Buildings as Intelligent Autonomous Systems: A Model for Integrating Personal and Building Agents

Vic Callaghan, Graham Clarke, Anthony Pounds-Cornish, Sue Sharples
University of Essex, Wivenhoe Park, Colchester, CO4 3SQ

1.0 Abstract

We describe a new application domain for intelligent autonomous systems – intelligent buildings. We show how a building can be regarded as a machine and how behaviour-based principles first proposed by Brooks for mobile-robot control can be applied to enable autonomous intelligent-building agents to adapt their control to suit the occupants. We present a novel approach to the implementation of Intelligent Buildings based on a multi embedded-agent architecture comprising a low-level behaviour based reactive layer together with a high- level deliberative layer based on evidential learning (a case-like learning mechanism). We also present a hierarchical agent architecture in which mobile agents (residing on body wearable devices) and fixed agents (residing in buildings) can be integrated, opening new commercial and personal possibilities. We discuss how this architecture is being implemented, using a combination of IP and Lonworks networking technology together with a Java programming environment. We consider future directions of this work, in particular how it might play a key role in intelligent interactive environments enabled by emerging technologies such as mobile phones and embedded-internet devices.

2.0 Buildings as Machines

Le Corbusier famously remarked that, "*A house is a machine for living in*". Modern buildings have strong physical similarities to machines in that they contain a myriad of mechanical, electrical, electronic, computing and communications devices. As building services become increasingly sophisticated they contain ever more sensors, effectors, computer based devices and networks. From a computer science viewpoint an Intelligent-Building (IB) can be described as one that "*utilises computer technology to autonomously govern the building environment so as to optimise user comfort, energy-consumption, safety and work efficiency*" [Sharples 99]. In intelligent-buildings computers together with AI techniques are used to orchestrate the operation of the building services (e.g. light, heat etc) to provide a level of control that we normally associate with human intelligence, such as reasoning, learning, or adaptation. Machines such as robots are able to do this through the inclusion of behaviour-based artificial intelligence (AI). There are enough similarities between machines (particularly mobile robots), and buildings to justify such techniques being applied to building control systems to make them behave more intelligently. Both deal with a highly dynamic, unpredictable world. As has been shown by other researchers [Brooks 91] this situation makes it almost impossible to model the world, or to plan in advance for every possible occurrence which makes traditional model-based control techniques difficult to apply. Both practical and market-driven factors require building control systems to have a small computational footprint. Hence in intelligent-buildings, centralised, traditional AI, with bulky planners and reasoning systems, becomes less attractive. Incorporating sophisticated control techniques into intelligent buildings presents a considerable design challenge. From the considerations above we suggest a modification to Le Corbusier's slogan so that in the future "*A building is a robot we live inside*".

3.0 The Challenge of Intelligent-Building Control

A classical control application in a building might be a controller varying heat output in relation to a sensed temperature. Such a single parameter control system would be well suited to traditional systems, such as thermostats. Using an agent to replace a thermostat would be clearly an overkill and so the value of an IB agent must lie in other aspects. In brief, the critical differences lie in (a) the agent's ability to learn and predict a person's needs and automatically adjust the system to meet them; and (b) the agent's ability to do such learning and prediction based on a wide set of parameters. This latter aspect of an IB agent is particularly challenging. It needs the ability to modify effectors for environmental variables like heat and light etc on the basis of a *complex multi dimensional input vector* that can't be specified in advance. For example, something happening to one system (e.g. reducing light level) may cause a person to change behaviour (e.g. sit down) which in turn may result in them effecting another systems (e.g. needing more heat); and people are essentially non-deterministic. Thus, an agent that only looks at heat levels is unable to take these wider issues into account. A large input vector provides the least constraints on the agent developing a good solution.

A number of research groups are exploring different control solutions to this multi-dimensional input vector IB problem [Brooks 97, Coen 97, Davidsson 98, Mozer 98], although we believe ours is unique in seeking to apply behaviour based techniques and particularised learning (see later) in the form of embedded-agents to intelligent-buildings.

3.1 Building Based Agents

People's activity is usually *room-based* so both the physical and logical unit of a building is a room. We have chosen to distribute control to room-level, with each room containing sensors and output devices connected to an *embedded-agent*, which is then responsible for the local control of that room. In this way the views of the building and control system architect are beneficially married. All embedded-agents are connected via a network, enabling collaboration or sharing of information to take place where appropriate.

