A guiding agent: smart dynamic technology for solving distributed problems

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ABSTRACT: Mobile technology is everywhere nowadays in the developed world. This technology is mature enough to support intelligent applications and smart devices. Over the last few years we have developed a number of applications for PDAs and Mobile phones. This abstract outlines an information system that incorporate a recommender agent that helps the users of a shopping centre to identify offers, to find people or to define a plan which in the shopping centre for a day. The multiagent architecture incorporates a smart deliberative agent that take decisions with the help of case-based planners. The system that uses past experiences to recommend future actions has been tested successfully.

KEYWORDS: nature inspired multiagent system, case based reasoning, planning and mobile devices

1. INTRODUCTION

Multiagent systems have become increasingly relevant for developing applications in dynamic, flexible environments, such as the internet, personalized user interfaces, oceanography, control systems, recommendation systems or robotic. Agents are bio-inspired systems that can be characterized through their capacities such as autonomy, reactivity, pro-activity, social abilities, reasoning, learning and mobility. These capacities can be modelled in various ways, using different methodologies. One of the possibilities is to use Case Based Reasoning (CBR). We have developed a distributed architecture whose principal characteristic is the use of CBP-BDI recommender agents. These deliberative bio-inspired agents incorporate a reasoning Case Based Planning (CBP) engine, a variant of CBR systems which allows the agents to learn from initial knowledge, interact autonomously with the environment and users, and allows it to adapt itself to environmental changes by means of discovering knowledge. The aim of this work is to obtain an architecture that allows the development of nature-inspired multi-objective agents, which incorporate CBP reasoning mechanisms and allow recommending plans in dynamic environments. To achieve this aim a specific problem, the possibilities of recommendation systems in the management of some aspects of a shopping mall, has been studied and an architecture that makes it possible to construct agents capable of making recommendations (such as promotions and orders suggestions for shop managers, and promotions, products, leisure places, restaurants suggestions for the clients, as well as visit dynamic plans for the users) has been developed.

Within this framework, the multiagent system technology developed in this project will make it possible to provide better services to the shopping mall clients. Our aim is to develop an open nature-inspired system, capable of incorporating agents that can provide useful recommendations and services to the clients not only in a shopping centre, but also in any other environment such as the labor market, educational system, medical care, etc. The system provides mechanisms for easy data consulting. Users are able to gain access to shopping and sales and leasing time information (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, it provides a tool for advertising personalized offers (a commercial manager will be able to make his offers available to the shopping mall clients), and a communication system between directorship, commercial managers or shopping mall clients.

The Mall has become one of the most prevalent alternative to traditional shopping. A shopping mall 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 developed are all in keeping with their surroundings. Every shopping mall has a permanent image and a certain common management. A shopping mall needs to be managed and, the management includes solving incidents or problems in a dynamic environment. As such, a shopping mall can be seen as a large dynamic problem, in which the management required depends on the variability of the products, clients, opinions, etc. Section 2 outlines de multiagent system developed and section 3 present some results and conclusions.

2 NATURE INSPIRED MULTIAGENT SYSTEM

This section introduces a multiagent system which has been inspired by the shopping centre business working flow and with the intention of providing the users of a dynamic recommending tool for assisting them when shopping or enjoying the leisure activities that the mall offers. Recommender systems have been widely studied and different artificial intelligence techniques have been applied. The application of agents and multiagent systems facilitates taking advantage of the agent capabilities, such as mobility, pro-activity or social abilities, as well as the possibility of solving problems in a distributed way. There are many architectures for constructing deliberative agents and many of them are based on the BDI model [7]. In the BDI model, the internal structure of an agent and its capacity to choose, is based on mental aptitudes. The method proposed in [13] facilitates the incorporation of CBR systems as a deliberative mechanism within BDI agents, allowing them to learn and adapt themselves, lending them a greater level of autonomy than pure BDI architecture [7]. The architecture proposed in this paper incorporates "lightweight" agents that can live in mobile devices, such as phones, PDAs, etc. [6, 9], so they support wireless communication (Wi-Fi, Bluetooth) which facilitates the portability to a wide range of devices [9].These agents make it possible for a client to interact with the MAS in a very simple way, downloading and installing a personal agent in his mobile phone or PDA. The system also incorporates one agent for each shop in the shopping mall. These agents can calculate the optimal promotions and services at a given moment. The core of the MAS is a Recommender agent that generates plans (routes) in response to a client's request, looking for the best shopping or leisure time alternatives. The agent has to take into account the client profile, the maximum amount of money that the client wants to spend and the time available. The route generation must be independent of the mall management, in the sense that it is not appropriate to use the same knowledge base (or all the knowledge) that the directorship controls. Only the knowledge corresponding to the offers and promotions at the moment of the recommendation should be used. Otherwise the client will be directed to the objectives of the shopping mall management. As can be seen in Figure 1 there are three types of agents: Recommender agent, Shop agents situated in each shop and User agents situated in the client mobile devices. Each User agent communicates to nearest shops and can communicate to the Recommender agent. Shop agents communicate to Recommender agent and User agents.

