The NOAH project: Internet of Things supporting seniors' independent living

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Abstract

Population ageing is severely challenging health- and social-care systems. By fostering ageing at home, both quality of life and care sustainability may improve. The NOAH (Not Alone At Home) Project, funded in the framework of AAL-JP European Programme, aims at introducing innovative technologies supporting independent living of older adults. Internet of things devices, cloud technologies, artificial intelligence and are exploited to provide a comprehensive framework suitable for continuous monitoring, based on behavioral analysis. End-users are deeply involved in both the design and testing phases, supporting trust, accessibility and acceptability of the proposed solutions.

1 Introduction

In the last years population ageing became more and more evident, deeply transforming the structure of age distribution, especially in western countries. The share of the population aged 65 years and over is increasing in every EU Member State [Eur18]. The increase in the last decade ranges from 4.6 % in Finland to 0.3 % in Luxembourg. The growth in the relative share of older people may be explained by increased longevity, a pattern that has been apparent for several decades as life expectancy has risen. On average in Europe a man or a woman at age 65 will have a life expectancy of approximately 18 to 21 years. At the same time only 9% of them will live these years in good health. The others are characterized by age-related morbidity due to one

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or more chronic diseases (multi-morbidity), resulting in an important reduction in quality of life and increasing cost to health care budgets. According to EU statistics around 14.1% of households in the EU-28 in 2016 were composed of a single person aged 65 years old and over. Especially in urban areas single 65+ persons have a higher prevalence of aging alone.

Drawing this picture makes clear the solutions that are required, which should make it possible for these people to age with a high quality of life, remaining in their own home as long as possible. ICT technology can provide much support to independent living, both in the form of assistive devices (compensating for impairments) and of monitoring tools (allowing for safer, more confortable and cooperative environments). A wide range of technical solutions can be devised, addressing actual user needs. Solutions may range from simple safety devices to more sophisticated frameworks, suitable for behavioral analysis or for controlling home automation. For example, vocal control or even Brain-Computer Interfaces have been integrated in assistive context to allow people with motion impairments to achieve communication or control home appliances [MDC15c, MDCd17, MDC15b, MDC15a].

Focusing most at creating assistive environments, at first it is important to provide simple safety features which detect changes like longer inactivity as well as restless activities or falls. Then, on long term, it is important to detect possible changes in behavior like the occur in case of slow-developing mental degradation as well as episode of depression as well as slow developing dementia etc. These effects can easily be seen by a slowly decreasing inactivity as well as less social contacts, infrequent wake ups at night, etc. The mentioned safety features might especially be relevant in cases of post-operation where increased frailty or insecureness leads to a higher depends on more regular control. All these effects can be monitored and automatically controlled over an Internet of Things home sensor network. Several groups presented methods for behavior analysis based on home sensor network data.

Also the home automation sensor which can be partially used by the mentioned application is today available from many vendors, most either follow a proprietary protocol or do not follow a real IoT approach and are connected the in house middle-ware platform as well as in house provider looked gateways. This makes it difficult to use in terms of post-data analytics as they do not provide direct access to the retrieved data. Especially in complex behavior analysis applications which are dependent and a diverse data pool the need of an IoT sensor setup with open protocol is a requirement.

The NOAH (NOt Alone at Home, funded in the framework of AAL-JP programme) project provides a set of different IoT sensors directly communicating over WLAN as well as an open standardized protocol. Such a setup makes it possible to easily extend the sensor network and to adapt the network to different applications as well as the possibility to merge the data with other data sources like wearable sensor data etc. Furthermore no complex IoT middle-ware is needed to connect more sensors. The inherent higher energy consumption of the single sensors is faced by careful hardware and firmware design. In the future, low energy Wi-Fi solutions are expected, further increasing the practicality of the approach.

