Neurocomputing 72 (2009) 2743–2753

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

An execution time neural-CBR guidance assistant

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ARTICLE INFO

Available online 16 April 2009

Keywords:
CBR systems
Multi-agent system
RFID
Shopping malls
Kohonen networks
RTPW neural networks

ABSTRACT

This paper presents a novel Ambient Intelligence based solution for shopping assistance. The core of the proposal is a CBR system developed for guiding and advising users in shopping areas. The CBR incorporates a neural based planner that identifies the most adequate plan for a given user based on user profile and interests. The RTPW neural network is based on the Kohonen one, and incorporates an interesting modification that allows a solution or a plan to be reached much more rapidly. Furthermore, once an initial plan has been reached, it is possible to identify alternatives by taking restrictions into account. The CBR system has been embedded within a deliberative agent and interacts with interface and commercial agents, which facilitate the construction of intelligent environments. This hybrid application, which works on execution time, has been tested and the results of the investigation and its evaluation in a shopping mall are presented within this paper.

1. Introduction

This paper presents a novel Ambient Intelligence [1] solution which consists of a case-based reasoning (CBR)-based multi-agent architecture, developed for guiding and advising users in shopping centres (also known as shopping malls). A shopping centre is a dynamic environment in which shops change, promotions appear and disappear continuously, etc. A CBR-based system is suitable for resolving problems in dynamic environments, given the capabilities for learning and adaptation obtained through memories [2]. The proposed system helps users to identify a shopping or leisure plan as well as to identify other users within a given shopping mall. Multi-agent systems (MAS) are specifically recommended for solving dynamic distributed systems [3], and are very appropriated to be applied in Ambient Intelligence solutions. In this particular case we propose an intelligent agent which is integrated within a CBR-based reasoning mechanism. This intelligent agent is the core of a multi-agent system designed to automatically manage certain aspects of a shopping mall, and incorporates a novel neural network planning mechanism, which notably improves the results provided by the Kohonen networks [4]. The application users require a wireless device (mobile or PDA) to download their own client agent and to interact with the multi-agent system.

This distributed system uses radio frequency identification (RFID) [5] technology to ascertain the location of users in order to provide security and to optimize their time in the mall. The motivation for the development of such a multi-agent system derives from one of the more distinctive characteristics of shopping malls, namely their dynamism. Nowadays, it is necessary to provide personalized solutions for the users, which can make use of their mobile devices to easily interact with intelligent environments. In many cases, for example, users are interested in a particular product and do not know where to buy it or have very little time, so new shops or promotions need to be advertised to shoppers [6]. The proposed MAS also helps users to identify or locate other users and provides the shopping centre personnel with updated information. The dynamic problems that exist in shopping malls require dynamic solutions provided by this technology. From the user's point of view the complexity of the solution is reduced with the help of friendly user interfaces and a robust and easy to use multi-agent system.

The shopping centre multi-agent system is composed of client agents, which allow people to interact with the multi-agent system; shop agents that manage certain aspects of each shop, such as advertising; and a manager agent, which carries out guiding and recommendation tasks. One of the main contributions of this paper is a distributed architecture for wireless environments whose main characteristic is a deliberative CBR guiding agent. The CBR agent incorporates a novel neural based reasoning engine [7] which allows the agent to learn from initial knowledge, to interact autonomously with the environment and users, and to adapt itself to environmental changes. The proposal presented has been used to develop a novel guiding application for the users of a shopping mall. However, the aim of this work is to obtain a generic architecture that can be easily adapted to other

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doi:10.1016/j.neucom.2008.08.020

similar environments such as the labour market, educational system, medical care, etc. An open wireless system combining Wi–Fi, Bluetooth, RFID technologies and handheld devices was developed, which is capable of incorporating agents that can provide useful guidance and advice services. The multi-agent architecture is founded on Ambient Intelligence (AmI) environments, characterized by their ubiquity, transparency and intelligence [1]. Ambient Intelligence proposes a new way to interact between people and technology, where the latter is adapted to individuals and their surroundings.

The proposed reactive user agents interact directly with a deliberative CBR planning agent [8]. The CBR planning agent is the core of the multi-agent architecture and is able to respond to events, to take initiative according to its goals, to communicate with other agents, to interact with users, and to make use of past experiences to find the best plans to achieve goals. A CBR agent [9] is a deliberative agent that works at a high level with the concepts of Believe, Desire, and Intention (BDI) [10,11]. The CBR planning system presented in this study incorporates a novel Routing Problems with Time Windows (RPTW) [12] neural network in the adaptation stage. RPTW are self-organized neural networks, based on Kohonen networks [4] that present certain improvements very appropriate for dynamic planning. This network incorporates an interesting modification that allows a solution or a plan to be reached much more rapidly. Furthermore, once an initial plan has been reached, it is possible to identify alternatives by taking restrictions into account.

The proposed MAS was tested in the Tormes Mall in Salamanca (Spain) with interesting results. The system performance was positive, after a period of technical adaptation. The user response was also positive, and some aspects of the mall's management have improved substantially. The shop owners were the most reticent to using the system for several reasons as explained in the conclusions.

The next section presents the problematic that motivated most of this research, focusing on a CBR-based multi-agent architecture for intelligent environments. The proposed architecture is applied to resolve a case study: an intelligent environment for shopping malls. Section 4 describes in detail the novel neural based mechanism used by the CBR-based intelligent agents to give guidance in the mall. Finally, Section 5 shows the results obtained after testing the architecture in a real scenario.

