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A Multi-Agent Pervasive Computing Architecture For Geographically Dispersed Care Environments

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Abstract

In this paper we describe a novel multi-agent architecture consisting of two remotely (geographically dispersed) associated intelligent environments aimed at establishing an agent-based care system. We will introduce the careAgents joint project, in which a collection of heterogeneous building and robotic embedded agents intelligently learns and cooperates to care for human occupants. We will show how our agent architecture facilitates inter-agent communication and how this system can be used to detect abnormalities from normal..

Keywords: Intelligent Inhabited Environments, Multi-embedded agent systems, Fuzzy Control, Healthcare, Abnormality.

1 Introduction

It is anticipated that the world's population – especially in Europe, North America, and Japan – will grow markedly older in the next 50 years. Maintaining and enhancing the quality of life of both older and disabled people in their homes involves facilitating independent living, safety, promoting greater social integration, increasing the availability and quality of care and technical assistance [7]. Here, technology has a fundamental role to play.

An Intelligent Inhabited Environment (IIE) is a region of the domestic world that is extensively equipped with computer-based artefacts. It can be regarded as an intranet in our homes, where the artefacts are networked and collaborate together to assist the occupants during their everyday activities and enhance their living conditions. For instance it is possible to automate home services (e.g. lighting, heating etc.), install work tools (e.g. service robots etc.), or enhance peoples safety through security and emergency measures [1][3]. Sometimes these artefacts appear in form of sensors or actuators that are electrical in nature, but also non-electrical everyday objects such as furniture, clothes, etc, augmented with microprocessors, will soon find their places within the IIE. In the future, the number of artefacts forming the IIE will be immense and their functionality will be diverse but they will share the following important characteristics: *Each of the artefacts connected to the home intranet can be accesses, monitored and controlled through the internet, facilitating tele-monitoring and -controlling services and more importantly, they will contain an embedded-agent*. The agent will provide an intelligent interface to enable the artefacts to learn from its occupant and environment and act autonomously on behalf of them. In other words, it can be regarded as the inclusion of some of the complex-decision making processes (reasoning, planning and learning), which is typical to a person, within the artefacts [4].

In this paper we describe a novel multi-agent architecture consisting two remotely (geographically dispersed) associated intelligent environments aimed at establishing an agent-based care. In Section (2) we introduce the careAgents project and intelligent rooms in Essex and KAIST. In Section (3) we describe the building agents and their learning systems. In Section(4) we present the abnormality detection system and we report on our experimental results.

2 The careAgents project

The general aim of this joint-project was to produce a soft-computing architecture based on a combination of distributed artificial intelligence (in form of networked building control agents and robotics) applied to the domain of intelligent inhabited environments to demonstrate how adaptive intelligent agents can be used to control the environment of a building to improve the quality of life of the occupants, especially elderly and disabled people.

The project's consortium consists of the following two institutions, University of Essex, UK and KAIST, Korea. The UK team addressed the development of the fixed intelligent Building Agents (BA) and the communication aspects between BA and multiple mobile agents. The KAIST team aimed to integrate mobile robot agents facilitating human-friendly and effective man-machine interaction systems for the human being and robots to coexist and cooperate.

2.1 The careAgents system architecture

The careAgents system architecture (Figure 1) composes of two geographically dispersed intelligent environments. Both, the Building agent (BA) at the University of Essex and the Mobile Agent Server (MA) at KAIST are interconnected and use a high-level communication protocol to exchange information and commands.

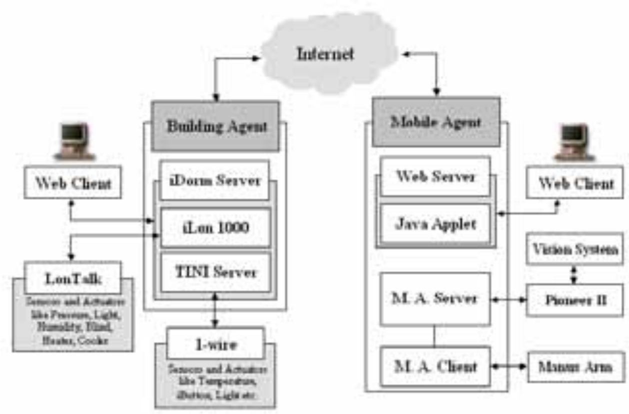

Figure 1: The careAgents system architecture

2.1.1 The Intelligent Dormitory

The BA is part of the *Intelligent Dormitory (iDorm)* located at the University of Essex. It is based on a 68000 Motorola processor with 4 Mbytes of RAM and an Ethernet network connection. It runs the VxWorks Real Time Operating System (RTOS).

