Non-Wearable IoT-Based Smart Ambient Behavior Observation System

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***Abstract*—A growing number of advanced smart systems and solutions are being designed for the elderly, helping them to live longer at home. These systems need to provide unobtrusive monitoring and safety for their users and information for the healthcare professionals and family members. Multi-modal sensor data enables the possibility for in-depth behavioral analysis. To gather multi-modal data, we propose an IoT-based smart ambient behavior observation system (SABOS). SABOS provides unobtrusive monitoring of daily living activities by utilizing various sensors integrated into the residential house. To reduce the amount of data, we present a data reduction algorithm. The data reduction algorithm effectively reduces over 90% of the submitted data with full recovery in the cloud. Data is sent to ThingSpeak for MATLAB visualization and analysis to generate graphical illustrations of daily living activities. In an emergency, an "if this then that" (IFTTT) service combined with ThingSpeak triggers an applet to send a defined message to a healthcare professional or a family member.**

***Index Terms*— Ambient assisted living, data reduction algorithm, the IoT, feeling factor, capacitive touch sensor.**

I. Introduction

THE need for smart ambient assisted living (AAL) systems is increasing with the number of elderly people. It is estimated that the percentage of people aged 60 or above will double (approximately 2 billion) by 2050 [1]. For those over 80 or 90, the need for smart AAL systems is clear. Smart AAL systems provide daily behavioral information of an elderly person's activities, allowing healthcare professionals to get early indications if there is a change in the elderly person's health status. If actions are needed, healthcare professionals can intervene and, in the best-case scenario, avoid hospitalization. Avoiding unnecessary hospitalization is important not only from the client's quality of life point of view but also to reduce the workload of hospitals, which is highly essential as the COVID-19 pandemic has spread worldwide. According to the latest statistic from the Center for Disease Control and Prevention, among adults, age is the key risk factor for severe infection due to COVID-19. The highest risk for severe disease lies in the age group of 85 and above. Moreover, eight out of ten deaths due to COVID-19 reported in the USA are among adults aged 65 and older [2].

In smart AAL facilities, a balance between the provided services and optimum privacy needs to be found. The assistant secretary for planning and evaluation (ASPE) [3], explained that people have a strong desire for privacy. Hence, their project team decided to keep privacy a vital aspect of the smart assisted environment. Hawes *et al.* [4] states that smart homes based on personal privacy are essential for patients. The results indicate that many smart facilities for elderly people consider this to be fundamental.

Keith Cheverst *et al.* consider in [5] that older adults are conservative, and they do not like it if their life habits and

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This work involved human subjects or animals in its research. The written consent was acquired from the participant before the experimental sessions. This was a non-clinical study without any harming procedure and all data were collected anonymously. The experiment procedures follow strictly with the principles of the Declaration of Helsinki.

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working patterns are changed too much. In particular, they are not interested in external or foreign devices that can affect their private lives and indoor freedom. When cutting-edge technological systems are implemented in assisted living facilities, the elderly fear losing personal privacy [6], [7]. They have an unpleasant feeling that they are being watched continuously (the Big Brother syndrome). This has also been demonstrated in [8], [9]. Therefore, it is counted as a key feature in the valuation and classification of such facilities.

An essential element for implementing the AAL systems is the Internet of Things (IoT) concept that connects physical objects having internet connectivity in the last two decades. IoT can connect numerous sensor nodes over the internet. According to Help Net Security [10], the number of devices connected to the internet worldwide was 22 billion at the end of 2018. The report predicts that around 38 and 50 billion devices will be connected in 2025 and 2030, respectively. IoT is anticipated to be the biggest producer of big data. Data sharing and collaboration will be necessary to enable sustainable ubiquitous environments, for instance, smart homes and cities. The smart home will be the fastest-growing segment over the coming years, and artificial intelligence (AI) will become pervasive in mobile, smart home, and computing platforms. According to Strategy Analytics, optimizing the user experience for multiple devices, operating systems (OS), and user interface will be the main battleground [10], [11].

IoT has gained a lot of popularity in academia and industry. Both are interested in developing new services utilizing the advancement of technology in digital twins, smart mobility, autonomous vehicle, industrial processing, public safety, environmental monitoring, and smart healthcare. The idea of IoT in healthcare, especially at home and elderly home care services, involves the integration of various sensors and actuators to assist inhabitants [12], [13].

Main Contribution and Novelty: The proposed Smart Ambient Behavior Observation System (SABOS) provides increased security for the elderly who like to take extra caution while living at home. By deploying non-visual-based sensors, SABOS takes extra measures for preserving its users' privacy. The main contributions of the article are:

- Design and development of a low-cost touch sensor with improved accuracy and comfort of use.
- A data reduction algorithm to reduce the amount of data without losing accuracy.

The data reduction algorithm effectively reduces over 90% of the submitted samples, maintaining data integrity. The low-cost touch sensor is based on a capacitive touch sensor (CTS) providing increased endurance and usability in various settings.

The rest of this article is organized as follows. First, we discuss related work in Section II. In section III, we define SABOS and its key features, functionalities, and main sensor nodes. After an overview of SABOS, we present the data reduction algorithm in Section IV. Next, we delve into the implementation of SABOS and discussing the results of the test in Section V and VI, respectively. We conclude the work to discussion in Section VII and conclusion Section VIII.

II. Related Work

A considerable amount of work is done in developing and designing a different kind of monitoring systems in recent years. In the IoT era, the monitoring systems and their sensor nodes are capable of exchanging information via the internet without any human intervention [14], [15]. Sensor nodes' practicality and feasibility depend on what kinds of actions are supposed to be perceived by them. For activity classification, different types of sensors were tested critically on trial bases, and two kinds of principle classification were recognized, wearable (obtrusive) and non-wearable (unobtrusive) [16]. Obtrusive devices, such as smartwatches and wristbands, are mostly worn and connected over body area network. Wearable sensors can measure the location and indicate health-changing parameters and critical well-being physiognomies [17], [18]. Non-wearable sensors are considered less intrusive and do not need collaboration from the user side.

Toshiro Suzuki and Sumio Murase used an infrared sensor approach for monitoring activities in a room. While it successfully detects and monitors within an enclosed environment, the system falls short of detecting complex patterns and offers minimal monitoring [19]. The camera-based system developed by Elloumi *et al.* [20] enables a vision-based framework. It offers real-time monitoring and analysis using machine learning algorithms. An effective and straightforward method to record elderly activities by using an RGB-D camera has been proposed in [21]. Where camera-based systems can be very effective in behavioral analyses, the main concern relates to privacy issues and data handling. In all camera-based monitoring systems, one needs to consider privacy issues carefully. A related question is also where video footage or images are stored and analysed. For privacy, hosting a local server is a plausible solution but they have limited storage capacity [22]. Sending the material to a cloud server needs, on the other hand, a fast and reliable internet connection.

