A Hierarchical Fuzzy Genetic Multi-Agent Architecture for Intelligent Buildings Sensing and Control

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Abstract:

In this paper, we describe a new application domain for intelligent autonomous systems – Intelligent Buildings (IB). In doing so we present a novel approach to the implementation of IB based on a hierarchical fuzzy genetic multi embedded-agent architecture comprising a low-level behaviour based reactive layer whose outputs are co-ordinated in a fuzzy way according to deliberative plans. The fuzzy rules related to resident's comfort are learnt online in a short time interval using our patented Fuzzy-Genetic techniques (British Patent 99-10539.7) from the resident's actual behaviour in a learning phase.Our approach utilises an intelligent agent approach to autonomously governing the building environment. We discuss the role of learning in building control systems, and contrast this approach with existing IB solutions. We explain the importance of acquiring information from sensors, rather than relying on pre-programmed models, to determine user needs. We describe how our architecture, consisting of distributed embedded agents, utilises sensory information to learn to perform tasks related to user comfort, energy conservation, and safety. We show how these agents, employing a behaviour-based approach derived from robotics research, are able to continuously learn and adapt to individuals within a building, whilst always providing a fast, safe response to any situation. Such a system could be used to provide support for older people, or people with disabilities, allowing them greater independence and quality of life.

1. Introduction

We define an intelligent building as "*a building that utilises computer technology to autonomously govern the building environment so as to optimise user comfort, energy-consumption, safety and work efficiency"*. In simplified terms, an intelligent-building is one that utilises inputs from building sensors (light, temperature, passive infra-red, etc), and uses this information to control effectors (heaters, lights, electronically-operated windows, etc) throughout the building [Sharples99]. A essential feature of an intelligent system is an ability to learn from experience, and hence adapt appropriately. Thus the notion of "autonomous governing" is important, as it implies a system which can adapt and generate its own rules (rather than being restricted to simple automation). In controlling such a system one is faced with the imprecision of sensors, lack of adequate models of many of the processes and of course the non-deterministic and sometime idiosyncratic aspects of human behaviour. Such problems are well known and there have been various attempts to address them. The most significant of these approaches has been the pioneering work on behaviour-based systems from researchers such as Brooks [Brooks 91] & Steels [Steels 95] who have had considerable success in the field of mobile robots. It might not seem obvious that a building can be looked upon as a machine; indeed "*a robot that we live within*", but, in other work we have justified this view that intelligent buildings, as computer-based systems are akin to robots, gathering information from a variety of sensors, and using behaviour-based techniques to determine appropriate control actions [Callaghan 2000]. This paper builds on these ideas and explains our use of a double hierarchical Fuzzy-Genetic system (similar to our previous work in mobile robotics [Hagras 99a, 99b]), to create *embedded-agents* for intelligent-buildings.

2. Distributed Architecture

The granularity of our distribution is room-based. Thus, each room contains an *embedded-agent*, which is then responsible, via sensors and effectors for the local control of that room as shown in Figure (1). This mirrors the architects vision of the functionality of the building. All embedded-agents are connected via a high level network (IP-ethernet in our case), thereby enabling collaboration or sharing of information to take place where appropriate. Within a room, devices such as sensors and effectors are connected together using a building services network (Lontalk in our case) and IP at the higher level. This DAI architecture is illustrated in Figure (1).