The intelligent Dormitory (iDorm) [6] is a multi-use space (i.e. contains areas with different activities such as sleeping, working, entertaining etc.) and can be compared in function to a room for elderly or disabled people. Because this room is of an experimental nature we equipped it with a liberal placement of sensors (temperature sensors, presence detectors, system monitors etc.) and effectors (e.g. lamps, blinds, mobile robot etc.), which the occupant can configure and use. Superficially, the room looks like any other but above the ceiling and behind the walls hides a multitude of networks and networked devices.

The iDorm is based around three networks, LonTalk, TINI 1-wire and IP. This provides a diverse infrastructure and allows the development of network independent solutions. To create a standard interface to the iDorm we have an iDorm gateway server. This exchanges XML formatted queries with the entire principal computing components, which overcomes many of the practical problems of mixing networks. The communication architecture is being extended to allow devices to be “Plug n Play” (enabling discovery and configuration).

2.1.2 The Intelligent Sweet Room

The main control unit of the *intelligent sweet room* [8] at KAIST is the mobile robot server (MA). The MA uses the principle of client-server architecture, where many mobile agents (in form of robots) can connect to the MA. The main mobile agents used in this project consist of a MANUS arm and a Pioneer 2 DX robot. The MA server transmits and shares information between each robot to accomplish cooperative tasks. For instance, the MANUS arm robot is attached to a bed to provide bed-bounded patients fundamental services such as handing objects, delivered by the Pioneer 2 robot, or pulling a quilt over etc. The vision system is used to supply the online position information of the objects and the robots in real time and provide a human-oriented interface to operate home appliances by pointing the hand at the equipments and by gesturing with predefined shape of hands.

2.1.3 The Common Information Protocol

The agents available to the BA and MA can be directly monitored and controlled through the Internet by using either the web-based GUI or a 3D virtual representation of the rooms using VRML, which have been implemented for both rooms. These interfaces are clearly of great use if we consider the following tele-care scenario: A Korean student studying in Essex can still care for his disabled mother by remotely controlling the robots to deliver medicine etc. at certain times. However instead of relying on the student himself these actions can be learnt directly by the BA and passed to the robots in Korea automatically. Hence, the BA and the MA have to be able to communicate with each other in a reliable way to exchange information and commands. For this reason, we have implemented a compact and flexible high-level information protocol..

The Common Information Protocol (CIP) comprises of a hierarchical and tagged structure defined by three main primitives: *Send*, *Receive* and *Notify*. The *Send* message is used to send to the remote agent, the *Request* message to receive sensory state and information and the *Notify* message to receive either feedback on the completion of a task or detected abnormalities situations.

The message consists of two main tags. Tag 1 specifies the domain where the message should be sent (here: MANUS Arm, Pioneer Robot, and Vision System at KAIST, and the BA at Essex). Tag 2 contains predefined tasks and/or control details of each agent. For example, one of the MANUS Arm tasks can be to carry a newspaper to the occupant that the Pioneer 2 robot delivers or to switch off the television and pulling the quilt over the occupant when it is bedtime.

More information on a full description of the CIP can be found at [2].

3 The Intelligent Building Agent

Building based agents learning is focussed around the actions of people. Buildings are, largely, occupied by people who for a variety of reasons (e.g. time, interest, skills, etc.) would not wish, or be able to cope with much interaction with the building system. Thus, in general, learning should as far as possible, be non-intrusive and transparent to the occupants [5]. Besides this, the user behavioural learning process needs to autonomously particularize its service to an individual since every person would define a “comfortable environment” different.