3.2 Body Based Agents (Personal Agents)

A key feature that characterises all our work is that intelligent habitat technology needs to be centred on the individual. The agents should tailor their behaviour base to an individual wherever possible rather than generalise across a group of individuals. We have proposed that an elegant solution to producing such a system would be to embed agents and sensors into wearable devices (e.g. mobile phones, watches, smart-clothing etc). Here agents and sensors reside in both body-wearable artefacts and buildings. The agents will share common functionality and be enabled to interact and work together.

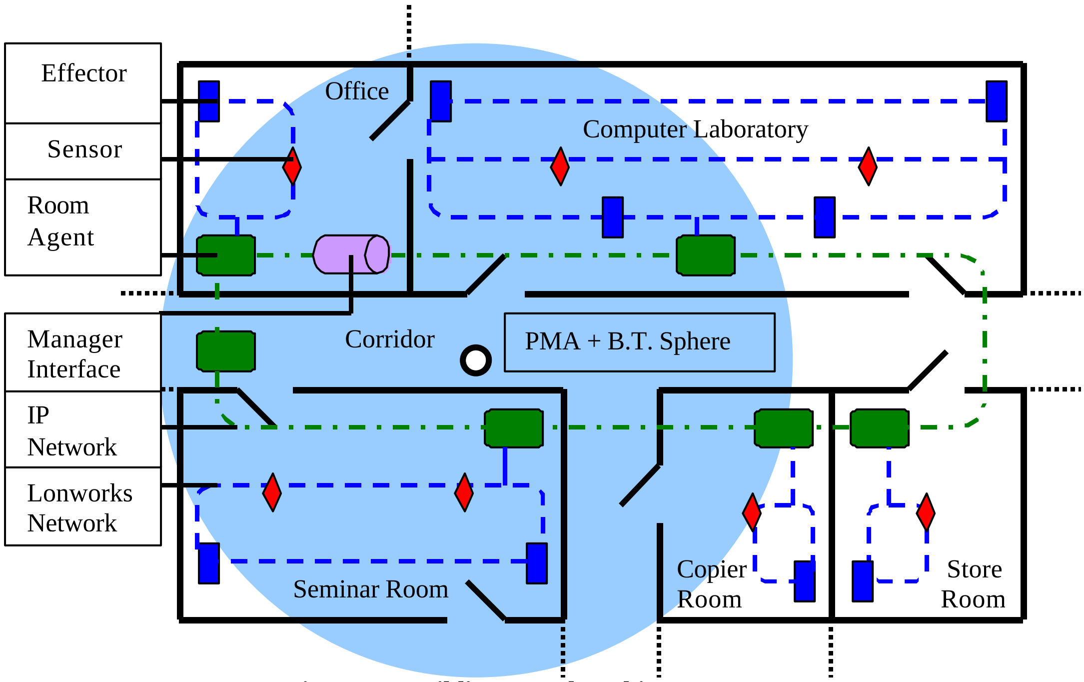

Figure 1 – Building-Based Architecture

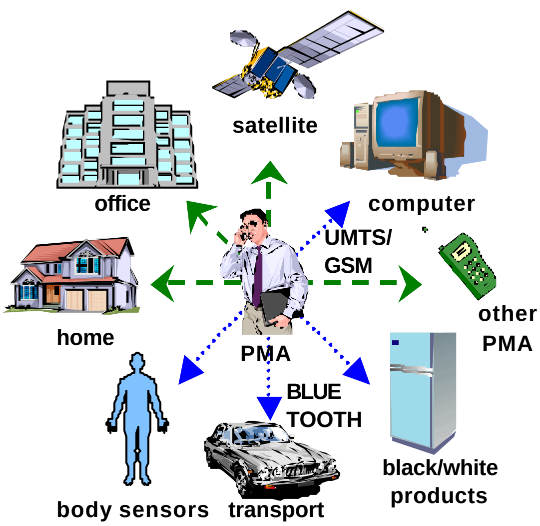

Figure 2 – Personal Agent Architecture

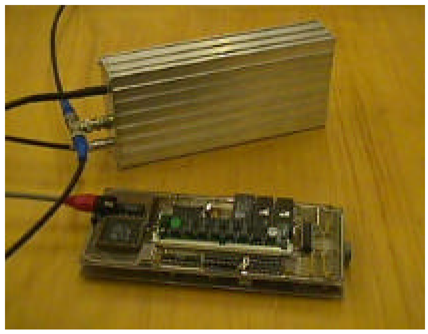

Photo 1 – SX Prototype Embedded-Agent

4.0 The Embedded-Agents

An embedded-agent is simply an autonomous intelligent control entity built into a device. In our case the embedded agent is constructed from a low-level *behaviour-based* reactive layer, which is managed by a higher level, *evidential-learning* based deliberative layer.

