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Home monitoring for older singles: A gas sensor array system

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ABSTRACT

Many residential environments have been equipped with sensing technologies both to provide assistance to older people who have opted for aging-in-place and to provide information to caregivers and family. However, such technologies are often accompanied by physical discomfort, privacy concerns, and complexity of use. We explored the feasibility of monitoring home activity using chemical sensors that pose fewer privacy concerns than, for example, video-cameras and which do not suffer from blind spots. We built a monitoring device that integrates a sensor array and IoT capabilities to gather the necessary data about a resident in his/her living space. Over a period of 3 months, we uninterruptedly measured the living space of a typical elder person living on his/her own. To record the level of activity during the same period and obtain a ground truth for the activity, a set of motion sensors were also deployed in the house. Home activity was extracted from a PCA space moving-window which translated sensor data into the event space; this also compensated for environmental and sensor drift. Our results show that it is possible to monitor the person's home activity and detect sudden deviations from it using a low-cost, non-invasive, system based on gas sensors that gather data on the air composition in the living space. We made the dataset publicly available at a data repository https://doi.org/10.24432/C5762W.

1. Introduction

The high uptake of smart home infrastructures capitalizes on recent research advances that position highly accurate and precise sensing technologies in an unprecedented strengthening of remote health industries. Beyond a precise characterization of parameters surrounding any sensor-equipped home, the possibility of tracking household residents underlines much of the potential of these technologies. The advent of the Internet of Things (IoT) and sensorised environments, including smart homes [1], has enabled the monitoring of a wide range of aspects of the life of a given person in relevant contexts. This has facilitated access to capturing details and characterizing activities in private settings that are traditionally out of reach. The information that can be tracked ranges from behavioral metrics to activity and ambulatory patterns, energy consumption, home appliance usage, or even physiological data. Previous research has been directed towards monitoring occupants in their home settings, from intelligent power meters [2], to advanced PIR sensors passing, inter alia, through infrared cameras characterizing presence [3,4], ambient sound recording systems keeping track of activity [5], and smart furniture and objects [6]. The development of such monitoring systems resulted in activity recognition applications and the monitoring of Activity Daily Living (ADL), aiming at better quality of life for semi-dependent people, in particular the elderly [7].

In the case of aging populations, this is in line with societal efforts to face the challenge of a global increase of life expectancy. However, the field of home activity tracking poses concerns about the ease of use of the technology and its overall acceptability. Issues of data ownership and interpretability, whether the level of obtrusiveness might compromise concurrent activities, and level of personal exposure that subjects face (different sensing options present differing levels of invasiveness) [8,9]. Video-based systems can pose serious privacy concerns [10] and are still affected by blind spots, thus requiring several systems to monitor a single living space. On the other hand, gas sensors for remote activity monitoring are non-invasive, pose fewer privacy concerns, and event detection is not restricted to a limited field of view. As a result, the detection range of chemical-based systems is larger,

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and the activity of an inhabited home can be monitored with fewer detection units. Moreover, chemical-based systems are also sensitive to other events, such as high concentration levels of volatiles [11], that may be relevant for monitoring older adults' homes. These can be indicative of danger (running natural gas, product spill, etc.) or anomalous behavior (rotten food, lack of ventilation, among others).

This paper aims to investigate the capability of a set of commercial gas sensors as unobtrusive and non-invasive sensing technology to monitor several ADLs and capture the pattern of activity of elderly living independently. The developed system was installed in a four-story apartment where an older person carried out their daily activities. We show that the system can capture patterns of behavior of the occupant and detect unexpected events thus providing information to caregivers and family. We made the dataset publicly available.

2. Related work

Previous and recent studies have shown that several types of sensors can be employed to monitor human activities. For example, Multiple Thermal Sensor Array (TSA) using low-resolution thermal imaging can be deployed at home to detect the human presence [12] or falls [13,14], while chemical gas sensors can improve room occupancy predictions [15].

In this context, it is worth to mention that in the late 90's, S. Hirobayashi and co-workers already employed a single commercial gas sensor to detect human activities by using an inverse of the sensor response [16]. More recently, an array of polymeric gas sensors was placed in a 200 m^3 room with semi-controlled conditions used by the JPL-NASA to simulate spaceship cabin atmosphere. Several volunteers performed physical activity and different common daily activities. It was possible to predict the level of activity performed in the room and detect the use of ethanol-based medication [17]. More recently, Pedersen, H. et al. showed that under simple and controlled conditions, all indoor climate parameters are highly correlated with occupant presence [18]. Results showed that room occupancy can be predicted with standalone measures of carbon dioxide or total volatile organic compounds in a test-room. However, when the system was placed in a three-room dorm apartment shared by two persons, performance of standalone sensors decreased significantly and they were coupled to PIR sensors.

Unlike previous works, we present a gas sensor array to capture daily activities and deviations from the pattern of activity.

3. Materials and methods

The following section describes the sensors used for signal acquisition, the communication system between the sensors and the database, and the deployment of the system. Next, the methodology is described, from signal pre-processing to the validation of the activity patterns with reference sensors.

3.1. Sensing device

We developed a sensing unit to sample indoor air composition. It was integrated into a customized electronic board with wireless communication capabilities to upload acquired data to the Cloud in real-time. The gas sensing system is a heterogeneous sensor array where the sensors are exposed directly to the environment, with no measurement gas cell. The absence of a measurement chamber shortens the response time of the system, since the slow dynamics of the chamber are avoided, but this makes the system sensitive to air turbulence in the vicinity of the sensors [19–21].

Specifically, the sensing unit is designed to hold four metal oxide (MOX) gas sensors, two carbon dioxide sensors, a carbon monoxide sensor, and temperature and humidity sensors. MOX gas sensors show a broad response to volatiles, although the sensing layer can be adjusted to heighten sensitivity to selected gases. To enhance the system selectivity and sensitivity, the selected MOX sensors are based on different commercially available sensing layers, provided by Figaro Inc.[2] They operate isothermally, applying a 5 V constant voltage on the built-in sensor heater. The incorporation of MOX sensors into the system is very convenient for the detection of a wide spectrum of volatiles and untargeted chemicals that are released during a range of indoor daily activities.

Table 1
Sensors included in the sensing unit.

Sensor and provider	Target
SHT-75, Sensirion	Temperature, humidity
MG811, Hanwei Co.	Carbon dioxide
CozIR-A, Gas Sensing Solutions Co.	Carbon dioxide
CO-B4, Alphasense Co.	Carbon monoxide
TGS 2602, Figaro Inc	VOCs, Ammonia, H_2S
TGS 2611, Figaro Inc	VOCs, Methane
TGS 2610, Figaro Inc	VOCs, Propane, Butane
TGS 2620, Figaro Inc	VOCs, Solvent Vapors

Carbon dioxide is suitable for monitoring room occupancy. Hence, two carbon dioxide sensors with different technologies have been included. Moreover, carbon monoxide sensors can be relevant in environments where incomplete combustion may occur, providing additional safety measurement to occupants of a building [22,23]. Although we expect that the CO sensor will rarely record measures above its baseline, we opted for adding it to enable further development to integrate a fire alarm system, a convenient feature for elderly safety. Finally, temperature and humidity sensors are also included to compensate for sensors' cross-sensitivity to environmental conditions. Table 1 shows the selected sensors, together with the corresponding target compounds.

