Preventing Health Emergencies in An Unobtrusive Way

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Abstract. The Ambient Intelligence (*AmI*) paradigm represents the vision of the next wave of computing. By relying on various computing and networking techniques, AmI systems have the potential to enhance our everyday lives in many different aspects. One area in which widespread application of this innovative paradigm promises particularly significant benefits is health care. The work presented here contributes to realizing such promise by proposing a functioning software application able to learn the behaviors and habits, and thereby anticipate the needs, of inhabitants living in a technological environment, such as a smart house or city. The result is a health care system that can actively contribute to anticipating, and thereby preventing, emergency situations to provide greater autonomy and safety to disabled or elderly occupants, especially in cases of critical illness.

Keywords: Ambient intelligent · Association rules · Data mining · DomoNet · Domotics · Home automation · Machine learning · Web services · XML

1 Introduction

Ubiquitous Computing and *Ambient Intelligence* (*AmI*) concepts refer to a vision of the future information society in which human living environments will be pervaded by intelligent devices that will be everywhere, embedded in everyday objects to provide the functionalities to integrate computing and telecommunications technologies.

According to the vision of Mark Weiser [1] (considered the father of ubiquitous computing), the most advanced technologies are those that "disappear": computer technology should become invisible, and the daily environment will enable innovative human-machine interactions in which autonomous and intelligent entities will act in full interoperability and will be able to adapt themselves to the user and even anticipate user needs [2]. Such innovative paradigms make *AmI* technology a suitable candidate for developing a wide variety solutions to real-life issues, including in the health care domain.

In this regard, one open issue regarding *AmI* is related to recognizing unusual or dangerous situations in order to anticipate health emergencies by monitoring users' habitual activities and capturing their normal behavior. Such functionalities can be implemented using systems based on machine learning techniques, which exploit artificial intelligence algorithms to learn users' habits by accumulating 'experience' on

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their normal day-to-day activities in order to be able to recognize ‘abnormal’ situations. A system able to anticipate danger before life-threatening situations arise would certainly lead to faster and more effective intervention when used to predict health problems in time and can thus often save lives.

If we focus on the home, *AmI* services may be seen as a layer on top of the domotic system, per se. In order to make the advent of genuine *AmI* applications possible, there is a crucial need that the environment in which they act be fully interoperable [3]. However, the current immaturity of the field of domotics and, more specifically, the lack of definitions of application requirements, have led to the development of a large number of ad hoc proposals, which unfortunately are often limited and difficult to integrate.

2 Related Works

A large body of literature underscores the currently great research interest in *AmI* and methodologies for anticipating user needs. Chin [4] has classified three different categories of rules for programming an *AmI* system: pre-programmed rules, user-programmed rules, agent-programmed rules.

As regards the ability to identify user actions, Rashidi et al. [5] describe a system that identifies frequent behaviors using a powered *Hidden Markow Model* approach. Aztiria et al. [6] propose a similar system based on pattern recognition to understand users’ behaviors and act accordingly to automate actions and devices. Chen et al. [7] present an interesting survey on user activity recognition.

Mileo et al. [8] uses logic programming techniques to reason about independent living. Another rule-based approach has been proposed by Aztiria et al. [9], while Puha et al. [10] provide a comparison between different methods for multiple people activity recognition.

3 Activity Recognition and Anticipating Needs

At the core of such *AmI* systems is activity recognition [11], whose goal is to identify user behaviors as they occur, based on data collected by sensors. In this regard, we define a ‘*scenario*’ as a set of events occurring in the environment that are in some way related to each other and are recognized as such through the mediation of the domotic devices. Users must simply behave as usual within their living quarters, ignoring the technology surrounding them.

In order to recognize such scenarios and anticipate the needs of inhabitants we have built a system called *DomoPredict,* which is a software client component of the *DomoNet* project [12]. *DomoPredict* is able to act in place of users, basing its actions on the data collected while monitoring their behaviors.

DomoNet has the capacity to abstract the peculiarities of underlying, well-established heterogeneous domotic technologies (e.g. KNX, Lon, UPnP, etc.), enabling them to co-exist and interwork without eliminating their peculiar differences.

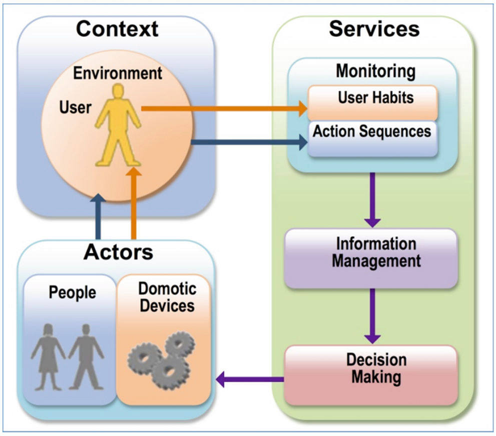

Fig. 1. Scheme of AmI based system

As shown in Fig. 2, *DomoPredict* is able to communicate with *DomoNet* and, through it, send commands to, and receive notifications of any state change in, any domotic device.

