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Programming iSpaces: A Tale of Two Paradigms

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Abstract

There is an increasing amount of research into intelligent space (e.g. pervasive computing, ambient intelligence, intelligent environments, smart homes etc). Much of the current research focuses on environments populated by numerous computing devices, sensors, actuators, various wired and wireless networking systems. A popular vision for such spaces is that lay-users will be able acquire unique sets of networked appliances and direct them to produce the collective functionality they desire (sometimes described as "decorating their iSpace). Thus, a significant question posed by such visions is how the non-technical user would be able to "program" an iSpace to produce the desired functionality. In this paper we discuss two different approaches to addressing this challenge. The first approach is based on the use of embedded autonomous agents which discretely sense the user's actions in the environment and, in a life-long learning mode, autonomously "programs" the iSpace to match the user's habitual behaviour (implicit programming). The second approach is based on the application of programming-by-example techniques (PBE) in which the system enters a discrete teaching phase in which the user "programs" the iSpace by demonstrating the required behaviour to the system (explicit programming). We give details of systems we have developed including the iDorm test-bed, our ISL & AOFIS agents, the dComp ontology (including the notion of virtual appliances and coordinated communities) and our TOP end-user programming methodology, reporting on results of various trials. We discuss the relative advantages of each approach covering topics such as performance, efficiency, cognitive loading, privacy and creativity, and conclude that future systems will probably require agents at lower system levels and end-user programming at the user level.

1. Introduction

"iSpace, the final frontier"; this parody of Startrek encapsulates many of our aspirations for this area as, in the longer term, iSpaces are likely to be the key to mankind's successful exploration of deep space. In outer-space, or hostile planetary habitats, it is inevitable that people will survive in wholly technologically supported artificial environments [Clarke 00]. Such environments will contain numerous communicating computers embedded into a myriad of devices, sensing, acting, delivering media, processing data and providing services that enhance the lifestyle and effectiveness of the occupant, and, in outer-space, preserving human life. Such environments will also include robots [Colley 01]. In today's iSpaces, whilst human life will not normally be at stake the underlying principles and technology are much the same. Today our homes are rapidly being filled with diverse types of products ranging from simple lighting systems to sophisticated entertainment systems, all adding to the functionality and convenience available to the home user [Chin 03]. The iSpace approach envisages that, one day soon, most artefacts will contain embedded computers and network connections opening up the possibility for hundreds of communicating devices, cooperating in communities serving the occupant(s). The seeds of this revolution have already been sown in that pervasive technologies such as the internet and mobile phones already boast over 200 and 680 million users, respectively [Facts 03] [GSM 01]. Today embedded computers account for 98% of all computer production, with an annual production of around 8 billion microprocessors [Metcalfe 01], most being integrated into domestic appliances such as video recorders, washing machines, mobile phones and all manner of everyday electronic appliances. Furthermore, nano-technology is opening up new possibilities such as embedding dust particle sized computers into hitherto unconventional mediums such as clothing fibres, paint pigments etc. Thus, the embedded market is massive and ripe for the addition of networking to realise the iSpace vision. Whilst these technological advances are fuelling significant changes in both the high-tech marketplace and living-environments, the most radical paradigm shift perhaps originated from the way these technologies can be applied. Firstly communities of appliances can collaborate to

provide new synergetic functionalities (e.g. a telephone ringing can be made to interact with other devices, such as pausing the TV), creating higher order "virtual appliances". Secondly the nature of the device is being questioned; is it a traditional appliance with multiple prefixed functionalities or is it an appliance with its constituent sub-functionalities, logically or physically, decomposed (functional decomposition is intrinsic to the pervasive computing world). Thirdly, programming of key functionalities (e.g. coordinated community actions) is transferred from the manufacturer to the user, empowering end-users to design novel functionalities that match their individual needs. When users are given the freedom to choose combinations of devices, then they can create unique and novel functionalities, some of which may not have been envisaged by the manufacturers, making pre-programmed solutions virtually impossible. One challenge, and the focus of much of the discussion in this paper, is how to manage and configure (program) such coordinated pervasive computing devices to do the end-users bidding, without the user incurring prohibitive cognitive loads; a task that, without support, could quickly become prohibitive and an obstacle to the achievement of the pervasive home networking environment vision. In this paper we explore the issue of programming iSpaces by examining two possible approaches to supporting programming in the end-users environment; the use of autonomous intelligent embedded-agents and the application of programming by example.