2. Ambient intelligence for shopping malls

The mall has become one of the most prevalent alternatives to traditional shopping. A shopping centre is a cluster of independent shops, planned and developed by one or several entities with a common objective. The size, commercial mixture, common services and complementary activities are determined according to regional demographics. Every shopping mall has a permanent image and a certain common management. A shopping mall needs to be managed and management includes resolving incidents or problems in a dynamic environment. As such, a shopping mall can be seen as a large dynamic problem area whose administration depends on the variability of the products, users, opinions, etc. [13]. The continuous growth of the internet and the unstoppable advance of technology suggest the need to make changes in commercial strategies. Among these new strategies, the development of different E-Commerce systems is worth mentioning [14]. E-Commerce allows users to shop through the internet, receive personalized promotions or request guidance. The incorporation of artificial intelligence techniques has led to further studies and to the modelling of the mall problem in terms of agents and multi-agent systems [15,16]. Those authors focus on the shopping problem and on the suggestions that can be made to users. The growing use of handheld devices in recent years has led to new needs, as well as great opportunities to both expand traditional commerce techniques and apply new ones. These new devices facilitate the use of new interaction techniques and require new solutions based on Ambient Intelligence. In this sense, the mall is converted in an intelligent environment, where the users are surrounded of technologies adapted to their needs and that can offer personalized assistance and value added services. Some systems focus on facilitating users with guidance or location systems [31] based on GPS or [17] based on Wi–Fi technologies. Bohnenberger et al. [13,18] present a decision-theoretic location-aware shopping guide in a shopping mall as a kind of virtual shop assistant. Bohnenberger et al. [13,18] propose the use of decision-theoretic planning, but their system cannot provide the option of replanning in execution time. iGrocer [5] is a smart grocery shopping assistant, capable of maintaining nutrition profiles of its users. Particularly useful for elders and disabled shoppers, iGrocer can aid and advice users on what products to buy and what to avoid based on nutrition criteria and price constraints, but does not provide dynamic planning capabilities and location abilities. Project Voyager [19] uses wirelessly networked mobile devices to create personal shopping assistants that delivers compelling web services to customers in a supermarket. It has the inconvenience of requiring a scanner to identify products. This solutions focuses on clients recommendations about products.

Ambient Intelligence proposes a new form of interaction between people and technology, where the latter is adapted to individuals and their surroundings [1]. In an Ambient Intelligence setting, people are surrounded by intelligent interfaces merged in daily life objects, thus creating a computing-capable environment with intelligent communication and processing available to the user by means of a simple, natural, and effortless human-system interaction [9]. The objective of Ambient Intelligence has focused on creating technologically complex environments in medical, domestic, academic, and other fields [1]. A shopping mall is a dynamic environment requiring Ambient Intelligence solutions. There are several aspects in a shopping mall that can be improved by means of Ambient Intelligence solutions. In this study we have focused on facilitating a personalized client access to the services, and providing suggestions and guidelines to the clients of the mall. The key concept in our proposal is a case-based planning (CBP) mechanism [8] which allows learning and adaptation capabilities. The CBP uses past experiences to solve new problems. The use of memories allows the CBP to personalize and suggest by consulting and adapting solutions recommended in similar past situations and their corresponding results. The CBP mechanism requires updated contextual information and a communication mechanism in order to achieve its objectives. The agent technology was chosen in order to provide a distributed problem-solving and communication mechanism. Agents are computational entities that can be characterized through their capacities in areas such as autonomy, reactivity, pro-activity, social abilities, reasoning, learning and mobility [3]. These capacities allow integration within a CBP mechanism and make the multi-agent systems very appropriate for constructing intelligent environments.

CBP [20] is a variation of the CBR systems [1] that specializes in generating plans. This paper focuses on a CBP neural based guiding mechanism integrated within an intelligent agent for wireless environments. The CBP agent incorporates a reasoning CBP engine which allows the agent to learn from initial knowledge, to interact autonomously with the environment and users, and to adapt itself to environmental changes by discovering knowledge "know how". The proposal presented has been used to

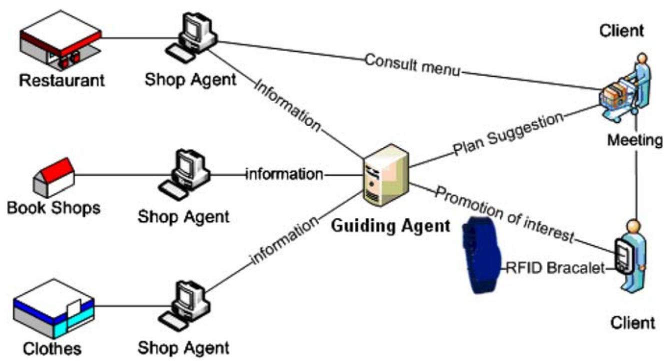

Fig. 1. Shopping mall scenario.

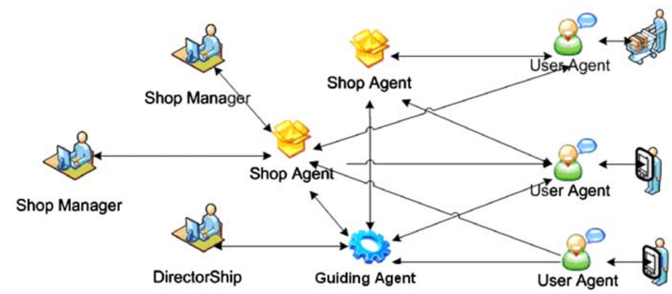

Fig. 2. Guiding agent, shop agents and user agents.

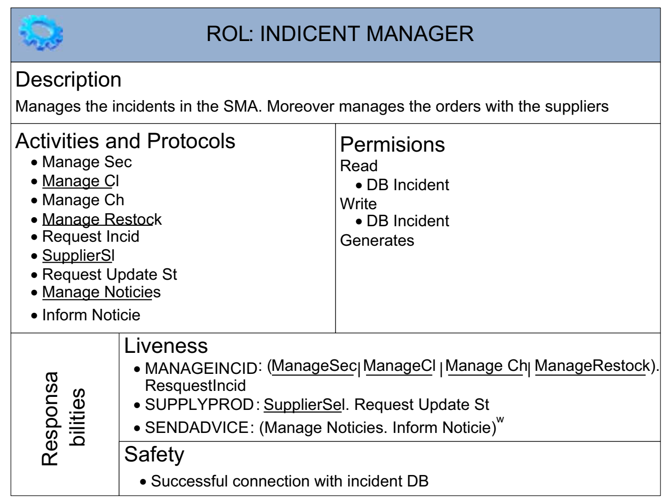

Fig. 3. Gaia Incidents Manager role model for the shopping mall problem.

develop a guiding system for users of a shopping mall that helps them to identify bargains, offers, leisure activities, etc. An open wireless system was developed and is capable of incorporating agents that can provide useful guidance and advice services to the users not only in a shopping centre, but also in any other similar environment such as the labour market, educational system, medical care, etc. Users (clients in the mall) are able to gain access to information on shops and sales and on leisure activities (entertainment, events, attractions, etc.) by using their mobile phone or PDA. Mechanisms for route planning when a user wants to spend time in the mall are also available. Moreover, the system provides a tool for advertising personalized offers (shop owners will be able to advertise their offers to the shopping mall users), and a communication system between management, the commercial sector or shoppers.