A simulation-based healthcare framework is proposed based on digital twin healthcare in [23]. In [24], Belal Alsinglaw et. al suggested and presented comparable work in a smart assisted environment. In another work, various sensors to record the subjects' behavior patterns have been implemented with the 2.4 GHz industrial, scientific and medical (ISM) band [25]. Further work is still needed to address properly energy efficiency and how to reduce the amount of gathered data. In another study, a theoretical framework was developed and tested empirically to determine the key factors that may impact the elderly users' acceptance of smart assisted living facilities [26]. In [27], a smart assisted living facility is proposed and implemented using various sensor nodes. They present a protocol for wellness sensor networks that could reduce the amount of transmitted data. SABOS, on the other hand, works at the edge of the network by reducing the data in the sensor nodes.

Temperature and humidity have an important role in the behavior and physical well-being of a person. How higher temperatures affect a person is very personal. Especially the

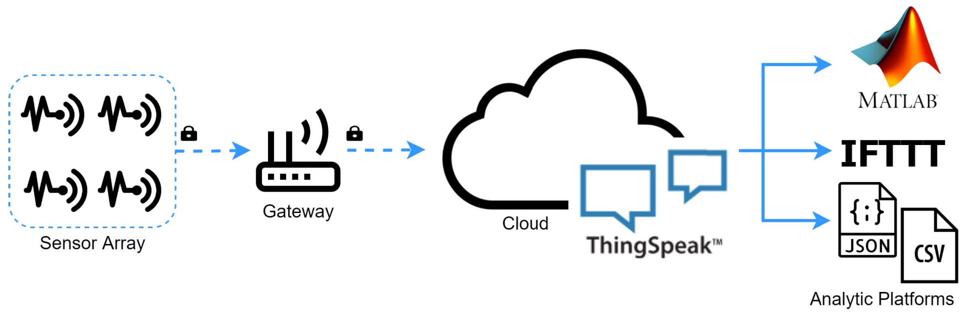


Fig. 1. Overview of the proposed system. Data flow from sensors through a gateway to a cloud where data is analyzed, for example, in ThingSpeak and MATLAB.

elderly are prone to temperature fluctuations because they have weaker physiological responses to heat. According to Mullins and White [28], low temperature adversely affects mental health. Higher temperatures increase adverse health consequences, and it is estimated that rising average monthly temperatures by 1-degree Fahrenheit leads to a 48% increase in mental health [emergency department] visits and a 35% increase in suicide. The research concluded that hot temperature affected mental health even for people accustomed to the higher temperature. Barreca *et al.* [29], White [30], and Heutel *et al.* [31] found a relationship between temperatures and clinical visits for many diseases. Therefore, SABOS will also monitor environmental conditions in an apartment. In the future, the environmental data will be augmented to behavioral data increasing its value.

SABOS provides an unobtrusive and smart environment for home and elderly care homes. It deploys various sensing nodes providing data to monitor the door opening and closing, sleeping hours, chair usage as well as the use of appliances. The gathered data is sent to a cloud server for analysis and visualization. This work extends our previous work that concentrated on defining the wellness status based on the collected data [32].

III. Smart Ambient Behavior Observation System

The Smart Ambient Behavior Observation System (SABOS) is illustrated in Fig. 1. SABOS sensors can be divided into environmental and behavioral sensors, such as touch, current, environmental, and motion sensors. Together these sensors provide context enriched behavior information. Each sensor node is individually connected to the cloud in the prototyping phase to ensure smooth, uninterrupted data flow.

The sensor readings are sent directly to a cloud where the system performs all the analyses. SABOS deploys ThingSpeak (an IoT analytics platform service in the cloud) and MATLAB integration for analyses and the "if this then that" (IFTTT) service [33] to respond to unexpected behavioral data and adjust environmental conditions. IFTTT is a free web service to create chains of simple conditional statements called applets. An applet can be triggered by the change that might occur within other web services, such as ThingSpeak. IFTTT is a REST-based API (application programming interface) server style architecture used for application program interface using

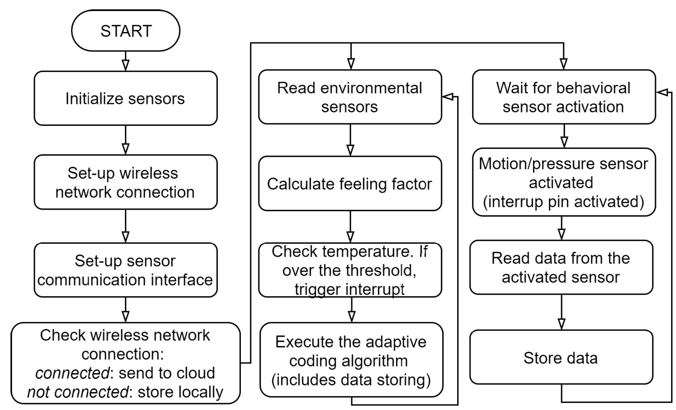


Fig. 2. Data detection and response flow diagram for environmental parameters monitoring sensor and touch sensor.

Hypertext Transfer Protocol (HTTP) requests to access and use data.

Fig. 2 illustrates the initial steps for starting to use SABOS. First, it initializes sensors, sensor communication interfaces, and a network connection. If the network is not available, SABOS stores data locally until the network is available. Second, it activates environmental and behavioral sensors. Third, it reads periodically environmental sensors and monitors the activation of behavioral sensors. This is repeated until the system is powered off. In the following section, we introduce designed sensors in detail.

A. Behavioral Monitoring

One essential thing for an AAL system is to know if an inhabitant is at home or not. SABOS deploys three different sensors to monitor a user's behavior.

1) Motion Sensor: SABOS monitors the presence of an inhabitant by using two motion sensors in the wall making systems transparent for its user. Entering and leaving home is detected by two modified Grove motion sensors. The modification (shown in Fig. 3) improves the accuracy of the sensor by limiting the field of view from 120° to 90°. Furthermore, SABOS requires that both of the sensors must be activated before it reacts. Also, to prevent false detection, a threshold between the activation of the sensors is set to three seconds. Based on our tests, utilizing two sensors with a predefined

Fig. 3. Original and modified Grove PIR motion sensor.