The fuzzy Incremental Synchronous Learning (ISL) forms the learning and control engine for the BA. The ISL architecture is shown in Figure 2. The ISL agent is an augmented hierarchical behaviour-based architecture, which uses a set of parallel Fuzzy Logic Controllers (FLC), each forming a behaviour. The behaviours can be fixed (safety, emergency and economy) or dynamic and adaptable such as comfort behaviours (i.e. behaviours adapted according to the occupant’s preferences). Each behaviour is implemented as a FLC and uses a singleton fuzzifier, triangular membership functions, product inference, max-product composition and height defuzzification. The rule base within the dynamic behaviours and the co-ordination parameters at the higher level can be learnt and modified [5]. The ISL system aims to provide life-long learning and adapts by adding and modifying or deleting rules. It is also memory based in that it has a memory enabling the system to use its previous experiences (Experience Bank) to narrow down the search space and speed up learning. A more exhaustive description of the ISL can be found at [4][5].

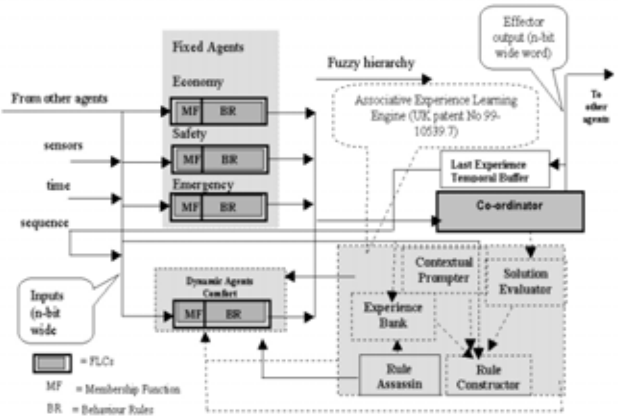

Figure 2: The Incremental Synchronous Learning architecture

4 Experimental Results

The first section describes the results of the experiments conducted with different users staying in the iDorm for different lengths of time. And then we report on initial experimentations on user abnormality detection after learning the “normal” behaviour of the occupant.

4.1 User behaviour Learning

We have conducted a number of experiments with different users staying in the iDorm for different lengths of time. Each user occupied the iDorm working and living for five and a half days (132 hours) during which time the iDorm was under the control of the building agent using the ISL architecture.

The input vector for the ISL comprises sensors and actuators available within the iDorm and Sweet Room. View list of all devices available within both, iDorm and Sweet Room can be found in [5] and [8] respectively.

During the experimentation period, the user used a wireless iPAQ portable agent (using a web-GUI to the iDorm gateway server) to monitor and control the iDorm environment whenever they were not unsatisfied with the current state of the environment. Upon every control change, the BA received the request, generated a new rule or adjusted a previously learnt rule and allowed the action through. The Agent’s success can be measured by monitoring how well it matches the environment to the user’s demands. If it does well, the user will cause less rule generation over time. If it does badly, the user cause more rule generation over time [4].

We have summarized the results of the experiments shown in the graph in Figure 3. The data making up the graph was generated by a monitoring program, which stored the number of rules learnt by the ISL along with a time stamp. It took a reading every five minutes for the duration of the experiment.