The sensor array is integrated with a customized board that includes the signal conditioning electronics and an ATmega32u4 microprocessor that interfaces with the Atheros AR9331 to enable wireless communication. The microprocessor was programmed to perform: (i) Continuous data acquisition from the chemical gas sensors through 10-bit resolution analog-to-digital converters at a sampling rate of 20 s; (ii) Temperature and humidity collection by means of the i2c communication protocol; (iii) Data storage in an SD memory card for back-up purposes; and (iv) data communication through a local wifi network to send the most recent data to a remote data server. Finally, a custom 3D printed enclosure was designed and implemented for the sensing units. The enclosure provides mechanical protection to the sensing unit while enabling direct environment sampling by the sensors. Fig. 1 shows the developed prototype for continuous activity monitoring. Additional images of the employed sensors can be found in the Supplementary Material.

3.2. Communications and database

The developed prototype sends live data to our database via an API application. The REST API was designed to receive the sensor data through the HTTP protocol and write them to the database. It was developed in Django (django REST framework 3.10.3) a programming framework for Python 3.6.8. In this way, every 20 s, the prototype sends the data to the database using to a specific URI of our API.

The database and the API application are hosted in the CloudUPC service. This service provides a dual-core CPU, four gigabytes of RAM, thirty-five gigabytes of storage memory with an Ubuntu 18.04.4 LTS operating system.

The database structure is defined by three relational tables (users, devices and samples). The user holds basic user information such as

[2] https://www.figarosensor.com

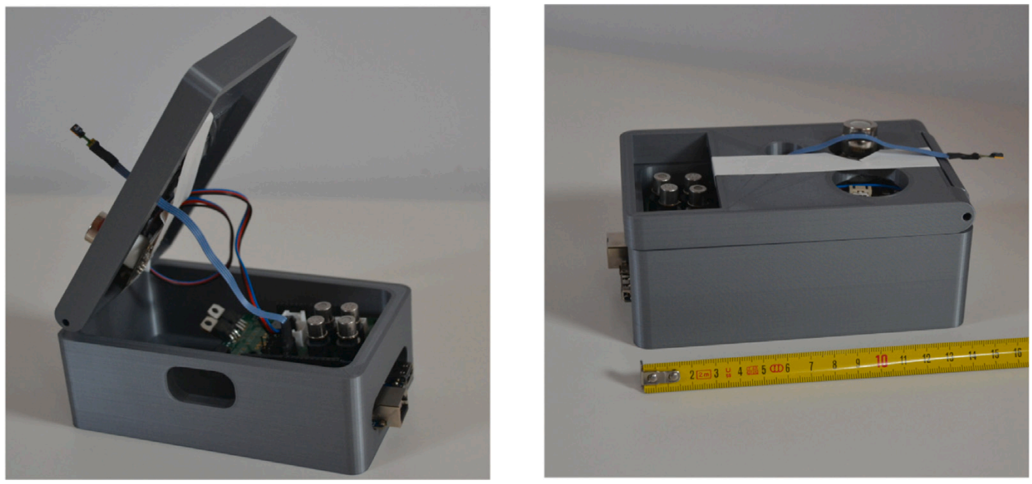

Fig. 1. Prototype developed for continuous activity monitoring including gas sensors and wireless communication to send data to a remote server.

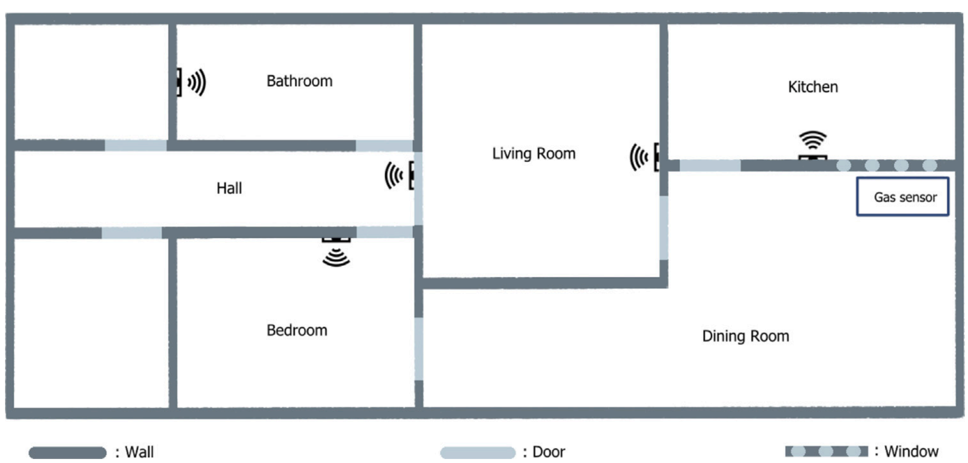

Fig. 2. Floor plan of the pilot home, indicating the position of the gas sensor prototype and the motion sensors used to obtain labeled information. Black lines indicate walls, gray lines indicate door openings or large windows.

email, username and password. The device table contains the following fields: name, type and UUID of the device; latitude and longitude coordinates of the device location; type of room and space where it is located; name of the location; user to which the device belongs. Finally, the sample table has the following fields: timestamp, temperature, humidity, average noise, maximum noise, CO2CosIRValue, CO2MG811Value, counter, MOX1, MOX2, MOX3, MOX4 and the device that is sending it. More details on the communication protocol and database can be found in the Supplementary Material.

3.3. Deployment and data acquisition

The home of an 89-year-old person was selected for the deployment of the system in a real environment. The house is located in Igualada, Barcelona, in an urban environment but one with low population density. The house consists of 3 bedrooms, a living room, a dining room, a living room, a kitchen and a bathroom. The behavior pattern of the occupant makes this house a favorable environment for a pilot test, as the occupant followed a well-established routine.

The floor plan of the pilot home is presented schematically in Fig. 2. The gas measurement system was installed in the dining room where the volunteer spends most of the day. In addition, the dining room has one window that communicates with the kitchen and another with the bedroom. This makes the dining room a perfect location to place the system since it will be able to measure any activity that changes the gas composition of the three rooms. Over the same time period, a set of motion detectors placed in the different rooms of the house recorded the activity of the volunteer.