2. Degrees of Intelligence and Autonomy

For the iSpace vision to be realised in domestic environments, people must be able to use computer-based artefacts and systems in a way that gives them some control over aspects of the system, whilst eliminating cognitive awareness of parts of the system they have no interest in, and are happy to leave to automation or implicit programming processes. Where the line between fully autonomous intelligent systems and manual programming should be drawn is a subject of much research and argument. At the University of Essex we have chosen to provide an approach that allows the full spectrum of possibilities to be experimented with; we have therefore developed a range of autonomous intelligent embedded agents and some user-centric techniques. In this paper we present a review of all these techniques, although we shall start by describing our test-beds for intelligent spaces the iDorm and the new iDorm-2.

3.0 The iDorm

The intelligent dormitory (iDorm) shown in Figure 1 is a real pervasive computing test-bed comprised of a large number of embedded sensors, actuators, processors and networks in the form of a student bed-sitting room. The iDorm is a multi-use, multi-user space containing areas for different activities such as sleep, work and entertaining. It contains the normal mix of furniture found in a typical student study/bedroom environment, including a bed, work desk and a wardrobe.

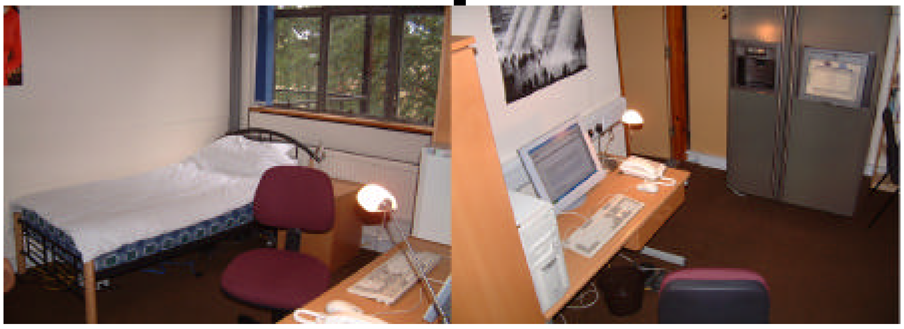


Fig. 1 - The iDorm

A common interface to the iDorm and its devices is implemented through Universal Plug and Play (UPnP) which is an event-based communication middleware that allows devices to plug and play thus enabling automatic discovery and configuration. A gateway server is used to run the UPnP software devices that interface with the hardware devices on their respective networks. Our experimental agent mechanisms are built on top of the low level UPnP control architecture enabling it to communicate with the UPnP devices in the iDorm and thus allowing it to monitor and control these devices. Figure 2 shows the logical network infrastructure of the iDorm.

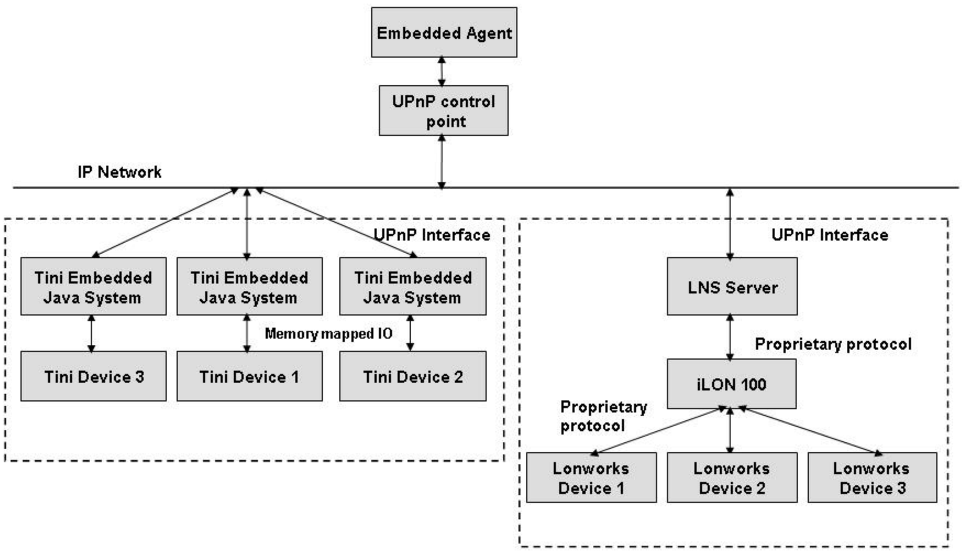


Figure 2 - The iDorm logical network infrastructure.

Entertainment is one of the behaviours used as a benchmark in the iDorm for performance assessment in projects such as the BT led PHEN[1] project. There is a standard multi-media PC driving both a flat-screen monitor and a video projector which can be used for both working and entertainment, see Figure 3.

