Quantitative Indicators for Behaviour Drift Detection from Home Automation Data

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Abstract. Smart Homes diffusion provides an opportunity to implement elderly monitoring, extending seniors' independence and avoiding unnecessary assistance costs. Information concerning the inhabitant behaviour is contained in home automation data, and can be extracted by means of quantitative indicators. The application of such approach proves it can evidence behaviour changes.

Keywords. Smart Home, Monitoring, Behavior Detection

1. Introduction

Thanks to the diffusion of low cost, small, and low consumption devices, Home Automation (HA) technologies and Smart Homes are nowadays reality. Consumer appliances and devices are gaining embedded information, computation power, communication technologies: this promises enhanced functionality, connectivity and manageability [1]. Such data gathering gives the possibility to monitor everyday life of fragile people, such as older seniors, enabling to recognize their routine. This means both to detect sudden domestic accidents and slow changes (e.g. dementia symptoms). The possibility to unobtrusively track the behaviour or older seniors can enhance their independent life, limiting external interferences. This paradigm is fostered also by Active and Assisted Living [2], as a mechanism both to contain the costs of population ageing and to improve the older seniors quality of life.

In the following section we analyse the literature concerning relevant works on domestic behaviour changes detection. The rest of this work is structured as follows: section "Quantitative Indicators for Behaviour Drift Detection" presents the quantitative indicators, while next section reports experimental results of the system testing. Finally, we report conclusions and future works.

2. State of the Art

As previously introduced, Behavioural Drift Detection is a very actual topic in the frame of Ambient Assisted Living (AAL) and Smart Homes research. A brief insight concerning the research projects in that area will be included in the next sections.

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Moreover, it is reported the analysis of the state of the art regarding *indicators for Behavioural Drift Detection*: these methods are intended to extract useful information from a Home Automation dataset through quantitative measures.

2.1. Smart Home Monitoring

Several research group are focusing their attention on monitoring through smart home data. As reported by Debes et al. [3], some have considered technological issues while installing a smart home, such as sensor selection and household invariance. The first issue concerns the choice of suitable devices and technology, considering several factors as cost, performances, installation issues, obsolescence, etc. As stated by Saidinejad et al. [4], these factors impact significantly on the success of the smart home system. Moreover Debes et al. believe smart home monitoring systems should be abstracting from the specific characteristics of each installation: being invariant to the house configuration enables them to obtain general and comparable results.

According to Atallah et al. [5], the research related to human monitoring can be classified in two broad categories based on the involved sensors. Some systems acquire data using ambient sensors which have the peculiarity of capturing relevant information about the environment and the dweller without needing explicit interaction. Wearable sensors are capable to directly measure physical, biological and psychical conditions of the dweller thus requiring the user to wear and maintain them [6, 1]. However the need to actively carry the sensors can be invasive and unpleasant for the person [7].

To limit the invasiveness of the system and to avoid maintenance issues several research projects involving smart home monitoring are adopting ambient sensors.

- CASAS (Center for Advanced Studies in Adaptive Systems) is a very active department at the Washington State University. They have published several datasets of Daily Living in Smart Homes with one or more residents [8].
- ARAS (Activity Recognition with Ambient Sensing) is a research published by Alerndar et Al. [9] together with a dataset collected by monitoring 2 single people in their daily living activities for a duration of 30 days each.
- GERHOME is a project published by Zouba [10] that involves older people, recording performed activities in a home automation laboratory.
- MIT Dataset is a dataset presented by Tapia et Al. [11] in the frame of Activity Recognition research. It is composed by data coming from two houses equipped with a great number of boolean sensors.
- KASTEREN Dataset is a dataset presented by the University of Amsterdam [12] and it refers to the installation of three smart environments. The inhabitants were asked to annotate their activities ground truth during the overall duration of the experiment.

Mangano et al. [13] present a system called BRIDGE, acquiring data from an instrumented real home. Several custom events are fired under proper conditions, rising alarms or providing useful information to higher level modules for analysis.

However, the data alone are often not enough to detect changes in behaviour. The next section reports briefly the works done to design behavior quantitative indicators.

2.2. Indicators for Behavioral Drift Detection

Candàs et al. [14] presents a method to detect behavioural changes in dwellers' life using an accelerometer embedded in a wristband. Such device measures the acceleration while person performs everyday activities. The underlying formula it is based on the Jerk-based Inactivity Magnitude and it is applied on different portions of the previously collected dataset. The system was tested on few volunteers, who recorded their activities on a diary. Even if the results seem promising, not much attention is given to the proper definition of Abnormal Behaviour.

