# Abnormal Behavior Detection for elderly people living alone leveraging IoT sensors

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***Abstract*—E-health home based solutions reduce healthcare costs and allow aging population to continue their daily life independently. Our objective, is to combine simple IoT sensors and machine learning techniques, in order to provide a home based solution that is able to detect behavioral changes of elderly people who live alone. For this purpose, we introduce a non-intrusive, spatio-temporal abnormal behavior detection approach. In this approach, motion and door sensor signals are elaborated to produce contextual metrics, which are filtered from any deviant observations, after performing a silhouette analysis on five outlier detection algorithms. Next, the combination of a classification and a regression based approach is proposed for detecting abnormalities in the metrics, both in the contexts of space and time. IoT sensor data from ten elderly people houses have been collected and seven different machine learning algorithms have been analyzed in order to evaluate the performance of the individual as well as the combined approach.**

***Index Terms*—Internet of Things (IoT), Active and Assisted Living (AAL), abnormal detection, machine learning**

## I. Introduction

The increasing usage of smart home technologies, combined with machine learning techniques, can provide valuable insights into people's behavior. As elders feel more comfortable to stay at their home, reducing healthcare costs and continuing their daily activities, Active and Assisted Living (AAL) solutions need to be constantly improving in order to offer independent life for aging population, with the least possible interference in their everyday life.

A variety of sensing systems, like cameras, wearables, smart devices and IoT sensors have been proposed for abnormal behavior detection in elderly people's homes. Cameras, are used to recognize complex daily activities that involve body and/or hands movement, such as cooking or watching TV [1]. At the same time, they are not easily accepted by the elders, who feel uncomfortable being recorded, especially in private spaces as the bedroom or bathroom [2]. In order to minimize privacy concerns, methods that employ wearables combined with environmental sensors, in order to capture body movements, have been proposed [3], [4]; however, these methods have a rather complicated and obtrusive set up. Wearable activity trackers on the other hand, are less intrusive, but still a relatively new and foreign technology for elders [5], which is best preferred for detecting physical activity changes [6]. In the same context, smart devices have been used for wellness determination [7], but offer a rather expensive approach that requires replacement of existing equipment. Environmental IoT sensors are considered one of the most common, non-intrusive sensor type proposed in the literature [8], thus several approaches propose systems, comprised mainly by pyroelectric infrared (PIR) motion sensors [9], [10], [11], since they are easily installed and have low cost and power consumption.

A wide range of techniques is applied for behavioral anomaly detection at home that could be categorized, giving a few examples, in: a) Statistical (cross-entropy [9]), b) Probabilistic (Cumulative Distribution Function (CDF) [12], Hidden Markov Model (HMM) [13]) and c) Machine Learning (Neutral Networks i.e. Convolutional Neural Networks (CNNs) [14], Support Vector Machines (SVMs) [15], Support Vector Data Description (SVDD) [16]). It is clear that the issue of abnormal behavior detection is a well-studied subject, for which, a variety of techniques has been proposed. Some of these techniques are applied directly on sensor data, while others on context-aware metrics, that are calculated from the raw data. While many of the approaches focus on temporal metrics, they have been criticized for easily producing false alarms in cases that a behavior appears a bit earlier or later in time [17]. At the same time, only a few propose regression based approaches, which is a common technique for real-time anomaly detection, in computing or networking domains [18].