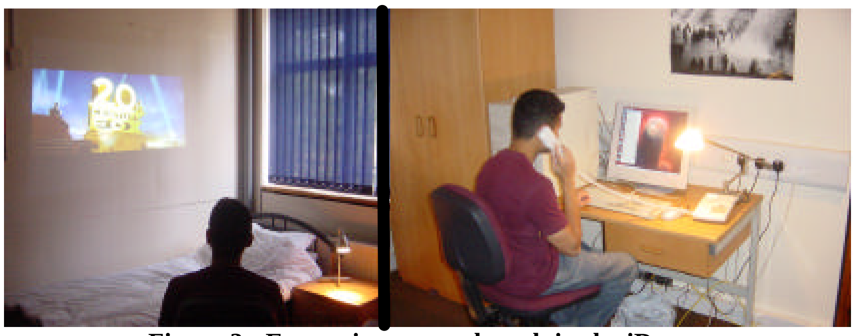
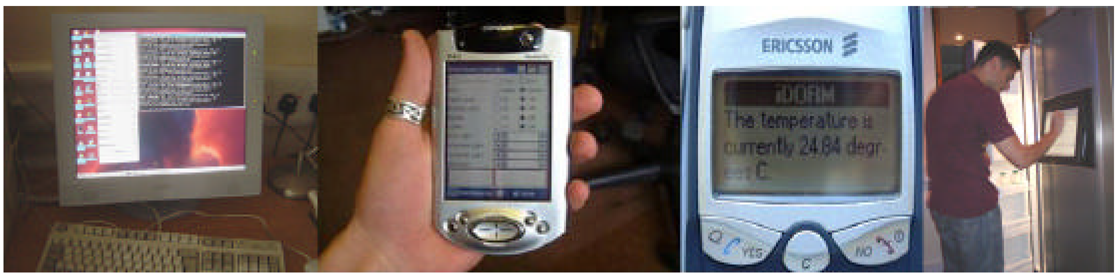


Figure 3 - Entertainment and work in the iDorm.

Any networked computer that can run a standard Java process can access and control the iDorm directly. Thus any PC can also act as an interface to control the devices in the room. Equally interfaces to the devices could be operated from wearable artefacts that can monitor and control the iDorm wirelessly such as a handheld PDA supporting Bluetooth wireless networking or a mobile phone shown in Figure 4. In principle, it is possible to adjust the environment from anywhere and anytime subject to user and device privileges. There is also an internet Fridge in the iDorm (see Figure 4d) that incorporates a PC with touch screen capability, which can also be used to control the devices in the room. Control can of course still be exerted directly on the devices themselves via conventional switches buttons etc.



(a) (b) (c) (d)

Figure 4 - PC interface. b) iPAQ interface. c) Phone interface. d) iFridge interface.

[1] http://iieg.essex.ac.uk/phen

There are a variety of computers in the iDorm which are used to interface with sensors and actuators and run agents; all of them being configured as JAVA environments. At the low performance end we use TINI[2] and SNAP[3] embedded internet boards, these are mainly used for sensors and actuators. There are also more powerful processor boards capable of running agents such as jStik[4] & ITX[5]. For experiments where maximum flexibility is required, it is also possible to run agents on UPnP enabled workstations. This allows the granularity of agent to device to be varied, from an agent controlling an entire environment, down to one-to-one mappings between devices and agents.

3.1 The iDorm-2

With the success of the iDorm, Essex University is currently constructing a new test-bed to support R&D in Pervasive ICT. The new facility, funded by the HE SRIF programme takes the form of a domestic apartment and has been called iDorm-2.

The iDorm-2 has been built from the ground up to be an experimental pervasive computing environment with many special structural features such as cavity walls/ceilings containing power & network outlets together with provision for internal wall based sensors and processors etc. There are numerous networks in place ranging from wired and power-line through wireless to broadband and high-bandwidth multi-mode fibre connections to the outside world. All the basic services are electrically controlled wherever possible (eg heating, water doors etc). The basic layout of the apartment is show in figure 5 (due to be opened in June 2005 at the international "Intelligent Environments 05" workshop). When finished this will be one of the few such facilities in the world.