Suryadevara et al. [15, 16] implement a system for Predictive Ambient Intelligence in a smart environment. The authors defined two equations to evaluate the level of abnormality of a given appliance usage, while the inhabitant is performing a daily living activity. A batch procedure is used to obtain scores of different portions of the dataset, that later are compared in order to detect changes. The system has been tested on few volunteers for a week. No significant validation of the indicators is reported.

Yang et al. [17] define four measures to analyze the activity profile of a single person in a smart environment:

- *Activity time ratio* denotes the frequency of an activity during a day.
- *Activity ratio* adds the concept of intensity of activity to the previous index.
- *Daily activity rate* denote the intensity of the activity of a given day.
- *Coefficient of variance of daily activities* denotes the distribution of activities during the day using the standard distribution.

This approach requires the system to continuously collect data but it computes the coefficient every 24 hours. The system was tested on the field, recording few unexpected happenings and identifying different habits on weekdays and weekends.

Eagle et al. [18] compute the entropy of information coming from wearable devices (GPS positioning and Bluetooth activity) to measure the level of predictability of a person's daily living. The goal of the authors is to discover patterns in human behaviour that can be interesting for routine monitoring.

Jain et al. [19], finally, propose a system able to detect and classify drifts in three different categories (cyclic, descendant, chaotic). The data are processed evaluating the correlation between different time periods related to portions of a dataset.

3. Quantitative Indicators for Behaviour Drift Detection

Starting from the home automation data, the aim is to identify a set of meaningful quantities reflecting behaviour changes of the inhabitant. Analysing the question at different level, it is possible to group such indicators in four main groups depending on their complexity and the mathematical instrument the leverage.

3.1. Sensor Activation Time

The simplest indicator we propose is applicable to presence sensors and other binary sensors related to everyday actions (e.g., bed or sofa pressure mat, motion detectors, door/window sensors, etc.). The principle is fairly direct, computing the amount of time a sensor is in active (or inactive) status over a certain time window (e.g., daily, hourly, etc.). A basic yet significant application of the Sensor Activation

Time (SAT) indicator can be the bed, quantifying the time spent in bed by the person per day and/or its distribution along each hour.

Given the simplicity of this first indicator, it is reasonable to draw only simple and limited deductions about the behaviour change. As a brief example, if the bed sensor is analyzed, it is expected to know the amount of time the person passes on the bed, not knowing whether he or she is actually sleeping rather than reading, watching TV, listening to music, etc. However, the simple information of the time spent relaxing and without doing any physical activity, can be still the focus of the behaviour analysis.

3.2. Complex Data Extraction

Changing the perspective of the SAT indicator, it is possible to increase the significance of the quantitative result obtained. Given that the house is providing a set of services (i.e. water, electricity, heat, etc.) quantifying the consumption of such resources provides information related to daily actions involving it. As an example, if we consider the water consumption monitoring the shower, the sinks, the washing machine, the WC etc. it is possible to build the hourly/daily water consumption pattern. To avoid the installation of expensive flow sensors it is possible to estimate the average flow at taps, using only a binary sensor to record the duration the tap remains open and obtain the water volume consumed. Moreover appliances consume a fixed amount of water per cycle, which can be directly cumulated to the overall consumption.

This Resource Consumption (RC) complex indicator in the example related to water is implicitly carrying information about cleaning activity and hygiene habits. It is expected, as experimental results prove, that a change in habits involving these activities can be evidenced by a numerical change in the indicator.

3.3. Pattern Recognition

In some occasions it might be necessary to identify a certain activity through a sequence of events while some conditions are met. A fairly general example can be the computation of the daily time spent watching the TV. This passive activity is indeed interesting to be monitored as a hint of inactivity and an early depression symptom.

Considering the identification of the time spent watching the TV, the action takes place when the inhabitant is sitting on the sofa and the TV is active, while the rest of the house is not active. Depending on the instrumentation of the house this implies to initiate and terminate the evaluation of the time lapse according to the status of the other sensors. In general, it is necessary to identify all the initiating or resuming conditions for the focus daily activity, as well as its terminating or pausing conditions. The resulting durations of the instances should be cumulated in a daily summation.

It is worthy to highlight how this kind of indicator is useful in case it is particularly interesting to monitor a target daily activity. As an example the duration of hygiene activities and the passive activities tend to increase in case of Alzheimer's Disease (AD) or dementia: monitoring the time spent along the day to perform them gives information that might be useful for an early diagnosis or to monitor the disease.