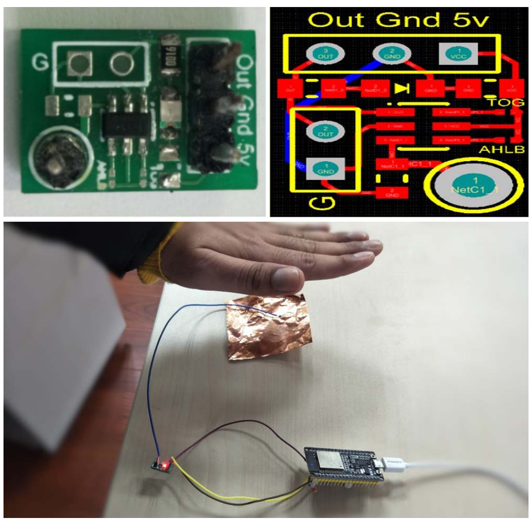


Fig. 4. Touch Sensor PCB layout actual implementation and sensing from a distance of 5 cm to 8 cm.

threshold can detect correctly 95% of events (verified with a manual push-button).

2) Pressure Sensor: Prior studies have observed that a pressure sensor becomes flat after certain intervals of activity, especially when using force-sensitive resistors [34]. This is impractical because pressure sensors are commonly mounted on furniture making. Therefore, we chose an electromagnetic touch sensor using a touchpad detector integrated circuit (The TTP223-4-BA6 TonTouch) for SABOS.

TTP223 is designed to replace the traditional direct touch-pad with diverse touch-pad sizes. By replacing the traditional touch key, it provides stable touch detection of the human body. Most importantly, it offers auto-calibration for life and the re-calibration period is just four seconds. According to the datasheet, using TTP223 requires caution, as the power supply must be stable; otherwise, it may cause sensitivity anomalies [35].

One of the TTP223 benefits for AAL applications is that it can be embedded inside or under a bed or chair, thus resolving pressure sensors' bending problem. The sensing area is enhanced by employing additional aluminium sheets diagonally across the sensing area, as shown in Fig. 4. This sensor can detect the human body's presence within the range of $5\,cm$ to $8\,cm$. This allowed us to implant it within the chair, bed, medicine packet, washroom commode, and toothbrush. The sensitivity can be adjusted with different panel thicknesses. Using the capacitive touch sensor instead of the pressure sensor improved the accuracy of the system. The error rate decreased by 83% to 90% depending on the sensitivity level when compared to a manual button. In the test, we used the maximum panel thickness. Fig. 4 shows the developed printed circuit board (PCB) layout and implementation.

The TTP223 touchpad detector can be operated with low power or fast mode on wide operating voltages ($2\,V$ - $5\,V$). It has a response time of around $60\,ms$ for fast mode and $120\,ms$ for the low power mode. Furthermore, it has adjustable sensitivity depending on the outside capacitance range from zero to $50\,pF$.

B. Environmental Monitoring

The indoor monitoring system follows room temperature and humidity levels using the DHT11 sensor. It measures humidity and temperature within the range of 20%-90% and 0-50$\,^{\circ}C$, respectively. It also measures the dew point and heat index. The DHT11 environmental parameters monitoring sensors make it easy to record humidity and temperature data, and thus it is perfect for smart home environmental monitoring and control systems. Based on the data, the SABOS system calculates a feeling factor (FF) inside the room. Feeling Factor together with data provides significant information that can be used in behavioral analyses.

C. Appliance Monitoring

SABOS monitors the usage of electrical appliances, especially for behavioral analysis. The variation of the behavioral pattern will be followed to find weak signals for the need to intervene. SABOS utilizes the ACS712 current sensor with high-power and low-power modules, allowing the sensor for all the chosen scenarios. ACS712 is a fully integrated, hall-effect-based current sensor IC which allows for non-contact discernment of direct and alternating current. ACS712 is a linear, fully integrated current sensor with 2.1-kilovolt root mean square ($kVRMS$) isolation and a small resistance ampere conductor. Also, it employs a low resistance conductor, which makes it an economical and precise solution. It uses its conductor to measure current applied to terminals and works on the Hall Effect principle. When an electrical device is connected to SABOS, an alternating current (AC) begins to flow through the sensor, and the output voltage starts to change, decreasing at $185\,mV$ per ampere (A) current for $5\,A$ module. When the appliance is unplugged, and ESP32 with ACS712 is powered on, then Vcc $= 5\,V$, while the output pin of ACS712 is $2.5\,V$ (Vcc/2). When current flows in one direction, the values rise from $2.5\,V$, and when it flows in the opposite direction, the values decrease from $2.5\,V$. In this way, the modules can measure both AC and direct current (DC). The typical supply voltage for ACS712 is $5\,V$.

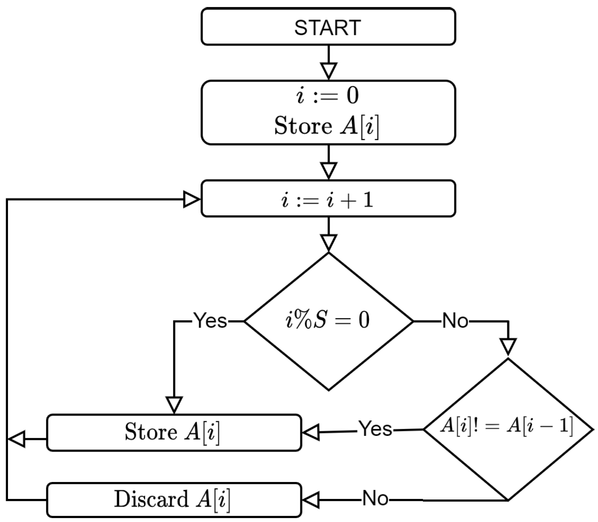


Fig. 5. Data reduction algorihtm stores a new sample if it differs from a previous one, otherwise the sample is discarded. Every Sth sample is stored always.

IV. Advanced Data Reduction

Applications deploying cloud services are common in the health sector for their easy integration and provided analysis services and user interfaces. Depending on the selected license, the number of the transaction might be restricted. Especially for low-cost monitoring systems, this restriction needs to be considered together with the energy efficiency if the system utilizes battery-powered sensor nodes. The sampling rate of a sensor node is defined by the application and what is monitored. For example, having a sampling rate of 1-sample/second leads to approximately 2500 thousand samples within just one month from one sensor node. Utilizing a free or low-cost license, a cloud service might receive only 1-sample/15 second.