Fig. 1 shows the multi-agent based shopping mall scenario. Clients use their personal agents to consult the catalogue of the shops in the mall, to receive advice or personalized promotions, to request guidance suggestions and to locate other clients (RFID technology is required) [5]. The Guiding agent, which is the heart of the system, receives updated information from all the shops in the mall and interacts with the clients providing personalized services. The novel neural based planning mechanism integrated within the Guiding agent is described in detail in the next section.

3. Multi-agent architecture for shopping malls

The architecture of the multi-agent systems incorporates "lightweight" agents that can reside in mobile devices, such as phones, PDAs, etc. [18]. These user agents make it possible for users to interact with the MAS by simply downloading and installing a personal agent on their mobile phone or PDA. The system also incorporates one agent for each shop in the shopping mall. These agents can calculate the optimal promotions (those of greater sales success) and services at a given moment by considering the retail data and the user profiles. The core of the MAS is a guiding agent in charge of generating plans (routes) in response to a user's request, and looking for the best shopping or leisure alternatives. The agent has to take into account the user profile, the maximum amount of money that the user wants to spend, and the time available. The generation of routes must be independent of the shopping mall management, since it is not appropriate to use the same knowledge base (or all knowledge) controlled by the management. Only the knowledge corresponding to the offers and promotions at the moment of guidance should be used, otherwise, the user will be directed to the objectives of the shopping mall management. As can be seen in Fig. 2 there are three types of agents in the multi-agent system: the Guiding agent, Shop agents situated in each shop, and User agents situated in the user mobile device. Each User agent communicates with the nearest shops and can communicate with the GUIDING agent. Shop agents communicate with Guiding agent and User agents.

One of the major problems in the development of an architecture based on a multi-agent system is that there are currently no clear standards or well developed methodologies for defining the steps of analysis and design that need to be taken. There are presently a number of methodologies: Gaia [21], Agent UML (AUML) [22], INGENIAS [23], TROPOS [24], MESSAGE [25]. The option chosen in this study to define an appropriate analysis and design methodology for the problem to be solved is one that combines Gaia [21] and AUML [22,26], in an attempt to take advantage of both [27]. Two models are obtained through the Gaia analysis: the role model and the interaction model. The roles identified in the system are Communicator, Finder, Profile Manager, Store Operator, Promotions Manager, Clients Manager, Analyst, Incidents Manager and Planner. These roles will be explained in detail in the following paragraphs. For each of these roles, it will be necessary to specify their particular attributes: responsibilities, permission, activities and protocols [21].

As an example, we shall present the Incidents Manager role. In Fig. 3 we can see how the Incidents Manager role is responsible for managing incidents, supply events, and the suggestion system. The protocols used are those requesting the execution of an action to solve an incident, request a store update, and send suggestions. The actions that are carried out manage different types of incidents (security, client lost, restock or charge), select the most suitable supplier, and manage news or suggestions. The role must have permission to access and update the incident database. Its liveness responsibilities are as follows: MANAGEINCID which continually solves incidents; SUPPLYPROD responsible for looking for the best supplier; and SENDADVICE, which makes it possible to manage the suggestions and news system. Lastly, the safety responsibilities that the Incidents Manager role has are those which can establish a valid connection with the incident database.

Once the Gaia analysis has been finalized, the Gaia design is carried out. There are three models considered in the Gaia design process: agent model, services model and acquaintance model [21]. As can be seen in Fig. 4, the agent model shows the types of agents that appear in the system, and the number of instances for each agent type that can be executed in execution time. For example, the Shop agent plays the Promotions Manager and Store Operator roles.

After applying Gaia, the result is a high-level abstraction design. At this point the Gaia design is transformed so that AUML techniques can be applied. The AUML design provides class diagrams for each agent, collaboration or sequence diagrams for each interaction, state and activity diagrams to represent internal states, and protocol diagrams to model communicative acts [22,26]. After studying the requirements of the problem, three agent types were chosen:

- *The User Agent plays three roles*: the Communicator role (manages all the communications of a user); the Finder role (looks for devices nearby, trying to identify other users with similar preferences or locate a given user—in this case the use of RFID technology is fundamental. In this way, a user can find other users with similar preferences to exchange experiences and opinions); and the Profile Manager role (obtains a user profile). This agent can ask the Shop agent about promotions data or product details.
- *The Shop agent plays two roles*: the Store Operator (in charge of managing the store—operations on stored products database—and monitors product shortages in order to prevent undersupply); and the Promotions Manager role (controls the retails in each shop, as well as the promotions that every shop is offering to its clients).
- *The Guiding agent plays four Gaia roles which are divided into seven AUML capabilities*: the Clients Manager role (deals with the management of user profiles and controls the connected users at any given moment); the Analyst role (attempts to provide good quality of service by carrying out periodic evaluations on retail, promotion and survey data trying); the Incidents Manager role (manages incidents in the mall, such as sending suggestions, or solving a wide range of problems such as security, alerts, lost children, etc.); and the Planner role, which is the most important role in our system given that it creates a route identifying the most suitable shops, promotions or events to the user profile and available resources at one particular moment.

As can be seen in Fig. 5, the Planner role is implemented through three AUML capabilities (Update, KBase and CBP), that make up the Case-based planning cycle explained in detail in

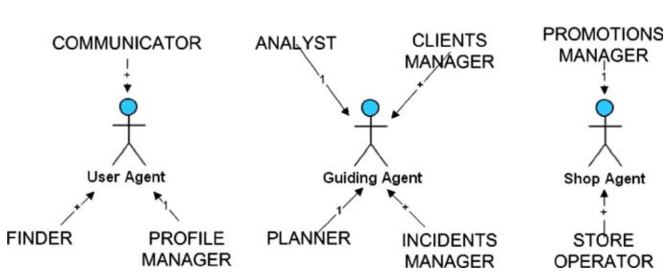

Fig. 4. Gaia agent model for the shopping mall problem.

