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Long-term deviation detection in human behavior

Kevin Fouquet, Gregory Faraut and Jean-Jacques Lesage

Abstract—World population ageing causes an important increase of people needing specific health care and monitoring. Dedicated institutions exist, but most of the elderly prefer to keep their autonomy for economic and personal reasons. To ensure a good quality of life and health to this population, Health at Home (HaH) solutions are explored. Many works focus on monitoring smart home inhabitant behavior to detect changes which might be due to health problems. These approaches are efficient to detect accident or short-term diseases such as a cold or influenza but tend to detect too tardily diseases which provoke slow declines in behavior. This is a problem as the elderly are likely to suffer from such troubles and early detection allows for better diagnosis and may help to prevent or reduce future worsening. In this paper, a novel approach for the detection of long-term behavior changes is introduced. It focuses on activity duration as this indicator is influenced by most diseases and give clear information about the inhabitant health status. This paper proposes data forecasting to detect future anomalies to assess existence of evolution in the current behavior. Information is sent to medical staff to refine their prognostic and adapt their treatment or call for a medical appointment. A case study based on a real smart home simulating a worst-case scenario attests for the efficiency of the approach and its resilience.

I. INTRODUCTION

Thanks to global improvement of living conditions and access to healthcare, life expectancy has increased in most regions of the world, leading to major changes in demography. According to projections from the United Nations (UN), more than 30% of most industrialized countries' population will be aged 65 or more within 2050 [1]. This population is likely to suffer from specific health problems and requires adapted healthcare. Several solutions already exists to provide medical support, such as retirement and nursing homes. However, most of the elderly prefer to keep their autonomy for personal and financial reasons [2]. Consequently, new solutions have to be developed to ensure to aged people living independently at home a quality of life and health comparable to people living in dedicated institutions.

Health at Home (HaH) is a field of research which tries to offer new opportunities so that frail people can live in good health and independently in their home. Many of these works focus on providing to medical staff information about the health status of the inhabitant to detect and diagnose various diseases [3], [4], [5], [6].

First symptoms of such diseases often concern inhabitant behavior, and influence the way he might carry out his everyday tasks. For instance, frailty is associated with a

decrease of physical activity, fatigue and changes in eating patterns leading to weight loss, while Alzheimer's disease may trigger erratic behavior [5], [7]. These diseases mainly concern elderly people and slowly alter their daily life.

To the best of our knowledge, most works considering behavior monitoring only examine brutal change detection, which are useful to detect various accidents or short-term diseases such as a cold, but detect too tardily long-term diseases. In this paper is presented a methodology to detect and evaluate long-term deviations of behavior in various activities. It focus on activity duration as it is a key indicator of human behavior and provides significant information about his health status. To assess the existence of a trend in the inhabitant behavior, data forecasting methods are used to detect potential future behavioral anomalies. This information helps medical staff to refine their prognosis, adapt the treatment or schedule a medical visit.

This paper is structured as follows: Section II explores existing solutions about long-term deviation detection in health data and identify human features which are the most relevant for medical staff. Section III presents the work hypotheses and the global methodology. In section IV, smart home databases are explored to evaluate the most adapted data forecasting method. The selected one is then introduced. Finally, in section V is proposed a case study based on a real smart home to demonstrate the relevancy of the approach.

II. STATE OF THE ART

Long-term deviation detection has been subject to some works since a few years. Most of them considered evolution of health relative metrics, such as body temperature or blood pressure. For instance, [8] uses Holt's linear method over heart rate-time series to detect slow increase or decrease which may be due to Tachycardia or Bradycardia. Early detection of these physiological signs allows for treatment and cardiopulmonary arrest prevention. In [3], the authors use the same technique applied on various vital signs, such as heart rate, O_2 saturation or body temperature to forecast future values and detect when it may reach abnormal threshold. If needed, alert are sent to medical services providers for intervention or medical appointments.