3.4. Entropy Based

Finally, the last proposed family of indicators is Entropy Based (EB). The level of activity of a binary sensor represents from a certain point of view its informational content. In Information Theory the information conveyed by a certain binary variable can be described by its Entropy. In the settings we are presenting, the informational content of a sensor it is interesting to describe its activity not only in terms of time spent in a certain status. In particular if we consider the bed sensor, the SAT and the EB indicators are providing various information, as it will be detailed in the following sections. For sake of clarity, the Entropy of the sensor s is computed as:

$$H(s,t) = \sum_{i=0,1} P_s(i) \log_2 P_s(i) \tag{1}$$

where $P_s(i)$ is the probability of the sensor to switch to the i-th status.

The same mathematical instrument can be applied not only to a single sensor, but also to all the sensors at once. In this case it is not a specific aspect to be analyzed, but the overall house activity. In details, the combinations of active sensors can be conveniently converted to decimal numbers. The Entropy of such variable can be computed considering the decimal values corresponding to the original binary statuses:

$$H(t) = \sum_{i=0}^{N_s} P(i) \log_2 P(i) \tag{2}$$

where N_s is the number of sensors statuses combinations (i.e. for k sensors $N_s = 2^k$).

In case of non-binary sensors, it is still possible to compute entropy reducing their dynamic to a set of discrete values. However in such case the direct conversion of the status to a decimal number it is not possible. The EB indicator on the whole house is resilient to mild changes, being thus more suitable to detect broad differences involving the whole dwelling (e.g., changes in home presence routine, vacations, illness, etc.).

4. Discussion

The system was tested on both real-world datasets and on simulated data. For sake of relevance here we report the results obtained with the two simulated datasets, for each of the indicators presented in the previous Section.

4.1. Dataset Characteristics

The datasets used for the tests comprise 90 days each, obtained using SHARON simulator [20]. They include the HA sensors activation of a virtual environment, reproducing the real-world settings in which it was recorded one of the ARAS datasets [9]. To make the dataset more significant than the ARAS original one, the daily routine was simplified, preserving workdays-weekend variations.

Finally, the possibility to drive the human agent behaviour, enabled to induce a linear variation of needs and activity parameters. In such a way, the condition of AD was emulated, elongating the duration of complex activities (e.g., having shower, toileting, preparing and eating meals, etc.) as well as passive activities (e.g., relaxing, watching TV, etc.). Furthermore, as it happen in those cases, the sleeping pattern was affected too, letting it be more irregular and unpredictable.

4.2. Experimental Results

Sensor Activation Time – SAT: As presented in previous section, the simplest indicator is based on the activation time of a single meaningful sensor. Choosing the same sensor presented in the example, the application of SAT indicator of the bed to the datasets enabled to evidence a significant quantitative change in the sensor activation, alternating overshooting spikes of extraordinary activation and inactivity days. In Figure 1 it is possible to appreciate the evidence of the drift.

Resource Consumption – RC: As already done, it was kept a parallel choice with respect to the one taken in the previous sections, and apply a Resource Consumption indicator to the water. As it might be expected, the increased time spent showering and performing other complex tasks, affected the overall consumption of water. This is clearly visible in Figure 1, where the water consumption rises over 150l/day, a threshold never reached by routine data.

Activity Daily Time – ADT: Concerning the ADT of "watching TV", in first instance we tested the implemented mechanism for the recognition of such activity. In particular, Precision and Recall were computed, considering the ground truth provided by SHARON minute by minute. In Figure 2 it is possible to see the results for both the datasets. The overall values were 0.95 Pre and 0.92 Rec. Moreover, concerning the ADT indicator built over such activity, it is clearly visible in Figure 2 that the daily time spent watching TV rises over 5 hours and more after day 25. This is concordant with the dataset, in which the usage of TV and the inactivity is augmented.

Entropy Based – EB: The application of the EB indicator to the bed sensor gives interesting results. Indeed the change in the sleeping routine causes a change in the indicator trend (Fig. 3). Moreover it is interesting to notice how the information provided is different with respect to the SAT of the same sensor obtained on the same dataset. Indeed the behavioural drift affects the regularity of sleep, thus it is possible to identify it with EB indicator, even before day 40 which it was not with SAT descriptor. The results provided by overall house EB indicator report only a small trend change, with a single wide negative spike (Fig. 3). Such wide change reflects a particularly drift in behaviour: the agent remains 18 out of 24 hours in bed, skipping one meal and few other activities. This result reflects how this last indicator is suited to identify broad changes in the daily routine, affecting the whole dwelling, as well as to detect unexpected happenings (e.g. domestic fall).