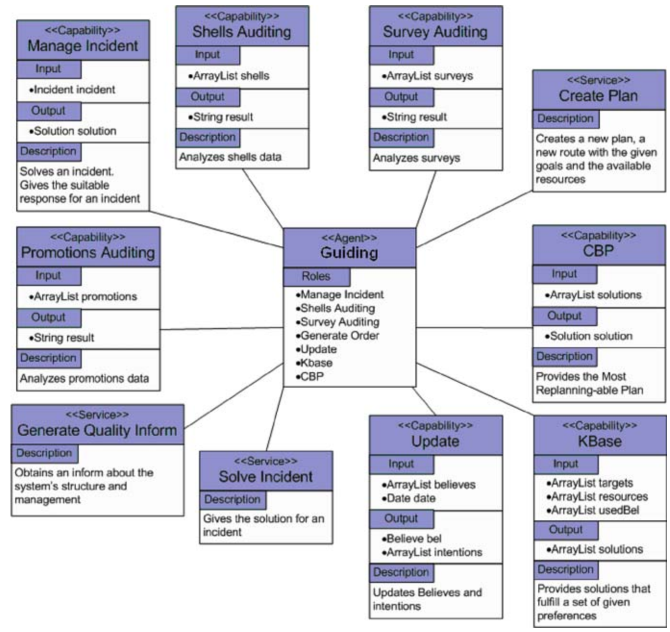

Fig. 5. Guiding agent class diagram.

Section 4 of this paper. The use of RFID technology allows the Guiding agent to locate persons in the mall for security or strategic reasons. Where there is a safety concern-as with young children or the elderly microchips or tags (Sokymat ID Band Unique Q5 with a chip Hitag S 256) can be placed on bracelets worn on the wrist or ankle [5]. These chips or transponders use a 125 kHz signal. The door readers (Hitag HT RM401 and mobile WorkAbout Pro RFID) sensors [5], are installed in strategic areas within the mall. Each reader sends a pulse of radio energy to the tags and listens for the tag's response. The signal received from a tag is sent to the Guiding agent in order to be processed.

4. CBP neural based planning mechanism

In this section we present a novel planning system based on the combination of neuronal networks and CBP systems [8], specifically designed to provide guidance suggestions. The proposed planning mechanism was initially configured to work in a shopping mall, but it can be easily adapted to work in many other similar industrial environments. Case-based planning allows us to retrieve past experiences when a new plan is created, which provides the system a large capacity for learning and adaptation [8,9]. The neuronal networks proposed within the framework of this research are self-organized, based on Kohonen [4] networks, but present certain improvements (RPTW Neural Network) [12]. These improvements allow the network to reach a solution much quicker. Furthermore, once a solution has been reached, it is possible to make new modifications taking restrictions into account (specifically time restrictions, as in the case of this study).

Case-based planning is based on the way a new plan is generated through experiences acquired in the past (after the creation and execution of plans to resolve problems similar to the current one). Case-based planning is carried out through a CBP cycle [8,20]. The CBP cycle is formed by four sequential stages: retrieve, reuse, revise and retain. In the retrieve stage the CBP recovers past experiences with a description of the problem similar to that of the current problem. In the reuse stage, solutions used in the past are adapted to create a new solution. In the revise stage the results attained after executing a new plan are evaluated. Lastly, in the retain stage, lessons are learnt from the new experience. Each one of the stages of the CBP cycle may be implemented in various ways, using different algorithms. In this study we present a novel model that allows the integration of planning based on cases within RPTW network. This model offers greater speed for obtaining Kohonen network solutions and incorporates restrictions to the network.

The main concept when working with CBR systems is the concept of case. A case is a past experience and is composed of three elements: a problem description, the solution applied to resolve the problem description, and the result obtained after applying the solution [1]. The case structure used to propose guidance suggestions in a shopping mall is described as follows:

- *Problem description*: Describes all the information available for the CBP mechanism at the moment of a new suggestion request. As can be seen in Table 1, the information consists of an initial location of the client, client characteristics obtained through their profile, the concrete preferences indicated by the client at the moment of the request, and a set of restrictions (time available, money available, opening and closing times, etc.).
- A client profile contains information about a client's personal data (gender, economic level, postal code, number of children, and date of birth) and interests, and retail data (retail time and frequency, monthly profit-both business and product). In our problem, three main attributes have been considered: personal data, retail/leisure time data and interest data. The retail/leisure attribute is composed of business type, business identification, product type, product identification, price, units and date attributes. The interest data attribute is composed of retail time and frequency, monthly profit both business and product, extracted from retail data, and the explicit attributes obtained from questionnaires. Each attribute has a value, noun or adjective, and a weight assigned. Clients indicate their preferences as a list of product preferences. The structure of a product preference is shown in Table 2.
- The global restrictions are applied on the whole plan and not on each of the individual shops. The restrictions contain information about the time and money available Table 3.
- *Solution*: Describes the sequence of actions (plan) proposed by the CBP to resolve the problem description. As can be seen in Table 4, the plan is composed of a list of product preferences and the proposed route to achieve the client objectives.
- A route is a list representing the suggestion presented to the client. As can be seen in Table 5, the route consists of various stages, each of which contains information such as the shop visited by the client, arrival time, the time spent in the shop, the products consumed by the client, and the next destination.
- *When a client purchases a product, the following information is stored*: date, money spent, product and shop details.
- *Result*: Contains the case id and a number indicating the plan efficiency. It is important to evaluate the plans executed because this metric can be used as an index to help optimize the retrieval strategy.

Table 1
Problem description structure.

Problem description	Object type
Case id	Integer
Initial location	Coordinate
Client profile	Client profile
Client preferences	Array list of product preference
Restrictions	Array list of restriction

Table 2
Product preference structure.

Product preference	Object type
Minimum price	Float
Maximum price	Float
Start time	Date
Finish time	Date
Product type	Integer
Shop type	Integer

Table 3
Planning restrictions.

Restrictions	Object type
Total time	Time
Total money	Float

Table 4
Plan structure.

Plan	Object type
Case id	Integer
Route	Route

Table 5
Route definition for a guidance suggestion.