2 The NOAH system architecture

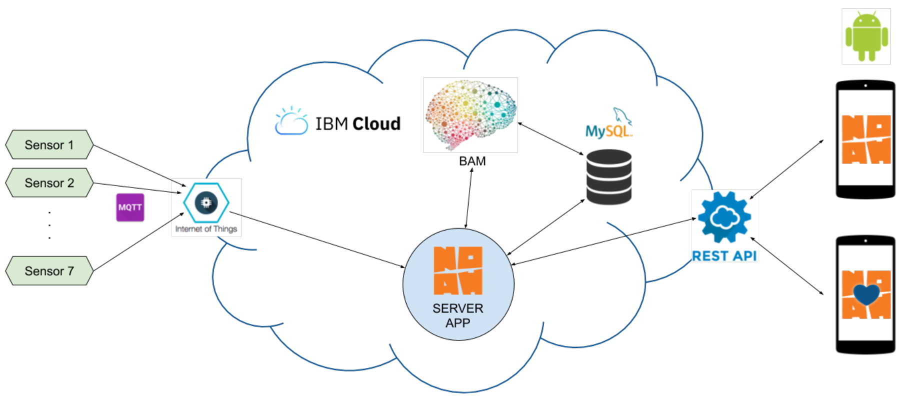

Figure 1: Schematic view of main components of NOAH system

As introduced above, the NOAH approach aims at exploiting IoT technology for continuous monitoring purposes. The overall system architecture is shown in Figure 1 , including:

- a set of IoT sensors, aimed at tracking behavioral features in a non-intrusive fashion. Details are given in Section 3 below;
- a cloud environment, built on a client-server framework:
  - The system's server side is developed and hosted on the IBM Cloud. This implies a continuously running cloud foundry application which uses two services: Internet of Things Service and Compose for MySQL. By running on a cloud environment, the NOAH System inherits all its advantages: dependability, accessibility, availability and scalability. The Internet of Things Service communicates with the registered devices (sensors) and has the role to collect data from the sensors and relay them to the server application, using the MQTT protocol, secured by SSL. Compose for MySQL provides the persistence for the sensor data and for all the other details that the system requires to run. To improve the speed of access, the sensor data is partitioned based on groups of sensors ("kits"), and is not directly linked to the end-user, keeping their anonymity. Also, the users' details and system configuration are stored by the RDMS (MySQL). The Behavioural Analysis Module (BAM) processes the sensors data to detect behaviour patterns that can indicate the well-being state of the monitored person and sends the results to the server application, which generates notifications for the system's users.
  - The system's client side is represented by two applications: one for the caregivers and one for the end-users. These are developed in native Android and can be used on a wide variety of devices, representing the user interfaces for the NOAH system. The NOAHCare application was developed to be used by the caregivers in order to monitor the daily activity of the elderly persons they take care of. Through the application, they can view the state of the sensors connected in the end-user home, they receive alerts and notifications regarding sensors and changes in the behaviour of the end-user, and, also, they can view statistics on different time periods related to the collected data. The NOAH application was developed for the elderly people, to receive a series of alerts (e.g. when a door is open). The elderly can register a feedback about how they are feeling in a certain moment (a "mood sensor"), so this information can be linked with the interpretations given by the BAM to the elderly's dataset. Also, the end-user can set two contact persons on speed-dial.
- Communication protocols, exploing REST APIs, over the HTTP protocol. The server application provides the coordination of all other components and it is a gateway to the NOAH system's features. The cloud application is built using the Node-RED developing environment, which runs over a Node.js server. The server application is responsible with collecting data from the Internet of Things Service, persisting it into a relational database, generating alerts and notifications, and serving the caregiver and end-user application through a REST API. A series of optimizations were made to the server application to ensure a high availability of the system and a low latency, by using several memory buffers and hash tables.

3 IoT device design

The IoT wireless sensor kit includes the following elements:

- Passive InfraRed (PIR) sensors for motion and room presence detection;
- Magnetic contact sensors, to detect opening and closure of doors, windows, drawers, medicine cabinets, cupboards, etc.
- Bed occupancy sensor
- Chair occupancy sensor
- Toilet usage sensor

