

Proactive Intelligent Home System Using Contextual Information and Neural Network Approach

Belghini Naouar , Gouttaya Nesrine , Sayouti Adil, Marah Bouchaib
LSI Lab, ESTEM Research Center, Casablanca, Morocco

ABSTRACT

Nowadays, cities around the world intend to use information technology to improve the lives of their citizens. Future smart cities will incorporate digital data and technology to interact differently with their human inhabitants.

Among the key component of a smart city, we find the smart home component. It is an autonomic environment that can provide various smart services by considering the user's context information. Several methods are used in context-aware system to provide such services. In this paper, we propose an approach to offer the most relevant services to the user according to any significant change of his context environment. The proposed approach is based on the use of context history information together with user profiling and machine learning techniques. Experimentations show that the proposed solution can efficiently provide the most useful services to the user in an intelligent home environment.

Keywords - smart home, pervasive computing, recommender systems, machine learning

I. INTRODUCTION

Advances in computer sciences over the last decade have made digital electronics smart, cheaper and smaller. Moreover, revolutions made in communication technology, has strongly contributed to the improvement of advanced networked systems. It is in this context that pervasive computing has emerged and developed.

Ubiquitous systems comprise a collection of devices embedded in the environment to make a wide range of systems capable to be self-managing and to achieve autonomic functionalities. Pervasive systems (also called Context-aware systems), are an emerging solutions that provide a way to adapt the behavior of applications in order to satisfy user expectations. It requires the capacity to perceive the current situation of the user, predict his needs and act spontaneously by offering the most appropriate services taking into account his contextual situation.

Home Area Networks can be considered as an important pervasive/recommender research area. It has received considerable attention from the computer industry in the past couple of years and many applications and projects have been developed in this field [1] [2] [3] [4].

The aim of smarter home is to learn how people live their lives and offers automatic assistance. This might be to turn on/off lighting when the inhabitant enter or exit the home, or it might be the suggestion of useful and personalized services according to the user's current situation, behaviors or preferences.

This paper proposes an approach based on machine learning (back-propagation neural network) that enables intelligent home to become context-aware. The proposed solution recommends preferred and personalized actions to be performed for the user according to a current context (turning off Radio when inhabitant left the home, turning on the air conditioning when the weather is cold, etc...). The proposed approach decides which services should be executed in the current situation and disables other unused services.

The paper is organized as follows: Section 2 gives a brief overview about Pervasive Recommender Systems. Section 3 introduces the definition of contextual information. In section 4, we present the principle of our proposed solution, followed by Section 5 which presents some experimental results.

II. PERVASIVE RECOMMENDER SYSTEMS

Recommender systems can be considered as a kind of Information Retrieval system providing personalized recommendations to users. They intend to facilitate research and access to information by offering suitable services. The principle of recommender systems is based on the process of filtering and adapting incoming information from users [5][6]

Regarding the pervasive Information Systems [7], they extend the Information System paradigm by introducing a set of novel characteristics and making services available anytime and anywhere. Contrary to traditional information systems, Pervasive systems have to support a multitude of

heterogeneous device and offering users appropriate services considering their goals and the context in which such goals appear, as well as the capability of anticipating upcoming goals in this context [8].

The main challenge of pervasive systems is to capture and model user's intention to assist him in his daily life by providing appropriate services at the right time and without "direct" intervention from him. Indeed, the intelligent environment must be no longer just to "react" to user commands but rather "acting".

Pervasive Recommender Systems (PRS) will greatly change the way computers behave. They combine the characteristics of pervasive systems and recommender systems to provide personalized user recommendations in pervasives environments "Fig. 1".

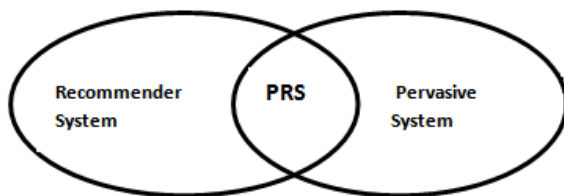


Fig1 Pervasive Recommender Systems

The basic idea is to implement various sensors, and tiny computers in the physical worlds. A huge amount of information can then be collected and processed enabling computer systems to deduce the user's situation and act correspondingly with user's intervention [9].