Route	Object type
Shop	Shop
Arrival time	Time
Service time	Time
Retail products	Array list of product
Next shop	Route

The CBP needs additional information to generate a plan. For example, the location (coordinates), accesses (coordinates) and a list of available products are stored for each shop in the shopping mall. The CBP uses cases to resolve problems so that when a new problem description is received, the CBP executes a new planning cycle and obtains a new plan (solution). The initial proposed plan will be modified (replanned) if an interruption occurs. If the user adds new shops to a route or modifies the initial preferences, then we are in a replanning situation, and the system generates a new plan for the new conditions. This is one of the main advantages of our system, the dynamic planning. During each reasoning stage the CBP performs the following actions:

4.1. Retrieval

In this stage, the CBP consults the case memory and recovers those cases with a problem description closest to the problem description of the current case. As a field of the problem description, clients indicate their preferences, which are represented as $p = \{p_1, \ldots, p_n / p_i = \{z_1, z_2, z_3, z_4, z_5, z_6\}\}$, where z_1 is the minimum price, z_2 is the maximum price, z_3 the start time, z_4 the finish time, z_5 the product type and z_6 the shop type. The CBP looks for cases that are suitable to the client's preferences. In order to do this, a modified version of a SOM (Self-Organizing Map) [4] using supervised learning was implemented. For each point of the Route, a function (1) is calculated taking into account that s_1 is the sex of the client, s_2 represents economic level, s_3 postal code, s_4 number of children, and s_5 date of birth. If the products p_j do not match the preferences, the value for this function will be zero:

$$f'(s_1,\dots s_5)=\begin{cases} f(s_1,\dots,s_5) & p_j\in p \\ 0 & eoc \end{cases} \tag{1}$$

To predict the adjustment of a product to the client profile, a SOM is used. This neural network uses supervised learning, so that in the first step, the network is trained using the client's profile $\{c_1,\dots,c_n/c_i=\{s_1,s_2,s_3,s_4,s_5\}\}$ and the corresponding retail data. In the second step, the neural network uses the experience acquired in the training phase to generate a prediction for the new problem. The general idea is to group the clients depending on if they are interested in a product or not, so that the output layer of the SOM network contains two neurons. The input layer contains neurons as variables in the user profile (2). Fig. 6 shows a graphic representation of the previously explained neuronal network. It does not contain any neurons in the input layer and only two neurons in the output layer. This network makes predictions about whether a client is interested in a product or not. S_i represents the input for the neuron i, p_{ij} represents the weight which links the input neuron i and the output neuron j, and finally y_j represents the output value obtained from the neuron j.

As can be seen in Fig. 6, in the first phase the input value of the client profile is standardized (2). In order to do this, the mean is subtracted in each of the values of the user profile, and the result obtained is divided by the deviation.

$$s_i=\frac{s_i-\mu}{\sigma} \tag{2}$$

This way, the network will be able to work without units in the input layer, and all the values will be comparable. This normalization is a compulsory step before beginning the clustering.

Once the input data has been standardized, the neural network can proceed with the learning phase. The learning phase is divided into two steps:

1. In the initial step, all the client profiles assigned to a given group are selected. Then, the weights matching each group are calculated using the k-mean method [28]. In this way, the weight can be obtained for each of the neurons of the group. If $e_r,\dots,e_t$ with $t>r$ is the pattern for a group, where e_i is the set $\{s_1,\dots s_n\}$, then p_{ij1} is given for

$$p_{ij1}=\frac{\sum_{k=r}^{t}s_i^k}{t-r+1} \tag{3}$$

where s_i^k is the input i in the pattern k.

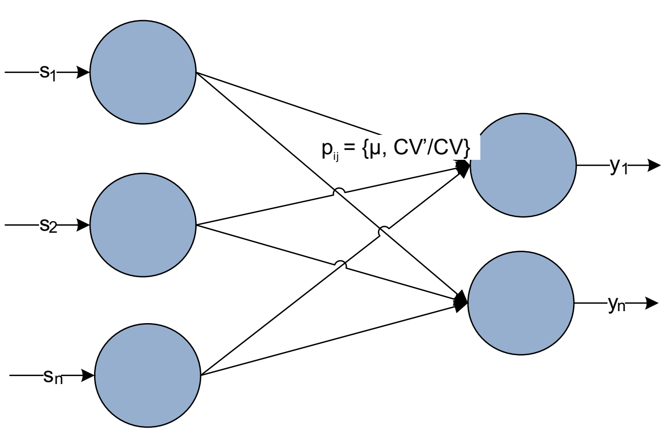

Fig. 6. Weighted SOM neural network.

2. In the second step, a new weight is calculated. The standard deviation of input pattern $e_1,\dots,e_n$ (4) and the pattern that belongs to a group $e_r,\dots,e_t$ (5) is calculated and a new weight is generated as described in the following equations. The objective of this weight is to weigh the distances of input values according to their importance in the classification (6).

$$\sigma'=+\sqrt{\frac{1}{t-r+1}\sum_{k=r}^{t}(s_k-\bar{s})^2} \tag{4}$$

$$\sigma=+\sqrt{\frac{1}{n}\sum_{k=1}^{n}(s_k-\bar{s})^2} \tag{5}$$

$$p_{ij2}=n^{*}\ln(|\sigma'-\sigma|+1) \tag{6}$$

When the values have been calculated, predictions can be made. The predictions will indicate the client's preference degree for a product. A high value in the resulting prediction indicates a high probability of a client's interest in a product. The prediction of the output value is calculated as follows:

$$y_j=\sum_{i=1}^{n}\left(|s_i-p_{ij1}|^{*}\frac{1}{p_{ij2}}\right) \tag{7}$$

The final value representing the preference degree of a client in relation to a product is obtained as follows:

$$f(s_1,\dots,s_n)=\frac{y_i}{\sum_{j=1}^{n}y_j} \tag{8}$$

Finally, each point (product in a shop) obtained is ordered according to the output value obtained from f and a new plan is created. The new plan contains those shops with a greater score for the product types indicated by the client. The shops containing product types and receiving a score $f(s_1,\dots,s_5)\leqslant 0.5$ will be rejected. In this way, a new plan with the recommended shops to visit is achieved. The case retrieved contains the plan and is the one with a problem description similar with a greater similarity to the current problem. At this point, all that remains is to order the shops according to the restrictions imposed by the client.

In the case that no similar plans could be retrieved, the clients must indicate explicitly the shops where they want to buy the products. Once the client selects the shops and establishes the time restrictions, the system generates the route to follow. The final information provided by this phase is represented as a tuple $\{t_1,\dots,t_m/t_i=\{x_1,x_2,x_3,x_4,x_5\}\}$ where (x_1,x_2) are coordinates, x_3 represents the arrival time, x_4 the departure time, x_5 the service time and m represents the number of shops. The service time is configured depending on previous times stored: if there exist data for the same user and the same day of the week, then these data is used, otherwise, an average of the times for users with similar gender and age is used. Time restrictions are taken into account only if the user has explicitly specified the initial and final time. In the rest of situations the restrictions are not taken into account because it is impossible to know a priori which will be the time assigned to a task before planning.

4.2. Reuse

In the reuse phase, once the shops that the client should visit have been selected $\{t_1,\dots,t_n\}$, the CBP planning mechanism calculates the route that will be suggested to the client. The CBP obtains the coordinates of the shops and calculates the route using a modified SOM neural network. This neural network presents a novel improvement which allows resolving the problem according to temporal restrictions.

