicity of extracting this data with the same results.
Another approach to the use of WiFi signals for HAR was investigated by *Xie et al.* (Xie et al., 2016). They developed an app which allows the localisation of a smartphone within the residence by examining which Access Points (APs) are available with which signal quality. This approach was evaluated in an urban space.

(ii) **Smartphone:**
Smartphones have become an alternative for wearable sensing due the diversity of sensors they internally support. Furthermore, the devices offer capacities for networking and processing (Reyes-Ortiz et al., 2016; Parra et al., 2015). Current research is primarily based on data from accelerometers and gyroscopes to draw conclusions about specific user actions. The investigations focuses on the optimization of algorithms of individual activities using various machine learning methods (e.g., Deep Belief Network (DBN) (Hassan et al., 2018), Supporting Vector Machine (SVN) (Reyes-Ortiz et al., 2016)).
In contrast the possibilities of using the internal sensors – especially camera and microphone – in an ambient environment are also being investigated (Parra et al., 2015; Chen et al., 2012). *Parra et al.* (Parra et al., 2015) analysed the use of smartphones for AAL and eHealth use cases. They identified the following possible applications: (i) heart rate monitoring (ii) breathing and pulse (iii) moods monitoring (iv) detecting stress (v) positioning and localization (vi) spirometry sensing (vii) sleep monitoring.

(iii) **Smart Meter:**
Clement et al. (Clement et al., 2012; Clement et al., 2013) have developed an approach for disaggregating smart meter measurements to draw conclusions about the use of individual technical devices. This in turn can detect a certain action of a resident.

(iv) **Home Weather Station:**
Wilhelm et al. (Wilhelm et al., 2020a) analyzed the carbon dioxide ($CO2$) readings of smart weather stations to determine the presence or absence of people indoors. The authors based their work on the fact that humans produce $CO2$ through their respiration, which is then distributed throughout the room. As a result, if one (or more) persons are in a room, a significant increase in $CO2$ concentration in the room can be noted. If a person is no longer in a room, the $CO2$ concentration decreases due to infiltration and the absence of the person can be indicated.

3 FURTHER DATA SOURCES

With this paper we analysed which further, already existing data sources from the residential infrastructure, are potentially suitable to detect human activities / presence within the residence. Therefore, we have systematically identified available and accessible data sources by examining different home automation software and evaluating them individually based on the literature. We limited ourselves to open source solutions under the assumption that the community has already programmed interfaces for the majority of potential data sources that can be present in a household. We first investigated which of the open source

Table 3: Open Source Home Automation Software (as per May 30th, 2020). Ordered by #GitHub Repositories.

Name	Language	Google-Trends Rank	#GitHub Repos.	#Forum posts	#Forum users
HomeAssistant	C++	8	3317	7043	2717
Homebridge	C++	4	3306	2534	194
OpenHAB	Java	1	2323	555000	36015
Node-Red	C++	9	1657	182368	22973
Domoticz	Java	3	1424	n.A	n.A.
IoBroker	PHP	6	1151	170000	8100
Jeedom	Python	5	789	48232	6985
FHEM	Eagle	2	753	n.A.	n.A.
MajorDoMo	C++	7	394	104864	4371
Pimatic	Python	11	394	973000	64400
EventGhost	Pyhon	12	103	n.A.	13
HomeGenie	Javascript	12	62	11416	1220
AGO Control	Java	10	53	1049	220
Calaos	NodeJS	12	45	40900	1500
MyController	Perl	13	40	1030507	22430
MisterHouse	NodeJs	13	22	439900	27000
OpenMotics	NodeJS	13	12	n.A.	2238
LinuxMCE	Perl	13	10	n.A.	n.A.
Gladys Assistant	NodeJS	13	9	n.A.	2462
piDome	Java	13	4	2800	562
Smarthomatic	NodeJS	13	3	120000	8900
OpenNetHome	PHP	13	1	114406	5418

solutions are most common by noting the following aspects (as per May 30th, 2020):

(i) Google-Trends Ranking (based on the *Google Trends* - Service) (ii) #GitHub Repositories (iii) #Forum posts (iv) #Forum users.
The applications are listed in Table 3.

We noticed that *HomeAssistant* has the most GitHub repositories and *OpenHAB* is the leader in Google Trends ranking. Therefore we investigated these two applications in more detail, since we assume that the developer community is most active on these systems and most integrations to existing data sources have already been developed.

