From Lab to Life: Fine-grained Behavior Monitoring in the Elderly's Home

Daniele Riboni* Claudio Bettini* Gabriele Civitarese* Zaffar Haider Janjua* Viola Bulgari◇
*Università degli Studi di Milano, Dept. of Computer Science, EveryWare Lab
◇Psychiatric Epidemiology and Evaluation Unit, Saint John of God Clinical Research Center, Brescia
Email: {daniele.riboni, claudio.bettini, gabriele.civitarese, zaffar.janjua}@unimi.it, vbulgari@fatebenefratelli.it

***Abstract*—Sensor-based activity monitoring systems promise to prolong independent living of frail elderly people, including those affected by cognitive disorders. Different solutions are already available on the market, which use wireless sensors installed in the home to track the daily living routines of the senior. Those systems provide caregivers with statistics about detected activities; some of them may trigger real-time notifications when they identify a risk situation. Long-term monitoring of fine-grained behavioral anomalies can be an important tool to support the diagnosis of neurodegenerative diseases. However, current commercial systems can only monitor high-level activity routines. For this reason, in a previous work we devised a novel method to recognize fine-grained abnormal behaviors of elderly people at home based on sensor data. Experiments in the lab showed the effectiveness of that method. In this paper we present our experience about the implementation of the system in the home of an elderly person with diagnosis of mild cognitive impairment. After illustrating the current implementation, we discuss preliminary results and outline research directions. In particular, a preliminary clinician's assessment indicates the potential utility of this system to support the diagnosis, and the benefits that would be gained by extending the system to monitor additional parameters, including neurovegetative aspects and motor behavior. We also discuss directions for addressing the encountered technological issues, for improving our reasoning algorithms with more extensive support of uncertainty, and for "closing the loop" by making the senior an active part of the system.**

I. Introduction

Ambient Assisted Living (AAL) systems are promising tools to prolong independent living for elderly people. Several research efforts have been spent in the last years to devise effective and unobtrusive AAL technologies for elderly people [1], and different AAL solutions are already available on the market [2]. Existing systems mainly monitor high-level activity patterns based on sensors deployed at the elderly's home. Some of those systems notify the caregivers when an high-level anomaly is detected, like "leaving home in the middle of the night". Other systems can detect long-term behavioral changes based on the observed home activities.

In a previous work [3], we tackled the challenging issue of recognizing abnormal behaviors at a fine-grained level, in order to provide reliable information about the functional status of the patient in an ecological context for supporting neuropsychological assessment. In particular, we targeted mild cognitive impairment (MCI): a clinical diagnosis describing the transitional state between healthy cognitive ageing and dementia, characterized by cognitive and functional impairments [4]. Growing evidences report subtle differences in performing instrumental activities of daily living (IADLs) among MCI patients compared to both healthy older adults and individuals with dementia [5]. Early detection of behavioral anomalies is of primary importance, since mild changes in IADL routines can be predictive of future cognitive decline [6]. Monitoring the execution of IADLs and evaluating their quality over time may support the diagnosis of cognitive impairments and alert the medical staff about potentially critical situations. We proposed a novel anomaly detection method based on a combination of probabilistic and symbolic reasoning, obtaining positive results performing an extensive evaluation of the system in the lab [3]. One of the future directions that we proposed was to evaluate the effectiveness of our method in the real world.

In this paper, we present and discuss our experience with the implementation of the system in the home of an elderly person with diagnosis of MCI. After illustrating the architecture, we discuss the results of our evaluation and we indicate research directions to overcome the encountered issues and to improve the system. In particular, a preliminary clinician's assessment indicates the potential utility of the system as a tool to support the early diagnosis of cognitive impairments, pointing out the benefits that would be achieved by extending the system to monitor additional parameters, including complex patterns of motor behavior and neurovegetative aspects.

With respect to other related works monitoring behavioral anomalies [7], we provide finer-grained descriptions of the occurred anomalies according to the parameters provided by clinicians. Many other systems for early detection of cognitive decline, including the one developed within the Bedmond EU project [8], constantly monitor the patient's ADLs to detect behavioral changes, but are not capable to detect anomalous behaviors. Other systems monitor the elderly's involvement in physical and social activities using gaming and interactive consoles [9], but those systems are hardly usable by people with MCI. Instead, our system does not require changing the normal routine of the elderly person.