4.1 The Reactive Layer

It is common practice in behaviour based systems for the reactive layer to consist of a *set of behaviours* operating in parallel, each of which decides when to become active, based on the current internal and/or environmental conditions. Behaviours can be decomposed into subsets that will be common to all agents within a given domain. Our behaviour decomposition consists of the following set of room based functions: a *safety behaviour*; an *emergency behaviour; economy behaviour* and a *comfort behaviour*. These behaviours, resident inside the agent, take their input from a variety of sensors in the room, and adjust device outputs according to pre-determined, but settable, levels. However, our architecture is not limited to pre-defined behaviours but has the ability to *learn* new behaviours dynamically, based on actions taken by occupants within the room.

4.2 Deliberative Layer

An essential need of an intelligent building is the ability to *particularise* its control strategy to that required by the individual occupant(s). Occupants have different personal needs, which means any mechanism that seeks to find generalised solutions such as regular neural or fuzzy systems is inappropriate. Our solution is derived from CASE based learning, which is a branch of traditional AI work [Aha 91]. The underlying learning mechanism is straightforward; the system takes a ‘snapshot’ of the room parameters at the time an occupant makes an adjustment to the state of the room. By gathering information from its sensors over a period of time, an agent can record how a particular person reacts to differing circumstances, and thus anticipate the behaviour itself and act on behalf of the person (or identify changing behaviour). The system creates new *instances* dynamically over time, enabling the system to adapt to new situations and occupants. To limit the population of instances we provide functions to perform nearness matching and learning inertia. In addition, our system eliminates behaviours that are not regularly activated. We have coined the term “*evidential learning*” to describe our mechanism which is based on gathering evidence dynamically from the environment.

4.3 Behaviour Arbitration

As is usual in behaviour based systems, some form of arbitration is needed to mediate between competing behaviours. We use a fixed priority structure; 1st safety, 2nd emergency, 3rd efficiency, 4th comfort (i.e. learned dynamic behaviours). A number of differing arbitration mechanisms are used, for example, vector summation is used to combine dynamic behaviours when there is more than one person in the room. Fixed constraints are applied to guarantee the operation and priority of the safety behaviour. The resulting interplay between fixed and dynamic behaviours produces an over-all control that tailors itself to individual preferences without compromising the fundamental issues of safety and efficiency.

5.0 Implementation

5.1 The Essex Hierarchical Hybrid Approach

IP has emerged as the most widely used computer network. Whilst the use of IP is widespread it has a number of drawbacks relating to building service control. These disadvantages have led to the development of more lightweight, cheaper building services networks. The majority of network-enabled building service devices are only available for standards such as Lonworks and X10 rather than IP. However, MIS and other systems need to interface to building service systems and have traditionally been based on IP. As a consequence there is a need for any practical architecture to support all these standards. We have accomplished this by utilising a two-tier hybrid approach that uses IP for inter-agent communications and Lonworks for room level control. The architecture is not tied to any particular standard and can work with whichever networks (or mobile phone standards) that eventually become dominant. From Figure 1, it can be seen that each agent in our systems is a node on *two* networks - both a local device network (such as a typical building network) and a building-wide network (i.e. Ethernet).

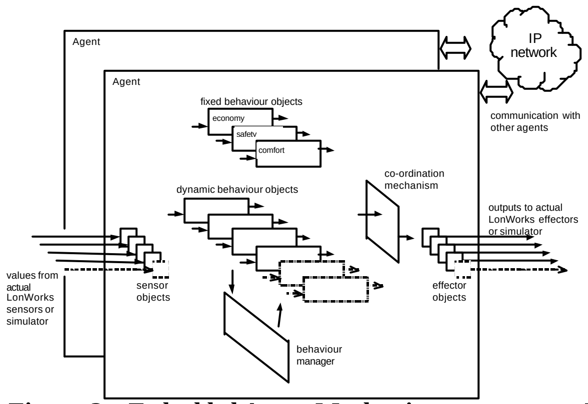

Figure 3 – Embedded-Agent Mechanism

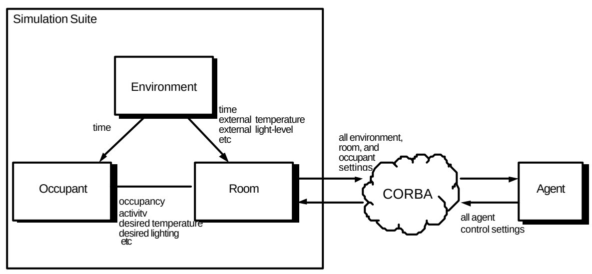

Figure 4 – IB Embedded-Agent Development System

5.2 The Programming Paradigm

The programming paradigm for our agent is based on Java that we feel offers significant advantages in terms of connectivity. Using Java, we implement dynamic behaviours simply by creating new instances of a default behaviour object with the appropriate parameters and pass messages via the DIBAL IB agent language [Cayci 00]. This is illustrated in Figures 3 and 4.