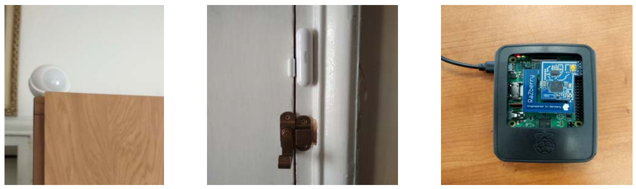
In our attempt to deal with the aforementioned issues, we propose a spatio-temporal approach that:

- is built upon a simple, low cost and the least non-intrusive sensing system found in the literature
- performs a filtering of deviant observations from the training data
- combines both a spatial and temporal behavioral analysis
- is evaluated for 10 elderly people who live alone, in comparison to lab testing with younger volunteers, which is found in most existing approaches

This approach, does not intend to make real-time detection, since the participants are equipped with a wearable panic button, but rather aims to detect significant changes in the elder's behavior at home and provide information concerning the time and place were the abnormal behavior was observed, in a daily basis, e.g. the elder starts spending more time in the bedroom or becomes more active during night hours than

The hardware infrastructure of this study was provided by ACTIVAGE EU project - https://www.activageproject.eu/

2471-7819/19/$31.00 ©2019 IEEE
DOI 10.1109/BIBE.2019.00173



(a) (b) (c)

Fig. 1. (a) Motion sensor placed on the kitchen's cupboard, (b) Door sensor placed on the main entrance door, (c) Raspberry Pi with Z-Wave Shield

usual, which may indicate the beginning of health related or psychological problems.

In a nutshell, this work introduces the following contributions:

- The method proposes the use of unsupervised, outlier detection algorithms, in order to deal with the usual lack of data annotations in real-life data
- To the best of our knowledge this method is the first to propose a combination of classification and regression based approaches for abnormal behavior detection

The rest of this paper is organized as follows; section II sets the basis for the proposed solution, describing the pre-processing phase, while the proposed methodology is presented in section III. In section IV the performance of the individual and the combined approaches is presented, while conclusions and future work are discussed in section V.

## II. Data Analysis - Behavioral Monitoring

### A. Sensing Infrastructure

Ten elderly people, who reside in the municipality of Pilea-Hortiatis in Greece, have participated in this study, in the context of VICINITY EU project [1]. The participants consist of 2 men and 8 women with an average age of 80.4 years old, and live alone. A set of four motion sensors (one per room), a door sensor (for the main entrance) and a gateway have been installed in their houses, in order to capture their movements. The sensors are wireless, battery operated and use Z-Wave technology in order to transmit measurements to a Raspberry Pi 3, which serves as the smart home's gateway. Figure 1, illustrates the installation of the sensors in the houses.

The sensor measurements, are transmitted from the Raspberry Pi to a service, which is responsible for securely storing them to a database. The communication between the sensing infrastructures (elder houses) and the service is handled in a secure and authorized way, via VICINITY IoT Platform [19]. All the data manipulated in the paper, was handled respecting the General Data Protection Regulation (GDPR).

### B. Pre-processing

The sensors' data, need to be processed before they are fed to the abnormal detection models. The pre-processing phase involves completing lost measurements based on the usual sensor's behavior, checking for outings and calculating the following behavioral metrics:

- *Activity level*: the number of movements detected hourly
- *Mobility level*: the number of room changes detected hourly
- *Inactive time*: the inactive time (in minutes) hourly
- *Duration in space*: the time (in hours) spent in each space during a day
- *Space usage*: how many times each space was visited during a day
- *User positioning*: the visited spaces sequence during a day

where as space it is considered one of the four rooms equipped with a motion sensor or outside the house.

The above behavioral data analysis constitutes the main outcome of the pre-processing phase, from which we have extracted one temporal and one spatial metric, in order to perform abnormal behavior detection. The *Activity level* was considered the most indicative metric, to identify an abnormal event in the temporal context, since it could possibly identify critical events i.e. a sickness causing decrease in movement. For the spatial metric, the combination of the *Duration in space* and the *Space usage* metrics, is considered, since it can capture significant spatial deviations i.e the elder makes more regular visits to the bathroom.