The gas measurement system recorded a total of 87 signal days. From these records, a data set was extracted from a three-month time interval, during which the volunteer lived alone and was autonomous. A data set without human activity was acquired at the same location (but this time without the volunteer) over the period of week. In this work, any change in signal trends whose origin is human activity is considered an event.

3.4. Data processing and activity detection

To detect events from the sensor signals we first correct environmental drift. Next, we use a moving window in the vector space. In particular, Fig. 3 summarizes the methodology to extract the level of activity. It shows two independent data processing branches that come together in environmental correction. The first branch processes all the data potentially due to human activity. In this branch, different signal-processing and machine learning techniques are used to detect statistically significant events. The second branch uses a set of "clean" data (without human activity) to parameterize the environmental variance and then use it for environmental correction. In addition to these two processing paths, the diagram shows three large boxes representing the three main processes of the algorithm these being the environmental correction, the parameterization of the environmental variance and finally, the processing of the data for event detection.

3.4.1. Preprocessing and environmental correction

First, to reduce signal noise due to signal interference and remove outliers, a centered median filter with a window size of 11 samples is applied.

Next, we aim at removing environmental variance to avoid false positives in event detection. The purpose of the environmental correction is to eliminate the variance component arising from factors unrelated to human activity, such as that arising from temperature or humidity changes over the course of a day, or longer-term sensor drift.

The method consists of principal component analysis (PCA) of the data without human activity which is then projected onto data with human activity. For this purpose, the data set without human activity has been used as reference data, since in the absence of human activity, the variance will be that produced by the environment. Hence, a low dimensional vector space is created with a PCA using the data without human activity only. Once this space is created, the environmental variance is parameterized. The objective of the parameterization of the environmental variance is to fit the variance that causes drifts in the trend of the sensor signals and which is of environmental origin. Then, a projection of the data with human activity is made on the vector space of the data without activity. In this way, the variance considered to be environmental is cancelled. Finally, the data with activity is reconstructed in the original vector space.

3.4.2. Event detection

The following section describes the methodology used to detect events with gas sensors. This section is divided into three parts. The first part introduces the use of moving window PCA to obtain the Mahalanobis distance to determine if a sample from a data set is an event. The second part introduces the computation of the T-squared limit to determine if the detected event is statistically significant. Finally, the third part presents the procedure to calculate the number of statistically significant events for each hour.

Moving Window PCA

The moving window PCA consists of running a time series using a sample window of size H to build a PCA model and projecting the subsequent observation (H+1) in the resulting vector space [24,25]. Once the projection of a new observation is done, the Mahalanobis distance is calculated to measure the distance between that observation H+1 and the distribution D formed by the data in the window H. This distance is a multidimensional generalization indicating how many standard deviations the point P is away from the mean of the distribution D. With each new observation, this window excludes the oldest observation and includes the observation from the previous time period. In this way, the entire data set is walked through.

The length of the window H is selected according to the rate at which the mean and covariance parameters change, with large windows being more suitable for slow change and small windows being more suitable for fast change. In our case, a window length of 360 samples was chosen to fit with the sampling frequency (a two-hour interval, since a sample is taken each 20 s).

T-squared limit

In order to determine whether a sample is statistically significant, the Hotelling T-squared statistic is calculated. Thus, if the distance of an observation to the distribution formed H is greater than the T-squared statistic, this sample is a statistically significant event. To calculate the T-squared limit the following equation is used:

$$T_{\alpha}^{2} = X_{\alpha}^{2}(m) \quad (1)$$

Eq. (1) means that the T-squared limit follows a chi-squared distribution with m degrees of freedom for a particular significance level. Although there are more conservative choices, our dataset meets the necessary requirements, so the existing error between the most permissive equation and the most restrictive one differs by less than 10% [26]. Hence, we used this approximation for the limit calculation.

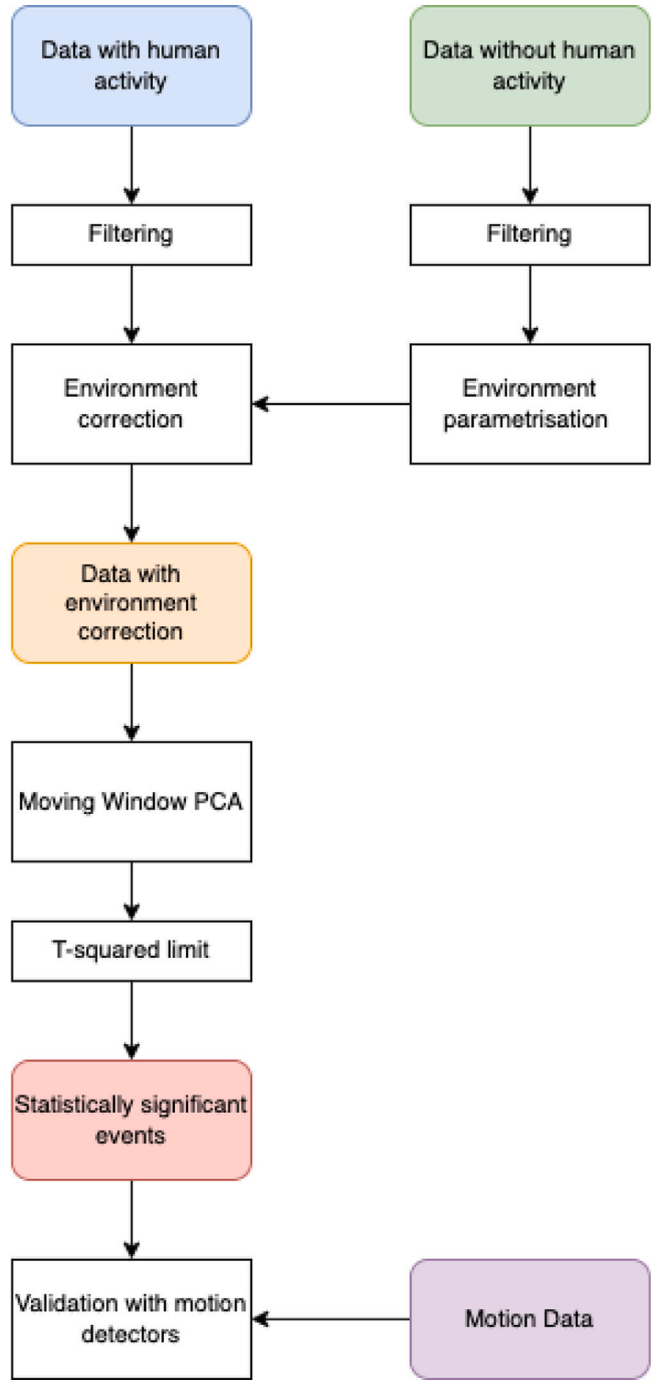

Fig. 3. Flow diagram to extract the number of events. Data without human activity is used to correct environmental variability. Motion sensors are used to obtain ground-truth data.