The paper is organized as follows. Section II presents our reference model and the lab prototype. Section III describes the system implementation at the elderly's home. Section IV discusses the lessons learned and future research directions. Section V concludes the paper.

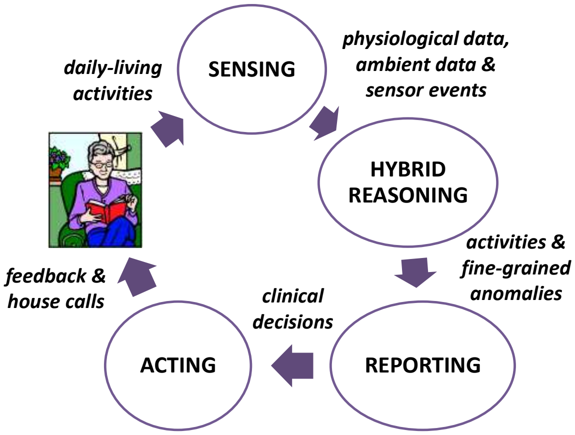

Fig. 1. Reference model

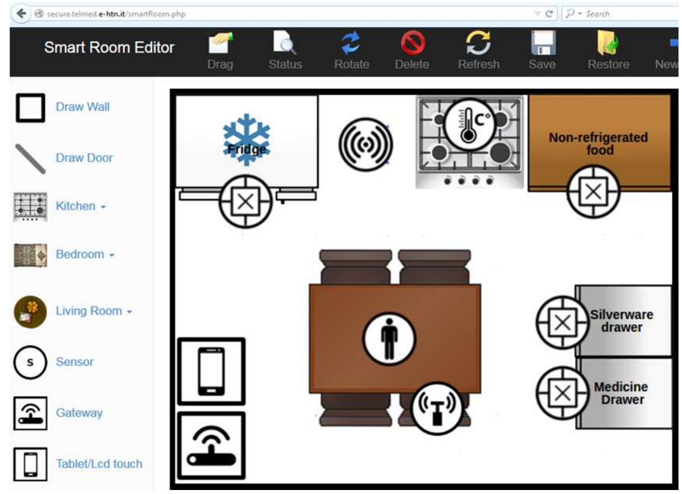

Fig. 2. Sensing infrastructure (shown in smart room editor Reporting tool)

II. Reference model and lab prototype

In this section, we illustrate our reference model and the prototype evaluation in the lab.

A. Model components

Fig. 1 shows the diagram of our reference model. Behavior monitoring is enabled by a **Sensing** infrastructure: ambient sensors deployed on various household items capture the interaction of the patient with the environment, and wearable sensors are used to acquire physiological data. A **Hybrid reasoning** module is in charge of aggregating the sensor data and executing statistical and symbolic reasoning to recognize the performed ADLs and the associated anomalies. Abnormal behaviors are modeled according to clinical models provided by neuropsychologists. Our reasoning methods are extensively presented in [3]. **Reporting** tools are provided to clinicians to let them inspect the recognized fine-grained anomalies and their temporal trend, supporting the early diagnosis of cognitive impairments. Besides clinicians, also caregivers and technicians are a fundamental part of the loop: caregivers are promptly alerted by the system about issues regarding the patient's situation, while technicians are in charge of the continuous and correct functioning of the system by using dedicated tools that allow them to constantly monitor the status of the smart home (for example, the battery levels of the sensor boards). Finally, **Acting** procedures close the loop by connecting clinicians and caregivers with the senior providing AAL functions and cognitive stimulation tools.

B. Lab prototype

Before implementing the system in the home of a patient, we have done extensive experiments with a prototype implementation in an instrumented smart room lab, using various types of ambient sensors. We have acquired a dataset of ADLs and anomalies by asking to voluntary actors to replicate the daily routine of several patients. We have considered three ADLs: *taking medicines*, *preparing a meal* and *consuming a meal*. The considered anomalies were chosen in collaboration with clinicians and researchers from the St. John of God Clinical Research Centre located in Brescia (Italy) –a leading center in the field of mental health research and research on neurodegenerative disorders. Anomalies are classified into categories based on their severity level. We considered two groups of individuals: healthy seniors and people with a diagnosis of MCI. We obtained encouraging results for both activity and anomalies recognition by achieving a high success rate. More details can be found in [3].