In particular, consistent with the *AmI* lifecycle (Fig. 1), *DomoPredict* functionalities can be divided into 4 steps:

- *Information Collection:* when a device changes state, an update message is sent from *DomoNet* to *DomoPredict*;
- *Collected Information Analysis:* identifying sets of actions that may lead to the recognition and creation of new scenarios;
- *Analysis:* recognizing if a new scenario is to be learned, or an existing one modified or removed;
- *Rules Execution:* the system applies a learned rule by invoking *DomoNet* to execute the corresponding commands to the appropriate domotic devices.

With the aim of learning as much information as possible, the system employs a hybrid method that exploits the advantages of two machine learning paradigms: data-mining and statistical approaches. Thus, the software is made up of two complementary, interoperating modules: the *association* and the *statistical rules managers*.

3.1 Association Rules Manager

The *association rules manager* is responsible for learning scenarios made up of a set of events or actions, called *itemsets*, habitually carried out by the user. These events are related to each other in the sense that they occur together within a specified short time interval, though they may be unrelated to any specific time of execution.

The manager applies a specific method for mining frequent sequences [13], in particular, associative rules. This enables the generation of opportune rules using binary partitions of the events determining the scenario being learned. An *unsupervised* learning technique has been adopted due to its ability to discover recurring sequences of sensor activities and in order to allow the creation of relationships and groupings between similar data [14].

By way of example, the system can learn a scenario that includes the two events: "switch on the light in the living room" and "switch on the TV". Once the user has switched on the light, it must be determined whether (s)he wants to turn on the TV as well. To do this, it is necessary to calculate the probability that the performance of one event (or group of events) implies execution of the other(s) in that same scenario.

The constraints of the *Apriori* data mining algorithm are used to define frequent scenarios. The algorithm finds *itemsets* commonly performed by the user and generates candidate action sequences via the standard method defined as *Fk-1 X Fk-1* [13].

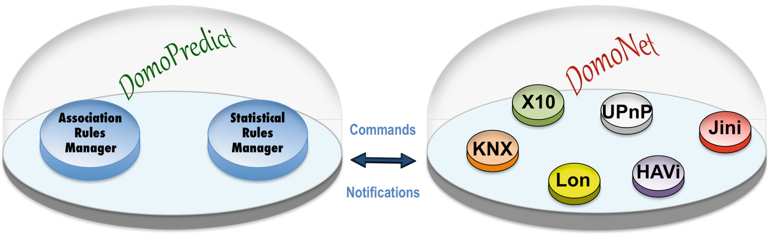

Fig. 2. *DomoPredict* is a *DomoNet* client

Such procedure requires a stage of data preprocessing, so as to determine the minimum set of events that enables recognizing the correct scenario.

Data mining algorithms are known to work well using large datasets. From this prospective, the usual techniques would seem unsuitable for our purposes, because our dataset is empty at startup and is populated in real time via the update broadcast messages sent by *DomoNet*. The solution adopted to overcome this obstacle is to act on the *support* parameter of the *Apriori* algorithm, bearing in mind that the few data available initially could lead to the acquisition of erroneous habits. In order to limit such inconvenience, the dataset is enriched with a new entry only when the *Apriori minimum support* parameter is greater than a prefixed threshold. So, simply increasing its value will make it more difficult for a given scenario to be learned, thereby preventing infrequent events from being considered.

When a change in learned habits or external factors occurs, the no longer valid scenario is modified or removed by the system using the *Apriori reinforcement* process, according to the newly acquired experience.

Lastly, decisions are translated into commands and sent to recipient domotic devices, which together with any reactions on the part of the human occupants, modify the initial settings.

3.2 Statistical Rules Manager

While recognizing and characterizing common normal activities, which account for the majority of the scenarios generated, is clearly crucial to the system's functioning, health applications require the ability to identify personal preferences as well as other events.

Thus a *statistical rules manager* has been designed to learn scenarios that are not captured by the *association rules manager*.

The data collected are recorded in tables, which indicate either the percentage time a device is in a particular state, or the percentage time that certain events occur [15].

The scenarios captured by the statistical rules manager are:

1. Scenarios made up of one or more events usually occurring at the same time of day or for a long period of time. If an action is performed every day at a certain time, we can assume that a relation exists between the action taken and the time of the day in question and we can thus perform it automatically.
2. Scenarios defined by personal living parameters (e.g. room temperature), which the system uses to configure the environment according the inhabitant's personal preferences.

4 Conclusions

Following a hybrid approach that applies both the data mining techniques of associative rule learning and statistical learning methods mitigates their respective limitations and leads to a more versatile and reliable domotic system.

The methods applied enable the system to anticipate user needs quite well, and system performance improved over time, as new experience was accumulated. The proposed method resulted also satisfactory in recognizing critical situations in advance.

To achieve more realistic results the prototype requires a dataset that is both more extensive and more detailed. The data acquired through the environmental sensors are simply not enough to achieve sufficiently reliability deductions. Such data must be integrated with the information that can be captured via wearable or implantable devices.

In the future it will be possible to design and develop smart environments able to instantly recognize not only different individuals interacting with the system, but also emotions subtly expressed by such individuals and respond to these emotions in an adaptive, personalized way. Consequently, such systems will aid in improving human health care by providing timely support and therapy.

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