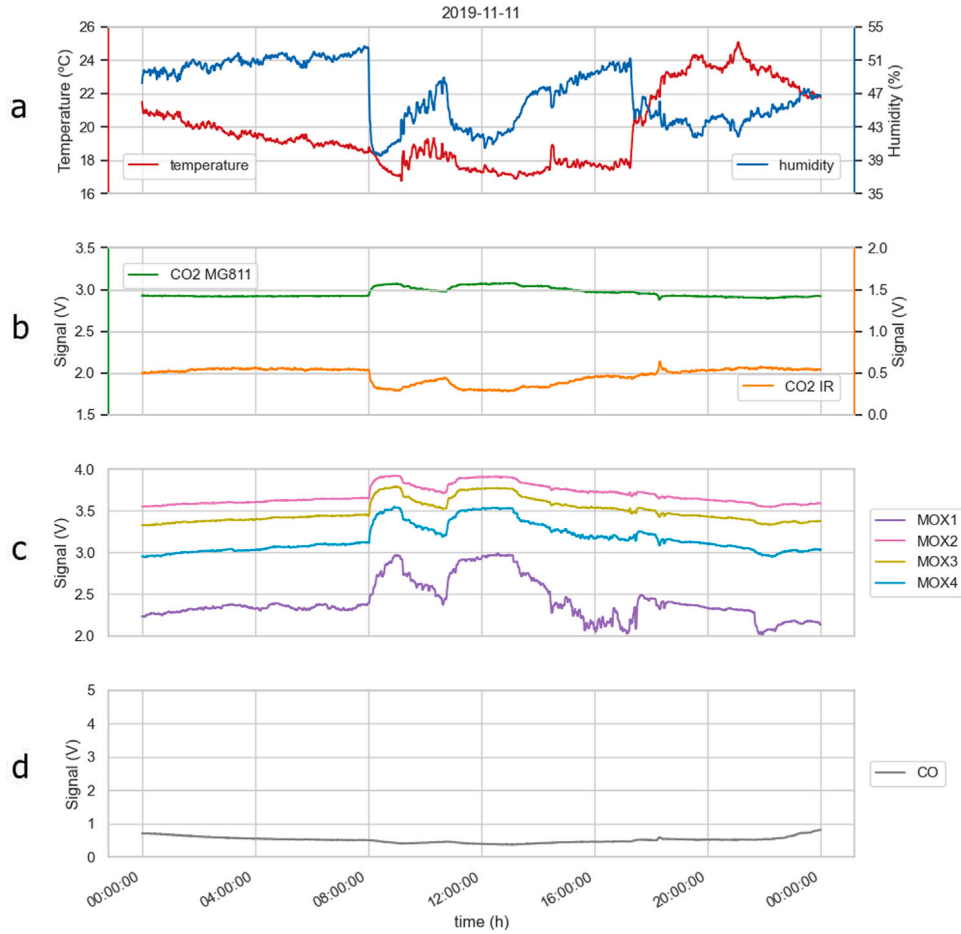

Fig. 4. Gas sensor signals and physical quantities after filtering. a: temperature and humidity. b: CO_2 sensors. c: 4 metal oxide sensors. d: CO sensor.

Sum of events

The objective is to obtain the number of significant events per hour. For simplicity, windows (intervals) of 1 h are chosen, but the algorithm can be generalized to windows of other time lengths. In this way, the number of statistically significant samples detected for a particular hour on different days can be compared.

First, all the Mahalanobis distance values were ordered by days, obtaining a matrix of $n \times 4320$, where n is the number of days analyzed and 4320 is the number of samples in a day. Second, the Mahalanobis distance was divided by the T-squared limit to obtain a ratio indicating whether that sample is statistically significant. Third, the matrix has been binarized so the significant samples are 1 and the rest are 0. Finally, this vector of ones and zeros is summed every 180 samples to obtain the number of event samples for that hour.

3.5. Annotation with motion detectors

In this study, the motion sensors have been deployed as a ground-truth strategy to detect the daily events without interrogating the participants, but also for bench-marking purpose with the gas sensor-based device. To do this, motion data, which had a time resolution of one minute (meaning that once the sensor was activated, it would not turn off after at least one minute), was converted into a sum of minutes of activity. Therefore, a movement sensor could have from 0 to 60 min of activity per hour. The more minutes of activity there were in an hour, the more activity was considered to be in that room.

To set a framework of the relationship between the activity measured by both gas and movement sensors, the reference week was also used. A reference for the level of activity performed at home was hence extracted from the motion detectors installed in the home, which was also confirmed by close relatives of the occupant.

4. Experimental results

4.1. Sensor signals

A visual inspection of the sensor signals confirms sensor sensitivity to home activities. In particular, Fig. 4 shows the acquired signals of the nine sensors over a twenty-four hour period. The figure is divided into four subplots. Subplot A shows the temperature (red) and humidity (blue) sensors. Subplot B shows the CO_2 signal sensor from two different sensors. There is a reverse dependency on the CO_2 sensors due to the sensor technology. Subplot C shows signals from the four MOX sensors. Finally, subplot D shows the CO signal.

In the presented example, there is no significant change in the gas sensor trends during the night period (from 00 am to 8 am). Instead, the variability of the signal trends appears during the periods of activity at home. The first event that causes significant change in the sensor signals is at 8am, when the occupant wakes up. At this moment the occupant opens the window and one observes the corresponding drop in temperature and humidity, that was accumulating over the night. Then, the highest variability in the sensor signals correspond to the periods with activity in the household, between 8:00 am and 8:00 pm. During this time, the occupant of the house performs the common daily activities, such as having a shower, ventilating the house, cooking, eating, watching television, and using the bathroom. One can observe a sudden change at around 5 pm, manifested mostly in a temperature increase that corresponds to the occupant turning on the heating.