In the context of reusing existing data sources for HAR / HPD, the investigations of *Perkowith et. al* (Perkowitz et al., 2004), *Philipose et al.* (Philipose et al., 2004) and *Wyatt et al.* (Wyatt et al., 2005) are particular noteworthy. The authors have shown that it is possible infer the specific activity of a person from the interaction with certain objects (e.g., coffee maker). Therefore, they tagged different objects with Radio Frequency Identification (RFID) tags and attached RFID readers on the wrists of the residents.

Table 4 lists the data sources that have been identified and are potentially suitable for HAR / HPD.

It was decided not to include mobile devices (e.g., Smartphone or Smart Watch) as these are more likely to be classified as wearable sensors.

4 CONCLUSION AND FUTURE WORK

This paper outlines that there exists numerous data sources in private households, which can potentially be used for HAR / HPD and so allow monitoring people within their residence without installing additional sensors. However, common systems use primarily proprietary sensor technology for detecting human activity / presence. Only the reuse of *smartphone* (Chen et al., 2012; Reyes-Ortiz et al., 2016; Parra et al., 2015; Hassan et al., 2018), *WiFi* (Wang et al., 2015; Pu et al., 2013; **?**; Xie et al., 2016), *smart meter* (Clement et al., 2012; Clement et al., 2013) or *home weather station* (Wilhelm et al., 2020a) data to detect activities / presence of persons within the home environment is already investigated in literature.

The results of this survey can now be used in further work to develop disaggregation algorithms for individual data sources and to investigate them in detail on their suitability for HAR / HPD or for emergency recognition as described by *Hamper* (Hamper, 2020). Thus AAL systems can be developed, which are detect potential emergencies within the resident without the need for proprietary sensors.

Table 4: Further potentially suitable data sources for HAR / HPD.

Data Source	Features	Potentials for HAR / HPD
air conditioning / ventilation	(i) status of the system (e.g., fan speed) (ii) the readings of integrated sensors – usually temperature and humidity sensors	A change of state (e.g., switching on/off) can indicate a human interaction, unless it is automated or sensor controlled. In addition, the measurement data can potentially be disaggregated analogous to *Wilhelm et al.* (Wilhelm et al., 2020a).
air quality and temperature sensors	(i) temperature (ii) humidity	Significant changes in indoor temperature or humidity can be caused by humans, which allows the detection of activity. The reason for such a change may be that windows or doors have been opened (Fitzner and Finke, 2012). In addition, the measurement data can be disaggregated analogous to *Wilhelm et al.* (Wilhelm et al., 2020a) due to the fact, that the human body radiates a natural warmth (Kessel et al., 2010).
alarm system	(i) alarm state / zone alarm (ii) armed away / stay indicator (iii) motion (iv) door / windows contact (v) water - alarm (vi) fire - alarm (vii) system state	Alarm systems are designed to detect human activity (e.g., by motion detectors), the data can therefore also be used for HAR / HPD in the AAL area.
aquarium monitoring system	(i) water temperature (ii) PH / NH_3 / NH_4 / oxygen level (iii) light level / kelvin	It is a natural process that the water quality in fish water aquariums changes constantly. One example is the so-called 'Nitrogen Cycle', whereby the NH_4 concentration in the water increases. A significant reduction in NH_4 concentration can be reached by filling up fresh water (Saint-Erne, 2017) – which represents human activity and can therefore be identified by the measurement results of the *aquarium monitoring system* .
bed	(i) state (ii) pressure	Smart beds offer the possibility to read out whether a person is lying in bed and also determine the pressure on the mattress. Thus the human activity can be determined directly. Furthermore, pressure changes show that the person lying in bed is still alive.
body scale	(i) weight (ii) fat ratio	When a person uses the body scale, which generates data, human activity can be detected directly.
car	(i) door-lock (ii) charge state / battery level (iii) climate (iv) inside-temperature (v) location (vi) speed (vii) engine state (viii) service	When a person interacts with the car, e.g., by driving it, locking it, or starting/ending a charging process, a clear human action can be determined from the data.
clock / alarm clock	(i) alarm-state (ii) timer (iii) radio	Changing the settings (e.g., alarm time) or changing the status of the alarm clock (e.g., turning off an alarm clock) requires human interaction.
coffee machine	(i) state (ii) operating mode	Using the coffee machine (e.g., by brewing a coffee) can be read from the data of smart coffee machines and therefore provide information about human activities.
computer	(i) state (ii) detail usage information	The use of a computer can be recorded and analyzed with great precision. Every interaction with the device indicates a certain human activity.