However, many health troubles affecting elderly people do not directly impact their vital signs but their everyday behavior [9]. These impacts are challenging to detect as each individual possesses his own unique behavior, composed of various features. From these features, the time required by an inhabitant to carry out specific tasks is a key information about his medical condition. This is why some works consider activity duration observation to detect potential

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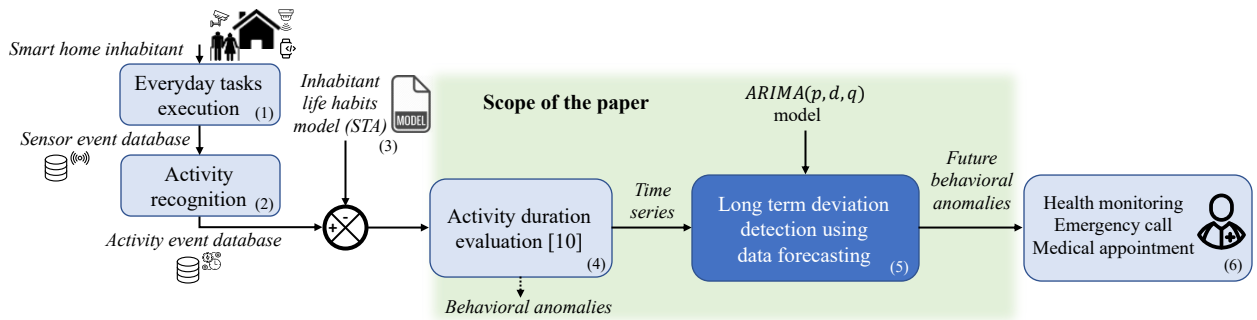


Fig. 1. Proposed methodology and scope of the paper.

behavioral anomalies which may be caused by specific health trouble. For instance, authors in [3], [10] model activity duration by probabilistic distribution to detect anomalies which might be due to a loss of appetite or cognitive decline for instance. In [5], the authors observe the duration of room transition, allowing to evaluate loss of mobility which can be due to frailty. Activity duration is also a key information for sleep disruption detection, as cognitive decline or urinary problems may disturb sleep cycle of an individual [6].

Yet, these works only consider anomaly or change point detection, which is a brutal change in inhabitant behavior. Anomaly detection is useful for short-term diseases detection such as influenza but detect too tardily slow behavioral declines such as cognitive impairment or frailty, which are common health trouble for elderly people, while their early detection is often critical. To the best of our knowledge, no existing work consider these slow behavioral declines.

In this work is proposed an approach to detect these long-term behavioral deviations impacting activity duration.

III. PROPOSED METHODOLOGY

Proposed methodology is illustrated in figure 1.

The inhabitant is at home, carrying his everyday tasks as usual (1). His smart home is equipped with various sensors, such as binary, movement or pressure sensors, or other more intrusive solutions such as cameras. By performing his everyday life, the inhabitant triggers these sensors and feed a sensor database. Existing works on activity recognition such as [11] allow to identify which activity is carried out (2). An activity database is generated from the sensor database, enlisting all carried out activities and their duration.

The inhabitant may be in good health, or may suffer from various illnesses, including diseases causing slow decline. To help prognostic of these diseases, slow evolution in smart home inhabitant behavior considering activity duration has to be detected and evaluated. To assess if a behavioral deviation might lead to a problematic situation or is simply a light change due to an external phenomenon, observed behavior is compared to the usual life routine of the inhabitant. To achieve this task, model representing inhabitant life habits (3) is required. Stochastic Timed Automaton (STA) presented in [4] is proposed as it offers to model each activity duration with probabilistic distribution. For most activities, log-normal distribution is used as it showed great results for

various activities and databases [4]. This model can be built by experts from general behavior habits shared by most of the population, or after observing the inhabitant living for a few weeks to get his personal life habits.

To evaluate the consistency between the observed behavior and the expected one described by the model (4), the approach presented in [10] is used. Each time a new occurrence of an activity is detected, the difference between its duration and the expected median time is computed:

$$\text{time distance}(t) = \frac{\log(t) - \mu}{\sigma} \quad (1)$$

where t is the duration of the newly observed activity and μ and σ are such that e^μ and e^σ are the parameters of the log-normal distribution of the corresponding activity. If the distance exceeds a given threshold, an anomaly is detected. The threshold value depends on the expected proportion of healthy behaviors to be observed. For instance, if 99.74% of observed activities are expected to be healthy, a time distance whose absolute value is above 3 is very likely to correspond to an anomaly, while 2 stands for 95.44%. Some examples of time distances are depicted in figure 2.