Therefore, we present the data reduction algorithm that reduces the number of samples sent to a cloud for storage and analysis. The proposed algorithm maintains data accuracy and integrity as it can fully reconstruct the discarded data, unlike lossy compression methods. The reduced amount of data that we need to transmit is also important from the energy efficiency point of view.

A. Data Reduction Algorithm

The proposed algorithm is lossless in terms of removing redundancy and preserving the necessary information to restore the original data in the cloud. The algorithm is illustrated in Fig. 5. Before the data reduction algorithm is executed, data is first stored in an array called an input array $A[n]$. The length of the array is adjusted based on the sensor node's resources. In SABOS, we store the first 100 samples before the algorithm is executed. The algorithm works as follows: The first sample $A[0]$ is always stored in a database along with every Sth sample thereafter. The next sample will be stored only if it differs from the previous one; otherwise, it will be discarded. Thus, the data reduction algorithm discards repetitive samples. Discarded data can be fully restored in the cloud based on the array index of stored samples. One benefit of saving every Sth data sample is also that the cloud services can ensure that the sensors are working properly.

TABLE I
DATA REDUCTION EFFICIENCY IN PERCENTAGE [%] FOR DIFFERENT SENSORS USED IN SABOS. THE FIGURES ARE PERCENTAGES OF THE FULL STORAGE ($S = 0$)

S	Touch (binary)	Temp (int)	Temp (float)	Humidity (int)	Current (int)
0	100	100	100	100	100
5	20	20	28	24	20
10	10	11	18	15	10
15	7	7	15	12	7
20	5	6	14	10	5
25	4	5	13	9	4
30	4	4	12	9	3

What is the optimal value of S depends on the application. Fig. 6 shows the efficiency of the data reduction algorithm with different values of S for the touch, humidity, current and temperature sensors. The temperature sensor values are shown for integer and floating point values with accuracy of $0.1°C$. Even by saving only every 5th sample, the amount of data is reduced by 72-80 percentage depending on the data as shown in Table I. Naturally, the data reduction algorithm is most efficient with binary values and for decimal numbers its efficiency decreases with increased accuracy. Also, the maximum saving potentiality depends on the used precision; for example, the temperature can have $1°C$, $0.5°C$, or $0.1°C$ precision. Higher precision means more variation in the temperature data, and thus more data samples are stored. The accuracy of the used sensors should be considered when deciding the accuracy of the stored data, and thus the value of S.

In SABOS, we chose to store every 20th sample because it provides sufficient level of performance as shown in Table I but it is also a multiple of array size (100) thus ensuring that the last sample will be always stored. This is mandatory to be able to perform full data reconstruction. Arrays size is not fixed and can be defined to match the used sensor and microprocessor.

V. SABOS Implementation

SABOS use cloud services for data storage and analysis. Sensor nodes are directly connected to a network, and samples are sent individually to the cloud. If the network connection is disrupted or not available, a sensor node stores the data locally in a memory card. When the sensor node regains the network connection, it automatically sends all the locally stored data to the cloud.

A. Cloud Implementation

SABOS utilizes the ThingSpeak cloud service. ThingSpeak is considered an excellent accompaniment to the existing innovative system in the IoT field, and it has a free version that was utilized during the test. Besides, ThingSpeak

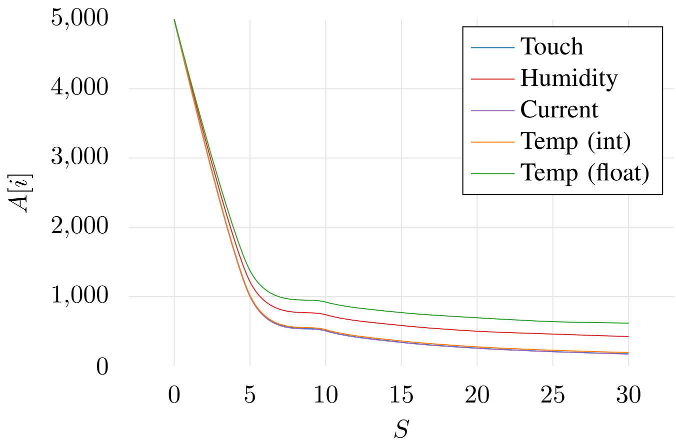


Fig. 6. Data reduction efficiency with different values of S. The y axis shows the amount of stored sample $A[i]$.

Fig. 7. Environment monitoring prototype.

helps integrate received data with various third-party cloud platforms, systems, web servers, and other top platforms, such as Arduino [36]. It also provides device communication, open API support, geo-location data, and plugin facilitation. In ThingSpeak, data can be imported and exported, and used for real-time analysis. It also provides integration MATLAB visualization and analysis [37]. SABOS uses the message queuing telemetry transport (MQTT) protocol for sending data to ThingSpeak. Rather than sending data packets continually, the transfer is scheduled to occur after regular periods of 30 to 120 seconds.

ThingSpeak offers secure and efficient transmission of data samples between sensor nodes and the destination. Secure data transfer is essential to maintain user privacy; ThingSpeak validates all data transfers using the service set identifier (SSID) and a password. After successful connection, ThingSpeak will check a channel ID and a field ID before receiving data samples from a client. Channels are created when the system is initialized, and they are the only way to send data to storage. Every channel has eight fields that can hold any data, three locations, and one status field. These are adjusted according to the specific sensor in use. Note, the free version of ThingSpeak has a 15-second delay before accepting a data transfer. Using a commercial version of ThingSpeak, this restriction can be avoided [38].

B. IFTTT: If This Then That

There are several end-user programming tools, such as IFTTT ("If This Then That"), Zapier and Microsoft Flow, that allow people to connect with multiple services by creating simple trigger action programs [39]. IFTTT is considered the most popular among mentioned services [40]. IFTTT is a web service that lets users create rules (known as an applet in IFTTT) to achieve intended actions. It also has library services and applets offering, e.g., readymade connection methods making the integration to different services easy. The main advantages of IFTTT are its customizability, mobile support, and integration. In addition, it provides connectivity with third-party apps on Google, Android, Windows, and iOS.

Emergency Response: In SABOS, we utilized IFTTT in the emergency response service. The emergency service is activated if a collected data sample go beyond a predefined threshold value. When the service is activated, IFTTT sends an alert message for a healthcare professional or a family member requesting attention. After sending the alert message, the sensor node continues the normal process. We have utilized the emergency response in the bed sensor to indicate if the user stays longer time on bed than usual time or follows his/her normal sleeping time and daily routines.

