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Integrated Sensing Devices for Disease Prevention and Health Alerts in Smart Homes

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Abstract. The rapid development of elderly population is changing demographics in Europe and North America and imposes barriers to healthcare systems that may reduce the quality of service. Telemedicine is a potential solution supporting the real-time and remote monitoring of subjects as well as bidirectional communication with medical personnel for care delivery at the point of perception. Smart homes are private spaces where young or elderly, healthy or diseased-suffering, or disabled individuals spend the majority of their time. Hence, turning smart homes into diagnostic spaces for continuous, real-time, and unobtrusive health monitoring allows disease prediction and prevention before the subject perceives any symptoms. According to the World Health Organization, health, well-being, and quality of life assessment require the monitoring of interwoven domains such as environmental, behavioral, physiological, and psychological. In this work, we give an overview on sensing devices and technologies utilized in smart homes, which can turn the home into a diagnostic space. We consider the integration of sensing devices from all four WHO domains with respect to raw and processed data, transmission, and synchronization. We apply the bus-based scalable intelligent system to construct a hybrid topology for hierarchical multi-layer data fusion. This enables event detection and alerting for short-time as well as prediction and prevention for long-time monitoring.

Keywords. smart home, health monitoring, unobtrusive monitoring, Internet of medical things, quality of life, International Standard Accident Number

1. Introduction

1.1. Aging Population

The life expectancy in many countries has increased due to several dominant reasons including (i) improved healthcare systems, medical science, and diagnostic technology; (ii) increased individual awareness on personal and environmental hygiene, health, nutrition, and education [1–3]. Demographically, this yields an increasing average age of populations. By 2035, one third of the population in Europe and North America will be older than 65 years [4]. Such a rapid growth of elderly will adversely impact the healthcare systems by increasing the human resources, imposing additional costs, and

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consequently reducing the quality of services [5, 6]. Furthermore, an increased life expectancy is connected with demands of the elderly for independence and higher quality of life (QoL) [7]. Hence, in order to adapt to these developing requirements in elderly healthcare services, it is fundamental to create low-cost, unobtrusive, and simple-to-utilize healthcare solutions [8]. Remote health monitoring allows medical personnel to keep track of environmental, behavioral, physiological, and psychological signs. Such an ambient assisted living (AAL) environment enables elderly to live longer autonomously but safely in their homes, maintaining privacy and independence [9]. Thereby, smart homes can advance autonomy, the feeling of prosperity, and empower the inhabitants to gain personal satisfaction [10].

1.2. Healthcare Systems

In our current healthcare systems, a subject meets a doctor when feeling sick, observing symptoms, or for regular check-ups. This yields treatment after diagnosis: medical professionals are mainly involved in the healthcare process by detecting symptoms, diagnosing, and curing after the outbreak of a disease. Their decisions are based on several physiological examinations (e.g., blood and urine tests, blood pressure, body temperature, and heart rate measurements). However, future visions emphasize the importance of prevention and prediction [11]. Next to regular check-ups of risk groups, this can be accomplished by telemedicine, mobile health (mHealth), electronic health (eHealth), and the Internet of medical things (IoMT) [12–14]. These trends aim at managing and integrating large volumes of heterogeneous (big) data, which is generated by sensing devices and stored in electronic health records (EHR). The automated fusion of data from multiple sensing devices minimizes uncertainty and improves the detection of trends in the individual's health status as well as adverse health events. Modern healthcare systems implement data analytics to find patterns and trends within the data, to detect abnormalities or symptoms at an early stage, and to provide decision making [15].

1.3. The Influencing Domains of Monitoring

The World Health Organization (WHO) refers to six domains on health, well-being, and QoL [16], four of them are measurable technically:

- *Environmental* parameters include hazardous or toxic gases that affect the indoor/outdoor air quality and physical parameters such as sound level, ultraviolet (UV) light index, temperature, or humidity [17];
- *Behavioral* parameters include physical activity of a subject (e.g. walking, body posture changes), gait parameters, activity of daily routine (ADL), habits, and nutrition [18];
- *Physiological* parameters include the vital signs (e.g., body temperature, heart rate, respiratory rate, blood pressure, and oxygen saturation) and non-vital signs (e.g., skin conductance) [19];
- *Psychological* parameters include the mood and emotions of an individual [20].

(Remote) sensing in these four domains requires appropriate technologies to measure the respective parameters. Furthermore, continuous and unobtrusive monitoring yields big data. Since the WHO domains are interwoven, fused data analytics and pattern recognition may significantly contribute to real-time event detection in the short-term, as well as prediction and prevention of adverse health events in the long-term, in particular, for vulnerable groups of the population (e.g., children, elderly) [21, 22].

1.4. Smart Homes

Prolonged life expectancy and reduced birth rates yield a fast-growing rate of the elderly. Furthermore, an increased anticipation of QoL aspects is observed that can be met by new healthcare systems [23, 24], supporting elderly to continue living in their own homes, as long as possible. In this new paradigm, the focus shifts from physician-centric to patient-centric healthcare systems, where AAL technologies will revolutionize the delivery of healthcare [25]. In this context, we define the term "smart home" as a residence equipped with sensors and actuators that are integrated into a platform, leading to the capability of monitoring the residents, improving QoL, and promoting independent living [26–29]. More specifically, the benefits of smart homes include monitoring the health status, detecting changes in health conditions, and predicting emergency events (e.g., fall). Hence, smart homes may help to reduce the costs of healthcare systems.