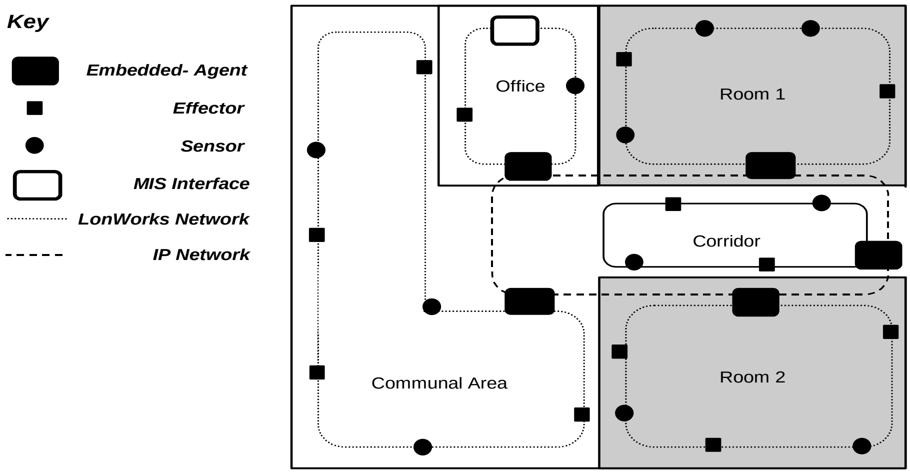

Figure (1): The DAI Building-Wide Architecture

3. The Embedded-Agents

Figure(2) shows the internal architecture of the embedded-agents which is based on the behaviour-based approach, pioneered by Brooks. Controlling a large integrated building system requires a complicated control function resulting from the large input and output space and the need to deal with many imprecise and unpredictable factors, including people. In our system we simplify this problem by breaking down the control space into multiple behaviours, each of which responds to specific types of situations, and then integrating their recommendations.

3.1 The Hierarchical fuzzy control architecture

The behaviour based approach, pioneered by Brooks, consisting of many simple co-operating units, has produced very promising results when applied to the control of robotics (which we argue includes IB) [Brooks 91].

The problem of how to co-ordinate the simultaneous activity of several independent behaviour-producing units to obtain an overall coherent behaviour have been discussed by many authors. [Brooks 91] [Saffiotti, 1997]. The work described in this paper suggests a solution based on using fuzzy logic to both implement individual behaviour elements and the necessary arbitration (allowing both fixed and dynamic arbitration policies to be implemented). We achieve this by implementing each behaviour as a fuzzy process and then use fuzzy agents to co-ordinate them. In the resultant architecture, a hierarchical fuzzy logic controller (HFLC) takes a hierarchical tree structure form and is shown in Figure (2). This hierarchical approach has the following advantages:

- It facilitates the design of the robotic controller and reduces the number of rules to be determined. It uses the benefits of fuzzy logic to deal with imprecision and uncertainty.
- Using fuzzy logic for the co-ordination between the different behaviours which allows more than one behaviour to be active to differing degrees thereby avoiding the drawbacks of on-off switching schema (i.e. dealing with situations where several criteria need to be taken into account). In addition, using fuzzy co-ordination provides a smooth transition between behaviours with a consequent smooth output response.
- It offers a flexible structure where new behaviours can be added or modified easily. The system is capable of performing very different tasks using identical behaviours by changing only the co-ordination parameters to satisfy a different high level objective without the need for re-planning.

Our room-based decomposition of behaviours consists of the following meta-functions. A S*afety behaviour* ensures that environmental conditions in the room are always at a safe level. In the case of an emergency this is the only active behaviour. Under normal circumstances each room has a fuzzy degree of safety (determined by fuzzy membership function) according to the needs of the room occupant. An *Economy behaviour* ensures that energy is not wasted. A *Comfort behaviour* ensures that conditions are maintained as the occupant would prefer (subject to being safe). This behaviour has an adaptable rule base, which learns from the room occupant's behaviour. This learning is done through reinforcement where the controller takes actions and monitors these actions to see if they satisfy the occupant or not, until a degree of satisfaction is achieved. Since this requires active responses from the user of the room this constitutes an unsupervised learning phase in the process. This process is clearly less appropriate where the occupants of the room are themselves in need of care or assistance as was the case in some of our earlier work [Sharples 99]. It would however be perfectly acceptable in other applications e.g. an hotel or apartment block. The complexities of training and negotiating satisfactory values for multiple use rooms depends upon having reliable means of identifying different users. The behaviours, resident inside the agent, take their input from a variety of sensors in the room (such as occupancy, light level, temperature, etc), and adjust device outputs (such as heating, lighting, blinds, etc) according to pre-determined, but settable, levels.

4. Overview of the Genetic Learning Architecture

For learning and adapting the dynamic comfort rule base according to the occupant behaviours we use an evolutionary computing approach based on a development of novel genetic algorithm (GA) technique. This mechanism operates directly on the fuzzy controller rule-sets. We refer to any learning conducted without user interaction, in isolation from the environment, using simulation as *offline* learning. In our case learning will be done *online* in real-time through interaction with the actual environment and user.