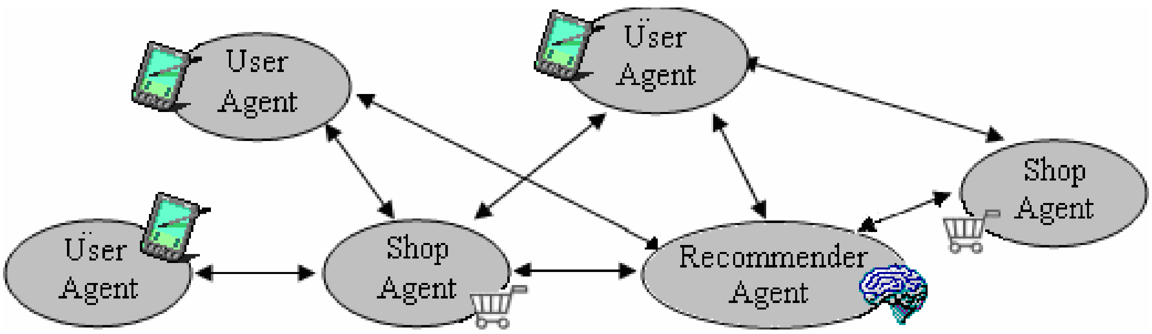

Figure 1: MAS: Recommender agent, Shop agents and User agents.

The option chosen to define an appropriate analysis and design methodology for the problem to be resolved is one that combines Gaia [17] and AUML [2], in an attempt to take advantage of both [4]. Studying the requirements of the problem, three agent types have been chosen: The User Agent plays three roles, the Communicator role manages all the communications of a client; the Finder role looks for near devices and the Profile Manager role obtains a client profile. The Shop agent plays two roles, the Store Operator is in charge of manage the store (data base operations on stored products), moreover monitors the products shortage, in order to prevent desupply; and the Promotions Manager role controls the retails in each shop, as well as the promotions that every shop offers to its clients. Finally the Recommender agent plays four roles, the Clients Manager role deals with the client profiles management and controls the connected clients at a given moment; the Analyst role carries out periodic evaluations on retails, promotions and surveys data trying to provide a good quality service; the Incidents Manager role manages incidents, such as sending advices, or solving a wide range of problems; the Planner role is the most important role in our system. The Planner creates a route printing the most suitable shops, promotions or events to the client profile and available resources at one particular moment.

As far as interaction is concerned, the dependences and relationships between roles are described. Each interaction in which roles are involved requires protocols. In the SMA presented in this work the next protocols have been considered: RequestPromotionsData when the Recommender or a User agents ask about promotions data and a Shop agent sends the response, SolveConsult when the User agent makes query to a Shop agent and receives the response, AlertShortage is used for a Shop agent to inform the Recommender agent about a product shortage, InformOrderSupplier is used for a Shop agent to inform the Recommender agent about an order carrying out, InformProductsState when a Shop agent inform the Recommender agent about its products state, InformPromotionsState is used for a shop to send periodic information about promotions to the Recommender agent, SolveIncident is used for a Shop or User agent to indicate to the Recommender agent that an incident has happened and receive the response, SolveRecommendation when the User agent asks the Recommender agent about a plan and receives the response, finally Notify is used for the Recommender agent to send notices to User or Shop agents. For example, when a client asks for a new route, the user agent uses the SolveRecommendation protocol. The Recommender agent sends the recommendation and keeps receiving the results of each of the subgoals proposed. If necessary a replannig will be maid.

The case structure for a client profile shown in Table 1, is defined using CBML [11]. The structure is defined through feature labels. The items, attributes and their values and weights are labelled. In our problem three main attributes have been considered: personal data, retail/leisure time data and interests data. The retail/leisure attribute is composed of business type, business identification, product type, product identification, price, units and date attributes. The interests data attribute is composed of retail time and frequency, monthly expense both business and product, extracted from retail data, and the explicit attributes obtained from questionnaires. Each attribute has a value, noun or adjective, and an assigned weight. Since the number and type of business is high, the businesses were classified into leisure time (cinema and recreational), catering (restaurant, fast food and pizza) and public retail (clothes, shoes, computing, supermarket and optical). The products have been also classified, for example the films are divided in action, comedy, terror and drama.