In summary, we identify three major reasons for health monitoring in smart homes:

- *Medical:* detect health conditions and changes that else might have stayed unnoticed;
- *Personal:* allow elderly to continue living at home and having their privacy and independence [26];
- *Economical:* save costs in comparison with living in a nursing home or hospital [30].

1.5. Transforming Smart Homes into Diagnostic Spaces

We consider the smart home as a private space that can be transformed into a diagnostic space [21]. A diagnostic space should enable simultaneous monitoring of parameters from all the four WHO domains. This concept is inline with the paradigms of shifting the: (i) subject-to-device in a hospital → device-to-subject in a point of perception; and (ii) diagnosis on symptoms → preventive medicine. This supports the idea of "an accurate forecast for a specific individual longest before the predicted event" [21]. Such an approach provides unobtrusive, continuous, and long-term data acquisition for real-time monitoring. Integrating inexpensive medical and non-medical sensing devices in smart homes copes with the requirements. Combining signal and bio-signal processing and reducing the hardware complexity by analytical software via artificial intelligence (AI)-based techniques may contribute to a valid diagnosis. The smart home as a diagnostic space potentially solves problems related to smart wearables and clothes, such as obtrusiveness and lack of power supply.

1.6. Target Groups

Several people benefit from transforming smart homes into diagnostic spaces:

- *Inhabitants*:
  - *Healthy individuals* who are unable to seek help in case of an emergency (e.g., fall, stroke, myocardial infarction) due to falling unconsciousness or living in communities with inadequate provision of health services (e.g., rural areas);

  - *Elderly* who suffer from physical impairment such as lowered auditive, visual, or muscular power and/or cognitive derogation (e.g., Alzheimer's disease, dementia);
  - *Disabled people* who need help in daily life to perform personal care (e.g., eating, toileting, getting dressed, bathing) and instrumental activities (e.g., cooking meals, taking medication, doing laundry).
  - *Patients* who suffer from chronic diseases and who need continuous monitoring [26].

- *Caregivers* including family, friends, and relatives of the inhabitants; and

- *Healthcare professionals* giving care either locally (e.g., nursing service, meal on wheels) or remotely by telemedicine systems [31].

1.7. Motivation

The IoMT paradigm has facilitated the interconnection of diverse devices and electronic sensors in an embedded way. Utilizing IoMT in a smart home enables the collection of heterogeneous data from a broad range of sensors. The chain of data aggregation begins with the perception of data via a sensor network tier, which is then reported to a personalized gateway and transmitted to an application tier (i.e., cloud/server) [32]. This architecture enables the communication between various sensing layers and yields telemedical diagnostics and care delivery at the point of perception [33]. Adequate decision making is supported by:

- *Complete integration* of parameters from all measurable WHO domains enables reliable detection of sudden events, such as accidents and emergencies, as well as long-term tendencies of particular diseases.
- *Continuous monitoring* of the health status of a subject requires real-time data analytics for timely alerts.

In summary, transforming a smart home into a diagnostic space (point of perception) requires medical and non-medical sensing devices, which must be integrated for simultaneous monitoring in all four domains. Due to limitations in infrastructure and adequate data processing, this has not yet been accomplished.

We structure this work as follows: in Section 2, we overview the sensor technologies and data management. Building upon that, in Section 3, we summarize typical smart home applications and current research projects making use of them. In Section 4, we show the limitations of current work and use a bus-based scalable intelligent system (BASIS) to enable the measurement of all four WHO domains and thus, we unfold the potential of smart homes as diagnostic spaces.

2. Methods

2.1. Technologies in Smart Home

As seen from its definition, the technologies involved in the smart home can be very broad. Smart home solutions utilize a wide range of technologies serving different goals.

Sensor technology and signal processing play the key role in (environmental, behavioral, physiological, and psychological) data collection; machine learning is essential in information extraction and knowledge discovery; and to implement proper automatic response functions, human-machine interaction (HMI) as well as automation control technology are also unavoidable. Therefore, we also classify the technology from the monitoring perspective according to the four WHO domains: environmental, behavioral, physiological, and psychological. In this section, we introduce the typically used devices/sensors for each category.

2.1.1. Environmental Monitoring

Air quality sensors: Measuring pollutants indicates the quality of air. Pollutants include toxic and hazardous gases such as carbon monoxide (CO), carbon dioxide (CO_2), nitric oxide (NO), volatile organic compounds (VOCs), particulate matter (PM_{10} and $PM_{2.5}$), and ozone (O_3) [34]. Pollutants cause serious health risks depending on their concentration, the subject's health status, and the length of exposure [35, 36]. Nowadays, small devices of convenient forms with low power consumption support continuous and unobtrusive monitoring in particular for elderly, children, and people who are suffering from cardiovascular and respiratory diseases. This has pushed air sensors to become an inherent part of in-home monitoring. Based on the target applications, several factors are considered: selectivity, reliability, resolution, response time, reproducibility, price, etc. [37]. Common technologies utilize metal oxide semiconductors (MOS), electrochemical detection (EC), photoionization (PID), and infrared (IR) [38]. Due to its lower power consumption and price, but higher reliability and easier calibration, EC technology is used mostly. EC sensors have a minimum of two sensing and counter electrodes, which are contacted internally by electrolytes (i.e., liquid as an ion conductor) and externally via an electronic circuit. The electrodes affect certain chemical reactions at the so-called 3-phase boundary, where gas, catalyst, and electrolyte are present. Furthermore, EC sensors provide enhanced signal quality and have a longer lifetime [39].