C. Sensor Node Implementation

For SABOS, we designed and implemented a sensor node as shown in Fig. 7. The prototype comprises the environmental sensor and an ESP32 low-cost, low-power microcomputer unit. ESP32 has a built-in Wi-Fi, Bluetooth, and a highly integrated system powered by a dual-core Tensilica Xtensa LX6 microprocessor. It can use either the internal phase lock loop of $320\,MHz$ or an external crystal. An oscillating circuit can also be used as a clock source at 2-$40\,MHz$ to create the master clock for both CPU cores. For high-performance applications, the clock speed can be up to $160\,MHz$. To address energy efficiency requirements, the clock speed can be adjusted to lower frequencies.

For a sensor node, ESP32 provides 16 pulse width modulation (PWM) channels (eight low-speed and eight high-speed), and every one of them is driven by four timers.

1) Power Management: Essential features of ESP32 are its different power modes that prolong the operation time when a battery powers it. In the active mode, Wi-Fi is ON, whereas, in a modem-sleep mode, all the radios (Wi-Fi and Bluetooth) are off, but the CPU is fully functional. There are also light and deep-sleep modes, where either both or only one CPU are operating at a lower performance level. Furthermore, ESP32 built-in Wi-Fi reduces latency, enhances scalability and range compared to Bluetooth [41].

The energy efficiency is increased by powering on and off the sensor nodes after a certain time of inactivity. A sensing node, after power-up, stays in active mode for at least 5 minutes. In the active mode, the whole system meaning all the peripherals, communication modules (Wi-Fi, Bluetooth), memory, and processor are active consuming around $200\,mA$

TABLE II
DHT11 CALIBRATION

Parameters	DHT11 Range
Humidity	$20 - 90\,\%\,RH$
Humidity Accuracy	$\pm 5\,\%\,RH$
Temperature	$0 - 50\,°C$
Temperature Accuracy	$\pm 2\,\%\,°C$
Voltage	$3 - 5.5\,V$

TABLE III
EFFECTS OF HEAT INDEX

Celsius	Instruction note
$26 - 32°C$	Could result in heat cramps
$32 - 41°C$	Heat cramps and heat stroke possible
$41 - 54°C$	Heat exhaustion and heatstroke probable

current. After five minutes of inactivity, the sensor node enters the light sleep mode. After 30 minutes of inactivity, the sensor node activates the deep sleep mode. Because of the deep sleep mode, the main functionalities of ESP32 are powered off it consumes merely $10\,\mu A$ current. The deep sleep mode turns off most of the memory as well. Therefore, setting the timer to 30 minutes for activating the deep sleep mode, is used to partly ensure that no data is lost without having a possibility to transfer it to ThingSpeak or in the memory card. The sensor nodes are activated through ESP32's GPIO pins that can sense capacitive variations.

To increase energy efficiency, sensor nodes do not send a data sample to the cloud service immediately but stores it locally until 100 samples are gathered. Before sending the samples, the adaptive coding algorithm is executed.

2) Environment Sensor Calibration: The DHT11 sensor is calibrated [42] before utilization using NaCl (relative humidity 75%) and humidity absorber (relative humidity 40%). To make the sensor saturated, a little water was added to increase the environmental humidity to 75%. Putting the sensor with NaCl inside a container ensured that there was no salt on the sensor's pins. A standard humidity measurement device was also placed inside the container, along with a standard temperature device probe. To stabilize humidity inside the box, it was left untouched for around three and a half hours. The DHT11 sensor showed 66%, while the standard humidity meter displayed 75.5%. The sensor temperature (around $20\,°C$) was close to that of the standard temperature meter. To ensure precise humidity measurement, the humidity was confirmed in a second point. The required humidity level was gained by using absorbers. After putting the absorbers in the container, it was left to stabilize for more than three hours. The humidity meter reading reduced to around 40%, while the DHT11 sensor reading was 22%. The temperature reading was similar to the standard device again. In the end, the Arduino IDE map function [43] was used to make a humidity calibration curve for the sensor. The DHT11 sensor calibration results are shown in Table II.

where RH is $\dfrac{\rho w}{\rho s} * 100$, ρw water vapor density, and ρs water saturated vapor density.

How hot it feels is determined primarily by a combination of two factors: temperature and relative humidity. The feeling is called *heat index* and its formula approximates HI in Fahrenheit to within $\pm 0.7\,°C$.

$$HI = c_1 + c_2T + c_3R + c_4TR + c_5T^2 + c_6R^2 + c_7T^2R + c_8TR^2c_9T^2R^2 \quad (1)$$

where T is ambient temperature, R relative humidity and the coefficients are $c_1 = -42.3$, $c_2 = 2.5$, $c_3 = 10.14$, $c_4 = -0.23$, $c_5 = -6.84$, $C_6 = -5.5 \times 10^{-2}$, $c_7 = 1.2 \times 10^{-3}$, $c_8 = 8.5 \times 10^{-4}$, $c_9 = -1.99 \times 10^{-6}$.

Temperature and humidity are essential factors in (1). In addition to HI, an essential factor in calculating a comfort ratio is *dew point*:

$$\text{dew point} = \frac{237.3 \times \text{N}}{1 - \text{N}} \quad (2)$$

where

$$N = \frac{\ln\left(\frac{RH}{100}\right) + \frac{17.27 \times T}{237.3 + T}}{17.23}$$

The comfort ratio is vital especially for the elderly, as discussed in [44]. A threshold has been defined for emergencies based on temperature, humidity, and heat index. This emergency threshold is adjusted based on Table III.

3) Appliance Sensor Calibration: To calibrate the zero point of the ACS712 as instructed in the data sheet, Arduino IDE's built-in function sensor.calibrate() was used. In the next step, the sensor's bandwidth was verified using the formula $(-3\ dB) = \frac{0.35}{tr}$, where tr is the rise time of step response. Both the rise time and response time of the ACS712 sensor are adversely affected by the eddy current losses detected in the conductive IC ground plane [45]. Without calibrating for zero offsets, with no current flowing through the sensor, the readings fluctuated between $58\,mA$ to $71\,mA$ in the alternating current (AC) mode and $46\,mA$ to $60\,mA$ for the direct current (DC) mode.

After calibration, the reading fluctuates around 35 mA for the DC mode and $40\,mA$ to $58\,mA$ for the AC mode, while there was no current flowing in sensors. To reduce the noise, a filter capacitor of $470\,nF$ value was selected. After the change of the filter capacitor and using the calibration function, current values were relatively stable with little noise between $4\,mA$ to $6\,mA$ without a load. In the AC mode, With $136\,mA$ load, it showed around $134\,mA$ with $\pm 16\,mA$.