Table 4: Further potentially suitable data sources for HAR / HPD (cont).

dishwasher	(i) state (ii) operating mode (iii) program	Switching the dishwasher on and off or even interrupting a running washing process indicates human activity.
doorbell/door intercom system	(i) events when the doorbell was pressed (ii) movements in front of the door (iii) pictures outside the door (iv) actions at the door relay	Since the doorbell itself is placed in front of the apartment, it is only conditionally suitable for HAR / HPD within the residential area. However, actions at the intercom system or at the door relay clearly indicate human activity in the residence. In addition, the images from video-based door intercoms can be analyzed to determine when a person leaves or enters the house (Tan et al., 2006).
EV charging stations	(i) vehicle loading (ii) vehicle state (iii) vehicle locked (iv) wall-box state (v) authenticated entity	When a loading process is started or stopped, human interaction is mandatory. In addition, changes in the vehicle state (e.g. unlocking or locking) also indicate human activity.
fridge /freezer	(i) state (ii) operating mode (iii) current temperature (iv) target temperature	Changes in device settings (target temperature) or operating mode directly indicate human activity.
garage door	(i) door status (ii) sun reflection (iii) switch status (iv) vehicle status	Opening or closing the garage door is always due to human activity. In addition, individual garage door opener systems offer the possibility to query whether the vehicle is in the garage. If this state changes, human activity must also be assumed.
heating system / heat pump	(i) current room temperature (ii) target room temperature (iii) temperature boiler (iv) hot water temperature (v) temperature flow / return (vi) operating mode	The heating system offers several opportunities to draw conclusions about human activity. First, a change of settings (e.g., target temperature) usually means that a person has executed an activity. Furthermore, the (warm) water consumption in apartments can be disaggregated to draw conclusions about human activity (e.g., person was showering). Modern heating systems are additionally equipped with extensive sensor technology, which monitors the indoor air quality. These could also be disaggregated analogous to *Wilhelm et al.* (Wilhelm et al., 2020a) to draw conclusions about human activity.
Hi-Fi system/ media receiver	(i) operating state (ii) amp power (iii) amp settings (iv) zone settings (v) current played per zone (vi) current mode per zone	State changes like turning on / turning of or change the amp power or settings indicates direct human interaction with the Hi-Fi system / media receiver.
home weather station	(i) temperature (indoor / outdoor) (ii) humidity (indoor / outdoor) (iii) CO_2 (indoor / outdoor) (iv) Air Quality Index (v) PM2.5 level (vi) rain (vii) wind (viii) UV index (ix) system state	Even if the outdoor information is not relevant to the HAR / HPD, significant changes in indoor temperature or humidity can be caused by humans, which allows the detection of activity. The reason for such a change may be that windows or doors have been opened (Fitzner and Finke, 2012). Furthermore, the carbon dioxide measurements ($CO2$) can be used to determine the presence or absence of people indoors as already investigated by *Wilhelm et al.* (Wilhelm et al., 2020a).
irrigation/ smart gardening system	(i) zone mode (ii) current operating (iii) temperature (iv) humidity (v) wind speed (vi) water level	Changes in settings or operating mode (if not automated) indicate human activity.

Table 4: Further potentially suitable data sources for HAR / HPD (cont).

lamp	(i) switch state (ii) dimmer (iii) color	Changes of state (switch on / off / dimmer or change color) indicate switching actions by humans, unless the lamps are controlled automatically.
lawn mower	(i) state (ii) mowed (iii) error	The systems basically work autonomously, but manual status changes can be made which can be interpreted as human activity.
lock	(i) status of the locks (ii) registering actions – i.e. accesses	Status changes or access events indicates clear human activity.
microwave	(i) state (ii) operating mode (iii) timer	The use of the microwave can be indicated by the resulting change in state.
oven	(i) state (ii) operating mode (iii) current temperature (iv) target temperature	Changes of state (e.g. operating mode or adjusting the target temperature) follows human interaction with the device.
power plug	(i) switch state (ii) current power (iii) energy	Switch state changes indicated direct human interaction with the device. The *current power* information can also be used to draw conclusions as to whether the connected device is currently active and thus to detect human interaction with the connected device (e.g., coffee machine) (Wilhelm et al., 2020b; Wilhelm et al., 2021).
printer	(i) state (ii) jobs (print/scan)	State changes (except for automated programs like cleaning) or new jobs indicates human activity.
radiator thermostat	(i) current temperature (ii) target temperature (iii) state	Significant changes in the indoor temperature can be caused by humans, which allows the detection of activity (e.g., opening a window) (Fitzner and Finke, 2012). Furthermore, the change of the target temperature indicates direct human interaction.
(rain) water pump	(i) water-level (ii) operating mode (iii) source used (iv) switch state	Water flow is mostly due to human activities (e.g., flushing toilets, garden irrigation). The corresponding data can be disaggregated to identify individual tapping points and thus to conclude on a concrete human-induced action (Froehlich et al., 2011).
remote control	(i) received remote (ii) received command	If remote control commands are received, this is due to human activity.
roller shutter	(i) position	Changing the position of the roller shutters indicates human activity.
router / network-switches / access points	(i) state (ii) power (iii) connected devices (iv) deep packet inspections (v) WiFi-link-quality	Various conclusions about human activities can be drawn from the general network information by analyzing the data consumption of individual end devices. Furthermore can the WiFi information be disaggregated as described by *Wang et al.* (Wang et al., 2015), *Pu et. al* (Pu et al., 2013), *Gu et al.* (Gu et al., 2016) or *Xie et al.* (Xie et al., 2016).
smart meter (gas)	(i) gas delivery (ii) gas valve position (iii) error code	Depending on the installed heating system and/or gas-powered appliances in the household, the smart meter offers the possibility of drawing conclusions about individual activities. For example, when hot water is being used or when cooking is being done.
smart meter (power)	(i) current power delivery (ii) current power production (iii) power failures (iv) voltage (L1, L2, L3) (v) current (L1, L2, L3) (vi) switch position (vii) error code	Power consumption data can be disaggregated, which allows conclusions to be drawn to determine which individual devices are currently active in the household. This, in turn, allows conclusions to be drawn about individual human activities (Clement et al., 2012; Clement et al., 2013; Wilhelm et al., 2020b).