Humidity and temperature sensors: Used in climate and weather evaluation, humidity indicates the likelihood of precipitation, dew, or moisture. An individual feels hotter under higher humidity, as it reduces the effectiveness of sweating to cool the body [40]. Furthermore, indoor humidity impacts temperature, air quality, health, and appliances [41]. Advanced semiconductor technology has reduced the dimensions and weights of sensors. Frequently, humidity and temperature sensors are combined. Thermal conductivity, resistance, or capacity are typical electrical effects used in these sensors [42]. Linear output voltage, stable output over long-term usage, and a wide range of measurements made capacitive technologies popular. The major sensor components are two curve shape electrodes made of aluminum, platinum, or chromium containing a porous dielectric substance (e.g., hygroscopic polymer film). The dielectric constant varies when humidity changes [43].

2.1.2. Behavioral Monitoring

Passive infrared (PIR) motion sensors: PIR sensors have a low power consumption and price. They detect objects through a changed light intensity [44]. Since the human body generates more infrared light than the indoor environment, this sensor is suitable to monitor human motion. The sensing component consists of a lens and a set of sensors with two slots. The slot is made from pyroelectric materials that are sensitive to infrared light. When the sensor is idle, both slots detect the same intensity, i.e., ambient radiation from the room or the walls. If a person passes by, the first slot generates a pulse. If the person leaves the sensing area, a negative differential is generated (Fig. 1). To monitor indoor behavior, PIR devices are attached to the living room, bedroom, kitchen, and specific facilities such as toilets or sinks (Fig. 2).

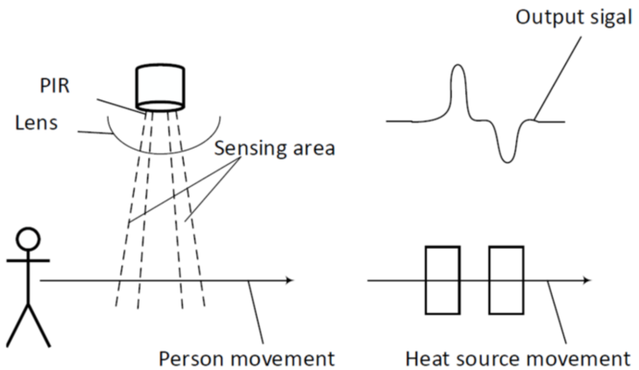

Figure 1. PIR sensing principle [43].

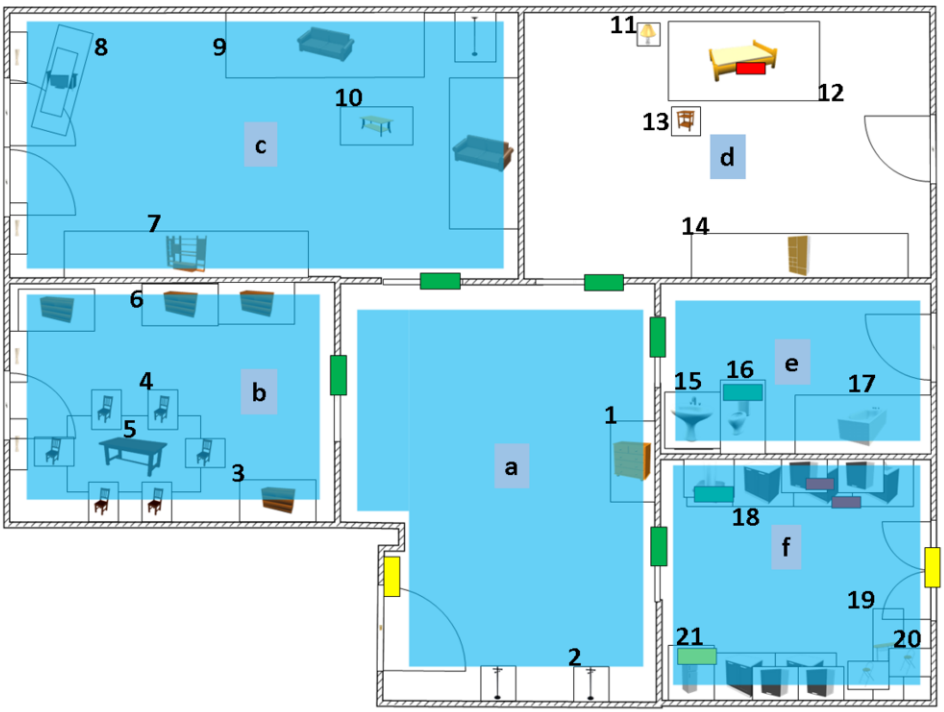

Figure 2. PIR placement in a smart home [46]. The green boxes show the positions of PIR sensors and the blue shadows are the areas under monitoring; the yellow boxes show the positions of contact sensors; red boxes show the position of vibration sensors. Areas and objects distributions in the smart hom; (a) hall: (1) drawer, (2) cloth hanger; (b) kitchen: (3) drawer, (4) dining seat, (5) dining table, (c) living room: (7) TV table, (8) rotating library, (9) sofa, (10) coffee table; (d) bedroom: (11) night light, (12) bed, (13) bedside table, (14) wardrobe; (e) toilet: (15) wash sink, (16) toilet, (17) tube, (f) working room: (18) drawer, (19) desk, (20) chair, (21) drawer.