Approaches that use contextual information in the recommendation process attempt to model and learn contextual user preferences. Such systems typically deal with data records of the form <user, context, service>. Each record captures how much a user uses a particular service in a specific context.

Pervasive Recommender System should have the following characteristics:

- **Context Awareness**

In computing world, many definitions have been proposed in the literature to define context and context-awareness. Most adopted definitions are:

"Any information that can be used to characterize the situation of entities (whether a person, place or object) that are considered relevant to the interaction between a user and an application, including the user and the application themselves." [10].

"Context is not simply the state of a predefined environment with a fixed set of interaction resources. It is part of a process of interacting with an ever-changing environment composed of reconfigurable, migratory, distributed, and multiscale resources [11]."

More details about context modeling and classification will be presented in the next section.

- **Proactivity**

In addition to the ability of context awareness, pervasive recommender systems need to be proactive. In other words, they must be able to provide, spontaneously, personalized services to the user in order to minimize his explicit interaction with the system.

- **Anticipation**

Pervasive Recommender systems should be able to anticipate future contexts of use and future user needs and preferences in a new contextual situation.

- **Scalability**

Pervasive Recommender systems must be also able to evolve over time in order to support any changes that may arise in user's context or in user's needs or preferences.

III. CONTEXT ANALYSIS

In context aware systems, making errors in interpreting or modeling the context information may affect the decisions made by the pervasive recommender system.

Pervasive systems typically consider many parameters to extract contextual information:

Table 1: example of some possible contextual parameters

Category	interpretation
User context	User's profile (who?): identifications, interests, etc
Physical context	Physical Environment: temperature, color, time of day, etc
Network context	Network environment: connectivity, protocol, etc
Activity context	What occurs, at what time: enter, go out, etc
Service context	Information on functions which system can provide: turn TV on a preferred channel, turn light off, etc...

So, in order to enable an efficient context-aware adaptation, context information must be well captured, collected and presented.

Many studies have been done in this context. Manzoor et al. [12] quantify the Quality of Context parameters to be used in pervasive environments. They also present a mechanism to tailor the Quality of Context (QoC) parameters according to a specific need of an application and then evaluate these parameters.

To simplify the programming issue of context-aware systems it is necessary to adopt a modeling method to represent the context information. This is very important to capture user's profiles and except their needs.

The most relevant context modeling approaches are classified by the structure of data used to exchange contextual information in the pervasive system. They are based on one of the following methods:

- **Key-Value Models**

The model of key-value pairs is the most simple data structure for modeling contextual information. A context is described by a set of two dimensional vectors. Each vector consists of a numerical value describing the situations and a number indicating the certainty that the user is currently in this situation.

- **Markup Scheme Models**

It is a hierarchical data structure consisting of markup tags (ex. XML). An example of this approach is the Comprehensive Structured Context Profiles by Held et al. [13].

- **Graphical Models**

A well known modeling instrument is the Unified Modeling Language (UML) which has a strong graphical component (UML diagrams). Due to its generic structure, UML is also appropriate to model the context.

- **Logic Based Models**

A logic defines the conditions on which a concluding expression (or fact) may be extracted from a set of expressions or facts. In a logic based context model, the context is defined as facts, expressions and rules.

- **Ontology Based Models**

Ontologies are widely accepted as instrument for the modeling of context information in pervasive computing applications.

In the context of computer and information sciences, an ontology defines a set of representational primitives used to model a domain of knowledge. The representational primitives are typically classes, properties, and relations among class members. It is a promising instrument to define explicit formal specifications of the terms in a domain and the relations among them.

A detailed survey of these models is presented in [14].