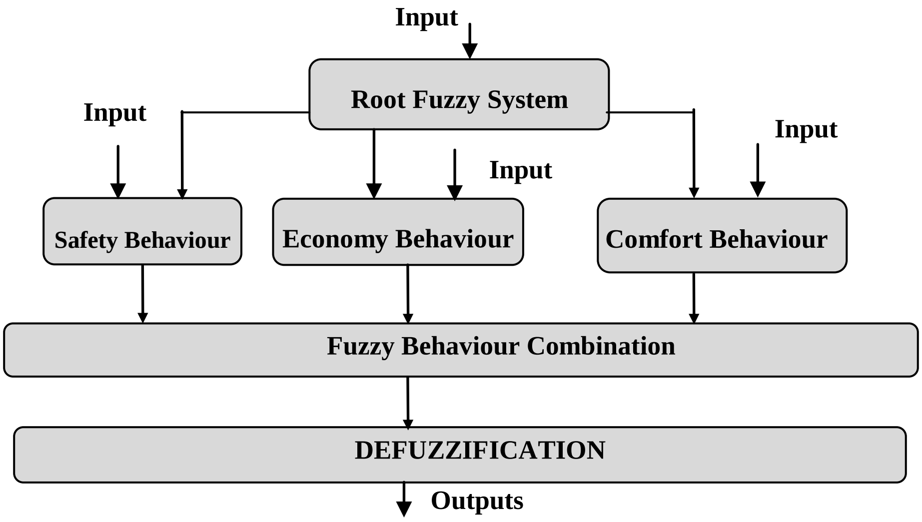

Figure (2): The Hierarchical Fuzzy Control System

4.1 The Associative Experience Engine

Figure (3) provides an architectural overview of what we term an *Associative Experience Engine* which forms the learning engine within the control architecture and is the subject of British patent application 99-10539.7. Behaviours are represented by parallel Fuzzy Logic Controllers (FLC). Each FLC has two parameters that can be modified which are the *Rule Base* (RB) of each behaviour and its *Membership Functions* (MF). The behaviours receive their inputs from sensors. The output of each FLC is then fed to the actuators via the *Co-ordinator* that weights its effect. When the system response fails to have a desired a response, the learning cycle begins.

The learning depends on the *Learning Focus* which is supplied by the *Co-ordinator* (the fuzzy engine which weights contributions to the outputs). When the *Learning Focus* is learning an individual rule base of a behaviour, then each rule base of each behaviour is learnt alone. When the *Learning Focus* is adapting the co-ordinated behaviours online, then the algorithm will adapt the rules in the comfort behaviour in response to the room occupant. The system recalls similar experiences by checking the stored experiences in the *Experience Bank*.

the most recent experiences that are stored in a queue. If these experiences show success then they are stored in the FLC and thereby avoid generating new solution for our system. The Experience Assessor assigns each experience solution a fitness value. When the *Experience Bank* is full, we have to delete some experiences. To assist with this the *Experience Survival Evaluator* determines which rules are removed according to their importance (as set by the Experience Assessor). When past experiences did not solve the situation we use the best-fit experience to reduce the search space by pointing to a better starting point which is the experience solution with the largest fitness.