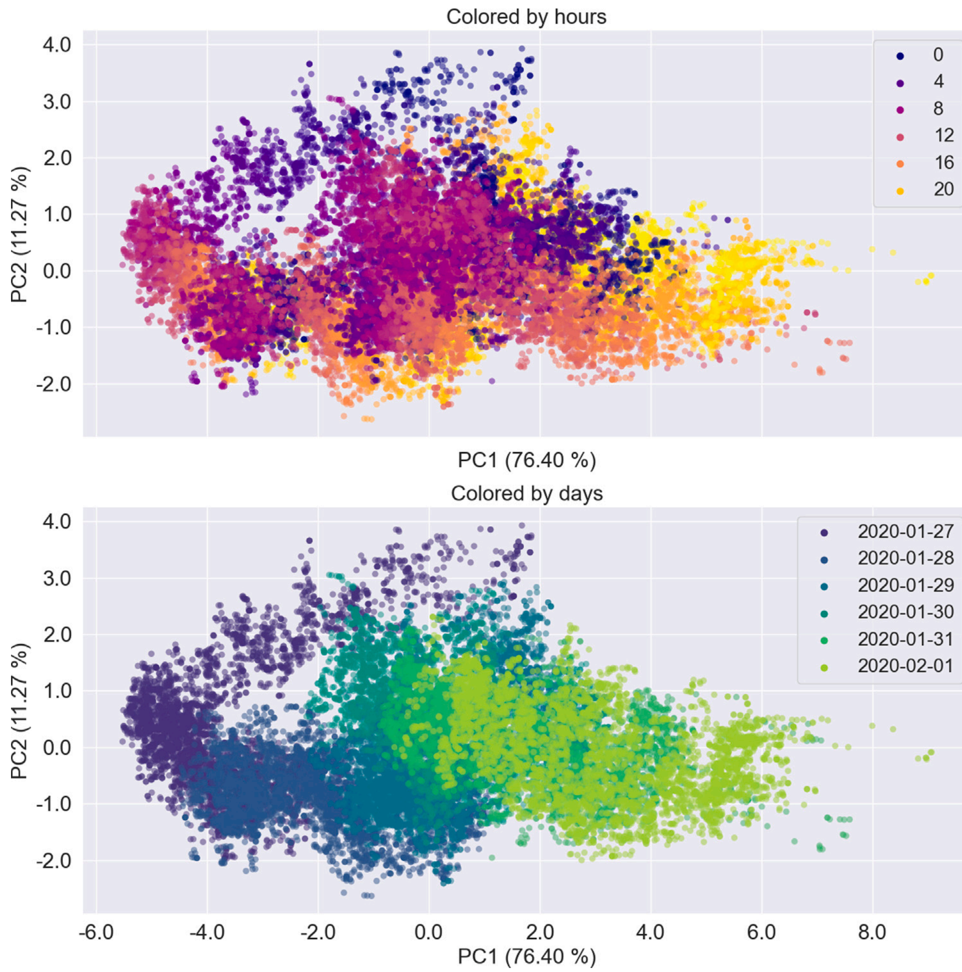

Fig. 5. PCA space representation of the data set without human activity before environmental correction. Samples colored by time of the day (top) and colored by day (bottom). Due to environmental factors, the samples are ordered by time of the day or by the day of acquisition.

The observed temperature range in the 24-h period is approximately 8 °C. Such variation caused by human activities is in accordance with the temperature variation observed in home settings [27,28]. The CO sensor does not measure CO levels above the background baseline, as expected under no combustion or fire conditions [23].

Hence, it is possible to extract human activities in home settings from the sensor raw signals. Such activities have noticeable effects on temperature, humidity and air composition, which are successfully captured by the deployed sensor system.

4.2. Parameterization of environmental variance

The first principal component captures 76% of the variance of the data during the reference week. The accumulated variance captured by the two and three first components is 89% and 95% respectively. Therefore, since the first component captures more than two thirds of the total variance of the data, it was decided that it is sufficient to parameterize the environmental variance. Thus, the first component of the PCA of the data without human activity is used as environmental variance for its subsequent elimination.

4.3. Environmental correction

To decouple the sensor variance due to the activities performed at home from the sensor responses due to environmental changes, the parameterized environmental variance was used. Fig. 5 shows the projection of the uncorrected data while there was no activity at home. The data are distributed following a daily trend and drift over time. For example, in the top plot, warmer values representing the last eight hours of the day are generally distributed below the samples with cooler colors, representing the first half of the day. Looking at a single day with this color scale, samples captured at 12:00 tend to be on the negative region of the x axis, and those captured at 00:00 tend to be on the positive side. Thus, a correlation can be observed between the daily cycle and the variance captured by the first principal component. More clearly, the environmental variance attributed to time drift is observed in the bottom plot of Fig. 5. The samples are colored by the days to which they belong, with dark to light green colors. The darkest greens are the days closest to January 27, while lightest greens correspond to the days close to February 2. As in the top plot, there is an ordering of the samples by day, from negative to positive values, that correlates with the magnitude of the first principal component.

Fig. 6 shows the same data after environmental correction. The extraction of the first principal component reduced the correlation between the first principal component and the environmental variance that is present in Fig. 5.

4.4. Detection of events

An event is composed of a set of statistically significant samples in a particular time period. In particular, Fig. 7 shows a recording of the 24-hour sensor signals along with the ratio that indicates whether a sample deviates from the mean of the distribution in a statistically significant way. Therefore, if the ratio for a sample is greater than 1, that

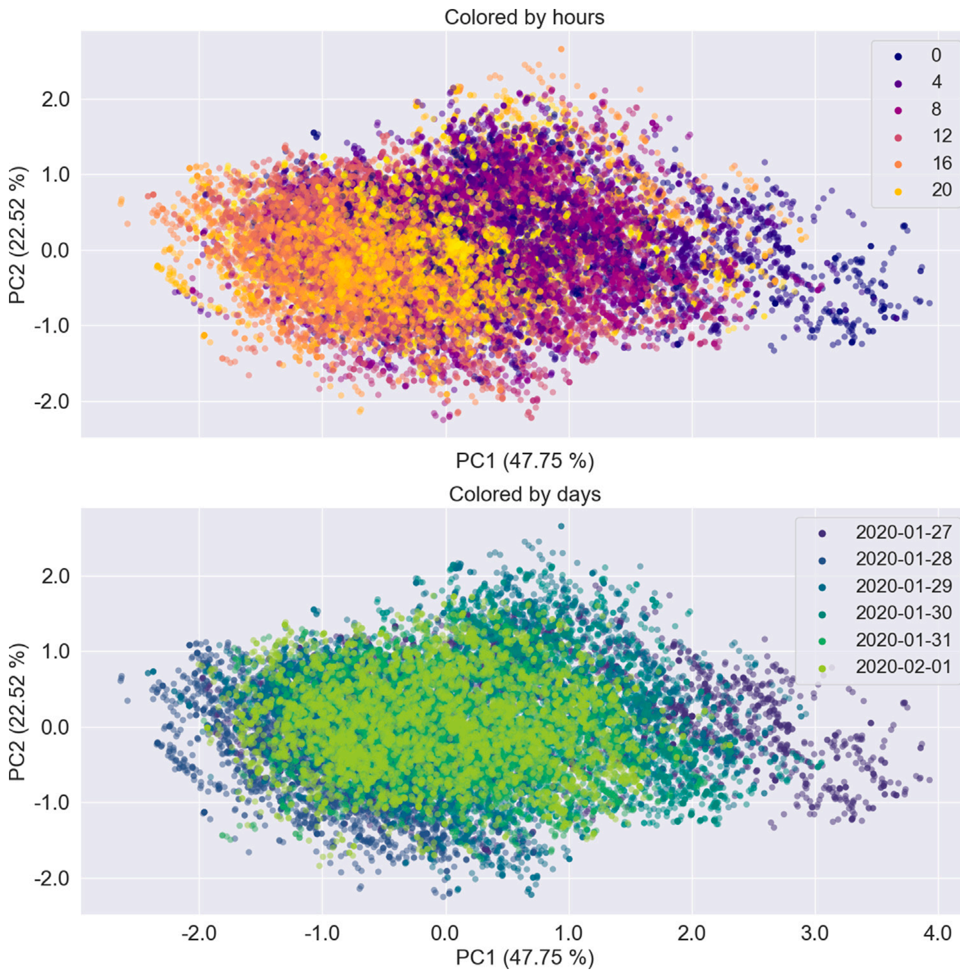

Fig. 6. PCA space representation of the data set without human activity after environmental correction. Samples colored by time of the day (top) and colored by day (bottom). The samples overlap each other, with a reduced structure on the environmental factors.