The self-organizing maps can be seen as a heuristic used to resolve the TSP (Travelling Salesman Problem) [7,29]. It is necessary to define a neighbourhood function in order to define the influence of a neuron on her neighbours. The neurons closest to the winning neuron are those which will modify their weights in a more important way. It is also necessary to define a decreasing function which allows calculating the learning rate of the neural network. The self-organizing map implemented in the reuse stage is a SOM (Self-Organizing Maps) and the function that allows the weights to be updated is defined as follows:

$$w_{ki}(t+1) = w_{ki}(t) + \eta g(k,h,t)(x_i(t) - w_{ki}(t)) \tag{9}$$

where w_{ki} is the weight representing the link between initial neuron i and final neuron k, t the iteration, η the learning rate, h the winning neuron, k the neuron of output layer, i the Neuron of input layer.

Due to the restrictions presented within this problem, all parameters must be configured automatically since the final clients are supposed to have no knowledge about the system operation.

The neighbourhood function $g(k,h,t)$ chosen for our problem will depend on the number of iterations to establish the neighbourhood radius:

$$g(k,h,t) = \operatorname{Exp}\left[\left(-\frac{|k-h|}{N/2}\right)\frac{\sqrt{(n_{k1}-n_{h1})^2+(n_{k2}-n_{h2})^2}}{\underset{i,j}{\operatorname{Max}}\{d^*_{ij}\}} - \lambda\frac{|k-h|t}{\beta N}\right] \tag{10}$$

where k is the index of winning neuron, h the index of current neuron, N the number of shops, β the constant with value between 5×50, λ the constant with default value 1, t the current iteration. Value between 0 and $\beta^* N$, f_{ij} the distance between shops $i \times j$ n_{ij} the Coordinate j in the neuron i.

In (10) we can see that the first multiplier decreases as the neighbourhood decreases, while the second multiplier increases as the distance between neuron decreases. Both terms always take values between 0 and 1. The third term takes values between 0 and $\lambda|k-h|$, where $\lambda = 1$, and the greater value for $k-h$ is $N/2$.

The learning rate must be configured so that it decreases when the number of iterations increases. This fact allows a better convergence in the initial phases and minor modifications in the final phases, resulting in a better adjustment. The function chosen for the learning rate is as follows:

$$\eta(t) = \operatorname{Exp}\left[-\sqrt[4]{\frac{t}{\beta N}}\right] \tag{11}$$

where N is the number of shops, β the constant with value between 5×50, t the current iteration with value between 0 and $\beta^* N$.

To allow resolving optimization problems according to the temporal restrictions imposed by the clients and the temporal restrictions imposed by the shops, it is necessary to modify the previously explained SOM network. The restrictions that must be considered are:

- *Service time*: Time employed for a client in a shop. This time is extracted from the memory plans (s).
- *Arrival time*: The initial time for the arrival (s).
- *Limit hours*: The time limit for the arrival (s).
- *Opening hours*: Even if clients arrive before this time, they will not be served until the opening hour (s).
- *Closing time*: After this time, the users will not be served (s).

In order to add these new restrictions, it is necessary to include new neurons in the input layer. Each of these new neurons represents one of the parameters mentioned. The information available to the input layer will be:

- Coordinates.
- Opening hours.
- Closing time.
- Service time.

The output layer is organized following the scheme of the TSP problem: contains N neurons, one for each of the shops to visit.

The modification of the values corresponding to the weights of the links between neurons will be made in the same manner as with the previously explained network, defining a new neighbourhood function.

Moreover, a new distance function will be defined. It will be called temporal distance and it replaces the previously used Euclidean distance in the neighbourhood function. In order to establish the arrival time at the shops, it is necessary to take into account the space per time unit that a client employs in going from one shop to another. For the sake of simplicity, let us assume that the length unit is equivalent to a temporal unit. The new function defined is

$$dt_{ij} \equiv dt(x_i, x_j) = \operatorname{Max}\{f_{ij} + t_i, b_j\} \tag{12}$$

where t_i the accumulated time to arrive to shops i plus the service time, b_j the opening hours, f_{ij} the distance between neurons i and j, n_{ij} the Coordinate j of the neuron i.

Therefore, the neighbourhood function will be

$$g(k,h,t) = \operatorname{Exp}\left[\left(-\frac{|k-h|}{N/2}\right)\frac{df_{kh}}{\underset{i,j}{\operatorname{Max}}\{d^*_{ij}\}} - \lambda\frac{|k-h|t}{\beta N}\right] \tag{13}$$

$$df_{kh} = \begin{cases} \sqrt{(n_{k1}-n_{h1})^2+(n_{k2}-n_{h2})^2} & si\ c_k - dt_{ok} < d^*_{kh} \\ 0 & eoc \end{cases} \tag{14}$$

where $d^*_{ij} \equiv d^*(x_i, x_j) = f_{ij} + s_j$ with s_j being the service time for the shop j, and c_k being the closing time of the neuron k. f_{ij}: its value is calculated using the Floyd algorithm [30].

The use of the new distance df_{kh} allows the neurons to be swapped with their neighbours if the temporal restrictions have not been overcome; nevertheless, this method does not guarantee that the system can achieve a valid solution.

The learning phase is completed when every point has a winning neuron. This factor is reviewed at the end of each iteration. If this condition is not achieved, the learning phase is reinitiated. If the system cannot provide a valid solution at the end of the learning phase, the system provides a solution that minimizes the delays.

As the intermediate points of a plan are achieved, it can be necessary to initiate a new replanning in case some of the objectives cannot be achieved. To replan, the reuse phase is applied by simply using the last visited shop as the initial point.

4.3. Revision/retain

Once the tour has been finished, clients indicate their degree of satisfaction. If the plan was satisfactory, the route carried out by the client will be stored in the cases memory and will be used for future planning.

In order to illustrate the proposed mechanism, we are going to present an example in which a user requests a new plan proposal and indicates personal preferences. As can be seen in Fig. 7 and Fig. 8, the user indicates preferences via a personal device. The preferences chosen by the user can be seen in Fig. 8b. In this case the user expects to watch a movie at 22:00, drink a coffee between 19:30 and 20:00, eat at a restaurant approximately between 21:00 and 21:45, buy some trousers and a shirt priced between 0 and 50€. This data is pre-processed and transformed into preference vectors $p = \{p_1,\ldots,p_5\}$:

$p_1 = \{0$, undefined, 21:45, undefined, cinema$\}$;
$p_2 = \{0$, undefined, 19:30, 20:00, restaurant$\}$;
$p_3 = \{0$, undefined, 21:00, 21:45, restaurant$\}$;
$p_4 = \{0$, 50, undefined, undefined, clothes$\}$; and
$p_5 = \{0$, undefined, undefined, undefined, clothes$\}$.