IV. THE PROPOSED APPROACH

1 Principle of the application

This paper proposes an approach that enables smart home to become more context-aware. It recommends personalized actions to be performed for the user according to a current context (turning on lights when enter to home, turning off TV when inhabitant left the living room, turning on the air conditioning when the weather is cold, etc...). The proposed approach decides which services should be executed in the current situation and disables other unused services in other home locations.

The approach aims to integrate, to pervasive recommender systems, the ability of expecting user

needs in new contextual situations that were not foreseen when building the knowledge base of these systems. And this, in order to serve the user in a proactive and uninterrupted manner in various contexts that may arise.

In this context, we propose a solution based on Artificial Neural Networks (ANN) that provides a suitable solution to the user according to the current context. The system analyzes the information contained in his context profile, and searches, for a given situation, his associated context. We considered a learning database (the contextual profile database) formed by different contexts with their associated preferences, and a test database formed by new contextual situations. The aim in this layer is to predict the user preference for a new contextual situation.

2. Architecture of the solution

In the remainder of this section, we describe the functional architecture of our approach in order to show the role given to each of its modules "Fig. 2":

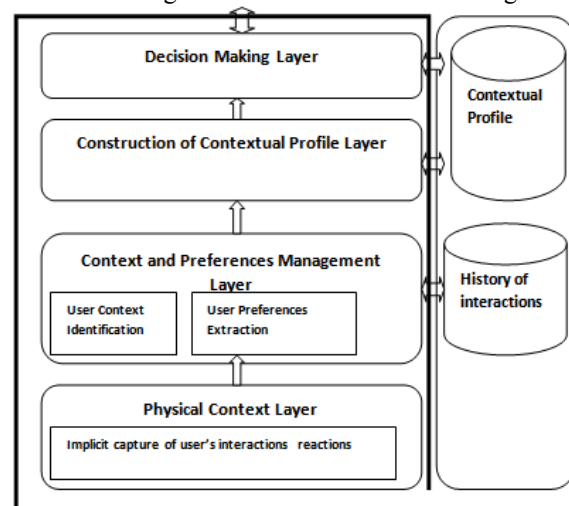


Fig2: The functional architecture of the proposed approach

- **Physical Context Layer:**

This layer is responsible of acquiring raw data from the physical context of the user and his interaction with PRS. It allows:

- The capture of physical context (temperature, light, etc.) using appropriate physical sensors for each type of information.
- The capture of user interactions: The interaction of the user with an PRS are explicit and/or implicit actions performed to satisfy a particular need. These captured information can be stored in log files, cookies, etc.

- **Context and Preferences Management Layer:**

The context management is the process of interpreting raw data (captured by physical sensors). These ones generally need to be transformed to be

used directly by the application. In the context of our approach, this operation is done by the context and preferences management layer. This layer allows to:

- Identify the user context: the context identification consists of recognizing a contextual situation of the user.
- Extract user preferences: it consists of analyzing data that represent explicit and/or implicit interactions of the user with the PRS. This analysis allows identifying user preferences.

The user interaction with PRS will be stored in

the historical interactions database using the couple (context, preference).

• Construction of Contextual Profile Layer

Only relevant preferences of the user will be considered to build his contextual profile. A preference is considered relevant if it is frequent, i.e its frequency exceeds a minimum threshold that we call MIN-FRQ-THRESHOLD.

To extract these relevant preferences, we applied the Apriori algorithm [15] on the user interaction preferences registered in the history of interactions database. Then, we combined these relevant preferences to their contexts (when they were occurring) and we save it in the user contextual profile database.

We note that this contextual profile database is periodically updated in order to track any eventual changes in user's behavior over time.

• Making decision Layer:

In this layer, we use a three-layer neural network based on back propagation algorithm. This solution allows the system to consider the history of user experiences and calculate what will be the more suitable service to be applied in a given context.

Our network consists of three layers: The input that represents the data (context parameters), an output layer which represents the service (user preference), and a hidden layer which perform the intermediate calculations.