sample belongs to a statistically significant event. The significant events detected with the gas sensor array and the ratio of the Mahalanobis distance over the T-squared limit matches with the activities performed by the elder, confirming the ability of the gas sensor system to monitor home activities.

4.5. Activity pattern

Using the detected events it is possible to build a map of activities performed at home. As shown in Fig. 8, the most active hours are in the morning, when several activities are carried out. In the afternoon the number of activities decreases, since the volunteer is usually watching television or going for a walk. Christmas Eve and Boxing Day, a regional holiday, show different behavior patterns from the rest of the monitored days. This is confirmed by family gatherings during those days in the monitored home, causing an activity outside the regular activity routine detected by the gas measurement system.

From the map presented in Fig. 8, activity patterns have been obtained by calculating the median and quartiles to obtain an overview of the data distribution. In particular, Fig. 9 shows a general description of the pattern generated during November by taking the data of all its days and calculating the average. The red line, representing the 24th of December, follows a very similar trend to the one observed for the average month practically all day long, but after 8:00 pm the number of detected events increases considerably due to the celebration of Christmas Eve. This activity is successfully detected as being outside the regular pattern of activity.

This behavior can also be observed in the PCA space of different days (see Fig. 10). For example, comparing three days, one with no human activity, a day with regular human activity, and Christmas Eve where human activity increases significantly.

Hence, a regular pattern of activity was set for the monitored home. Days (or part of a day) that follow different level of activity fall outside the established pattern. This information can be sent to the care-givers and family members to provide relevant information from the monitored elder.

4.6. Benchmark with motion sensors

The activity captured by the movement sensors is used to set a ground-truth reference for the developed system. Fig. 11 shows a benchmark between the activity measured by the movement sensors and the calculated by the gas sensing node, during two different days with different level of activity and a reference day with no activity at all. It becomes evident that the gas-measured activity is affected by the real activity in the house. The average of the normalized gas-activity (0.196) is approximately three times higher when there is activity as compared to the empty house (0.066). The bottom plots of Fig. 11 show a stationary state of the empty house up until a sudden activity at 3 pm (affecting the gas-activity as well). This data corresponds to

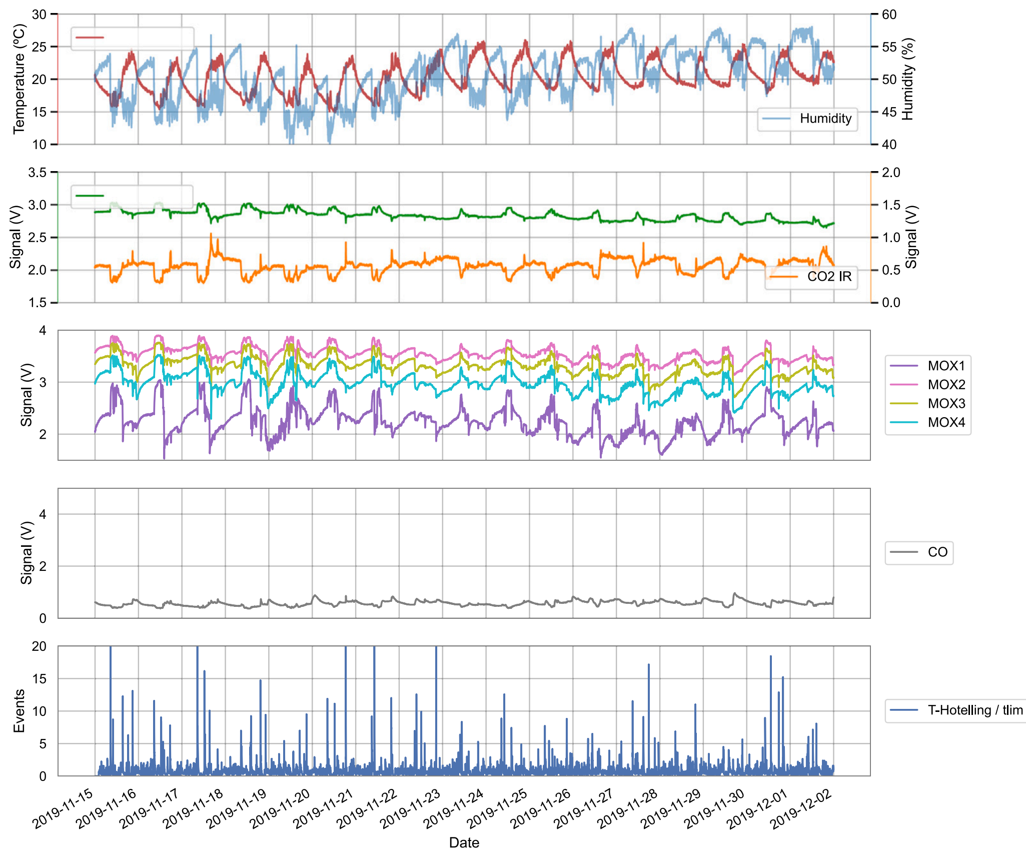

Fig. 7. Sensor signals (temperature and humidity signals; CO_2 sensors; metal oxide sensors; CO sensor) and detected events (ratio formed by the Mahalanobis distance divided by the T-squared limit) over a period of 18 days.