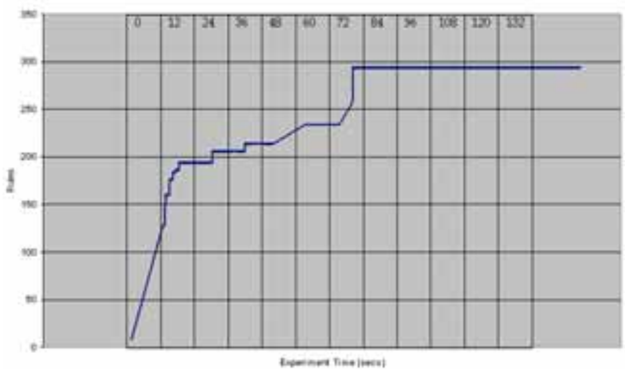

Figure 3: The ISL Rule Learning Rate

In the first section from *0-24 hours* where it starts from an initial rule base is empty, it can be seen that a very large number of rules are learnt in a comparatively short amount of time. These results are consistent with the BA learning and making incorrect decisions for the user in the initial stage. However, as the end of the period is reached it can be seen that the learning rate of the Agent (Rules/Time) reduces drastically. This is also consistent with the Agent’s reactions requiring less correction by the user and is therefore consistent with the Agent making useful decisions about the environment state based on the user’s requirements. The second section of the graph from *60-72 hours* shows a sharp increase in the learning rate of the Agent. This is explained by the intentionally novel activity of the user at the time. The third section 72-132 hours shows that in the last two days the agent had not generated any new rules, this reflects the control period where the user was absent from the room thus showing that the Agent won’t learn rules from anything other than the user. The agent has learnt the 280 rules needed to capture the behaviour of this user over the 132 hours experiment. We can conclude that the Agent managed to pick out the pertinent behaviour of the user over time. Figure 3 shows that the Agent had to learn less new rules about the user as the experiment progressed; the latter was one of our criteria for measuring the Agent's success. Using the evidence of the continual reduction in the learning rate, we can conclude that the Agent managed to pick out the pertinent behaviour of the user over time.

4.2 User abnormality detection

In this section we describe ongoing implementations on detecting user abnormalities. Abnormality in this context describes any unexpected situations that occur on the behaviour of an inhabitant. This function is of great importance for applications such as tele-care and tele-monitor. An abnormal situation can be in the form of a change in the behaviour or a bad medical condition of the occupant. Of course it is very complex to detect medical condition abnormalities without using sensors that provide information about e.g. heart beat, blood pressure etc. but in this project we consider abnormalities purely caused by behavioural changes. However it should be noted the user's behavioural change could also result on different aspects, such as external weather conditions, mood, etc. but here we assume that the change occurs unintentional. A change in the behaviour can be measured by comparing the existing regular behaviour (learnt by the ISL) with the current behaviour that invokes the system to adapt to a new behavioural change. We have added another module into our system that monitors the ISL learning process and starts monitoring behavioural changes after the rule stagnation within ISL takes place. In case of a rule adaptation (need of a change of an existing rule), the BA in Essex signals, using the CIP, the MA in Korea automatically the abnormality occurrence and sets the control phase of the and iDorm to standby. At this time, the user of the sweet room can control the devices within the iDorm by e.g. switching on the alarm etc. The standby modus of the ISL resolves after the occupant in the iDorm response to the alarm.

5 Conclusions

In this paper we have reported on the results of a two years joint-project, called careAgents. We have presented a novel application where we associate two geographically dispersed intelligent environments that integrate a large number of building and mobile robot agents used to assist elderly and disabled people. We described a new information protocol used for the high-level communication of both, the BA and MA. We evaluated the ISL, a technique used in the iDorm for online user behavior learning and adaptation and demonstrated the capability of the method to provide learning in both non-intrusive life-long learning and particularizing to the user desired action rather than generalizing for a group of users. We also briefly described the initial experiments on detecting behaviour abnormalities. We are pleased to mention that this collaboration work has attracted a sponsorship of LG Digital Appliances Labs. to support our work in the abnormality detection.

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Service Oriented Architecture (SOA) and agent frameworks renders tools for developing distributed and multi agent systems which can be used for the administration of cloud computing environments which supports the above characteristics. This paper presents a SOQM (Service Oriented QoS Assured and Multi Agent Cloud Computing) architecture which supports QoS assured cloud service provision and request. Biomedical and geospatial data on cloud can be analyzed through SOQM and has allowed the efficient management of the allocation of resources to the different system agents. A multi-agent system (MAS or "self-organized system") is a computerized system composed of multiple interacting intelligent agents. Multi-agent systems can solve problems that are difficult or impossible for an individual agent or a monolithic system to solve. Intelligence may include methodic, functional, procedural approaches, algorithmic search or reinforcement learning.