Sensors produce raw data, which are fed to the behavioral analysis process. All sensors are conceived for minimizing installation and maintenance burden: instead of exploiting most diffused Wireless Sensor Network (WSN) protocols (e.g. ZigBee, as reported in [GBG+15])) NOAH sensors are straightforwardly connected to the standard home Wi-Fi (IEEE 802.11 b/g/n) network. This makes installation straightforward and scarcely intrusive. Sensors are directly connected to the WiFi router, with no need of a dedicated home sensor hub. Hence, the approach is highly flexible and adaptable: new elements of the IoT wireless sensor kit can join the WiFi network at any time by means of standard Wireless Protected Setup (WPS) procedure, which simplifies the device deployment. All devices share a common platform, based on the microcontroller and network processor embedded in the CC3220 SoC (*System on Chip*) by Texas Instruments. This allows for Wi-Fi certified compliance (IPv4 and IPv6 protocols), and accounts for IoT networking security, device identity and keys, relying on industry-standard, optimized BSD sockets (both TCP and UDP), secured by SSL/TLS. Cloud connection is achieved through the MQTT (*Message Queue Telemetry Transport*) communication protocol, which is a lightweight, data-agnostic protocol, particularly suitable for IoT applications. MQTT relies on a broker for data exchange between publishers and subscribers, and it supports *Quality of Service* (QoS) at different levels.

In order to ease installation in users' homes, devices are battery-powered: this minimize the risk of electrical hazard and allows unconstrained placement of sensors in the home environment. WiFi protocol, however, is much more power-demanding, with respect to dedicated WSN protocols: hence, careful planning of power budget was needed. Devices were designed for adopting inexpensive alkaline batteries: however, with respect to Lithium-based ones, alkaline batteries exhibit higher ESR (*Equivalent Series Resistance*) and generally feature a more rapid performance degradation. Close to the end of their discharge curve, the alkaline battery's ESR increases to the point it prevents sourcing of required high-peak transient current. To prolong safe operation time, super-capacitors were included in the power section, offloading batteries from supplying such high peaks. Other power optimization features include:

- Control of low-power and low-quiescent current devices. For instance, FRAM (*Ferroelectric Random Access Memory*) memory is adopted for non-volatile storage (requiring less power than flash memories); low quiescent current switching regulator and analog signal conditioning ICs are selected as well, to keep sleep-mode currents as low as possible.

- Scheduling of messages: instead of event-triggered streaming of sensor data, such information is temporarily committed to on-board non-volatile storage and sent at regular intervals (e.g. hourly). This prevents multiple WiFi connection and disconnections, effectively lowering average radio usage.

By means of such design strategy, battery lifetimes in the order of several months can be achieved, which allowed for practical deployment.

4 Behavioral analysis

Home sensors allows for unobtrusive and continuous acquisition of behavioral data: however, such data often lacks a straightforward and intuitive correlation with health and wellness status, due to large variability in human behaviors. Hence, reference thresholds are not available, to discriminate behavioral anomalies and a personalized interpretation scheme is inherently needed. Apart from gross anomalies, relevant trends and patterns have to be evaluated in a relative fashion, i.e., by checking behavioral changes with respect to individually personalized profiles. This requires the Behavioral Analysis Module (BAM) to account for learning capabilities. Application of Artificial Intelligence techniques have been reported in the context of smart homes, to predict user's behavior or activity [MMC18, MGR+19, DMS+16]. E.g, the CASAS system [CCTK13] aimed at recognition of activities of daily living (ADL) by exploiting Support Vector Machine (SVM) classifiers.

Based on recognized ADLs, one can also check for regularity of ADL patterns: in [LJV16], a clustering approach is applied to sensor data to discover anomalies; [DCSE16] discusses how relative changes in ADL patterns correlates to cognitive and mobility tests performed by clinicians. Different approaches are followed to discover ADL patterns: a "quantitative" approach, relying on *(i)* a large number of sensors (especially PIR motion detectors) and, *(ii)*, a significant corpus of user-annotated data and a more "qualitative" one, relying on more expressive semantics of data [SMWR13], coming from "specialized" sensors, linked more directly to specific activity (e.g., bed sensors).

Within the NOAH project, we selected the latter approach, due to its inherently lower intrusiveness and expensiveness. As mentioned above, several sensors are included in the NOAH home kit: in the following, for the sake of conciseness, we shall limit to a few examples, with illustrated methodologies being straightforwardly extended to other cases. Main goal of NOAH's BAM is to detect meaningful patterns and anomalies which might remain unnoticed otherwise, to trigger caregiver's and medical doctor's attention: no diagnostic power is assumed, with the proper assessment of the actual relevance of inferred "symptoms" remaining the responsibility and prerogative of the care professionals.