The purpose of the learning process is to optimize the network parameters to better predict user preferences in a given context. To do so, we try to reduce the error that represents the difference between the outputs produced by the network and the desired outputs. The produced errors will be corrected via the back-propagation method and weights of the network will be changed until convergence of the system.

In the test process (where new situations arise), we calculate the maximum similarity between this new context and those in the learning database.

3. Modeling the contextual user profile

By definition, a user profile is "a set of preferences that characterize a user or a group of users". Besides, in terms of services, the user preferences are naturally affected by its context. These preferences differ from one context to another. For example, a user may prefer to listen to the radio in the morning and watching TV in the evening. So the preferences of a user are strongly related to his context and his profile.

We define the contextual profile of a user by his preference in a given context and we set it by the couple:

Contextual profile = (user Context, user preference)

In order to save the contextual user profile we must model these two components: user context and user preference.

1) User context

We define the user context by all context parameters that may influence the user preferences in relation to an intelligent service. A context parameter (P_i) is a parameter which represents fully or partially a context information.

We use the model value-attribute to represent parameters of the context. The user context is represented as follows:

User Context = $\{P_i / i= 1, \dots, n\}$

n is the number of parameters that define a relevant context for an intelligent service.

2) User Preference

We define a user preference with a set of descriptions including : what a user intends to do.

Example of some scenarios:

- The user is usually interested to political news. He prefers watching "France24" daily during the lunch break.
- In the afternoons during weekends, he watches sport programs.

Consequently, a user preference can be presented by the following parameters: The name of the service (TV, Radio, etc.), its associated type (Information, movies, documentaries, etc.) and the title of the chain or the radio station.

In general manner, we represent a user preference by:

User preference = $\{Pref_j / j= 1, \dots, m\}$

Where m is the number of parameters that define a set of descriptors, for this preference, in relation to an intelligent service.

V. EXPERIMENTATION

In this section, we introduce the way of utilizing the proposed approach. First, original data are generated by sensors. Then, the information context is defined using several parameters.

In this study, we define the context of the user profile by:

User Context = {P1= Time, P2= Localization, P3= temperature, P4= Special Event}

Where attributes:

- P1 : represents the current time of the day {1-6, 6-8, 8-10, 10-12,12-13, 13-14, 14-16, 16-18, 18-20, 20-22, 22-01}
- P2 : indicates the current location of the user {kitchen, living room, bedroom, dining room}
- P3 indicates the daytime temperatures {cold, warm, hot}
- And P4 indicate the name of the special event if it exists (weekend, Holiday, Sporting event, Cinema event, etc.).

And we define a smart home service by 3 parameters: The service identifier, the state of the service (ON/OFF) and user preferences.

Where:

- Service-id : represents the name of a specific smart service: {Light, TV, air-conditioner ,etc...}
- State: represents the state of the service : {ON,OFF}
- User Preferences = {Pref₁= Service name, Pref₂= Associated type, Pref₃ = ChanelTitle}

The proposed system activates or deactivates the appropriate candidate solutions (TV, radio, air-conditioner, stores, and lighting) according to a given context. The following table (table 2) shows some considered scenarios:

Table 2: some scenarios of trained data

EXAMPLES OF SOME SCENARIOS						
USER CONTEXT				SERVICE		
Time	location	temperature	Special Event	Services-	state	User preferences
22-01h	living room	warm	Week end	Light, TV	On	TV, Cinema, MBC4
20-22h	living room	cold	any	Light, Tv, air-conditioner	On	TV, Info, France2
7-8h	bedroom	warm	any	stores	On	-
08-09h	Dining room	cold	Week end	radio, air-conditioner	On	Radio, variety, MFM
20-22h	Dining room	warm	Sport competition	TV	On	TV, Sport, Beinsport
>1h	bedroom	warm	any	Light, stores, air-conditioner	Off	-

The learning process was accomplished using information stored in the contextual profile database.