D. Software Implementation

SABOS uses multi-tasking in executing its functions by utilizing the metro library and the ESP32's dual-core processor capabilities. The metro libraries are used mostly in serial communication and to control servo motors, such as in robotics [46], but work equally well in implementing various sensor interfaces for health appliances. A huge benefit of using the metro libraries is that it is faster than the default delay protocol in the Arduino sketch, improving the execution time. The default delay is a blocking function, and thus multi-tasking cannot be achieved with a delay function; it prevents the

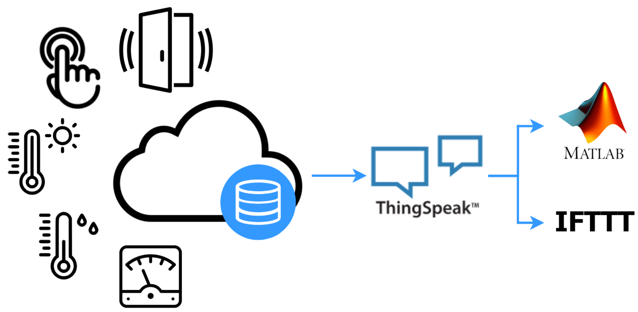


Fig. 8. The experiment utilized various sensors whose data were analysed in MATLAB. The experiment utilized IFTTT to react to environmental changes.

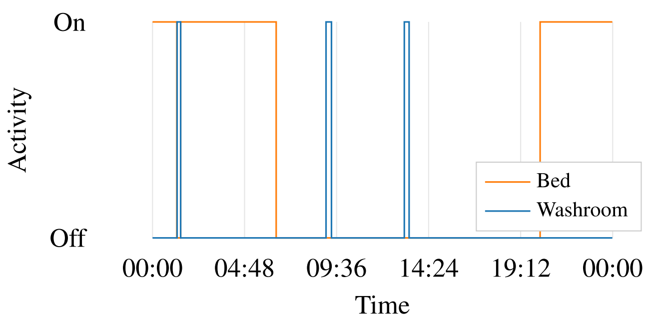


Fig. 9. Bed and bathroom activity during one day.

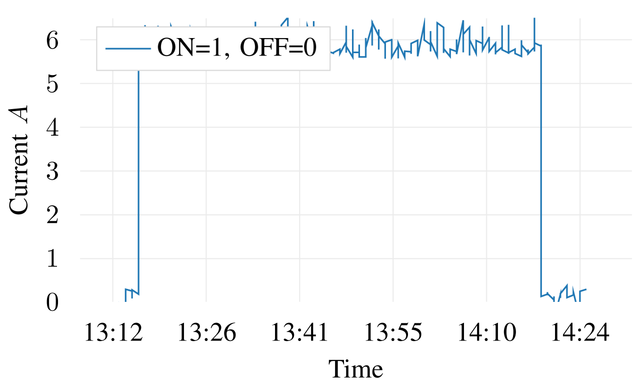


Fig. 10. Current sensor showing the usage of the heater.

program from executing another instruction until a particular task is complete. The waiting period is defined in the delay function parameter.

The Arduino IDE programming language can be considered a subset of C++, thus following the object-oriented programming (OOP) concept. The benefit of using OOP structures is the ability to gather all state variables and functionalities to operate sensors into a class providing better organization and encapsulation of the program, thus increasing quality and making the code smaller and faster to run. The necessary header files and libraries have been added to Arduino IDE to run it on ESP32.

VI. Results

We tested SABOS utilising five current sensors, four motion sensors, six capacitive touch sensors, and two environmental monitoring sensors. Data from these sensors is directly sent to the cloud using the local web server and is stored in ThingSpeak as shown in Fig. 8. When the connection with the cloud server cannot be established, data can be stored locally. The system utilizes the developed and existing algorithms for data acquisition, Wi-Fi connection, sample reduction, activity recognition. The established system was installed in an apartment to record an elderly persons' behavior.

TABLE IV
Comparison of the Execution Times of the SABOS System to a Non-Optimized System

System	Multi-tasking	Execution time for 1000 iterations	Execution time for 2000 iterations
Non-optimized	No	$\sim 500\,s$	$\sim 1000\,s$
SABOS	Yes	$\sim 1563 - 2130\,ms$	$\sim 4000\,ms$

A. Performance

In Table IV, the execution times for two algorithms is compared: Non-optimized and SABOS. The non-optimized algorithm reads sensors each $500\,ms$. The $500\,ms$ time interval is required by the Arduino programming environment for the sensors. The maximum sampling frequency of the environment sensor DHT11 is $1\,Hz$, and for the touch sensor TTP223, the response time is $60\,ms$ to $220\,ms$.

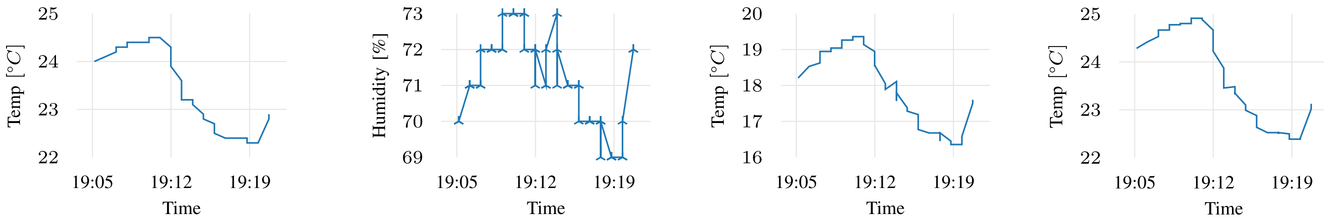
The sensors' normal operation interval can be achieved either by the default Arduino delay() or using any external libraries like the Metro library. The disadvantage of utilizing the delay() function for sensor reading is that it is in a "busy wait" mode that monopolizes the processor. The millis() function, on the other hand, allows multi-tasking and shorter execution times. Therefore, SABOS deploys the millis() function provided by the metro library. The benefits of deploying the millis() function are shown in Table IV; the execution times for SABOS are a magnitude faster than for the non-optimized algorithm.

B. Data Reduction Algorithm

Fig. 12 shows the how the data reduction algorithm works for humidity sensor data. The first figure (Fig. 12 (a)) gives the original sampled data that is stored in the input array. The next image (Fig. 12 (b)) shows what is left after executing the data reduction algorithm in the sensor node. In the cloud side, we have received the same data (Fig. 12 (c)) allowing us to reconstruct the original data samples that is shown in (Fig. 12 (d)).