4.0.1 Regression Framework and Applications

Generalized Linear Models (GLM) can be exploited to build a behavioral model and assess deviation from habits. In the case of discrete-valued variables (e.g. toilet visit count) Poisson regression can be used, with the count data Y_i being modeled as random, independently distributed Poisson variables, subject to the influence of k covariates $\boldsymbol{x_i}$:

$$P(Y_i = y_i | \boldsymbol{x_i};\ \boldsymbol{\beta}) = \frac{(\boldsymbol{x_i^T \beta})^{y_i}}{y_i!} e^{-\boldsymbol{x_i^T \beta}}, \tag{1}$$

where $\boldsymbol{\beta}$ is a vector of $k+1$ parameters (for the k covariates, plus a bias term) fitted on observed data. In particular, it is known that the conditional mean count, given the vector of covariates $\boldsymbol{x_i}$ is:

$$E[Y_i | \boldsymbol{x_i}; \boldsymbol{\beta}] \triangleq \mu_i = e^{\boldsymbol{x_i^T \beta}} \tag{2}$$

For toilet usage analysis, at each point in time t_i, the last 30 daily counts are modeled using the Poisson regression framework, under the effect of a bias term (*baseline*) and three covariates:

- an *abrupt trend*, focusing on the most recent days (e.g. the last 5).
- an intermediate period, before the abrupt trend, that allows to account for a past abrupt trend, without raising the baseline too much.
- a *linear trend*, to model long term trends over the whole window.

This model may reliably detect statistically significant factors, such as recent, abrupt behavior changes. To this purpose, only statistically-significant factors are considered (i.e. with $p < 0.05$) for model fitting, to provide proper explanatory power. Detected events (either meaningful trends or anomalies) triggers automatic alerting of the caregiver, through the caregiver app. An example is given in Figure 2, which shows the outcomes of such daily-rolling regression analyses, on data coming from a real trial environment. The blue, dotted line represents the predicted mean counts, explained by the statistically significant factors, relative to the last day (day 1 in the graph accounts for the previous 30 days, not shown). For each daily step, the last day likelihood is computed, given the fitted model: if it is such that the point is outside the interval of the 95% most probable values, the point (marked in red in the graph) is labeled as *unexplained* and signaled for further potential analysis. The "outlyingness" threshold can be adjusted to make the system more reactive, if needed. To better evaluate anomalies, however, it is convenient to check for more expressive trend indicators: both "long-term" and "abrupt" trend could indicate clinically-relevant changes and are shown in figure. In the case at hand, the long-term, linear trend does not suggest any slow behavioral change, whereas some unexpected events happens at around day 30: initially the system recognizes some abnormal days, and then evaluates them as an abrupt behavioral change (i.e., different from singularities), shown by the black dashed line. The trend is expressed as a relative increase/decrease, with respect to the baseline: statistically significant changes are highlighted by the shaded area. Such information can be exploited to properly and promptly warn the caregiver and, at the same time, to suitably update the model. Subsequent days prediction are thus accordingly adjusted, this avoiding the anomaly to result in multiple detections.

Similarly, regression frameworks can be easily adapted to real-valued values. For example, bed usage data may be exploited for monitoring sleep duration and distribution. Short bed presences, unrelated to sleep activity (as it frequently happens in real-life data), are filtered out. On the other hand, fusion with data coming from other sensors allows for better characterizing sleeping routines.

4.0.2 Sensor Profiles and Applications

Besides quantitative evaluations (such as sleep duration or toilet visit count) it is worth considering lifestyle and habits, which manifest themselves by means of temporal patterns. Discovering meaningful alteration of behavioral patterns is not a trivial task, because of the inherent variability of human behaviors, which may greatly change from person to person and, for the same person, from time to time. E.g., with reference to resting habits, quite different behaviors may result in the same overall sleeping duration: for instance, some naps can be taken during the day, having different duration. In order to appreciate such details (not described by a cumulative figure), *Sensor Profiles* (SP) are introduced. Time is discretized over a suitable number of time bins