Contact sensors: Humans open or close doors and windows, and simple contact sensors can track such behavior. The reed switch sensor consists of a contact pair in a glass hermetic shell (Fig. 3). One end of the contacts is fixed, while the other is covered with electro-conductive material and can move freely under the effect of a magnetic field [45]. Once a magnetic field is applied to the switch, the free end moves towards the fixed end. The switch is turned on, which yields a binary signal. Beside doors and windows, contact sensors also monitor the use of furniture or appliances such as cabinets and fridges.

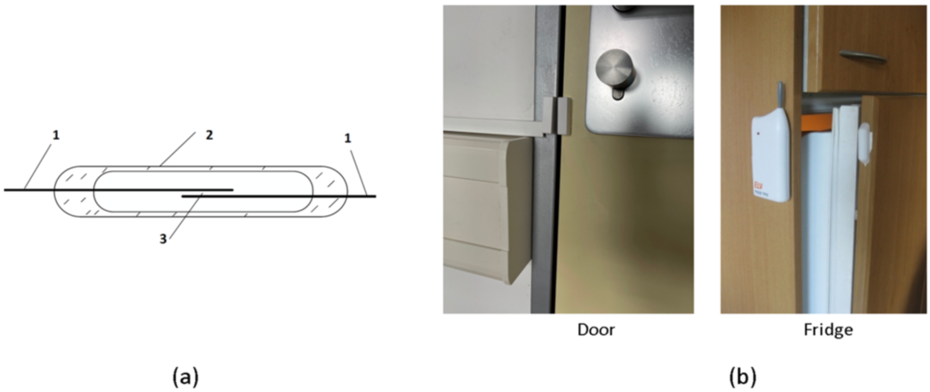

Figure 3. Reed switch. (a) construction: 1 – contact elements (springs) from permalloy; 2 – glass hermetic shell; 3 – working gap. Once there is a magnetic field applied on the switch, the working gap disappears and current passes. (b) application

Smart floors: Passive monitoring of behavior can be implemented resistively, capacitively, piezoelectrically, and triboelectrically [46]. Data includes location of the inhabitant, gait parameters (e.g., walking speed), and posture (e.g., fall). However, smart floors are costly. Specific locations include the bedroom, bathroom, and kitchen, where accidents occur frequently. Then, an alert is generated. Smart floors also create behavioral patterns for long-term monitoring.

2.1.3. Physiological monitoring

Electrocardiography (ECG): ECG is usually measured with wet or dry electrodes, which are in direct contact to the skin. In contrast, capacitive electrodes use the human body as one pole of the capacitor, and clothes or a gap between the skin as the other [47]. Sitting on a chair or lying in a bed with integrated cECG supports continuous monitoring of vital signs. In a cECG chair, the sensing and reference electrodes are attached to the backrest and the seating pad, respectively. In a cECG bed, all electrodes are layered beneath the bed sheet (Fig. 4). Using cECG, we can record the ECG unobtrusively and obtain significant health parameters such as the heart rate (HR) and the heart rate variability (HRV) [48, 49].

(a) (b)

Figure 4. (a) cECG smart armchair and (b) smart bed. Capacitive electrodes are on the backside of the smart armchair and beneath the smart bed.

Ballistocardiography (BCG): Due to the physical law of conservation of momentum, the cardiac ejection of blood results in small velocity of the whole human body. BCG is a non-invasive method to measure such body motion in three dimensions (3D) [50]. However, most devices focus on the longitudinal, i.e., head-to-toe component, as it delivers heart rate and respiratory rate. Piezoelectric sensors and accelerometers are usually adopted to acquire a BCG signal. In smart beds, they are attached to the frame [51] or under the mattress [52].

2.1.4. Psychological monitoring

Psychological monitoring is realized indirectly using the approaches of the aforementioned domains. Physiological parameters can evidently reflect psychological performance. For example, the heart rate, galvanic skin response (GSR), and electroencephalography (EEG) are frequently used for psychological measurements. Also, behavioral changes indicate psychological health [53] (Fig. 5).

Some devices particularly support psychological monitoring. For instance, nighttime wandering monitoring systems (NWAS) support patients suffering from dementia. Nighttime wandering potentially endangers patients in terms of injury (e.g., fall), unattended home exits, and negatively impairs the caregivers' sleep [54]. The sensing delivers bed occupancy, inhabitant location, and use of objects. Fusing behavioral and physiological data yields context understanding and allows actions to calm down the patient, guide him/her back to the bed, and send an alarm to caregivers if the home is left [55].

2.1.5. Using Cameras in Emergency and for Physiological Measurement

According to the Department of Health and Human Services, approximately 28–35% of people aged 65 and over fall each year; and this figure increases to 32–42% for those over 70 years of age [56]. This requires robust approaches for automated event detection and timely delivery of first aid, and depth as well as video cameras use machine learning for fall detection [57–59]. Taufeeque et al. applied long short-term memory (LSTM) networks for human pose estimation and support multi-camera systems as well as multi-person scenes. Their results yielded an F1 score of 92.5%. [60].