Table 4: Further potentially suitable data sources for HAR / HPD (cont).

smart meter (water)	(i) water delivery / heating delivery (ii) water meter valve position (iii) error code	Water flow is mostly due to human activities (e.g., flushing toilets, showers). The corresponding data can be disaggregated to identify individual tapping points and thus to conclude on a concrete human-induced action (Froehlich et al., 2011).
smart speaker	(i) commands / interactions (ii) volume (iii) music played (iv) Bluetooth connections (v) reminders (vi) routines (vii) messages (viii) connected devices	When humans interact with intelligent speakers, human activity can be detected based on the commands/interactions given.
smoke detector	(i) smoke alarm state (ii) manual test active (iii) ui color (iv) battery state (v) connection state	According to *Rashidi and Mihailidis* (Rashidi and Mihailidis, 2013) and *Uddin et al.* (Uddin et al., 2018) smoke detectors are already commonly used for HAR. It is also possible to read out when a manual device test is performed so that human activity can be detected.
surveillance camera	(i) picture / recording (ii) motion (iii) sound (iv) state	If surveillance cameras are installed indoor, they can directly detect human activities within the residence. For example, image recognition algorithms can be used (Rashidi and Mihailidis, 2013; Uddin et al., 2018; Tan et al., 2006). Human activities can also be monitored via the internal microphones of some surveillance cameras (Rashidi and Mihailidis, 2013; Uddin et al., 2018).
swimming pool	(i) temperature (pool / spa / air) (ii) pump state (iii) spa pump state (iv) heater state (v) *PH* (vi) pool light	Changes in the operating status of the pump, heating or lighting may be caused by human activity. Under certain circumstances it is even possible to infer human activity in the pool from the change in water quality (Wyczarska-Kokot, 2015).
switch / dimmer / relay	(i) switch state (ii) input (iii) current power	Switching state changes indicate direct human interaction, unless it is an automatically controlled system (e.g. by a timer). The *current power* information can also be used to draw conclusions as to whether the connected device is currently active and thus to detect human interaction with the connected device (e.g., coffee machine) (Wilhelm et al., 2020b).
telephone system	(i) calls (incoming / outgoing) (ii) connected to (iii) missed calls	When incoming calls are accepted or outgoing calls are made, human activity can usually be assumed. Special features such as automatic answering machines must be considered.
tv / beamer	(i) state (ii) commands (iii) current playing (iv) mute / volume (v) source (vi) (only beamer) lamp	Changes in state, source or the current playing program indicates in general a human action.
vacuum robot	(i) state (ii) battery level	If the devices are not set to an automatic program, a status change indicates human activity.
washing machine / tumble dryer	(i) state (ii) program (iii) phase (iv) programmed start-time	State changes or programming a new start-time are caused by human interaction with the devices and so indicates human activity.
water softner	(i) alam / alert (ii) current flow (iii) water hardness (inlet / outlet) (iv) salt remaining (v) water pressure	Water flow is mostly due to human activities (e.g., flushing toilets, showers). The corresponding data can be disaggregated to identify individual tapping points and thus to conclude on a concrete human-induced action (Froehlich et al., 2011).
window	(i) position	Status changes are related to human activity.

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