To assess existence of slow evolution of this time distance over time and allow for their early recognition, future anomaly detection before their occurrence is proposed (5). Selection of an appropriate method relies on the type of input data and the information it might possess. As time series are manipulated, data forecasting approach is a promising solution. Next section explores most used forecasting algorithms: exponential smoothing and ARIMA, and introduces a method to select the most appropriate one. The selected approach is then formalized.

If an anomaly is forecast, it means there exist a slow decline in the behavior which may lead to a health problem. In that case, medical staff is notified with the concerned activity, the expected date of the anomaly as it informs on the critical nature of the behavioral trend, and if the activity is getting shorter or longer than usual (6). With this information, medical staff may adapt their treatment, or call for a medical appointment for further investigation.

IV. DATA FORECASTING

Several works already explored the issue of forecasting future data from time series. Most used models are exponential smoothing and ARIMA [12].

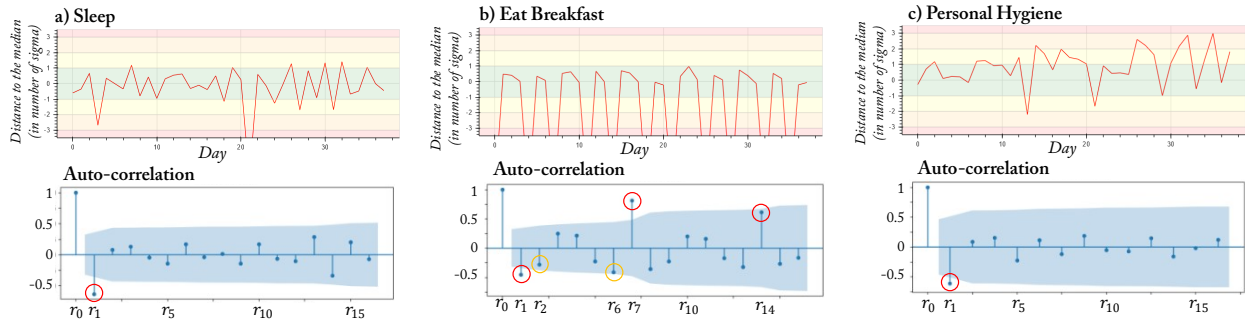


Fig. 2. Times series of various activity duration evaluation for 40 days associated to the correlogram of the differentiated values.

Exponential smoothing relies on weighted average of past observations, with the weights decreasing exponentially as the data get older. It requires to model key components within the time series: level, and optionally trends and season. A trend is a long-term evolution in the data, while season is a pattern which occurs with a fixed frequency, for instance a weekly pattern. ARIMA model, on the other hand, aim at describing the auto-correlation in the time series, i.e. correlation of a time series with its lagged values. To decide which approach to use, existing smart home databases are explored. If real time series possess auto-correlation, ARIMA models might give relevant results. Otherwise, exponential smoothing may be more adapted.

A. Public database exploration

To extract relevant information, study of a few months long smart home database with a single inhabitant carrying his tasks every day to make auto-correlation study relevant is proposed. Such database is extremely scarce. Hh103 home from the CASAS research group in Washington State University fulfills these requirements [13]. In this smart home, a single inhabitant carries out his everyday life for 2 months. The home is equipped with two door sensors, three temperature sensors, ten motion sensors, ten light sensors, and five light switches.

An activity database, enlisting every activity carried out by the inhabitant and their duration, is generated from the list of sensors triggered thanks to existing activity recognition algorithms. In total, 60 consecutive days of data are labeled. During these two months, only activities "Sleep", "Personal Hygiene" and "Eat Breakfast" are labeled every day or possess interesting patterns. Additionally, these activities are often monitored by medical staff as they are likely to offer relevant information about inhabitant health status [7]. Consequently, this section will focus on these three activities. As one value per day is desired to build a time series, activity duration is summed if a specific activity is carried out several times the same day. The first 20 days are used to generate the STA model depicting the usual life routine of the user. The next 40 days are evaluated conforming to the protocol described in section III and generate a time series per activity. 40 days are enough to observe potential autocorrelation or weekly seasonality within the inhabitant behavior. These are depicted in figure 2; Additionally, they are then differentiated

to ensure working on stationary data. Details are given in subsection IV-B. Figure 2 illustrates their auto-correlation score.