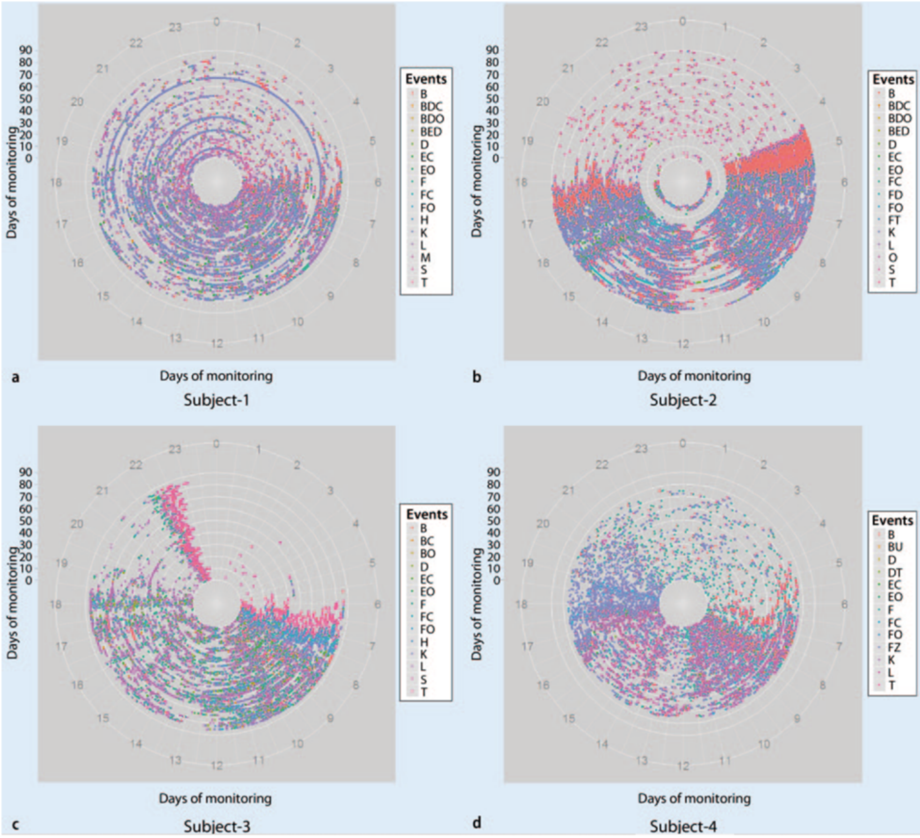

Figure 5. Four subjects' sensor data visualized by means of a spiral plot. The different colored dots represent single sensor events [53].

Furthermore, cameras can measure physiological parameters and vital signs indirectly. This includes heart rate and heart rate variability, SpO2, and others [61–63]. Such systems are applied in several environments, for instance smart cars ([64, 65]) and neonatal intensive care units [64, 65].

2.2. *Data Integration and Management*

A healthcare telemedicine system is a hierarchical multi-layer model for care and aid delivery [66]. The layers include (i) a network of sensors and sensing devices for measurement and monitoring, (ii) a gateway for aggregating the sensors' data, and (iii) a local server for fusion, processing, visualization, and interfacing the point of perception to external healthcare systems. The sensor network has two layers. The first layer aims at measurement, collection, and transmission. The second layer is an application for the first tier of local processing, fusion, and analysis. The decision-makers require data analysis. This is the consequence of complete monitoring, acquisition of extensive data from distributed sensing devices, and data processing under the umbrella of data fusion. The aim is instant event detection (e.g., fall) or long-term monitoring for predicting and preventing abnormalities [67]. In the following, we describe the components and the function of layers.

2.2.1. Sensor integration

A sensor is an edge-integrated node in the network. It measures physiological or non-physiological parameters and connects to an embedded system. It is not capable of data processing and transmission. A sensor neither has computational resources nor memory storage [68]. It differs from a sensing device in terms of memory, computational unit, operation, and processing [69, 70].

2.2.2. Sensing device integration

A sensing device is an embedded system connected to one or multiple sensors (on-board or add-on integration). The sensing device is an intelligent edge device to collect and pre-process data. Its functionality depends on the topology of the network. A sensing device may have restricted computational resources and memory storage. It is the first networking layer in a hierarchical data model.

An embedded system is a microprocessor-based computer hard- and software system that performs a dedicated function, either independently or as a part of a larger system architecture. Its core is an integrated circuit for real-time operations [71].

2.2.3. Data management

Measuring various parameters, sensing devices deliver an enormous amount of data (big data). We describe the data management in four stages:

1. Data acquisition and processing: Topology of the network, correlation of parameters, and applications address multi-level data acquisition and processing, as [72]:

- Low-level: On the lowest level, a single embedded system connects to several sensors related to one application for data processing. Synchronizing sensing devices, rate of sampling and transmission, the capability of processing and the topology are critical technical factors.
- Middle-level: The mid-level combines the processed data of several sensing devices from the previous stage. It implements pattern matching.
- High-level: The highest level links the point of perception (i.e., diagnostic space: smart home) to the external healthcare systems. It performs complex temporal-spatial fusion and bottom-top (sensor → gateway → server) data flow for long-term monitoring and early-stage detection (diagnosis → prediction → prevention) (Fig. 6). The external server as the third layer is optional and deployed according to the requirements at the point of perception.