### C. Outlier Detection

Abnormal Detection is a 1-class classification problem, which considers a metric's normal history to detect anomalies in new observations. In this study, we are not aware, if the metrics' history is clean from deviant observations, thus we perform outlier detection, before abnormal detection. Five, well-known outlier detection algorithms have been compared, namely, Robust Covariance, One-Class Support Vector Machines (OCSVM), Isolation Forest, Local Outlier Factor (LOF) and DBSCAN. Silhouette coefficient, was used to validate the algorithms' performance in clustering normal and abnormal data, with values closer to 1 indicating that an observation is well-placed to its cluster. Table I shows the average silhouette coefficient per algorithm for the two metrics. The results show that Isolation Forest and DBSCAN algorithms perform better on our data sets, thus they were chosen for our approach.

TABLE I
Outlier Detection algorithms silhouette analysis

| | **Robust Co-variance** | **One-Class SVM** | **Isolation Forest** | **Local Outlier Factor** | **DBSCAN** |
|---|---|---|---|---|---|
| Spatial metric | 0.48 | 0.46 | 0.51 | 0.47 | 0.69 |
| Temporal metric | 0.32 | 0.28 | 0.37 | 0.33 | 0.47 |

## III. Proposed Methodology

A spatio-temporal approach that combines a classification and a regression based approach, in order to detect abnormal

[1]VICINITY EU Project - https://vicinity2020.eu/vicinity/

behavior in elderly people's houses, is presented in this section. Each individual model can detect the presence of an abnormality for the particular context. In order to avoid false alarms to caregivers, their combination is examined, to consider a day as abnormal.

The methodology of our approach is presented in Figure 2. The first step of our approach concerns the analysis and pre-processing of the sensor data, as it was described in the previous section. In summary, the sensor measurements are fetched and processed for the generation of contextual metrics. A spatial and a temporal metric are employed for describing the elder's behavior and an outlier detection algorithm is applied on each metric, in order to filter out any deviant observations, before training the two abnormal detection algorithms. The spatial metric is used to train the classification algorithm, while the temporal metric is used to train the regression algorithm. It is worth to mention that a separate model is created for each elder and each space.

The next step of our approach is comprised by the detection phase, which provides daily outcomes, whether the elder's behavior was considered normal or abnormal. The new sensor data are fetched, pre-processed and compared with the created classification and regression models, in order to determine whether an abnormality exists. A day is considered abnormal, only if the outcomes of both approaches agree, which produces an alert to the caregivers. The classification and the regression approaches are described in more detail in the next paragraphs.

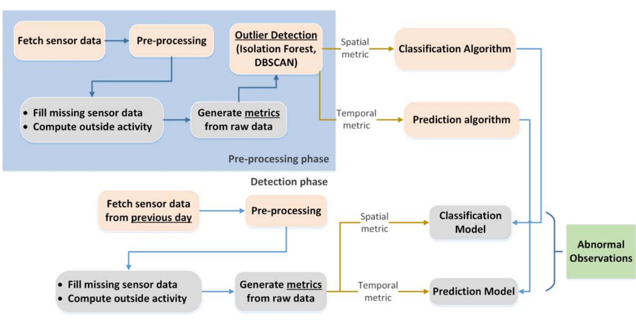



Fig. 2. Abnormal detection Methodology

### *A. Classification based approach - Abnormal Detection in Space*

A classification approach is proposed for abnormal detection in the context of space. The spatial metric is calculated from raw sensor data and is filtered by the outlier detection algorithm, before it is fed to the classification algorithm.

In a daily basis, the sensors data are collected and pre-processed, producing the behavioral profile of the elder for this day. The produced spatial metrics are compared with the decision boundaries of the trained models, which decide upon any abnormalities. As spatial abnormality we consider any change in the usage of a space, either in the duration or the number of visits. For our analysis, we have compared the performance of four well-known algorithms, which are used for novelty detection, namely Robust Covariance, OCSVM, Isolation Forest and LOF. The results are presented under section IV.

### *B. Regression based approach - Abnormal Detection in Time*

A regression based approach is proposed for the abnormal detection in the temporal context. Since hourly predictions can be often incorrect, i.e. the wake-up activity appears one hour earlier than usual, which is not a critical event but produces noise on data, we have decided to consider *Activity level* metric with a 3-hour resolution.