6.0 Experimental Set-up

We are currently experimenting with two different set-ups. We use a suite of purpose-built simulation software in order to develop the agents further. This software consists of individual Java applications that simulate a room containing sensors and effectors, a person taking control actions and the environment. These applications provide a controlled means of testing the room-agent without being restricted to real-time learning. We currently use CORBA to facilitate communication between the simulation suite and agent(s) although our more recent agent work now includes Jini and Javaspaces rather than Corba.

In addition to this simulation, we are deploying the system in an area of the Department of Computer Science. This experimental framework consists of two rooms - a private and a public space. The private space is office space. In it are various sensors and effectors including heating and light controls. This is used for potentially disruptive non-public experiments such as situations where there may be extreme variation in temperature or light levels. The activity in the room is restricted to some degree as the IB team are themselves the test subjects. The public space is a seminar room that hosts a variety of activities ranging from small group meetings, tea/coffee making, seminars and social activities. Again it is populated with a variety of sensor and effectors including heating and lighting.

7.0 Results and Future Directions

Our work is at an early stage and experiments are still underway. However, early bench based results show the approach to be effective in capturing the particularised aspects of an individual's behaviour. In our evidential learning system we are working on improving the nearness matching and learning inertia mechanisms. We have also recently developed some alternative Fuzzy, Genetic Algorithm and Connectionist agents based in a novel hybrid approach that includes particularisation mechanisms. More detailed results are reported elsewhere [Callaghan 2000].

We believe there is enormous commercial and personal potential in the integration of fixed building based agents with mobile personal agents (cell phones, watches etc). The fixed building agent would themselves be hosted on embedded-internet devices with all the advantages this connectivity could bring. Such agents would enable the current IB model to be expanded to provide new functionality that is currently not possible, and usher in a new era. In the longer terms we believe the ultimate vision for intelligent-building technology is in the creation of the future generations of space vessels and planetary habitats where technologically supported environments will be critical to survival in the harsh extra-terrestrial conditions of space. As such we are investigating a number of projects that aim to integrate our intelligent building techniques to the above applications.

Finally, we believe that the combination of embedded computers, networks and intelligent-agent techniques will transform our world by enabling the development of not only "intelligent-appliances" but also intelligent environments that will touch and change all areas of our lives.

References

[Aha 91] D.W.Aha "Case-Based Learning Algorithms", Proc 1991 DARPA CBR Workshop, Morgan Kaufmann.

[Brooks 97] R. Brooks, "Intelligent Room Project", Proc 2nd Int'l Cognitive Technology Conference (CT'97), Japan 1997

[Callaghan 00] Callaghan V, Clarke, G., Colley, M., Hagras, H. "A Soft-Computing DAI Architecture for Intelligent Buildings", Journal of Studies in Fuzziness and Soft Computing on Soft Computing Agents, Physica-Verlag-Springer, July, 2000

[Cayci 00] Cayci F, Callaghan V, Clarke G, "*DIBAL - A Distributed Intelligent Building Agent Language*", The 6th International Conference on Information Systems Analysis and Synthesis (ISAS 2000), Orlando, Florida, July 2000

[Coen 97] M.H.Coen, "Building Brains for Rooms: Designing Distributed Software Agents", Proc. Ninth Innovative Applications of AI Conf., AAAI Press, 1997

[Davidsson 98] P Davidsson "Energy Saving and Value Added Services; Controlling Intelligent-Buildings Using a Multi-Agent System Approach" in *DA/DSM Europe DistribuTECH*, PennWell, 1998

[Mozer 98] MC Mozer The Neural Network House: An Environment That Adapts To Its Inhabitants. In *Proc of American Association for Artificial Intelligence Spring Symposium on Intelligent Environments,* pp. 110-114, AAAI Press, 1998.

[Sharples 99] Sharples S, Callaghan V, Clarke, G "A Multi-Agent Architecture For Intelligent Building Sensing and Control", Int'l Sensor Review Journal, Vol 19. No. 2. May 1999