2. Data transmission: In a hierarchical multi-layer model, we differentiate data transmission in the inter- and intra-connected network layers. T The intercommunication of sensing devices is hybrid: short-range wireless data transmission (e.g., Bluetooth, Bluetooth Low Energy (BLE), Zigbee) and bulky data transmission with security shield and compression over the long-range (3G/ 4G/ 5G cellular networks, Wi-Fi) [73].

3. Data synchronization: The hybrid topology improves network flexibility and sensor integrity but increases the complexity in terms of data management. Event detection and any change to the parameters are subject to data correlation among all WHO

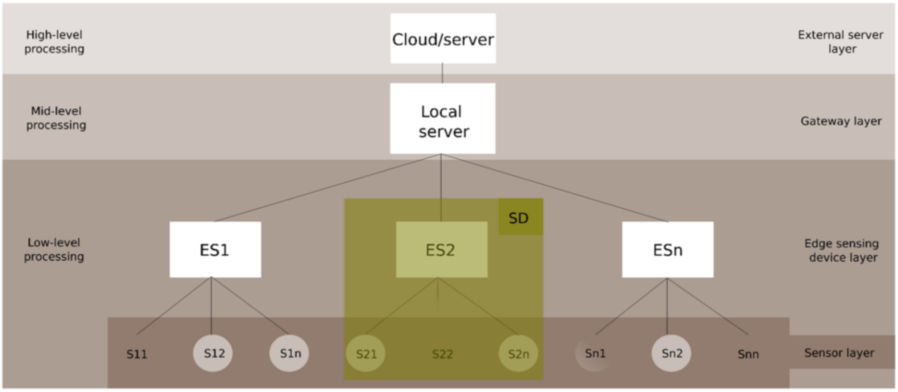

Figure 6. Multi-level data acquisition and processing in smart homes. The abbreviations stand for S: sensor, ES: embedded system, SD: sensing device.

QoLdomains. Thus, every embedded system delivers every parameter with a respective timestamp for synchronization [73].

4. Interfacing with healthcare systems: A complete chain of the healthcare system includes point of perception (i.e., smart home: alerting system), rescue team (responding system), and hospital (curing system). Therefore, a smart home as an alerting system involves responding and curing systems upon the occurrence of an emergency through opening the communication on the local server. The local server is also the bridge with external healthcare system through establishing a bidirectional communication for (i) delivering the emergency aid and rescue service; (ii) delivering care in real-time, and observing the rehabilitation progress by medical personnel; (iii) creating a personalized database by data collection from multi-sources (e.g., car, bike, and wearable) related to the user.

3. Application

We distinguish the applications in disease prevention and automated health alerts in smart homes into (i) health prognostics, (ii) emergency detection, and (iii) assistance and response. We differentiate the applications from long to short-term monitoring.

3.1. Long-term Health Prognostics

In current healthcare systems, a subject consults a doctor for disease diagnosis after the onset of the symptoms, and the level of discomfort is beyond a subjective threshold. This is problematic as many diseases (e.g., cancer) deliver symptomes at a very late stage, often too late for successful therapy and survival. Continuous measurement over the long term offers early stage detection of subtle changes. Simultaneous measurement of environmental, behavioral, physiological, and psychological parameters yields a high prognostic value. Although the environmental domain has a high value for respiratory diseases, this domain is typically not used for prognosis but for emergency detection. In the following, we give examples of prognostic measures in physiological monitoring.

We can assume the ECG as the modality with the highest prognostic value because of a more-or-less direct cardiac activity measurement. Besides, many diseases influence the cardiac system. Each cardiac cycle is represented by a pattern of waves (PQRST). The R-R interval defines the duration between two cardiac cycles and the reciprocal value is the HR. Other patterns allow insight into cardiac health. For instance, a prolonged QT interval is a predictor for sudden cardiac death [74].

Photoplethysmography (PPG) is an optical technique with lower diagnostic value than the ECG but it is more unobtrusive. We can derive theHR and the peripheral oxygen saturation (SpO2) from aPPG signal effortlessly. These parameters are used in emergency settings such as intensive care. SpO2 also shows a prognostic value, e.g., for predicting pulmonary fibrosis [75], respiratory failure [76], or arterial stiffness [77], which is a powerful predictor of cardiovascular mortality [78].

BCG is of value for health prognosis [79] but has not received dissemination comparable to ECG or PPG. This is because of the large number of confounding aspects. The reasons are lack of standardization, the complex origin of the waveform, and a low specificity and reliability for clinical applications [80]. Recently, developers integrated this method into wearable sensors [81] and household items [51].

We have identified a few research projects with prognostics based on devices sensing the behavioral domain. They focus on detecting unique events straightforwardly. However, there are several aspects of health that result in a measurable subtle change in behavior. Depression [82] and dementia [83] change gait, which is measurable by video cameras, smart floors, or distance sensors. Although researchers have proposed camera-based fall risk assessment [83] or disease detection [13], prognostic use of fused sensing devices from multiple domains has not yet been reported.