Fig. 7. Screenshot representing how a client indicates his preferences (a) and the plan suggested to the client (b).

Fig. 8. Screenshot representing the steps for a plan (a) and the results obtained for the plan (b).

Once the preferences have been obtained, the system consults the user profile, represented as a vector $c = \{$male, 20.000–25.000, 37006, 0, 81$\}$. With this information the most appropriate shops and service times are selected as indicated in Section 4.1. The result obtained after executing the retrieval stage can be represented as a set of tuples $t = \{t_1,\ldots,t_7\}$:

$t_0 = \{145, 247$, undefined, undefined, $0\}$;
$t_1 = \{269, 266, 16{:}30, 21{:}00, 0{:}18\}$;
$t_2 = \{377, 229, 16{:}30, 21{:}00, 0{:}31\}$;
$t_3 = \{320, 133, 19{:}30, 20{:}00, 0{:}26\}$;
$t_4 = \{438, 119, 16{:}30, 21{:}00, 0{:}27\}$;
$t_5 = \{438, 199, 16{:}30, 21{:}00, 0{:}19\}$;
$t_6 = \{438, 288, 21{:}00, 21{:}45, 0{:}56\}$;
$t_7 = \{402, 77, 21{:}45, 22{:}00, 2{:}19\}$; and
$t_f = \{461, 64$, max, undefined, $0\}$,

where t_0 represents the starting point and t_f the final point. This final point is chosen as the shop with a higher value because of the opening time and will be automatically scheduled as the last point to visit.

Once the shops have been selected, as shown in Fig. 7b, and the time restrictions have been obtained, the reuse stage is executed in order to schedule the tasks. The result obtained in this phase is a plan containing times and locations. This plan can be represented as a sequence of tasks, as shown in Table 6. The plan is represented on a 2D map and sent to the user device as shown in Fig. 8a.

As can be seen in Table 6, the arrival times are calculated depending on the restrictions imposed by the user.

5. Results and conclusions

The system presented in this paper was tested in the Tormes shopping mall, located in the city of Salamanca (Spain), during the last months of 2006 and the first months of 2007. An intelligent environment based on the use of Wi–Fi, Bluetooth and RFID and handheld devices was implemented in this mall. The intelligent environment improves the services offered in the shopping mall by providing personalized services through handheld devices. The clients can receive personalized promotions, recommendations about products or shops and guiding suggestions. They can also receive news or advises of their particular interest, or information about other clients with similar preferences (with whom they can communicate), as well as make use of indoor location services. The Tormes shopping mall has 84 different businesses including shops, restaurants, cafes, cinemas, hair salons and a day nursery. The core of the intelligent environment is a Guiding agent [8] which integrates a neural case-based planning mechanism [12]. The Guiding agent attends to clients requesting suggestions. The clients then use their personal agents installed on their handheld devices (PDA, mobile phone, etc.) to interact with the intelligent environment. The Guiding agent proposes guidance suggestions depending on client preferences and the shops' capabilities. After taking the user's interests into account, places to visit are selected, routes are tracked to include those locations, and an easily re-plannable route is proposed in the event that the initial plans are interrupted. This is done while bearing in mind the time available, and the schedule for shopping and leisure activities. Once the optimum plan has been generated, the Guiding agent sends it to

Table 6
Route proposed to the user.

Shop	Coordinate	Arrival time	Departure time	Opening time	Closing time	Service time	Distance
Origin	(145, 247)	18:37	18:37			0:00	115.35
Mango	(269, 266)	18:43	19:01	16:30	21:00	0:18	28.02
H&M	(377, 229)	19:03	19:34	16:30	21:00	0:31	15.62
Cafe	(320, 133)	19:35	20:01	16:30	22:30	0:26	102.02
Zara	(438, 119)	20:07	20:34	16:30	21:00	0:27	16.97
S&P	(438, 199)	20:35	20:54	16:30	21:00	0:19	16.97
McDonalds	(438, 288)	20:55	21:51	16:30	23:00	0:56	27.31
Cinema	(402, 77)	21:53	24:12	21:30	03:00	2:19	41.87
Destination	(461, 64)	24:15	24:15				

the client agent. The client agent displays the route proposed to the client on a map (using R^2 coordinates) and monitors the execution plan. The client can easily consult the route displayed on the mobile device. The client must indicate the beginning and the end of each step of the plan. Fig. 7 presents a screenshot of the user agent at the moment of indicating preferences for a recommendation. In Fig. 7a it is possible to observe the shop types that the client can select. Moreover, for every shop type, the client can select the product type. Fig. 7b shows an example of a route proposed to a client as a response for a suggestion request. The map displayed to the client contains information about the proposed route, shop types and location, recommended products and assigned times for each of the stages of the plan.

The multi-agent system prototype was tuned and updated during this period and the initial results have been very successful from a technical and scientific point of view. During this period of time the values for the parameters of the learning phase of the neural networks were configured, as indicate the Eqs. (8)–(10) corresponding to the CBP guiding agent. Moreover, the RFID readers and the Wi–Fi networks were reallocated and reconfigured. The construction of the distributed prototype was relatively easy given that previously developed CBR-BDI libraries [17] were used, and that the Mall has a Wi–Fi network and provided the businesses with Bluetooth and RFID technology [5]. A shopping mall scenario provides an adequate framework for the analysis and design of distributed agent-based systems which incorporate CBP mechanisms. The formalism defined in [9] facilitates the straight mapping between the agent definition [3] and the CBR construction [1]. The system performance was studied by monitoring the evolution of the impact on the environment, focusing primarily on the planning mechanism. To evaluate the planning mechanism, the success of the plans proposed and the number of replannings were studied.

In order to recommend guidances efficiently, the CBP mechanism needs to have certain client information available. That is why the CBP system manages client profiles. Client profiles are created depending on the client's personal data, purchase habits and personal preferences indicated on the forms presented at the time of registration. The system controls the connected clients and provides mechanisms for advising clients. The advice service can also send news as well as personalized bargains or promotions to the client, depending on the client profile. Moreover, if clients are near each other, the Bluetooth protocol facilitates direct user identification, otherwise it has to be done using the Bluetooth, WI–FI or RFID networks of the Shopping Centre. Finally, in Fig. 8a we can see the guidance given to a user in which a particular plan is suggested according to specific characteristics and preferences, while Fig. 8b illustrates the result obtained from the suggested plan.