Case Field	**Measurement**
PERSONALDATA	Client Personal Data (ClientData)
RETAILDATA	Retails (RetailsData)
INTEREST	User interests (UserInterest)

Table 1: User profile case fields.

The agent controlling recommendations is a CBP-BDI agent. This agent deals with multiple objectives derived from the tasks of coordinating all the shops, the client management and planning and optimization of routes. The routes and promotions proposed to a client consider the client profile and their resources (money and time) at the moment of the route request. It maintains a mall map and an estimation of the time employed walking by a client. The Recommender agent is able to generate routes, analyze retail and promotion data, manage incidents and manage clients at the same time. To solve the problem of route recommendation the Recommender agent uses an innovative planning mechanism: the Case Based Planning. CBP provides the agent with the capabilities of learning and adaptation to the dynamic environment. Moreover, the Recommender is able to apply a dynamic replanning technique, the MRPI (Most RePlan-able Intention), which allows the agent to change a plan at execution time when an incident happens [13]. The Recommender agent implements the reasoning cycle of the CBP system by means of three capabilities: Update, KBase and VCBP (Variational CBP) capabilities. The Update capability implements the retrieve (neural networks based on the application of Topology Preserving Ensembles methods [18] and using PCA Ensembles methods [19] to identify and discard outliers) where the past experiences are retrieved and retain stages, while the KBase capability implements the reuse stage (neural network based on pondered weight technique [12]) and the revise stage VCBP capability, where the user opinion is evaluated. The VCBP capability also controls the dynamic replanning task.

The platform chosen for implementation was Jadex [16], a JADE add-on. The Jadex agents deal with the concepts of beliefs, goals and plans. A belief can be any type of java object and is stored in the beliefs base. A goal represents a motivation that has influence in the agent behaviour. A plan is a java procedure and is executed in order to achieve goals. Moreover all the JADE communication advantages are provided (even the LEAP add-on).

2.1 NATURE INSPIRED RECOMMENDER AGENT

The purpose of case-based reasoning (CBR) is to solve new problems by adapting solutions that have been used to solve similar problems in the past [1]. The CBP is a variation of the CBR which is based on the plans generation from cases. The deliberative agents, proposed in the framework of this investigation, use this concept to gain autonomy and improve their recommending capabilities. The relationship between CBP systems and BDI agents can be established by implementing cases as beliefs, intentions and desires which lead to the resolution of the problem. As described in [13], in a CBP-BDI agent, each state is considered as a belief; the objective to be reached may also be a belief.

The intentions are plans of actions that the agent has to carry out in order to achieve its objectives [7], so an intention is an ordered set of actions; each change from state to state is made after carrying out an action (the agent remembers the action carried out in the past, when it was in a specified state, and the subsequent result). A desire will be any of the final states reached in the past (if the agent has to deal with a situation, which is similar to a past one, it will try to achieve a similar result to that).

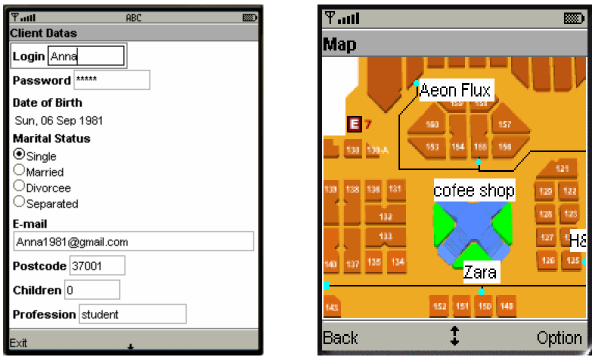

Figure 2: Screen shots for user profile and inform route.

Figure 2 shows a simple example: The mall main entrance has been taken as the origin of coordinates. Different positions (user, shops, leisure areas) are represented by means of coordinates in a plane. Bearing in mind the user's interests, places to visit are selected, then, the routes that include these points are traced, and the route most easily replanned in the event of interruption of the initial plans is proposed; this is done bearing in mind the time available, the shopping time and leisure activities schedule. The chosen route is surrounded by the greatest density of alternative routes, thereby ensuring the success of the proposed plan.

3. RESULTS AND CONCLUSIONS

The system was tested at the Tormes Shopping Mall in the city of Salamanca during 2005 and 2006. The multiagent system has been tuned and updated, and although the system is not fully operational and the aim of the project is to construct a research prototype and not a commercial tool, the initial results have been very successful from the technical and scientific point of view. The construction of the distributed system has been relatively easy, using previously developed CBR-BDI libraries [4, 9, 10]. AUML [2] and Gaia [17] provide an adequate framework for the analysis and design. The formalism defined in [13] facilitates the straight mapping between the agent definition and the CBR construction. Figure 2 presents two screen shots of the User agent. It shows the form for introducing personal data and the route generated for a client trying to buy clothes and see an action movie. The security problem was tackled by using the FIPA https protocol and a private network to connect Shop agents with the Recommender agent.