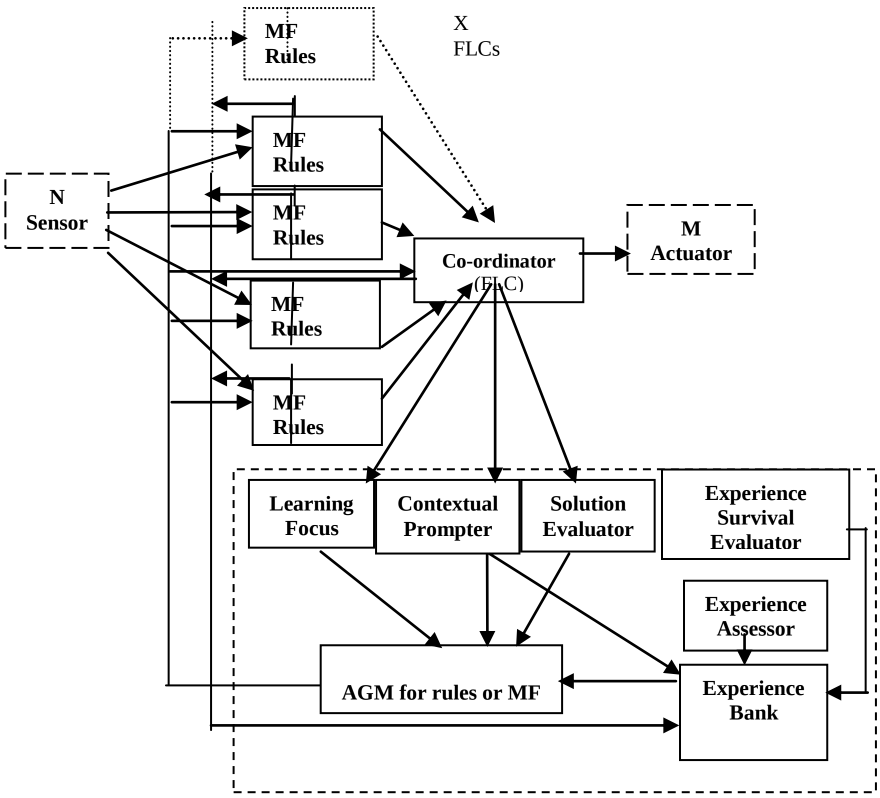

Figure (3): Architectural Overview of Associative Experience Learning Engine (UK patent No 99-10539.7)

The controller tests different solutions from the *Experience Bank* by transferring We then fire an *Adaptive Genetic Mechanism (AGM*) using adaptive learning parameters (except when learning behaviour with immediate reinforcement, we use optimum mutation parameter) to speed the search for new solutions. The AGM is constrained to produce new solutions in certain range defined by the *Contextual Prompter* which is supplied by sensors and defined by co-ordinator according to the *learning focus* in order to avoid the AGM searching options where solutions are unlikely to be found. By using these mechanisms we narrow the AGM search space massively improving its efficiency. After generating new solutions (either rules or MFs) the system tests the new solution and gives it fitness through the *Solution Evaluator*. The AGM provides new options until a

satisfactory solution is achieved. From a users viewpoint the system functions as follows. A user is asked to select his preference for any given programmable setting. The system then tries to adapt its rules to achieve this setting. The user is prompted to confirm or deny his satisfaction with the result. The system then either tries to re-adjust rules or , if the user is satisfied, the current rule set is accepted. Experiments to date show the *experience engine* achieves a satisfactory solution in a small number of iterations which most users find acceptable.
This same architecture was used in mobile robots learning and learnt rapidly (max 75s) complicated behaviours in a dynamic agricultural environment without simulation or human intervention [Hagras 99a, Hagras 99b].

5. Experimental setting

In our preliminary experiments we had used an IB agent based on 68000 Motrolla processor, the agent is equipped with light and heat sensors and actutaors in the form of a heater and a light source, the IB agent is shown in Figure(4). This agent is used as a prototype simulator to simulate the control of light and temperature in a room with various condition such as multiple occupancy, different levels of natural light and temperature and different times of the day and different human desires. There is a built in economy behaviour that should switch the heat low and ventilation off after the room is vacated. It is arguable that there should also be a safety behaviour that prevents the heat going below a minimum safe level (e.g. zero degrees which would result in pipes freezing). Furthermore there is the comfort behaviour of the person himself which will be learnt using our patented fuzzy-genetic techniques.

The agent is dealing in a proactive way with the human occupier(s) and it just asks if the the action done is satisfactory or no, and if it is required to decrease or increase the heat or light levels. The agent have 5 input membership functions (which were found empirically to be the smallest number of membership functions that give a satisfactory response) to represent the input temperature and light sensors and 7 membership functions to repersent the heat and light. The agent using our patented techniques shown in Section (4.1) was able to find a satisfactory rule base for the different users in an average of 5 trials which is a small number of iterations. Also the agent is using the *Experience bank* of our patented technique so each time it identifies the room occupant it just retrieves his favourite rule base, if he changes his behaviour the agent can adapt by changing the necessary rules to adapt to the human desirse rather than changing the whole rule base and repeating the learning from the beginning. If the agent locates a new room occupant it just tries to start learning his favourite rule base from a similar rule base that was stored the Experience Bank.

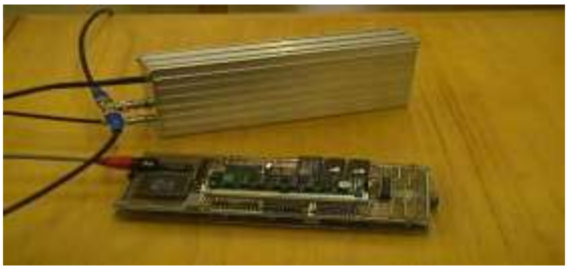

Figure (4): The IB agent

For our future work, we will construct intelligent rooms equipped with these agents and we will try to deal with more inputs and deal with different human desires in different rooms in a house.

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