The temporal metric is calculated from raw sensor data and is filtered by the outlier detection algorithm, before it is fed to the regression algorithm, in the form of training data. In a daily basis, the temporal metric is computed and compared with the prediction of the algorithm for this day. The prediction error is used as an indirect metric to indicate an abnormality. If there is a change in the elder's activity, the prediction error is expected to be high. If the error lies in the right tail of its distribution, then we consider an abnormality. The first ten days of tracking are employed in order to estimate the average and standard deviation of the distribution of the mean absolute prediction error ($MAE$). Consequently, we consider as abnormal the days that the under study models yield an error higher than 3 standard deviations of the latter distribution. Equation 1, presents the z-score that is used to classify a day as normal or abnormal.

$$z_i = \frac{e_i - \overline{e}}{\sigma} \tag{1}$$

where $e_i$ is the $MAE$ of the prediction for day $i$, $\overline{e}$ is the estimated mean of $MAE$'s distribution and $\sigma$ is the corresponding standard deviation.

Apart from global abnormalities that concern the whole day, we can also detect local abnormalities in a similar way. We set the prediction's absolute error confidence interval for time point $t$ of the day (being a 3 hours period), using the formula $\overline{e}_t \pm z\sigma_t$, where $\overline{e}_t$ is the average prediction absolute error concerning time point $t$ across the first 10 days of monitoring, $\sigma_t$ is the corresponding standard deviation and $z = 3$.

Three well-known prediction algorithms have been compared for this approach: a) Seasonal Auto Regressive Integrated Moving Average (SARIMA), which is a general purpose technique for modeling temporal data with seasonality, b) Random Forest, which is a combination of a predefined number of randomized decision trees using the bagging technique and c) the Long short-term memory network (LSTM), which is a state of the art recurrent neural network. The results are presented under section IV.

## IV. Results

The results of the performance evaluation of the individual as well as the combined approach, are presented in this section. The seven, aforementioned machine learning algorithms, have been applied for the individual approaches. The combined approach, consists of the individual approaches that performed the best accuracy. For the evaluation of the proposed methodology, we consider the Accuracy and the F-score indices. To compensate the lack of ground truth, we have collected manual annotations of abnormalities from the health professionals, who monitor the elders.

A data set from IoT sensors in ten elderly people's houses has been collected for this evaluation. Ninety days of data, constitute the training set for both classification and regression approaches, while the first ten days of tracking are employed to estimate the average and standard deviation of the distribution of MAE, for the regression approach. The data from the next thirty consecutive days constitute our test set. The results are presented in Table II.

TABLE II
PERFORMANCE EVALUATION OF PROPOSED ABNORMAL DETECTION APPROACHES

| Approach | Accuracy | F-score |
|---|---|---|
| Classification based (LOF) | 0.86 | 0.61 |
| Classification based (OCSVM) | 0.47 | 0.39 |
| Classification based (Robust Covariance) | 0.85 | 0.56 |
| Classification based (Isolation Forest) | 0.68 | 0.45 |
| Regression based (SARIMA) | 0.88 | 0.57 |
| Regression based (Random Forest) | 0.84 | 0.52 |
| Regression based (LSTM) | 0.86 | 0.51 |
| Combined (SARIMA + LOF) | **0.89** | **0.62** |

The individual approaches that performed the best accuracy are, the classification based approach with the application of LOF model and the regression based approach with the application of SARIMA model, thus they comprise the combined approach. The results for the regression based approach, show that a linear model i.e. SARIMA outperforms the state of the art sequence modeling neural network LSTM. This fact in general is not anticipated, but in this study the data set comprises a limited number of training samples, thus it is considered as justified by the authors.

Out of the eight compared approaches, the combined approach has the best performance in terms of Accuracy (89%) and F-score (62%). The results indicate that the approach can more accurately detect abnormal events, while keeping a good compromise between precision and recall, comparing to the individual approaches.