III. Implementation in a patient's home

After the preliminary experimentation, we have implemented the system prototype in a patient's home, considering the same activities and anomalies. After signing an informed consent, the patient underwent a multidimensional clinical assessment including a standard neuropsychological tests battery and a medical evaluation. The patient is an elderly woman aged 74, with a diagnosis of MCI and medical comorbidities, who lives alone. The patient has to take three different medications per day; she has to take two of them both in the morning and in the evening, and the third one only in the evening. The experimentation started in October 2014 and at the time of writing it is still ongoing. Currently, our prototype provides the Sensing, Reasoning and Reporting functions.

A. Sensing

In order to monitor the patient's interaction with the environment, we deployed different kinds of sensors on various household items in the kitchen. The sensing infrastructure is illustrated in Fig. 2.

- Magnetic contact sensors (Fig. 3(a)) are used to monitor opening and closure of five repositories: the fridge, the non-refrigerated food cabinet, the cooking pot cabinet, the silverware drawer, and the medicine cabinet.
- RFID tags are attached to the three medicines boxes. Whenever the patient retrieves a medicine box, she has to pass its tag near the RFID reader, in order to let

(a) Magnetic contact sensor on the fridge door

(b) Passing a tagged medicine box over the RFID reader

(c) A board with temperature sensor over the stove

(d) Passive infrared presence sensor over the kitchen table

Fig. 3. Part of the deployed sensors

the system identify the medicine (Fig. 3(b)). Other tags are attached to cards graphically illustrating 15 different food items (rice, fish, potatoes, . . .). Whenever the patient takes a food item from the repository, she has to swipe the related card to the RFID reader.

- A temperature sensor is deployed over the stove in order to detect its usage (Fig. 3(c)). For this purpose, a threshold mechanism is used: when the temperature exceeds a properly calibrated threshold, we assume that the stove has been turned on; when the temperature goes under the threshold we assume that the stove has been turned off.
- A passive infrared (PIR) sensor is used to monitor the presence of the patient in the proximity of the dining table (Fig. 3(d)).

Moreover, the patient periodically uses Bluetooth-enabled physiological sensors to measure blood pressure, heart rate and O_2 saturation.

Three sensor boards are used to collect event data from the sensors. The boards are powered by rechargeable batteries; a technician is in charge of periodically change and recharge the batteries. The measurements collected by the boards are transmitted to a gateway using the ZigBee protocol. We use a Linux-based commercial gateway that can communicate using different network technologies (WiFi, Ethernet, 3G, ZigBee). The gateway stores sensor measurements received from the boards in a local MySQL database. Once a day at midnight, the gateway sends the daily sensor detections to an Android application running on a dedicated smartphone placed inside the patient's home, which is in charge of executing the reasoning algorithms. The smartphone is not directly used by the patient, and it is constantly connected to a charger. The Android application receives the data from the physiological sensors via Bluetooth on a daily basis.

B. Reasoning

The reasoning methods of our system are extensively described in [3]. In the following we briefly summarize the reasoning framework.

Since some anomalies depend on patient-related characteristics, as well as common sense knowledge, the reasoning module takes into account some background knowledge. In order to recognize anomalies related to misplacement of items, our system is aware of whether a food item must be kept in the fridge or not. The system is also aware of which foods must be necessarily cooked, in order to recognize anomalies related to meal preparation. Medical prescriptions are considered to recognize anomalies related to medicine intake, and typical meal times are considered for recognizing abnormal food consumption routines.

The activity recognition module implemented on the Android smartphone relies on Markov Logic Network (MLN) [10], a probabilistic logic that unifies statistical and symbolic reasoning. A set of uncertain weighted rules is used to correlate windows of consecutive sensors measurements with the time instants of start and end of the performed activities. The weights of these rules are learned using supervised learning techniques during a training phase. The anomaly recognition system relies on a first-order knowledge base. For this purpose we used *tuProlog* [11], a lightweight version of *Prolog*. The inference algorithm combines the information of the detected activities and the background knowledge in order to infer fine-grained abnormal behaviors. Daily, after data processing, the mobile device transmits the detected activities and anomalies, as well as physiological data, to the back-end of a telemedicine service company based in Italy.