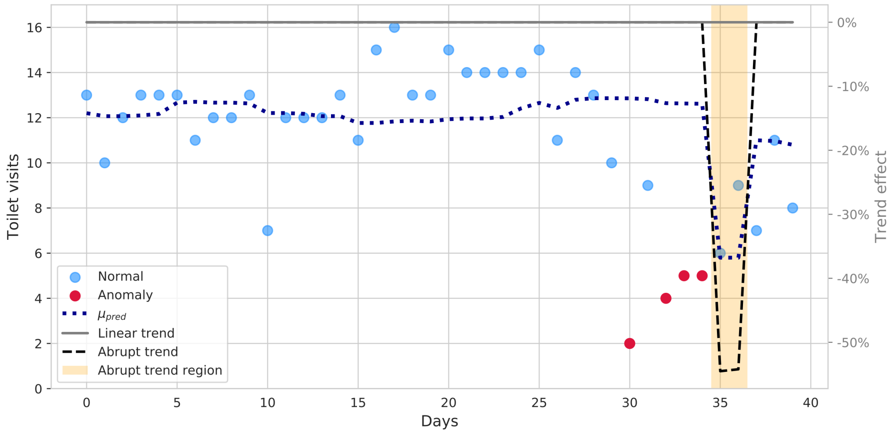

Figure 2: Analysis of toilet count data by a rolling Poisson regression model.

(e.g. 15, 30 or 60 minutes intervals), and SP model the expected probability of having a sensor active within each bin (bed sensor in the example at hand, even though the approach is more general). SP analysis aims at capture temporal habits rather than computing precise events duration. Indeed, each time bin carries the information whether the given sensor was seen sufficiently active in that time frame (either a minimum number of activations or minimum continuous active time, in order to discard non meaningful interactions). Bin size is of course relevant and depends on the observed quantity: setting bins that are too long may lead to a suppression of relevant behavioral information, whereas bins that are too short may yield noisy estimates. A bin width of 30 minutes in the example at hand. For each bin and for each day, if the sensor is active for at least t_{min} minutes, it is marked as a "positive" event (i.e., a value of 1 is associated to the bin); otherwise it is marked as negative (i.e. a value of 0). Thus, each time bin can be represented as a random variable X_j, whose realizations are drawn according to the following rule:

$$X_j^{(i)} = \begin{cases} 0, & \text{if } t_{active} < t_{min} \\ 1, & \text{if } t_{active} \geq t_{min} \end{cases}, \tag{3}$$

where $X_j^{(i)}$ is the *i-th* realization, corresponding to day i, of the *j-th* time bin, t_{active} is the time the bed sensor was active (i.e. person laying in bed) on day i in time bin j. The time bin X_j can be modeled as a $Bernoulli(p)$ random variable: the parameter p can then be interpreted as the expected probability of activating the sensor during the considered time bin. Through the principle of Maximum Likelihood Estimation (MLE), it is stated that $\hat{p} = n_{POS}/N$, where $\hat{p}$ is the estimated probability parameter, n_{POS} are the number of positive realizations (i.e. days with sensor activation within the considered time bin), and N is the total number of realizations (i.e. days). Daily behaviors are considered as independent from each others. Confidence intervals allows for quantifying the $\hat{p}$ parameter uncertainty. The procedure can be repeated for each time bin X_j, with $j = (1, ..., 24h/bin\,width)$, therefore modeling the probability of bed presence throughout the day.

The SP framework allows for automatic detection of behavioral pattern changes: two periods can be compared to detect statistically significant deviations in estimated probabilities associated to each time bin. For each couple of time bins (X_j, X_k), having associated probabilities ($\hat{p_j}$, $\hat{p_k}$), it is possible to compare them by applying the binomial proportion statistical hypothesis testing framework. This can take the form of analytic tests, such as Chi-square, or other Bayesian methods using MCMC (*Markov Chain Monte Carlo*) simulations, which can be more robust (i.e. less extreme) in reduced sample size problems. The resulting *p-values* can be adjusted by using the Holm-Bonferroni procedure, in order to account for multiple comparisons of all time bins.