The outcomes of the classification and the regression based approaches, for a normal and an abnormal day of an elder, are presented in Figure 3, as an example. The classification approach is based on LOF algorithm, while the regression approach is based on SARIMA model.

Figure 3a presents the actual activity level (blue line) of the elder for that day, which mostly follows the predicted activity level (green line) for the same day. The absolute prediction error of each time point (red line), is also presented to display any local abnormalities. As it can be seen, it is mostly inside the confidence intervals, except from a local abnormality, which indicates a higher than usual activity during night hours. The value of z-score for this day, is below the set boundary ($\pm 3$), thus the day is considered as normal. Moreover, the

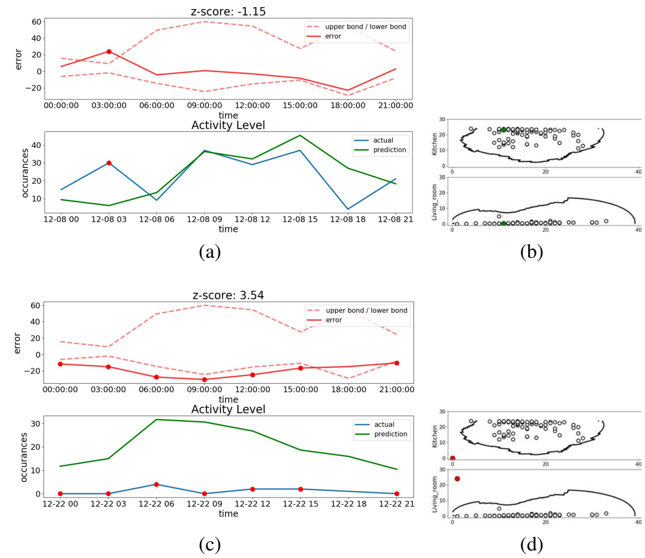



Fig. 3. (a) Normal day - Regression based approach, (b) Normal day - Classification based approach, (c) Abnormal day - Regression based approach, (d) Abnormal day - Classification based approach

classification based approach, presented in Figure 3b, shows that the spatial metric for this day (green circle), lies within the decision boundaries, and so the day is considered as normal by this approach as well. While we observe a local abnormality for a certain time point, for the rest of the day, the elder's behavior is as expected, and at the same time no abnormal behavior is observed for the spaces usage, thus we consider as justified the classification of the day as normal.

Figure 3c on the other hand, presents a day that the actual activity level of the elder deviates a lot from the predicted activity level for the same day. Moreover, the absolute prediction error of each time point is mostly below the lower confidence interval. The value of z-score for this day, is above the set upper boundary, which classifies the day as abnormal. Figure 3d, shows unusual decrease in the duration of the visits in the Kitchen and increase in the duration of the visits in the Living room, which classifies the day as abnormal by this approach as well. We observe that the elder's behavior both in the context of space and time is unusual, thus it is considered as justified by the authors that the day was classified abnormal.

## V. Conclusions and Future Work

We have proposed a spatio-temporal approach that is based on the combination of a classification and a regression based approach for abnormal behavior detection. Data from IoT sensors in ten elderly people houses, have been elaborated to create their behavioral profiles and detect any deviations from them. The encouraging results show that our method is able to detect abnormalities, in a daily basis and provide meaningful information to the caregivers concerning when and where the abnormality occurred.

This work could be further extended to identify different severity levels of abnormalities, in order to give a better understanding to the caregivers or enhance the behavioral profile of the elder, with other indoor environmental quality data from IoT sensors, as the carbon dioxide level, the luminosity or the temperature of the different spaces in the house.

## ACKNOWLEDGMENT

This work is supported by the H2020 VICINITY project, which has received funding from the European Unions Horizon 2020 research and innovation programme under grant agreement No 688467. This paper reflects only the authors views and the Commission is not liable for any use that may be made of the information contained therein.

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