C. Reporting

The Reporting component of our system has been implemented as a Web-based dashboard. It is integrated with the electronic health record management system of a telemedicine company. Two types of actors interact with the dashboard: clinicians and technicians. The dashboard view for clinicians, shown in Fig. 4, includes three tabs:

- The Activities tab displays the recognized activities. Each activity instance reports the start time, the end time

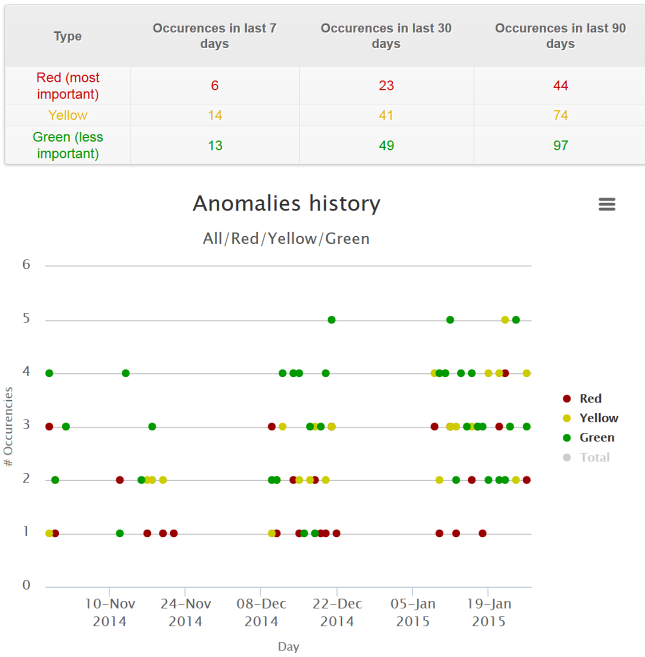

Fig. 4. The Anomalies tab of the Web dashboard for clinicians

and the list of anomalies that occurred within it. Each occurred anomaly is represented by a numbered link, bringing to the anomaly details. Clinicians can browse the history of activities sorting them by time, activity type, and number of associated anomalies.

- The Anomalies tab shows the detected anomalies. Each anomaly reports the timestamp at which the anomaly occurred, the anomaly description, and a link to the associated activity instance (if any). Clinicians can inspect various statistics and monitor the behavioral changes occurred in the daily life of the MCI patient over time. A table reports, for each anomaly category, the number of occurrences in the last seven, thirty, and ninety days. Two plots show the temporal trend of anomalies over the last weeks.
- The Physiological Data tab displays the history of physiological data: blood pressure, heart rate and O_2 saturation.

Technicians are in charge to setup the system platform and to monitor the correct functioning of its components. For this purpose, our dashboard provides them with a tool called Smart Room Editor, shown in Fig. 2. This tool allows the technicians to use a graphical interface and drag-and-drop features to create a visual representation of the smart home, including sensors, gateway, and mobile devices. The tool also supports remote monitoring of the system status, including battery levels and history of recently detected sensor events.

IV. Lessons Learned and Research Directions

In this section, we discuss the lessons learned and research directions.

A. Evaluation

1) Sensing infrastructure: The choice of the actual sensing infrastructure was not completely satisfactory. The infrastructure was not very easy to install; each sensor is connected to its board through a cable (see Fig. 3), and in some cases it was not easy to securely fix the board to the proper place. In terms of obtrusiveness, it was impossible to completely hide the presence of sensors and cables. Moreover, the modality of medicine and food item identification, based on manual RFID tag scans, is feasible only for a prototype evaluation, as the one we are carrying out; it is clearly not well suited to long-term monitoring. Indeed, we observe that in some occasions the patient either forgets to pass the tag, or does not bring it close enough to the reader for successful registration. Moreover, the sensing platform is less reliable than we expected based on the preliminary evaluation in the lab. This is partly due to difficulties in sensor calibration at the patient's home. In particular, the PIR sensor used to detect the presence at the dining table, despite properly tuned and shielded, in some cases produces false detections when the person walks near the table. A pressure sensor, used in the lab to reveal that a person was sitting on the kitchen chair, could not be reliably deployed in the patient's home. The mechanism we use to detect the event "turning the stove on/off" is sensitive to changes in ambient temperature and humidity; hence, it occasionally produces false detections. From a user acceptance point of view, the sensing system maintains the privacy of the elderly by avoiding the use of audio or visual sensing. Moreover, the system does not require handling electronic instruments, which could be problematic for elderly people and especially for MCI patients.