Use case: We have equipped a 3-room apartment (bedroom, bathroom, living room) with several sensing devices aiming at continuous monitoring for prognosis. We connect all sensors via a universal sensor node to a bus and aggregate the data into a local data warehouse. For physiological sensing, cECG sensors are integrated into the bed and chair [14] and conventional ECG is embedded into a "smart mirror". This allows ECG monitoring in all rooms. We have installed video cameras with single-board computers. If the camera detects a face, it estimates the heart rate from skin color changes [84]. For behavioral sensing, we integrate three camera systems for pose recognition [16]. Furthermore, we embed contact sensors in each room, at doors and windows, showing the status (open/close). Furthermore, IR sensors detect activities within a room. We also use VoC, air humidity, temperatures, and luminosity sensors to measure the environmental conditions. Hence, we have covered all four WHO domains.

3.2. Short-term Emergency Detection

In this section, we focus on emergencies, aiming at real-time detection and alerting. Again, we consider all four domains. This type of event detection requires real-time sensing and processing of sensor data.

Regarding environmental monitoring, there are many sensing devices available for direct alarming gas, fire). Video cameras also can detect emergencies such as a fire [85]. In an emergency, high sensitivity and specificity are crucial. However, to date, there are only commercial solutions for automatic alerting, which are usually installed in public places such as hospitals, government buildings, or schools, but significantly less in private homes.

Regarding behavioral monitoring, there are several opportunities for emergency detection. Video cameras monitor resident's abnormal behavior, e.g., fall, heart attack [86] or seizure [87]. Smart floors and PIR sensors are also capable of detecting abnormal behavior in the elderly [88] or falls [89]. Secondary use of sensors in home automation, such as monitoring the status changes of simple switches (e.g. light switches) detect similar events [90]. However, there is not yet an alert based on this data. Physiological signals, foremost ECG, shows many cardiac diseases such as elevation of the ST interval [91], which indicated myocardial infarction (STEMI) Hyperkalemia [92], genetic disorders [93], and toxic events [94]can also be seen in the ECG. PPG also has excellent value for detecting emergencies [95]. It is used nowadays mostly in emergency departments and in-home event detection [96], e.g., for overnight measurements [97].

Psychological monitoring is less established in smart homes [29]. In addition, we are not aware of any commercial solution in the smart home for automatic alerting based on a combination of environmental, behavioral, physiological, or psychological sensing devices.

Use case: The International Standard Accident Number (ISAN) [98] aims to provide an emergency communication platform [99, 100] realizing interconnectivity between a smart home (alerting system), a responding system, and a curing system. We use technological, semantical, and syntactical interconnection of these systems to share the relevant emergency information. Our approach supports immediate emergency alerts without any humans in the loop. The core of our approach is the ISAN token, which is uniquely generated upon an event. It uniquely identifies an emergency and provides embedded data describing the accident circumstances (time, location, unique identifier of the alerting system, i.e., point of perception). A demonstrator has been implemented. Once the smart home detects an event (e.g., fall, STEMI), it generates the ISAN number automatically and sends it via the communication platform to the nearest responding and curing systems.

3.3. Assistance and Response

We aim at reducing the time between the occurrence of an emergency and the delivery of first aid. Automatic alerts shorten the time between the event and the call for assistance. Such systems have been commercialized already using bracelets or necklaces with a button that, once pressed, starts a voice connection (human to human) to an emergency center [101]. A similar project is an e-call system embedded in all cars manufactured in the EU [102]. Once the car inflates an airbag, the e-call system automatically establishes a telephone call with the emergency service (human to human) and transmits a minimum dataset (system to system). The systems can be triggered manually, too. Furthermore, smartphone apps provide such panic buttons.

On the contrary, we have described the smart home as a diagnostic space that automatically detects events and directly informs the responding system (system to system) without any humans in the loop.

However, we can also shorten the response time after the call for assistance has been received. Using the ISAN number, the smart home can provide floor maps and other information that helps the rescue team to deliver the first aid faster. This includes not only location but also navigation and additional health information such as ECG or heart rate [100].

In future applications, the smart home could also request for automatic assistance. Robotics and drone technologies have already shown effectiveness in the delivery of first aid kits [103, 104] and performing first aid, such as automatic cardiopulmonary resuscitation [105].

4. Discussion

The WHO defines six domains influencing health, well-being, and QoL. Sensor technology is capable of recording parameters from four of these domains: the environmental, behavioral, physiological, and psychological domains. There are mutual interactions among these domains.

4.1. Relationships Among the Four Domains

Environmental → Physiological/Behavioral/Psychological: The impact of air pollutants on the risks of cardiovascular and respiratory diseases, lung cancer, and early death is well identified and documented [106]. New research has emerged concerning the effect of air pollution on the brain and mental illness (e.g., depression) [107]. The determinants of psychological well-being have also been correlated with air pollution [108]. More precisely, higher levels of air pollution let people spend less time outside, which worse psychological distress by limited exposure to sunlight, reduced physical activity, and increased social isolation [109, 110].

Behavioral → Physiological: Physical activity decreases the risk of several non-communicable diseases, including obesity, cancer, type II diabetes, hypertension, chronic cardiovascular, and respiratory diseases [111]. However, despite a strong commitment of WHO and the European Union in supporting health-enhancing behavior regardless of gender, age, and social status, approximately 31% of adults and 80% of young people (age: 13-15 years) worldwide are physically inactive and do not comply with guidelines of healthy living [112, 113].