Such comparison, however, inherently rely on the unrealistic assumption of a unique "reference" behavior, with respect to which behavioral changes can be estimated. This does not hold true, in general, with multiple behavioral patterns being exhibited depending on external circumstances, such as the weekday, the weather, the mood. All such patterns should be considered "normal" and not trigger any alert. This implies comparing current behavior with a set of several behaviors assumed to be "normal", based on learning from observation of previous time-frames. The SP framework also lend itself to such daily pattern clustering. By considering the feature vector composed of daily time bins realizations $x^{(i)} = [x_1^{(i)}, ..., x_{Nbins}^{(i)}]^T$ (with superscript i referring to a given day), it is possible to perform pattern clustering by means, for example, of Agglomerative Clustering. An example is given in Figure 3, which refers to data coming from a pilot environment. Bed occupancy SP were constructed, representing the probability of bed occupancy at a given time of the day, with a time resolution of 30 minutes. Agglomerative Clustering was applied to such sensor traces, in order to extract recurrent patterns. A cosine similarity metric is used to compare daily traces, and the optimal number of clusters n_{CLUS} is automatically selected according to two criteria:

1. in order to be considered, a cluster should have at least n_{SAM} samples (in this example, $n_{SAM} = 5$);
2. the parameter n_{CLUS} that maximizes the average silhouette score of valid clusters (according to criterion 1) is selected.

In the case at hand, a value of $n_{CLUS} = 2$ parameter was inferred from data, manifesting the existence of two main clusters, corresponding to most frequent behavioral patterns, shown in Figure.

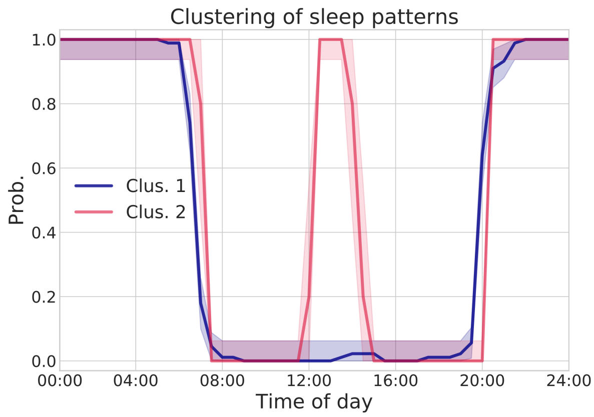

Figure 3: SP visualizations, resulting from data-driven pattern clustering. Average SP are plotted as solid lines, whereas shaded areas represent the 95% confidence intervals of such values.

Each cluster represents an SP trace as a function of time: solid lines represents the MLE estimate $\hat{p}$ (i.e. probability of bed utilization at that specific time), whereas shaded areas quantify the uncertainty of those estimates (95% confidence intervals). From the analysis two different sleep routines emerge, differing in the after-lunch behavior: cluster 2 exhibits bed presence during the [13:30-15:00] interval, which is not shown in cluster 1. To assess the statistical meaning of such findings, the binomial proportion hypothesis testing framework is exploited, allowing to compare differences between two SP populations (i.e. clusters) in terms of expected activation probabilities of each time-of-day point. In particular, statistical significance is achieved, comparing the [13:30-15:00] interval ($p < 0.01$). This result is also visually confirmed in Figure 3, where confidence intervals of both clusters' SP do not overlap and are widely spaced. Despite the obvious interpretation (afternoon nap), the example underlines potential of the SP approach in modeling habits:in real life, not necessarily a unique reference behavior exists, and multiple behavioral "modes" may occur, all of them to be considered "normal". Since different behavioral modes are extracted, current behavior can be compared with all of them, and anomalies can be inferred when a profile does not match any of the identified daily prototypes.

Finally, within the SP framework it is also possible to introduce a *Novelty Score* (NS), describing how much a given day differs from a reference period. In particular, let us suppose to have extracted a prototype pattern from said reference period, represented by a vector $\theta = \{\theta_1, ..., \theta_{Nbins}\}$ (each θ_j is the MLE estimate $\hat{p_j}$ of the time bin's probability parameter). As mentioned above, for a given day i, let us then consider its vector of realizations $x^{(i)} = [x_1^{(i)}, ..., x_{Nbins}^{(i)}]^T$; by assuming conditional independence between time bins j, it is possible to compute the log-likelihood of a day $x^{(i)}$, with respect to the model θ, as the sum of the log-likelihoods of each time bin realization $x_j^{(i)}$. The negative log-likelihood can then be taken as the NS indicator:

$$NS = -\sum_{j=1}^{Nbins} \log p(x_j^{(i)}; \theta_j) \tag{4}$$

The greater the difference of the day-vector $x^{(i)}$ with respect to the reference prototype θ, the higher the NS score is. Comparing such score with a sufficiently high threshold, makes automatic flagging of deviant days possible. In Figure 4 (a), the centroid of cluster 1 ($\hat{p}_{CL1}$) is assumed as the reference pattern; NS metric is then computed on all SP traces, with respect to such prototype. Deviant patterns can be highlighted by visualizing NS scores' distribution and checking against a suitable threshold. Here, the threshold is automatically computed from data, by means of simple Inter-Quartile Range filter:

$$Daily\, trace = \begin{cases} inlier, & \text{if } NS < IQR_{Thresh} \\ outlier, & \text{otherwise} \end{cases}, \tag{5}$$

where IQR_{Thresh} is set to $75^{th}_{percentile} + 1.5 * IQR$. For the data being considered, an $IQR_{Thresh} \approx 10.1$ is derived. More sophisticated solutions for computing the threshold, including Isolation Forests or Local Outlier Factor, could be used as well. In Figure 4 (a), the reference pattern is shown as blue dashed line; on the same figure, all patterns that yield an NS score higher than IQR_{Thresh} are plotted as well (red thinner lines). As can be noticed, all patterns with a high NS score largely differ from the reference one. Actually, the identified deviant patterns are those from cluster 2, together with a couple too far from both clusters (part of a cluster which was under-represented according to criterion 1 above). This *outlyingness* is more evident in Figure 4 (b), that shows an histogram representation of the computed NS scores. From such plot, the NS score is shown to allow for neatly discriminating deviant patterns.

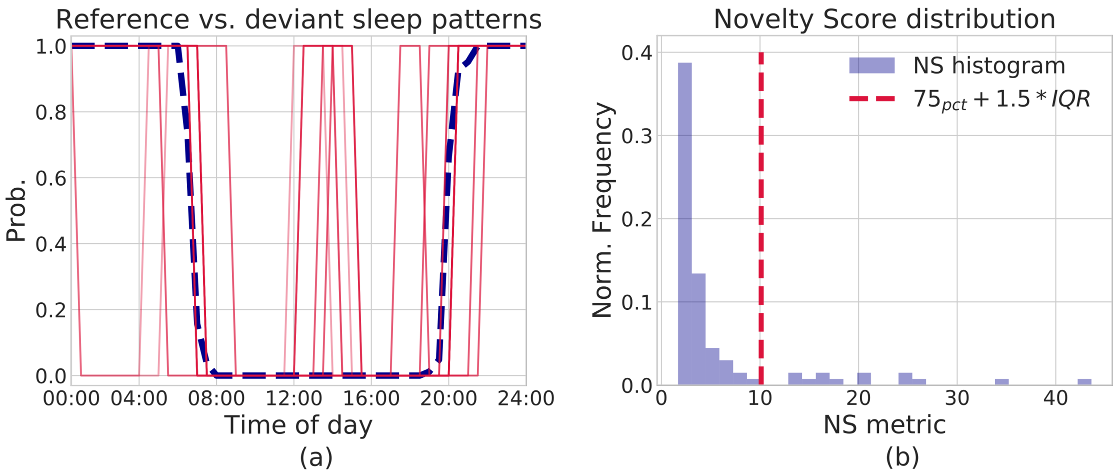

Figure 4: (a) Graphical representation of "deviant" patterns, discovered with the NS score. Blue, dashed line represents the pattern taken as reference, whereas solid red lines show profiles with a high NS score, i.e. deviating from the reference. (b) Histogram approximation of NS distribution obtained from SP traces shown in (a). Deviating patterns are identified by means of a simple filtering based on Inter-Quartile Range

5 NOAH testing and pilots

The NOAH system described so far has been deployed at three different pilot sites in Belgium, Romania and Italy. Before going to end-users home, an extensive phase of design refinement and validation was carried out, through both technical testing and co-design sessions, involving end-users and main stakeholders. Almost 60 end-users from the three different countries were involved, with each country having its needs and development. End-users and their caregivers were involved in the starting analysis, focusing on health and social needs for improving quality of life. Huge differences between the project openness and expectation from the elderly emerged. While in Italy and Belgium the end-users look at the project like something that could happen in a usual way, in the third country Romania, people were more than happy that they have the opportunity to be involved in project activities. These differences were observed in the focus groups with the end-users in the first meetings of the project, raising some worries about possible negative fallbacks. Trying to understand users' needs, they were involved them in different activities. At the beginning, all of them were given a smartphone for a better communication with their relatives and friends and to develop mobile device knowledge. Meanwhile, the NoAH project has developed an evaluation protocol (called the NoAH Roadmap) regarding the involvement of users in the project and the use of their experiences in developing and improving this concept. Various questionnaires and involvement in focus groups were used to know their views.