Auto-correlation r_k express the correlation between each i^{th} and $(i-k)^{th}$ values of a time series:

$$r_k = \frac{\sum_{i=k+1}^N (y_i - \bar{y})(y_{i-k} - \bar{y})}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (2)$$

with N length of the time series, $k \in \mathbb{N}$, y the observed times series with y_i its i^{th} value and \bar{y} its mean.

If a r_k value exceeds $\pm 2/\sqrt{N}$ threshold, the associated auto-correlation is considered strong, which testifies the existence of auto-correlation within the time series [12]. If the auto-correlation is strong for a value and its multiples, it may evidence a season in the data. For instance, if $\forall k \in \mathbb{N}, r_{4k}$ all have significant values, time series is likely to possess a 4-day period season.

In figure 2, activities "Sleep" and "Personal Hygiene" possess significant values for r_1 . This might be due to the inhabitant spending less time on a specific activity after dedicating it a long time the previous day and inversely. Additionally, these values do not repeat attesting for the absence of seasonality. Considering activity "Eat Breakfast", r_1 and r_7 are strong while r_2 and r_6 have notable values. Moreover, r_{14} also has high value which might testify existence of seasonality for this specific activity.

As all activities possess auto-correlation, ARIMA appears as a good candidate. However, exponential smoothing may also give relevant results for activities possessing seasons, or without or with low auto-correlation. This is discussed in the conclusion section. Next section introduces ARMA and ARIMA models and method for parameters estimation.

B. ARIMA forecasting

If $y_t \in \mathbb{R}$ is a times series of length N with t an integer index, an $ARMA(p, q)$ model is then given by:

$$y_t - a_1 y_{t-1} - \dots - a_p y_{t-p} = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \dots + \theta_q \varepsilon_{t-q} \quad (3)$$

where $\{a_i\}_{i \in [1, \dots, p]}$ is the set of the p order AR (Auto Regressive) coefficients, $\{\theta_i\}_{i \in [1, \dots, q]}$ are the q order MA (Moving Average) coefficients, and ε_t is the error-term associated to y_t . By considering the backward shift operator B with $B^m y_t = y_{t-m}$, the previous model can be written:

$$\Phi_p(B)y_t = \Theta_q(B)\varepsilon_t \quad (4)$$

where

$$\Phi_p(B) = 1 - a_1B - a_2B^2 - \dots - a_pB^p \quad (5)$$

$$\Theta_q(B) = 1 - \theta_1B - \theta_2B^2 - \dots - \theta_qB^q \quad (6)$$

ARMA model aims at describing correlation within stationary time series. It implies two prerequisites for ARMA use:

- Data have to possess correlations which can be expressed by the model. Subsection IV-A highlights existence of such correlation in most activity duration.
- Data have to be stationary, which means data does not depend on time.

As this paper objective is to detect potential trends in behavior, this second hypothesis is not very likely to be validated. Consequently, it is proposed to make the time series stationary by differencing it before applying the ARMA model. Differencing can be done by subtracting successive values in the time series $y'_t = y_t - y_{t-1} = (1 - B)y_t$. More generally speaking, $y_i^{(d)} = (1 - B)^d y_i$.

Thus is defined the *ARIMA*(p, d, q) model:

$$\Phi_p(B)(1 - B)^d y_t = \Theta_q(B)\varepsilon_t \quad (7)$$

To estimate the coefficients of this model, d, p, q orders must be chosen, then coefficients $a_{i \in \{1, \dots, p\}}$ and $\theta_{i \in \{1, \dots, q\}}$ have to be evaluated. Maximum Likelihood Estimation is the most used technique for their evaluation. It consists in finding the vector parameters $\theta = (a_1, \dots, a_p, \theta_1, \dots, \theta_q, \sigma^2)'$ which maximizes the log-likelihood function:

$$\hat{\theta}_{MLE} = \arg \max_{\theta \in \Theta} \log L(\theta|y) \quad (8)$$

with Θ parameter space and the log-likelihood function being, under the assumption that the error-term ε_t follow a Gaussian white noise $N(0, \sigma^2)$:

$$\log L(\theta|y) = -\frac{1}{2} [N \log(2\pi) + \log |\Gamma(\theta)| + y' \Gamma(\theta)^{-1} y] \quad (9)$$

with $\Gamma(\theta) = E(yy')$ the $N \times N$ covariance matrix of y depending on θ .