The system was tested between August 2006 and September 2007 and obtained promising results. The E-Commerce techniques facilitated user motivation since users can easily find their

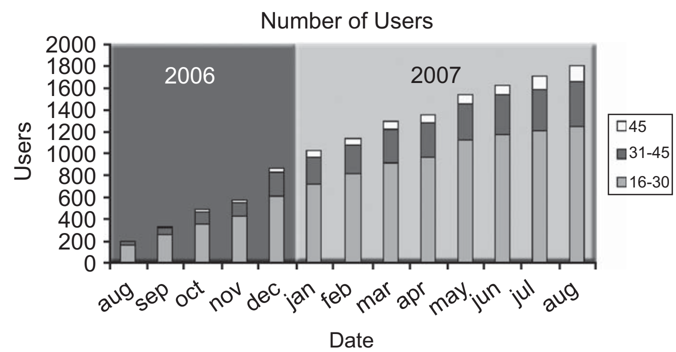

Fig. 9. Evolution of the number of users registered in the system. Users are classified according to age.

products of interest, spend their leisure time more effectively, and contact other users with whom to share hobbies or opinions. The degree of user satisfaction has improved, as observed in the surveys. The first autonomous prototype was implemented with a test set of 30 users who were selected among users with specific models of terminals supporting the application (they used their own Wi–Fi, Bluetooth devices). Different versions were implemented in order to get compatibility with the most number of terminals possible. The results obtained show that the majority of users, nearly 67%, were people between 16 and 30 years old, while those older than 40 were less than 3%. However, there were no significant differences with respect to the gender of users. The interaction between the number of clients and the impact index can be seen in Fig. 9. The y axis represents the number of clients, while the x axis represents the month and year. Each bar is fragmented in three groups representing the age of the users: 16–30, 30–45 and more than 45 years old.

As the number of clients registered in the system increased, the plans retrieved during the retrieval stage and their influence over the suggested plans improved notably, as well as the number of replannings required per plan and the degree of client satisfaction. In Fig. 10 it is possible to observe that while the quality of the proposed plans increases, the degree of client satisfaction increases as well. With the experience acquired, the number of plans successfully completed increases, while the number of failed plans and the number of plans needing replanning both decrease. The quality of the plan can be calculated by an Eq. (15) where s is the number of shops to visit and f' is defined in (1). The satisfaction is represented as a percentage in relation to the total number of plans that have been successfully accomplished and those that do not. The percentage of plans needing to be replanned, and those that were successfully completed are both calculated in a similar way:

$$\frac{\sum_{i=0}^{s} f'_i(s_1, \ldots, s_5)}{s} \qquad (15)$$

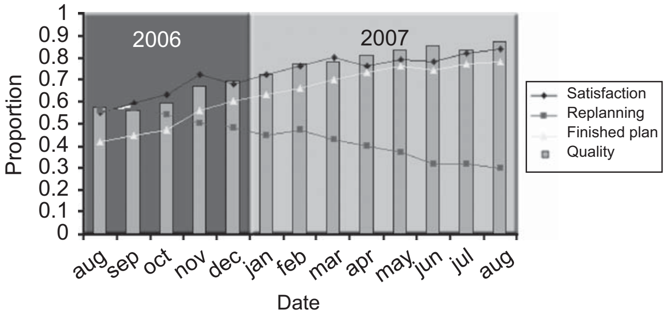

Fig. 10. Planning system evolution. The efficiency of the system and the learning rate are both evaluated by taking into account the quality obtained for each plan. Related to this parameter it is possible to observe the increase in the degree of client satisfaction and the number of successfully completed plans, and the decrease of the need of replanning.

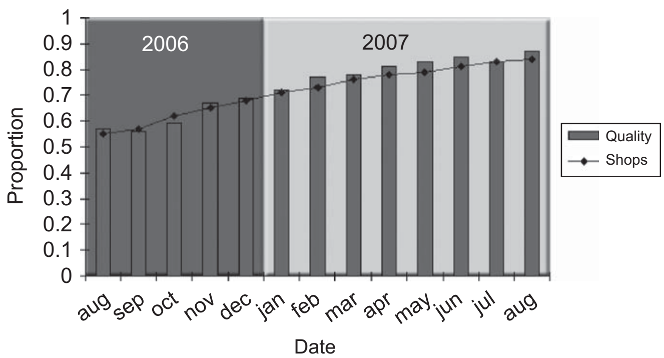

Fig. 11. Percentage of the number of shops visited in relation to the number of shops initially proposed in the plan. The graph represents the interaction between this percentage and the quality of the proposed plan.

Finally, it would be interesting to study the interaction that exists between the total number of shops suggested in a plan and the number of shops visited by the client. This study was carried out for those plans that were successfully completed. The results obtained can be observed in Fig. 11.

As the system obtains more information about user profiles, products and habits, the knowledge increases and the CBR agent provides more optimal plans. The users also need time to get used to the system. The proposed guiding system has been improved to be able to provide adequate guidance in a dynamic way and in execution time. In this sense it is a unique system useful for dynamic environments and flexible enough to be used in other environments such as health care residences, educational environments or tourist related environments. One of the most demanding services is the identification of someone with a given profile, along the lines of web services such as Match.com or similar sites. In this sense, the system performance was correct from a logical point of view, although there were a few technical problems during the initial months of the experiments due, in particular, to the Bluetooth network. This service is used by an average of 46% of the users. The shop owners are the most reticent about using the guiding system for several reasons: (i) they do not trust the partiality of the guiding systems, since they cannot control whether it is biased or not, (ii) updating the information about products and offers of the shop agents requires specialized human resources and time, since they are not currently integrated with their software packages, (iii) they believe that the CBR agent may favour big shop stores with many offers and (iv) some of them argue that the CBP may confuse some users. Nevertheless most shop managers believe that the proposed system has more advantages than disadvantages and that the system has helped their businesses attract more customers and, in general, to sell more. They tend to argue that the CBP should incorporate a method that guarantees impartiality. This is our next challenge.

Acknowledgements

This work has been supported by the Spanish Ministry of Science and Technology Project TIN2006-14630-C03-03 and the JCyL Project SA071A08.

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