In the same order of ideas, in order to know the ones who have the responsibility of the first users, social workers and care professionals were involved, as they are the dynamic link between the project organizers and its beneficiaries. Involvement in a focus group on the explanation and involvement in the "NoAH Road Map" regarding the questionnaires to be used in the UTAUT Model [EBC+15]. Other questions introduced were regarding daily experiences, health status, personal utility, involvement in social actions, use of personal housing, performance expectations of the future system, level of effort made, attitude regarding the use of technology, skills usability, social influences, facilitation conditions in use and implementation, personal efficiency (desire to involve and use this system), fear/anxiety (in using the system), behavioral intention to use this system (pros and cons). Based on such assessment, the technical design was validated and better tailored to the emerged users' needs.

To allow for technical validation, besides, Mobilab built the Experience lab, a combination of a simulated living environment and high-tech care room. The purpose of the Experience lab is to provide a controlled environment in which monitoring research can be deployed. Given pre-defined scenario's, all kinds of behavior can be assessed using the monitoring system. The Experience lab is conceptualized to have new technology (e.g., sensors, IoT, communication, etc.) easily installed and evaluated. In the same way, this new technology can be demonstrated to other parties.

Within the Noah project, the Experience lab was used to install the Noah sensor kit. In first instance, the sensors and communication channels to the BAM were tested and debugged. The testing was done following a set of scenario's as agreed upon by the Noah technology team, including normal operation (e.g., opening and closing the door, sitting on a chair or toilet, walking around in the room, walking in front of the sensor each 10 minutes), abnormal operation (e.g., sitting or lying down and quickly standing up), and error situations (e.g., unplugging the sensor). After this initial testing and debugging, the system was used to evaluate the Noah system as a whole. Also, as part of the dissemination of the project, the system was demonstrated in the Experience lab to a broad range of external parties, e.g., universities, research centers, etc. Over the course of this period, over 700 persons visited the Experience lab.

According to the main project's concept, the pilot installations are intended both as a technological test and as a service evaluation (qualitative assessment). On this latter point, pilots represent a unique opportunity to assess the impact of the adopted devices on the end-user's life, involving the caregiving service, the professionals and the informal caregivers. The qualitative assessment is carried out at three different levels: psychological impact, physical impact and organizational impact. Psychological impact involves changes of behavior, effects on familiar and social relationship, anxiety. Physical impact involves factors as visual impact, discomforts, obstacles and any other interference with everyday occupations. Organizational impact involves any bias or interference on the caregiving relationship, any additional burden on the daily work-routine and any conflict or lack of information within the professional equipe. A specific protocol (called the pilot manual) discloses the audit procedures and the tools to be used during the pilot.

At present, about 30 sensor kits were deployed at different households in the three countries. In this first stage, we assessed a good acceptability of the sensor technology, which does not require significant intrusion in the home environment and does not require relevant technological skill to the end-user. Data collection is started and technical validation of BAM is being carried out. In order to assess effectiveness in supporting care strategy, though, some more data need to be collected in the next months.

6 Conclusions

In this paper, the NoAH system has been introduced: it is based on a genuine Internet of Things approach, and exploits such technology to provide older adults with continuous and non intrusive home monitoring features. In order to elicit health- and wellbeing-related information from raw data coming from sensors, a toolkit has been implemented, featuring several strategies supporting behavioral analysis. In particular, automatic detection of meaningful trends and anomalies have been accounted for, thus relieving care professionals from interpretation burden. The NOAH system exploits commercial cloud environments, taking advantage of their inherent scalability and flexibility. User interfaces have been designed through a participated design approach, looking for better acceptability and accessibility. The system is currently being tested over a set of European pilot sites: at present, functional validation of the overall approach has been achieved, with pilot run expected to provide data suitable for assessing its effectiveness and practicality in the target context, aiming at providing technology-based support to the independent living of older adults.

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