On the other hand, ARIMA orders p, d, q can be estimated by data inspection and auto-correlative, partial-correlative and stationary estimation. Yet, these tools often require manual inspection and decision-making, while long-term behavioral deviation affects numerous smart home inhabitants, whose each activity must be inspected.

Another automatic method exists. All models with orders $p, q \in \llbracket 0, 7 \rrbracket$, as it is not expected to have more than a week-long auto-correlation, and $d \in \llbracket 0, 2 \rrbracket$, as higher differencing are very unlikely to produce more stationary data [12], are generated. This generation process is only a few seconds long. Then the model minimizing the Akaike Information Criterion (AIC) is selected. AIC is an efficient tool for model selection as it estimates the trade-off between goodness of fit and the complexity of the model, allowing to avoid overfitting.

$$AIC = 2k - 2 \log L \quad (10)$$

with $k = p + q + 1$ the number of parameters of the model and $\log L$ the maximum value of the log-likelihood function defined earlier.

This methodology and model is applied on a real smart home database in the next section.

V. CASE STUDY

To highlight the relevancy of the proposed approach, global methodology is applied to a real smart home database. To attest of its resilience, an artificial database is generated from the life habits of a real smart home inhabitant, simulating a worst-case scenario as data auto-correlation is weak or null by generation. Both healthy and sick behaviors are created to testify the accuracy of the method. DOMUS smart home is chosen as it covers various morning activities and well-defined life habits.

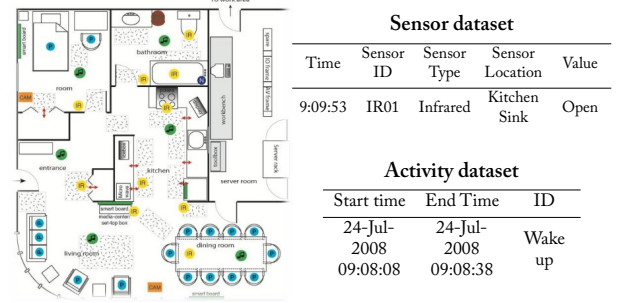


Fig. 3. DOMUS smart home plan, with instances of the sensor and activity databases.

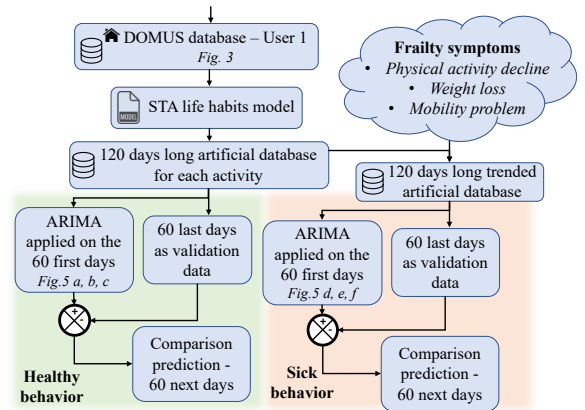


Fig. 4. Methodology for healthy and sick behavior generation.

A. Database description

DOMUS laboratory [14], [15] from the Université de Sherbrooke, Canada, is a 4-room apartment equipped with various sensors such as door and switch contacts, infrared movement detectors, lamp light switches, flow meters and pressure detectors. In this smart home, 6 participants carried out their morning routine 10 times each. By doing so, participants trigger sensors generating events recorded in the sensor event database. Through manual labeling, an activity events database enlisting activities carried out by