2) Reasoning results: Since we could not exactly reproduce the lab's environment at the patient's home, we had to re-train the supervised algorithm based on data acquired in the new environment. For acquiring the training set, we labeled the patient's activities based on the observation of raw sensor data; this was possible since the considered activities are relatively easy to distinguish based on sensor readings. While our effort is still ongoing, the activity recognition rate of our algorithm in the patient's home is currently significantly lower than the one we achieved in the lab. An explanation for the lower success rate is due to the larger amount of noisy sensor readings in the home with respect to the lab environment. Since anomaly detection depends on the correct recognition of activities, we also observe a reduction in the anomaly detection success rate.

3) Clinicians' assessment: Of course, in order to thoroughly assess the value of the system from a clinical point of view, it is necessary to perform a long-term experimentation with a large number of patients and a stable implementation of the system. For the sake of this paper, we report the results of a preliminary evaluation carried out by clinicians and researchers of the St. John of God Clinical Research Centre, based on the current system implementation and data acquired both from the patient's home and from lab simulations. Based on this assessment, it turns out that the data visualized by the Reporting tool is of considerable interest to the clinicians, since it illustrates the patient's behavioral patterns in a real-world setting during daily life activities. The observation of the IADLs performed by the MCI patient may provide useful information to be added to the neuropsychological test for a more comprehensive interpretation of the cognitive and behavioral impairments and their functional sequelae. Additionally, observing the rates of anomalies across defined periods of time (i.e., every 30 days), this module allows clinicians to investigate the course of the cognitive performance over time and to recognize possible deviations from the standard behavioral patterns of the patient. Clinically, this is of primary importance for the quality of care and for the early detection of cognitive decline. Since the cognitive correlates of impaired functional status among MCI individuals are mainly represented by executive and memory dysfunctions [12], it would be important to extend the set of monitored behaviors and anomalies to more extensively evaluate the efficiency of these cognitive domains. For example, a record of different behavioral anomalies such as omissions, consecutive but contrasting actions, repetitive actions and/or confusion, may lead clinicians to hypothesize a poor executive control and low attentive resource; this may be responsible for several cognitive difficulties. On the other hand, a record of continuous omissions, reduction of motor activities, confusion, psychomotor slowness and wandering, may lead clinicians to hypothesize memory difficulties or mood disorders (i.e., depression and/or apathy). Moreover, comparing motor behavior with the baseline would support the diagnosis, since MCI subjects tend to move slower than cognitively healthy seniors in late afternoon and evening compared to morning [13]. Hence, it would be of primary importance to monitor additional behavioral aspects, including psychomotor retardation/agitation, elation, irritability, aberrant motor behavior, as well as neurovegetative aspects such as sleep and night-time behavior disorders and appetite and eating disorders. Other IADLs of interest regard the observation of medical prescriptions; e.g., doing the prescribed exercises and observing the diet prescriptions, if any. Finally, to have a clearer picture of the patient's situation, it would be important to evaluate his/her daily mood alterations. For instance, sporadic depressive symptoms, or agitation caused by specific external events, may be the actual reason of behavioral anomalies recorded in a particular period of time. From a usability point of view, it would be useful to extend the dashboard with a more flexible tool to graphically correlate the temporal trend of different parameters; for instance, average activity duration vs number of anomalies. Of course, clinicians may decide to directly assess the patient on the basis of the anomalies recorded by the system, in order to better clarify his/her clinical conditions, and decide if such anomalies might require specific therapeutic interventions. In this sense, this system could be of critical importance to improve the clinical decision making, the health status of the patient and the quality of care.