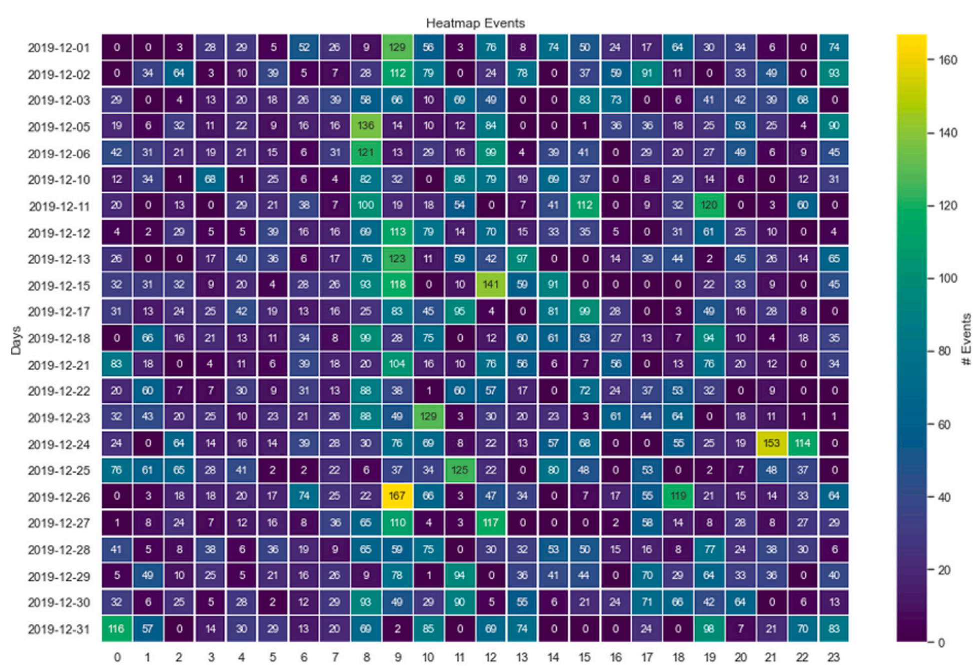

Fig. 8. Heat map representing the number of significant samples detected per hour. The *x*-axis represents 24 h per day and the *y*-axis represents different days. Within each cell there are number of samples that are statistically significant events. The coloring goes from cool to warm colors as more events are detected.

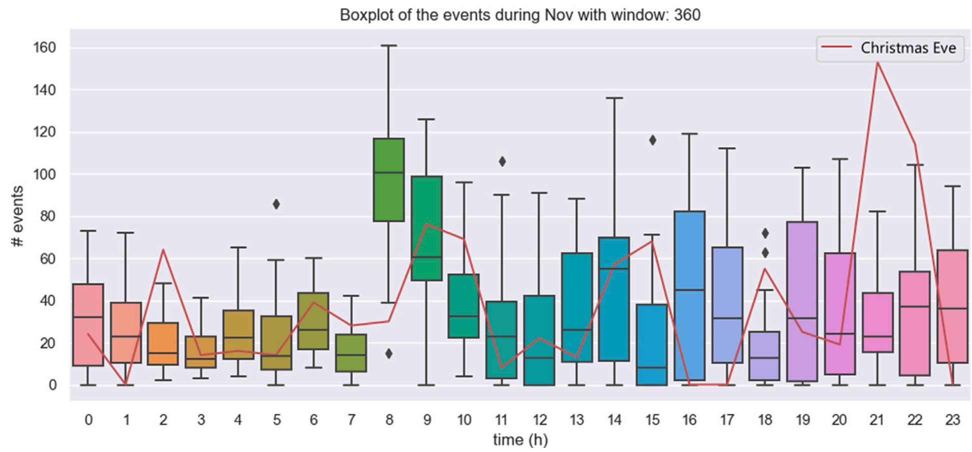

Fig. 9. Box plots of the activity detected for each hour of the day, using data acquired during the month of November. Activity detected during Christmas eve (in red). The number of events detected during dinner time in Christmas Eve deviate from the regular pattern of behavior due to a family gathering.

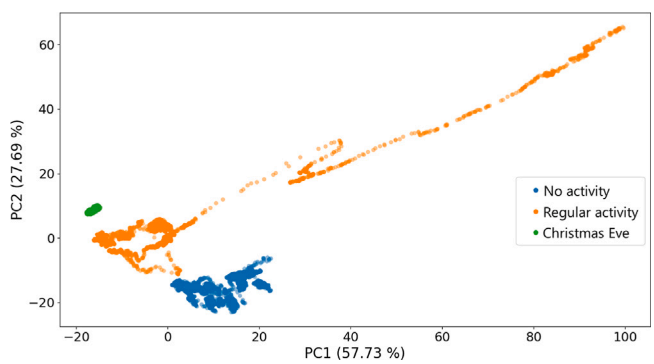

Fig. 10. PCA space representation of the data set for three different days. The x and y axes represent the first two principal components that capture 85% of the variance of the data. Each point in the graph represents a sample and has been colored according to the day to which it belongs (blue: normal activity day; green: no activity day (reference day); orange: very active day (Christmas).

a day during which the house was unoccupied, but at around 3 pm, someone entered to the apartment for a short period of time and stayed mainly in the living room and the bathroom. This data illustrates that gas sensors react to human activity fast and the changes induced in the air composition remain after the activity in the house has finished.

Fig. 12 shows the activity during a regular day, breaking down the movement activity into its different rooms of origin. This result shows that a system based on gas sensors is not affected by blind spots and can produce a pattern of activity covering different rooms with one single unit, unlike presence sensors and video-cameras.

5. Discussion and conclusions

This paper demonstrates that an array of chemical sensors can collect data related to activities in an inhabited space. Furthermore, since the activity of a person, specially an older one, tends to follow stable routines, the more data is collected, the better the behavior of that person can be predicted, making the system more efficient at finding anomalies. For example, levels of activity measured by the gas sensor always rise when the person wakes up. The lack of events at that time can be an important event by itself, setting an alarm signal if the elder has not started the morning routine at the time they usually do.

We showed that human activity patterns (and thus deviations from these patterns) can be linked with air composition using a single unit of gas sensors as an event tracker. An accurate measure of the concentration of target compounds is not necessary to detect an activity: our system relies on the relative changes of gas composition in air, rather than their absolute values. A full system calibration would provide additional information to the caregiver, but linking activities to chemical signatures requires specific calibration for each activity. For instance, the activity "cooking" will depend on the meal under preparation and the activity "cleaning" will depend on the used chemicals and cleaning products. Instead, in this work, we focused our efforts in building activity patterns using directly the time signals of the sensors.

Actions such as opening a window can translate into events more important than daily routines. In this case, one could use context, such as information about the routine of the monitored person, to expand further our method. Hence, our results show that a chemical gas sensing node coupled to the pattern activity of the elder is an effective tool to warn about unexpected events.

The lack of invasiveness might help to gain users and caregivers acceptance, but it does come at a cost. On the one hand, deploying several gas sensing nodes will result in a higher-resolution network that will provide faster response to activities. The sensors will be exposed to the changes in the air composition faster since the gas sample will need less time to travel to the sensing node. Also, if one is interested in finding out the exact room where an event took place, several nodes are necessary. Nevertheless, we showed that a single sensing node deployed in a representative location can capture the activity performed in a home setting. On the other hand, data collected with chemical sensors may not be as precise as other technologies, such as video-cameras.