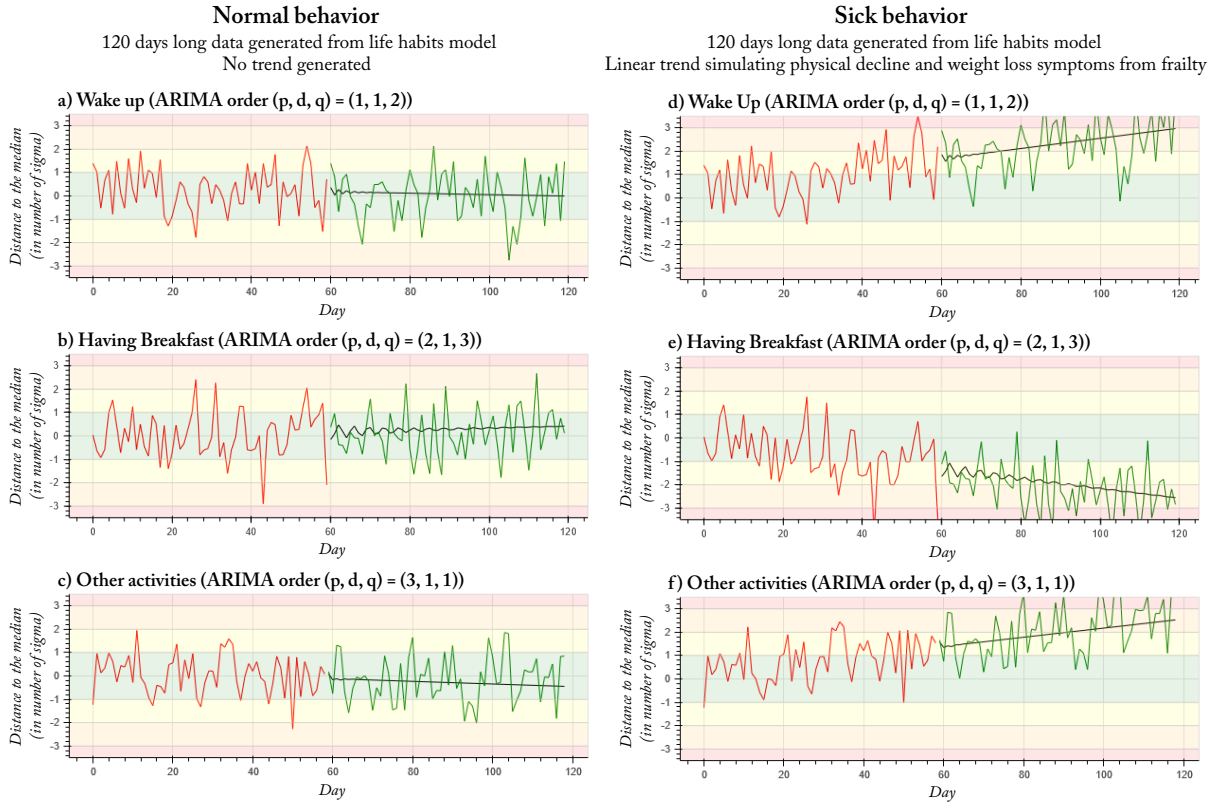


Fig. 5. Prediction for activities Wake up, Having breakfast and Other activities for original artificial data (a, b, c) and artificially trended data (d, e, f). First 60 days are training data in red, last 60 days are validation data in green, ARIMA forecasting in black.

the experimenters is generated. Figure 3 represents the smart home plan and examples of activity and sensor database.

B. Case study methodology

To validate the proposed approach, methodology is applied on a healthy and a sick behavior. To be the most realistic possible, a health problem most elderly will meet in their life is chosen: frailty. Frailty is a decline in the physical state of an individual which alters their endurance and capability. It may result in disability, hospitalization, and in some severe cases death. Early symptoms of frailty include weight loss, weakness, and low physical activity. These symptoms evolve slowly, from being hardly noticeable to having a major impact on the inhabitant behavior. Early detection can help to reduce the process, and in some cases to reverse it [5].