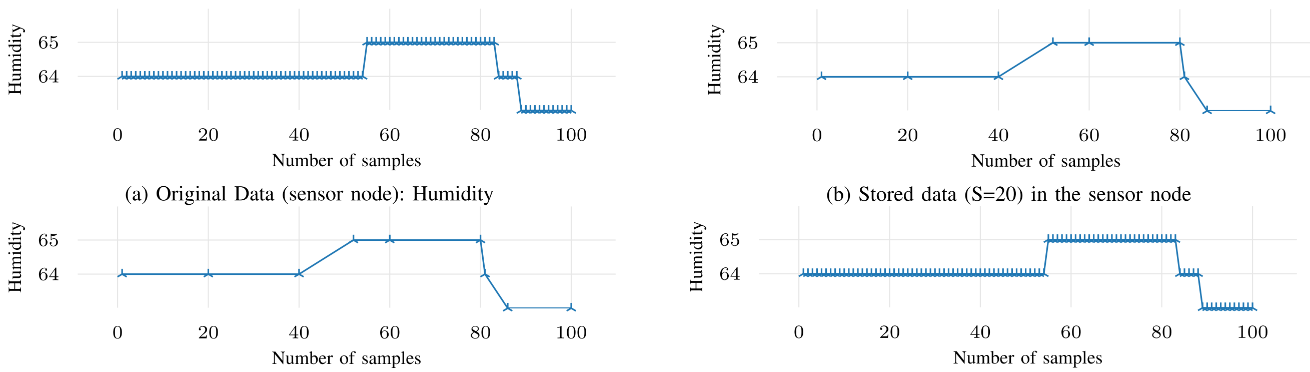
C. Behavioral Sensors

For testing, touch sensors were embedded in the bed, placed in the washroom commode, attached to the toothbrush, installed under the chair, and attached in medicine packets. All the sensor nodes worked as designed. Fig. 9 illustrates one-day activity on the bed and washroom commode as an example of the received data. The data used for Fig. 9 was downloaded from ThingSpeak in the CSV format. From the gathered data, we can see that the person woke up at 6:27. After breakfast and doing other morning activities, the person goes to a washroom at 9:03 spending there 17 minutes. Finally, after all-day activities, the person goes to bed at 20:13.



(a) Temperature (b) Humidity (c) Dew point (d) Heat index

Fig. 11. Multi-modal data of the room environmental sensor, DHT11.



(a) Original Data (sensor node): Humidity (b) Stored data (S=20) in the sensor node (c) Received data in the cloud (d) Reconstructed data (cloud): Humidity

Fig. 12. Implementation of data reduction to reduce and reconstruct samples.

D. Environment Sensors

The environmental conditions within the room were measured using the DHT11 sensor. DHT11 monitors the temperature, humidity, heat index, and dew point, as discussed earlier. Fig. 11 shows the data when we intentionally changed the room temperature to see the systems' response. The temperature was first warmed up to 24.50 $°C$ after it was cooled down until the temperature dropped to 22.50 $°C$. DHT11 shows the variation in the room temperature as well as the change of the humidity index (b), dew point (c), and heat index (d). Based on these four parameters, the feel factor is calculated, which delineates the person's feeling inside the apartment. Feeling values are: OK, Too hot, Too cold, Too dry and Hot & Humid.

E. Appliance Sensors

The current sensors are connected in series with electrical appliances, such as a heater, a juicer, and an oven. Similarly, with all the other sensor nodes, the data was sent using the wireless network connection directly sent to ThingSpeak cloud for the MATLAB visualization and analysis.

Fig. 10 shows the usage of the heater on the selected time interval during the experiment. Similar data was gathered from other appliances as well. The approximate usage of the five electrical appliances during one day of the test are: lights ∼ 700 minutes, heater ∼ 430 minutes, oven ∼ 23 minutes, juicer ∼ 13 minutes, fan 0 minutes. Depending on the season, the heater is naturally used more (winter) or less (summer). During the experiment, the heater was used for around seven hours a day, while the light was used for three hours. Other appliances such as a television, a juicer, and an electric kettle were also used for a few minutes during the day. By comparing daily usage patterns and the schedule of appliances, individual behavior can be drawn to find subtle changes in the behavior to indicate a need for a healthcare professional.

F. Sensor Nodes' Current Consumption

ESP32 uses advanced power handling technologies and provides various modes of operation that reduce current consumption. In SABOS, a capacitive touch pin is used to wake up from deep sleep to active state for data transmission to ThingSpeak. There are other methods to wake ESP32, such as timer (max time for every sleep mode is 4294967295 microseconds as ESP32 is a 32-bit micro-controller). However, in our system, the touch pin offers a better solution as it does not require physical touch due to the capacitive touch sensor's higher sensitivity.

Many researchers have implemented systems sending data packets continuously [27], [47]. In SABOS, using the sleeping stages of ESP32, systems are kept in sleep mode in the idle state. Some nodes do not require a battery in assistive living facilities such as temperature sensors, current sensors; however, a few sensor nodes, such as those embedded in chairs, beds, and sofas, require batteries. Elderly people might feel unsafe if power is provided to nodes directly from the main supply lines. To overcome this discomfort, sensor nodes are powered by a battery. Current consumption is reduced to 57%, 87%, and 95% for bed, chair, and washroom sensors, respectively. In the current sensor, environmental sensor, and motion sensor, nodes are supplied power through a charger. Current consumption reduction is depicted in Table V.

TABLE V
CAPACITIVE TOUCH SENSORS (CTS) CURRENT CONSUMPTION COMPARISON IN DIFFERENT UNITS

CTS Unit	Total current [A/day]
Standard Current Consumption of ESP32 in Active state	$\sim$ 4.80
SABOS Bed-Node	$\sim$ 2.18
SABOS Chair-Node	$\sim$ 0.55
SABOS Washroom-Node	$\sim$ 0.21

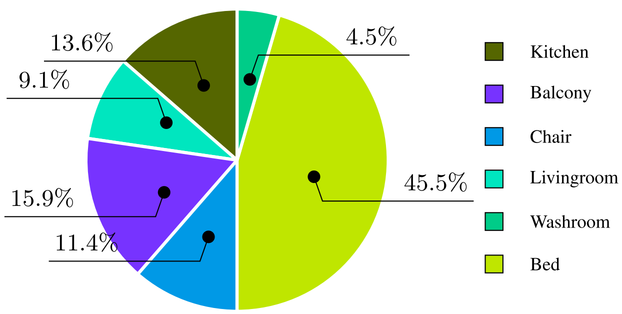


Fig. 13. Activities during the 30 days of the experiment.