In the test process, new contextual situations were considered. The aim was to predict the user preference in new contexts.

Experimental results show that the system responds well with a prediction rate that reaches 93%.

VI. CONCLUSION

It is certain that the next-generation of smart environment will make use of new technology thanks to the low-cost of sensors and advanced achieved in the field of artificial intelligence.

Hopefully to have an intelligent computing structure vanished into the environment; the aim of this paper was to incorporate the Contextual information in the automatic recommendation process of smart home environment.

The general idea was to facilitate user interaction with some context aware applications by determining, on behalf of the user, the application to be performed. The proposed solution extracts user's preferences and launches automatically, in a specific context, the appropriate services and disables other unused services inside the smart home environment.

ACKNOWLEDGEMENTS

Moroccan Government is actually working towards numerous major reforms to develop its own Smart City models. This work is part of the Casablanca smart city project aiming to support city systems and offer citizens a high quality of life.

REFERENCES

- [1]. MC Mozer. Lessons from an adaptive home. On Smart Environnements, 2005: 271–294.
- [2]. S Das , D Cook , A Battacharya , E Heierman , T Lin . The role of prediction algorithms in the MavHome smart home architecture. IEEE Trans. On Wireless Communications, 2002,9(6):77–84.
- [3]. R. Katharina. *Smart assistants for smart homes*. Phd Thesis, 2013,Stockholm, Sweden.
- [4]. Q Ni, AB García Hernando, de la Cruz. The Elderly's Independent Living in Smart Homes: A Characterization of Activities and Sensing Infrastructure Survey to Facilitate Services Development. Kyriacou P, ed. Sensors (Basel, Switzerland). 2015;15(5):11312-11362.
- [5]. M. Montaner, B. López , and J. L. De La Rosa, "A Taxonomy of Recommender Agents on the Internet, Artificial Intelligence Review, pp. 285-330,June 2003.
- [6]. M. Weiser. The computer for the 21st century. On Scientific American, 1991, 265(3): 94-104.

- [7]. R. Burke, "Hybrid Recommender Systems: Survey and Experiments", *Journal of Personalization Research, User Modeling and User-Adapted Interaction*, vol.12 , pp. 331 - 370 , November 2002.
- [8]. T. Cioara, I. Anghel, I. Salomie, M. Dinsoreanu, G. Copil, and D. Moldovan, "A self-adapting algorithm for context aware systems," in *Roedunet International Conference (RoEduNet)*, 2010 9th, June 2010, pp. 374 –379.
- [9]. P. Nixon, F. Wang, S. Terzis and S. Dobson. "Engineering context aware systems," *Proceedings of the International Workshop on Engineering Context-Aware Object-Oriented Systems and Environments*, 2002.
- [10]. A K Dey, G D Abowd. "Towards a better understanding of context and context-awareness". *Proceedings of the Workshop on the What, Who, Where, When and How of Context-Awareness*. 2000, ACM Press, New York .
- [11]. J. Coutaz, J. Crowley, S. Dobson, and D. Garlan. "Context is key." *Communications of the ACM* 48(3), March 2005.
- [12]. A. Manzoor, H. Truong, & S. Dustdar. On the Evaluation of Quality of Context. In *3rd European Conference on Smart Sensing and Context*. pp. 140-153, 2008
- [13]. A. Held, S. Buchholz and A. Schill. Modeling of context information for pervasive computing applications. In *Proceedings of SCI 2002/ISAS*, 2002.
- [14]. Claudio Bettini, Oliver Brdiczka, Karen Henricksen, Jadwiga Indulska, Daniela Nicklas, Anand Ranganathan, Daniele Riboni, "A Survey of Context Modelling and Reasoning Techniques". *Journal of Pervasive and Mobile Computing*, 6(2):161-180, Elsevier, 2010.
- [15]. R. Agrawal, "Fast algorithms for mining association rules". *Proceeding of the 20th International Conference Very Large Data Bases*, pp. 487–499, August 1994.