Consequently, protocol illustrated figure 4 is proposed. First, inhabitant life habits model is generated from the 10-day long DOMUS database. Only user 1 is considered. This model is presented in [4]. From this model, 120 days of data are artificially generated for each activity which is long enough to assess the potential existence of decline in the behavior of an individual. Each activity duration is created according to the probabilistic distribution defined in the STA model. This generation provides time series which are not likely to possess auto-correlation as each duration is generated independently from the other. This situation is the worst case scenario for the ARIMA method. The first 60 days are used for ARIMA training, while the next 60

days are used as validation data. These 120 days long data are also duplicated and modified to simulate a sick behavior: Meal related activities duration is reduced leading to weight loss, while duration of most other physical activities is increased due to slow walking speed and difficulties to carry out physical efforts. Time series is modified by adding a linear trend $-\frac{3t}{120}$ to "Having breakfast" activity and $\frac{3t}{120}$ for other activities, with t time series index $t \in \llbracket 1, 120 \rrbracket$. These trends simulate a slow decline in inhabitant behavior leading to noticeable anomalies after 120 days. Then, the same methodology is applied.

C. Results

Results for activities "Wake up", "Having breakfast" and "Other activities" are depicted in figure 5 for healthy behavior (left) and sick behavior (right). As data possess low auto-correlation, ARIMA forecasting only give information about the trends within the data, which is enough to assess the health status of the inhabitant.

Considering healthy behavior data, time distance sometimes reaches important value the first 60 days, which means behavioral anomalies are detected. For instance, activity "Having breakfast" is particularly short ($t = -2.92$) the 44th day. However, these anomalies are scarce and are not repeated, which seems to attest they are due to normal randomness in human behavior rather than medical problem. Additionally, data forecasting does not evidence for the existence of trend in behavior as no time distance above

3 or below -3 is forecast. Consequently, this behavior is considered healthy. This prognostic is confirmed by the next 60 days of data as no anomaly is detected.

Regarding trended data, some anomalies are sometimes detected the first 60 days. For instance, activity "Wake up" is especially long ($t = 3.49$) the 54th day, while activity "Having breakfast" is short the 44th and 60th days. As their number of occurrences is low, this does not testify for the presence of a medical problem. Nevertheless, due to trends in behavior, ARIMA forecasting highlights possible anomalies in the future. Activities "Wake up" and "Other activities" are expected to have most of their duration beyond the 3σ limit around day 120 and 140, while the majority of duration of activity "Having breakfast" may be below the -3σ around day 140. This information attests of the existence of a slow evolution in the current behavior of the inhabitant. These forecasts are consistent with the artificial trend and the validation data as future anomalies are detected after the 80th day, whose number become concerning after the 100th day.

This case study highlights the relevance of the proposed approach as slow decline was detected the 60th day, while anomaly detection alone could detect the existence of a potential medical problem only after the 100th day. Additionally, data forecasting testifies for the existence of slow evolution in the behavior, while anomalies alone cannot distinguish a behavioral change due to brutal changes to those resulting from a long-term deviation. Moreover, as it successfully detected slow declines in a worst case scenario, case study attests of the proposed methodology resilience. Thanks to this information, medical staff will be able to have early and more precise information about the health status of the patient, which will ease the medical prognosis.

VI. CONCLUSION

In this paper was proposed a methodology for long-term deviation detection in smart home inhabitant behavior. Observing slow changes in behavior is crucial as these changes are often linked to specific health trouble, such as cognitive decline or frailty, which are difficult to detect. Detecting these changes before they get critical can help to prevent further worsening and in some cases can even help to reverse the process. To detect such health problems, data forecasting using ARIMA to detect future anomalies is proposed. This paper focus on activity duration as this feature is a key information about the health status of an individual and may give relevant information about the disease the inhabitant suffer depending which activity is affected. Additionally, activity duration is affected by most diseases provoking slow decline in behavior.

To highlight the relevancy of this approach, a case study is proposed. It is based on a real-life database from the DOMUS smart home in the Université de Sherbrooke, with artificially generated trends depicting real life symptoms of frailty, a common disease for elderly people causing slow decline in physical activity, endurance and eating patterns. It also represents a worst-case scenario as artificial data is

not likely to possess auto-correlation, reducing the quality of ARIMA forecast. Despite this, these trends are correctly detected and the proposed method gives insightful information to medical staff. In particular, case study shows that data forecasting method allows to detect health trouble earlier than relying on anomaly detection alone, which is critical as early detection increases odds of being healed.

Future works will consider exponential smoothing over ARIMA data forecasting techniques for activities which possess seasonality or low auto-correlation score. Additionally, monthly seasons will also be investigated with a sufficiently long labeled database.

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