The proposed method to detect events relies on a moving 2-hr window. Though the window prevents the event space from capturing events due to the natural ambient changes in the air, this can present false negatives (events) under certain conditions. For example, in Fig. 8 it can be seen that when a lot of events occur in a single hour, the following hour(s) have a noticeably low number of events. This effect can be seen during Christmas Eve, where the number of events at 9 pm and 10 pm is high but decreases at 11 pm. This can be explained by the window effect. It is possible to adjust the span of the window to enable the detection of large events, although the sensitivity to short events will decrease. However, events larger than the window size are still detected by the system, but it but fails to follow it up properly. Any attempt to modify the behavior of the window under certain conditions, would degrade performance by introducing discontinuities into the system. Hence, the window size is a parameter that can be adjusted according the expected duration of the events.

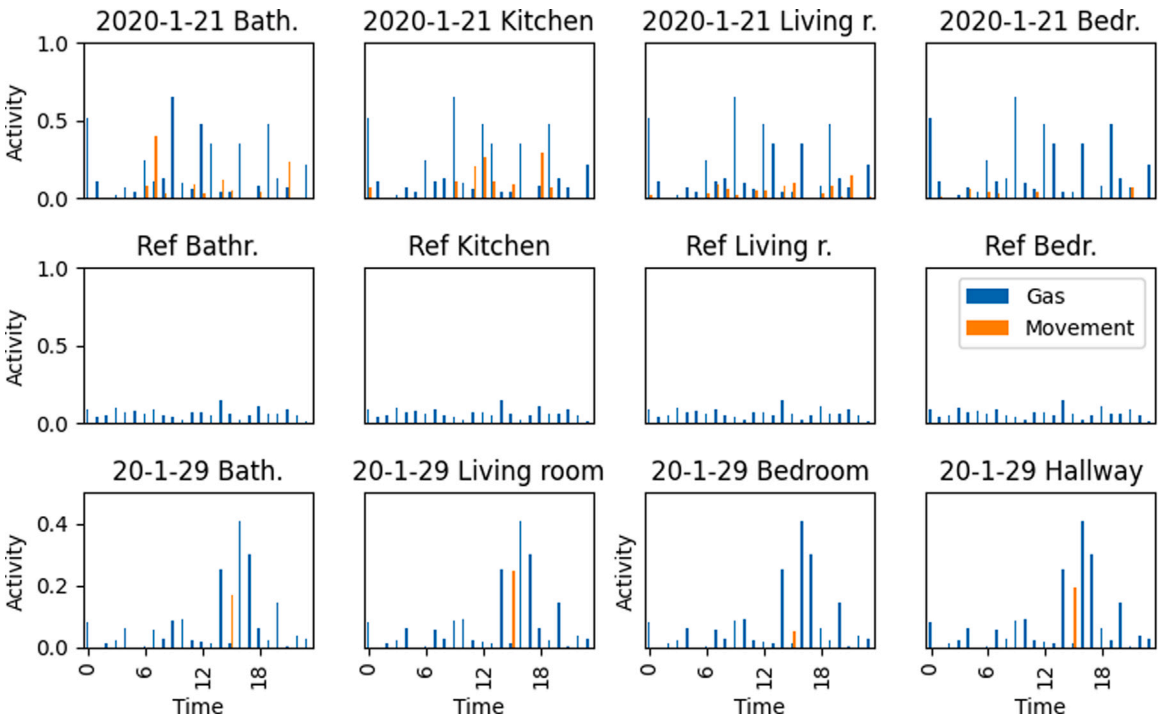

Fig. 11. Events detected with gas sensors (blue) and motion sensors (orange) during a day with regular activity (top), the mean of the days with no activity at all (middle), and a day with a short and sudden activity at 3 pm.

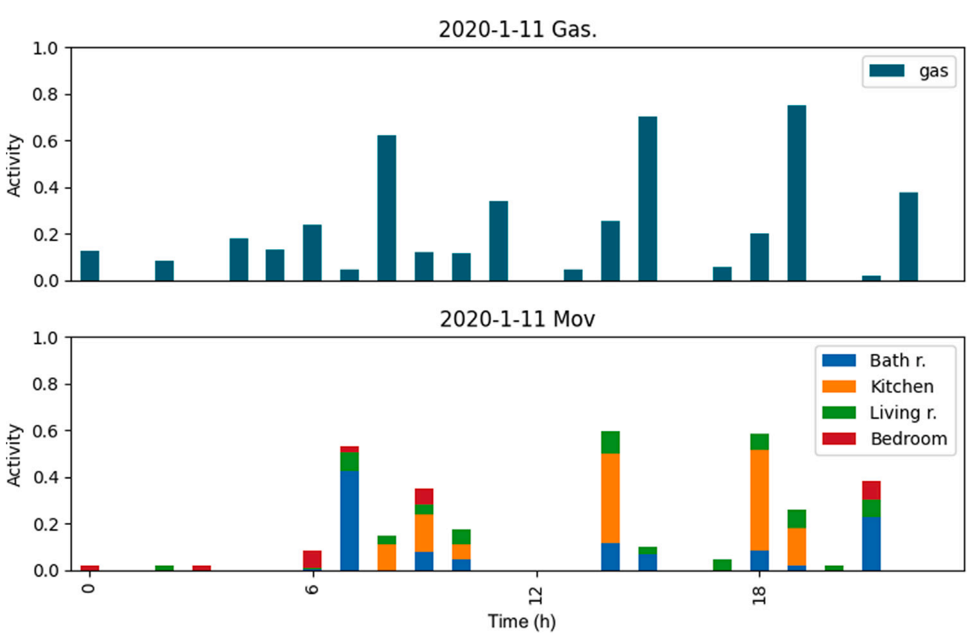

Fig. 12. Activity detected with gas sensors (top) and movement sensors (bottom). The gas sensing system is able to detect activities that occur in different rooms.

In the paradigm of smart home monitoring, gas sensors can provide relevant information to caregivers and family for older people living independently, regarding the home activities but also the surroundings and the environment that may lead to accidents and/or be harmful for their health (e.g., toxic gas detection, high level of fine particulate matters, lack of ventilation, etc.). The integration of such sensors in a domestic environment inside the IoT network collecting data on the ADL and can provide additional information to a virtual assistant or virtual caregiver [29] and further assist elder adults in their own home.

CRediT authorship contribution statement

Daniel Marín: Writing – original draft, Data curation, Software, Investigation. **Joshua Llano-Viles:** Writing – original draft, Data curation, Software, Investigation. **Zouhair Haddi:** Writing – review & editing, Validation, Investigation. **Alexandre Perera-Lluna:** Conceptualization, Writing – review & editing, Resources. **Jordi Fonollosa:** Conceptualization, Software, Investigation, Validation, Writing – original draft, Resources, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data is made publicly available at the UCI repository: https://doi.org/10.24432/C5762W.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.snb.2023.134036.

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