Psychological → Physiological: The psychological domain also influences physical activity [114]. For example, psychological stress increases the HRV as well as the blood pressure [115].

These examples show the intensive correlation and interaction of the four domains. The environment as an external domain affects the other domains (subject-related domains) but is itself not affected. Whether the aim of monitoring is long-term health prognostics and short-term emergency detection and assistance, the processing and decision-making is subject to data acquisition from multi sensing systems in multi domains. Thus, simultaneous monitoring of parameters in several domains is important.

4.2. Incomplete Monitoring in Related Work

However, current research aims mainly at recording in one domain [116] and to enhance the quality of data processing and analysis [22, 117]. Efficient acquisition of application-specific data is essential for the design of healthcare services [118]. Lack of appropriate data acquisition complies with incomplete monitoring of the domains [31].

Some studies aimed at monitoring user behavioral changes in daily routine by using sensors in home automation [119] [120]. Projects such as INCA [121] and Veterans Health Administration [122] implemented the infrastructure fulfilling telemedical requirements for disease management and care. FairforAge [123] and OASIS [124] are focused on the aging society at home and in work environments supporting mobility and life with cross-sectional topics on systems development. OASIS develops information and communication technology (ICT) architectures for products and services in aging societies. These leading projects cover three domains (environmental, behavioral, physiological) by observing daily living (ODL).

4.3. *Our Vision: Complete Monitoring*

We have introduced a concept on measuring all four WHO domains within a home. In our smart homes, we apply the bus system BASIS to connect all sensing devices. This yields the time synchronization of all measured data in all the four domains. The four-line bus has two lines for power supply and two lines for serial data transmission, and small bus couplers are bridging the sensing devices with BASIS. We use ambient sensors to extract behavioral patterns such as inactivity or motion. Our ambient sensors include PIR, light switches, ultrasonic distance, door and window connectors, and power consumption for the oven, fridge, and electrical outlets. We monitor the environmental domain by sensors such as VoC, air humidity, air temperature, and luminosity light.

There are three major concerns about the direct integration of sensing devices from the physiological and psychological domains: the devices (i) record the raw data at high sampling rates (e.g., ECG with typically 1 kHz); (ii) require higher computational power; (iii) support wireless data transmission, which BASIS does not. During the research phase, we add embedded systems (e.g., Raspberry Pi, NVIDIA Jetson) to the sensing devices and transfer onset and offset via the BASIS bus for time synchronization, while we transfer the raw data using Bluetooth, BLE, or Wi-Fi. In an application physe, the raw data is processed directly in the embedded system and not stored at all. This hybrid topology (wired/wireless) reduces latency and enables local and distributed on-board data processing and multi-layer fusion to detect an emergency in any layer. Therefore, we:

- process the simple tasks locally on the embedded systems, to reduce the network latency and bandwidth,
- reduce the potential risk of security, by multi-layer data fusion and not push all raw data to the external server,

This promotes the smart home concept to diagnostic spaces covering all four domains.

4.4. *Future Trends in Healthcare System*

Simultaneous monitoring of the four domains improves the semantic interoperability of the smart home as a diagnostic space in precise and valid diagnostics before occurrence. However, private spaces are also smart vehicles. Smart cars can be transformed into diagnostic spaces as they have a controller area network (CAN) bus which is similar to the BASIS in the smart homes [125]. Monitoring an individual in a smart diagnostic car will add valuable information supporting unobtrusive, continuous, and simultaneous measurements in all four domains while driving. Extending the continuous health monitoring to 24/7 specifies the role of wearable devices, e-bike, and smart offices (smart city). This complies with the anything, anyone, anywhere, and anytime (A4) approach [31]. In the near future, we expect more dynamic and mobile points of perception. Seamless integration of the environments is challenging with respect to privacy and security. However, we expect automated data fusion from multi-sources (e.g., smart home, smart office, smart car, e-bike, and smart wearable) at distributed locations, leading to a personalized database. This empowers valid diagnostics and decision-making. Real-time monitoring and event detection is supported by linking the point of perception to external healthcare systems. In particular, the responding and curing systems are involved for real-time care and emergency services delivery at the point of occurrence.

5. Conclusion

Integrating sensing devices that mutually measure parameters from the four WHO domains of health, well-being, and QoL is essential for disease prevention and automatic health alerts in smart homes and smart cars. We integrate medical and non-medical sensing devices. Enriching the sensory layer network and developing hierarchical multi-layer data fusion based on powerful computational nodes, supporting wired/wireless communication, facilitates on-board and distributed data acquisition and processing. This will reduce the traffic of raw data aggregation to high-level fusion. It also adds invaluable processed information at a lower level and shortens the processing time for information extraction out of the raw data. Bus-inherent synchronization supports data fusion for long-term diagnostics and event detection. The young and the elderly, the healthy and the disease-affected will benefit. In particular, we support the United Nations' 2030 Agenda for Sustainable Development [126], where the sustainable development goal (SDG) 3 is to ensure healthy lives and to promote well-being for all people of all ages as well as the WHO 13th General Programme of Work [127], which has three interconnected strategic priorities to ensure healthy lives and well-being for all: (i) achieving universal health coverage, (ii) addressing health emergencies, and (iii) promoting healthier populations.

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