5. Conclusions

The hereby presented work proposes four main methods to design quantitative indicators to be applied to home automation data streams. Through their variations it is possible to identify behaviour drifts, at different levels of complexity.

To prove the validity of the proposed approach the system implementing them was fed with simulated data. The induced drift, designed to reproduce some of the symptoms of Alzheimer's Disease, was evident in all the indicators, with some limitations in the whole house EB descriptor.

In the near future the BDD system is planned to be provided with a notification mechanism, able to provide proper warnings and alarms to the family, according to the indicators exploited.

Moreover it would be interesting to integrate the indicators system hereby proposed in home automation systems. In such way it would be possible to feed the system with real world data to monitor the inhabitant behaviour.
However it has to be remarked that automatic diagnoses or a medical evaluations of health conditions are far to be obtained. This is not due to limitations in the approach,

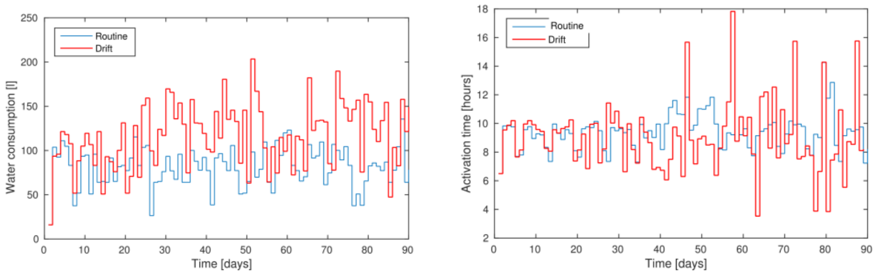

Figure 1. SAT (left) indicator - bed activation time - and RC (right) indicator - water consumption referred to the whole house -. It is noteworthy how the irregularity introduced in the behavior induces spikes in the SAT bed indicator value. On the right RC indicator, when complex actions like showering, toileting, etc., are elongated in the drift dataset the resource consumption inevitably changes.

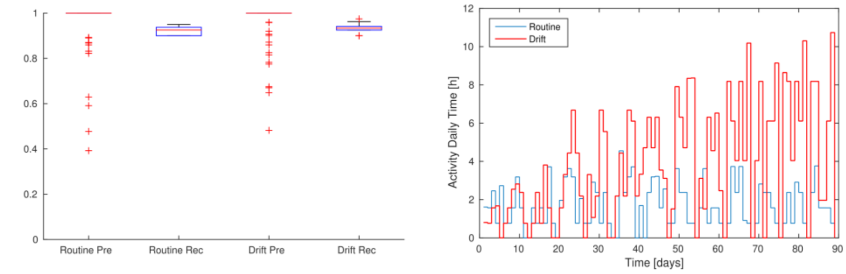

Figure 2. Results of Watching TV recognition (left) in both datasets in term of precision and Recall depicted in a box plot. ADT indicator (right): the "watching TV" activity increases, being one of the passive daily activities. It is evident how the indicator detects the behavioral change.

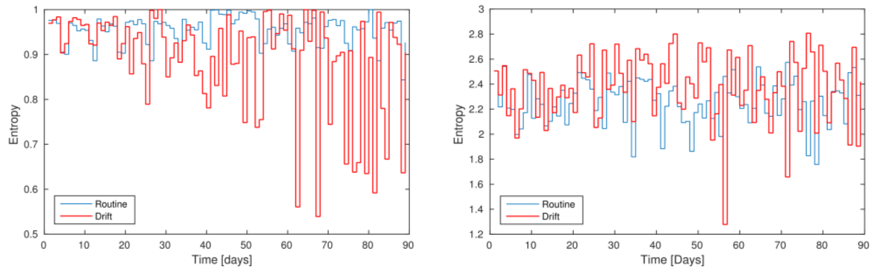

Figure 3. EB indicator for the bed (left): the entropy carries a different information with respect to the simple sensor activation reported by SAT indicators. In the picture it is possible to start identifying consistent changes in the sleeping pattern even between days 30 and 40, while SAT evidenced a drift after day 40. EB indicator for the whole house (right): even if the drift is not immediately visible, a set of sudden spikes in entropy are present after day 50. It is reasonable that the impact on the overall house EB indicator is limited since the person is still living his/her life without extreme changes.

but rather to the necessity of a proper evaluation of the persons conditions done by professionals. The proposed approach has to be considered a tool providing objective suggestions and warnings collected unobtrusively.

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