B. Research directions

1) Alternative sensing technologies: Based on our experience, we are considering to experiment different sensing technologies in future implementations of the system. We already started experiments with tiny sensorized boards equipped with micro-localization technologies. In particular, off-the-shelf Bluetooth low energy (BLE) beacons [14] not only include micro-localization features, but are also integrated with accelerometers and other sensors. When attached to furniture, such off-the-shelf devices could be used to detect instrumental actions. Moreover, by letting the senior wear a BLE-powered device, the beacon infrastructure could be used to locate him/her inside the room [15]. By matching the inhabitant position with the sensor events it should be easier to identify the actor, facilitating multi-inhabitant behavior monitoring. Another challenging issue is how to detect the interaction of the user with objects of interests. Methods proposed in the literature rely on wearable RFID readers attached to gloves or bracelets to detect close proximity with RFID tagged objects [16]. Wearable BLE-powered devices and BLE beacons attached to particular items –such as food containers and medicine boxes– may make that approach more practical. We also plan to test alternative integrated solutions like the CASAS smart-home-in-a-box [17], despite they may have to be extended both in the sensing infrastructure and in the algorithms in order to capture our target activities and anomalies.

2) Probabilistic anomaly detection: The inherent inaccuracy of sensor readings, especially in real-world deployments, calls for reasoning methods taking into account uncertainty. Currently, sensor data provided as facts to our activity recognition algorithm are not associated with confidence values. To solve this limitation, context facts should be provided as probabilistic axioms to the MLN reasoner. Moreover, the current algorithm applies Maximum-a-Posteriori estimation [10] on the MLN knowledge base to compute the most probable activity; hence, detected activities are not given a confidence value. A different MLN inference method could be used (e.g., marginal inferencing) to obtain probabilistic recognition of activities. Currently, the anomaly recognition method is based on non-probabilistic rules that strictly determine the detection of an abnormal behavior based on a strict set of observations. Such method cannot capture person-specific anomalies. The method should be extended with probabilistic reasoning, possibly deriving person-specific rules by mining the past behavioral pattern of the senior.

3) Elderly's involvement: Including the elderly in the loop is a key factor to ensure the success of AAL systems, and elderly-centered design is mandatory for user acceptance [18]. Different acting strategies may be adopted to involve the senior in enhancing his/her independence and to manage potential risks. Different commercial systems already include reminders, provided through wearable/mobile devices or wall-mounted tablets. While those tools provide a practical support to the elderly and may help reducing the stress on caregivers, from a clinical point of view the use of memory aids may somehow replace the cognitive efforts of the patient or, at least, may not contribute to sustain it. Hence, their effect should be counterbalanced by cognitive stimulation methods, which, according to growing evidences, have positive effects in contrasting the cognitive decline [19].

4) Monitoring additional behaviors: The preliminary clinicians' assessment provided hints about additional behaviors that should be considered by the monitoring system. Some data, such as sleep quality, could be acquired by simply integrating off-the-shelf devices into our system. Other behavioral data are more challenging to acquire. Measures of psychomotor agitation and aberrant motor behavior could be acquired monitoring the mean number of exits per day, the average time spent outside per day, the mean number of crossing domestic doors, the time spent idle and the walking speed. Measures of motor activity in the home could be estimated based on the number of sensor firings. A relevant reduction over time of the amount of motor activity compared to the usual activity patterns of the patient may be associated with non-cognitive symptoms, including depressive symptoms, apathy, early fatigue, psychomotor slowness, reduced attentional resources. Conversely, a significant enhancement in the amount of activities may be associated with psychomotor agitation, aggression, disinhibition, irritability, aberrant motor behavior. Of course, those measures are strongly influenced by the personal habits and the social life of the senior. Since many MCI patients are still socially active, those measures should be considered in correlation with the senior's activities and situation, and should be monitored over time.

V. Conclusions and future work

In this paper we presented our experience in deploying a complete system for fine-grained recognition of abnormal behaviors in the home of an elderly person with a diagnosis of mild cognitive impairment. We described the many issues that we encountered despite the same system was extensively tested in a smart home lab; we reported the results of a preliminary clinicians' assessment, and we indicated promising research directions. A key requirement for future extensions of the system is to closely collaborate with clinical neuropsychologists to precisely identify the behavioral parameters to be monitored for supporting the early diagnosis of neurodegenerative disorders. From a technical point of view, we plan to improve the sensing infrastructure by using different sensors and data acquisition modalities, including wearable devices and beacons. Given the unavoidable noise generated by sensors in real-world environments as well as the variability of activity execution, we also intend to extend our algorithms to more comprehensively support reasoning with uncertainty. Other future extensions regard the development of tools to enhance the elderly's involvement, and the evaluation of the clinical utility of the system based on larger case studies.

Acknowledgments

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