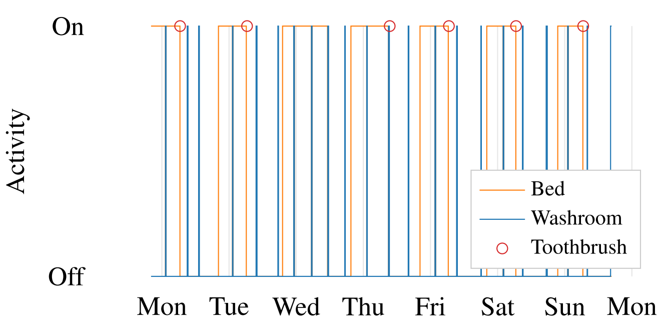


Fig. 14. Bed, bathroom and toothbrush activity during one week.

G. IFTTT: If This Then That

During the experiment, IFTTT with ThingHTTP (Method = Get, Triggering condition data type = Numeric) was used to alert a caregiver in an emergency by sending an email and SMS using the IFTTT Android app. A threshold for the temperature and bed sensors was defined in the ThingSpeak to trigger the applets in IFTTT. During the experiment, applets with Gmail and SMS reacted in average in 4 seconds providing quick response time.

Considering other messaging services instead of the Gmail and SMS applets, we also tried the Twitter applet. However, in our experiments, Twitter sometimes took a few minutes. Thus, Twitter does not provide sufficient reaction time for emergency services. Another emergency service to take into account is the VoIP (voice over IP) applet that can deliver a voice message within 10 seconds. This can provide an excellent alternative to phone call services. This applet can deliver phone call messages through the IFTTT app to caregiver devices and is available internationally. To use this service, the only requirement is to have the latest version of the IFTTT app.

Some consideration is needed in the cloud side to ensure the quality of service. After a few weeks running the experiment, a trigger occurred with the temperature applet; however, the IFTTT site listed it as not occurring. This was solved by reinstalling the IFTTT app in the phone. Missing a temperature warning is not a high risk situation, but preventive measures must be taken to mitigate the effect of a lost alert.

H. Summary of Activities

The SABOS system was tested in a 30-day experiment. During the 30 days, the volunteer lived life normally, not letting the prototypes affect daily activities. Fig.13 shows the proportions of different activities during the experiment. From the activities the SABOS systems followed, most of the time was spent sleeping, then on the balcony chair, and in the kitchen: 45.45%, 15.9%, and 13.6%, respectively. Less time was spent on the washroom commode (4.5%). This information is essential in recognizing anomalies in daily living activities, as discussed in our previous work [32].

Fig. 14 shows activity during the one week of the experiment. From the data, it can be seen the daily patterns that can be used to personalize SABOS to all users. In this case, the user woke up every night to visit a bathroom, after which (s)he continues sleeping on a bed.

VII. DISCUSSION

Fundamental design issues that are considered while designing IoT systems are operation and communication latency, scalability, and energy efficiency. SABOS answers the last one by deploying ESP32's power modes and forcing the sensor nodes to deep sleep after predefined inactivity. With the chosen measures, the operation time of the battery-powered sensor nodes can be extended considerably. In addition to the ESP32, we implemented the data reduction algorithm to reduce the amount of data transmitted to the cloud. The power consumption by using the algorithm is negligible compared to sending all the measured data points to the cloud. Scalability is more affected by the cloud side. The free version of ThingSpeak prevents to use of the full potential of SABOS. In the future, this limitation can be excluded by getting a license. The integration of MATLAB analysis and IFTTT services was considered essential for testing the planned features. SABOS uses software-based multi-threading to reduce latency and especially increase SABOS' energy efficiency.

From a practical point of view, the experiment showed that SABOS works well in the chosen environment. Especially the modified motion sensors and designed sensor node worked as planned. The chosen capacitive touch sensor and developed sensor node worked as planned and detected the presence of a person from 5 cm to 8 cm distance. Some improvements for the accuracy of the behavioral sensor node will be needed, especially when used in a bed. The behavioral sensor located in a bed was rebooted twice during the experiment. This was noticed after getting corrupted data packets. From the capacitive sensor point of view, this is not a problem because

TTP223 offers auto-calibration for life and the re-calibration period is just four seconds. During the time-limited experiment, the durability of the capacitive sensor node was not a problem. The durability issue will be addressed when building the next version of the sensor node.

In the future, SABOS will include non-wearable sensor nodes for measuring the vital signs of a user. For example, a non-wearable IoT-based monitoring system for electrocardiogram (ECG), heart rate variability (HRV), and photoplethysmography (PPG) augmented with the environmental and behavioral data would allow to deepen the understanding and create more accurate behavior patterns to estimate and predict future healthcare needs. We will also deploy machine learning algorithms for finding weak signals from the data that can be used to alert healthcare professionals to estimate the situation and the need for immediate actions.

VIII. Conclusion

We presented a smart ambient behavioral observation system (SABOS). The system provides an unobtrusive monitoring solution for elderly care homes by gathering data using environmental and behavioral sensors. SABOS utilised integrated touch and motion sensors to follow user's daily activities, current sensors to follow appliances' usage, and environment sensors to follow living conditions. To assess the comfort level in terms of temperature and humidity, we defined and calculated comfort status. SABOS sends the data directly to a cloud deploying wireless network connection that reduces latency. The next step is to add intelligence to the edge by performing analysis in the sensor nodes, and thus further reduce the amount of transmitted data.

To reduce the amount of data that SABOS transmits to a cloud server, we designed a data reduction algorithm. With the data reduction algorithm, we can reduce over 90% of the amount of transmitted data. Naturally, the data reduction algorithm is most efficient with binary values and for decimal numbers its efficiency decreases with increased accuracy. Also, the maximum saving potentiality depends on the used precision and sensor quality. Because the data reduction algorithm is lossless, the original data can be restored fully in a cloud service.

The operation of SABOS was verified by implementing a prototype system and specific sensor nodes. For the sensor nodes, the low power ESP32 microcontroller provides efficient energy-saving modes together with powerful microprocessors and communication interfaces for gathering data and running, for example, the data reduction technology. The sensitivity of the designed capacitive touch sensor was increased enabling its usage with different furniture. With increased sensitivity, the modification resolved the used pressure sensor's bending issue prolonging its lifetime. The prototype utilized ThingSpeak for storage and MATLAB for analyses and visualization. SABOS also utilised the IFTTT service to inform healthcare professionals for a possible need for care or support. Data were downloaded in the CSV format for analyses during the test.

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