The fundamental concept when working with a CBR system is the concept of case, so it is necessary to establish a case definition. A case managed by the Recommender agent, is composed of the attributes described in Table 2. Cases can be manipulated manually or automatically by the agent (during its revision stage, when the user evaluation obtained through questionnaires is given to the system). The agent plans can be generated using different strategies since the agent integrates different algorithms. The metrics mechanisms proposed in [8] facilitates the retrieval stage, but the products base and the promotions base must be defined and sorted including metrics that facilitate searches for similitude, for example the time expected for buying each product. The client profile is obtained from retail data and periodic questionnaires. The system has been tested from October 2005 to February 2006 obtaining promising results. The e-commerce techniques [3] have facilitated the client motivation since a user can easily find the products he/she is interested in, spend his leisure time in a more efficient way and make contact with other clients with whom he/she can share hobbies or opinions. So the degree of client satisfaction has been improved as observed in the surveys.

Case Field	Measurement
CLIENT	Client profile (ClientProfile)
MONEY	Money to spend (Money)
TIME	Time (Time)
INIT	User initial location (Location)
PREF	User preferences (Preference)
SOLUTION	Solution and efficiency (Solution)

Table 2: Recommendation case fields.

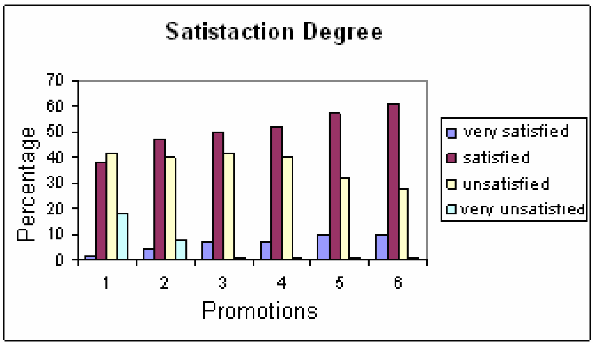

Figure 3: Clients satisfaction degree.

The first autonomous prototype started to work in October 2005 with a test set of 30 users, with up to 75 that gave their evaluations in the final promotions and a final number of different users of 157 with 328 evaluations, at least 50% of users giving an evaluation more than once. The users were selected among clients with a terminal supporting the application (Wi-Fi, Bluetooth). The results obtained show that the greater part of users, near 67%, were people aged between 16 and 30 years old, while the percentage of people older than 40 is less than 3%. However there were no significative differences with respect to client sex. Figure 3 shows the clients degree of satisfaction during the 6 promotions studied. The tendency indicates that as promotions were launched, the client satisfaction degree grew. As expected, at the beginning, the system obtains a low evaluation, basically due to the causes derived from the system start up; but as more cases were incorporated, the promoted products were closer to the user profile. Users have noticed the utility of the dynamic replanning, since it is quite usual for them to change opinions/objetives in the middle of a plan. The MRPI tool is greatly appreciated and optimizes the time spent in the shopping mall.

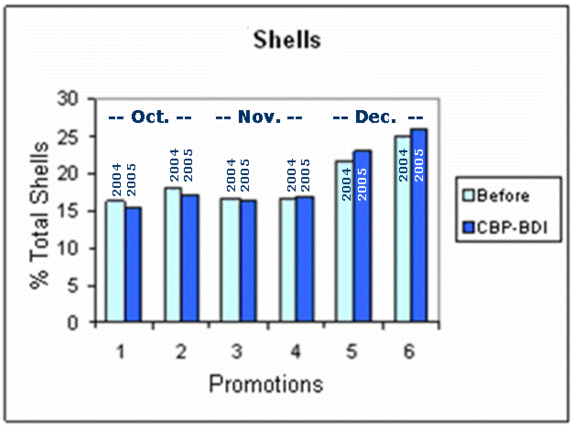

Figure 4: Retail promotional products and retail total products.

The percentage of sales of promotional products, shown in Figure 4, has slightly grown over the total. The basic reason is that clients have instant information about the products they are interested in, and the information is very accurate and customized. Figure 4 presents the percentage of the sales of 6 different products during a predefined period of time before the system was developed and after the system was in use. It can be seen that the system is learning with time and in the third promotion it starts to increment the sales. As the system obtained more information about client profiles, products and habits, the system knowledge increases and the recommender agent provides more optimal plans. The clients also needed time to get used to the system.

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