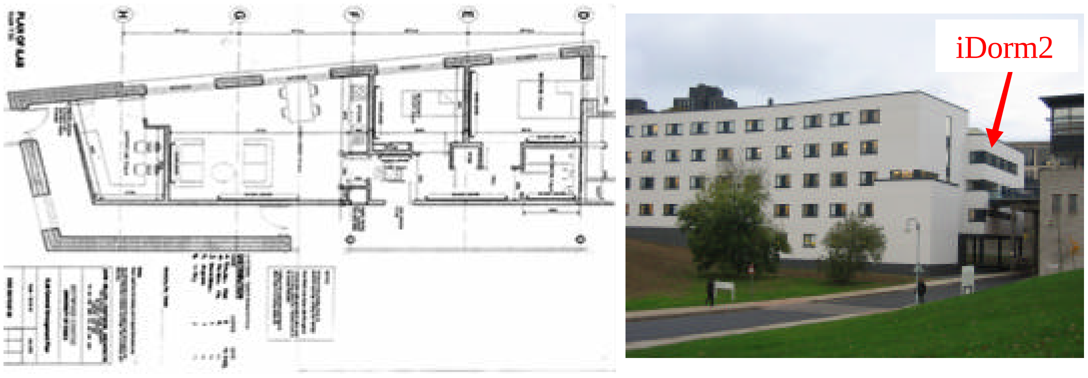


Figure 5. iDorm-2

4.0 Embedded-Agents

The principal argument in support of utilising artificial intelligence (AI) in support of the creation (programming) and management (control) of intelligent pervasive computing based spaces is that much of the cognitive load associated with using the technology (which is an obstacle to market penetration) can be off-loaded from the user to software processes. However, this is far from easy as such "intelligent entities" operate in a computationally complex and challenging physical environment which is significantly different to that encountered in more traditional PC programming or AI. Some of the computational challenges associated with creating systems of intelligent-artefacts are discussed below.

4.1 Embedded-Intelligence

Embedded intelligence can be regarded as the inclusion, in an artefact, of some of the reasoning, planning and learning that people possess. An intelligent artefact would normally contain only a

[2] http:// www.ibutton.com/TINI/
[3] http://www.imsys.se/
[4] http://jstik.systronix.com/
[5] http://www.mini-itx.com/

minimal amount of "embedded-intelligence", sufficient to do the artefact task in question. Embedded-computers that contain such an intelligent capability are normally referred to as "*embedded-agents*" [Callaghan 00]. Intelligent Artefacts would, in effect, contain an embedded-agent. Individually, such an embedded-agent can harness intelligence to undertake such tasks as enhancing device functionality (i.e. enabling the artefact to do more complex control tasks), as well as reducing configuration or programming complexity and costs by enabling the pervasive computing system to autonomously learn its own program rules, or alternatively assisting the lay-end user to program rules in a non-technical way (see TOP, later in this paper).

4.2 Embedded Agents and Intelligent Spaces

There are a variety of approaches to this problem, perhaps the most relevant being those originating from the context-aware and embedded-agent communities. In embedded-agent work the goal is to utilise some form of artificial intelligence (AI) to relieve the cognitive loading associated with setting up and running an iSpace system (i.e. transfer some of the cognitive processes from the person to the computer). Typically researchers have employed approaches such as neural networks, based on traditional machine learning theory, to control the users' environment. However, these approaches utilise objective functions that either aim to derive a minimal control function that satisfies the needs of the users "average" or are aimed at optimising between a number of competing needs (e.g. energy efficiency and user comfort). In both cases the user has little control over the system and has to accept some degree of discomfort, or adapt to the conditions determined by the iSpace agents [Mozer 98].

A contrasting agent based paradigm is to see the "User as King" and create agents that "particularise (rather than generalise) to a specific users needs, and respond immediately to whatever the end-user demands (providing it doesn't violate any safety constraints) "[Callaghan 01a]. [Callaghan 01b]

Work at Essex University (as part of the EU's Disappearing Computer programme and the UK Governments UK-Korean Scientific fund) has addressed this problem using behaviour based systems (pioneered by Rodney Brooks [Brooks 91]) and soft-computing (fuzzy logic, neural networks and genetic algorithms). This approach stems from our finding that embedded-agents used in pervasive computing are equivalent to robots, experiencing similar problems with sensing, non-determinism, intractability, embodiment etc [Callaghan 01a]. Our earlier work [Callaghan 01b, Hagras 00, Hagras 01] was in the field of robotics, which has allowed us to recognise the underlying similarities between robotics and intelligent artefacts. Models in both robotics and pervasive embedded computer devices have proved difficult to devise, mainly because of the intractability of the variables involved (and in the case of modelling people, non-determinism). A principal advantage of behaviour based methods is that they discard the need for an abstract model, replacing it by the world itself; a principle most aptly summarised by Rodney Brooks as, "the world is its own best model".

4.3 Agent Learning

Learning can be viewed as the process of gathering information from the environment and encoding it to improve the efficiency of a system in achieving a certain goal. However the difficulty that arises concerns finding the most appropriate learning algorithm/technique to use. Most learning algorithms use a measure of the quality of the solution, given either by examples of the desired behavior of a system, or by an assessment of the quality of the internal and/or external state. The learning algorithm very much depends on the characteristics of the "problem" itself. The best choice of learning algorithm can be made by comparing the problem characteristics against the learning algorithm characteristics. The following describes a limited number of these characteristics:

a. *Problem's characteristics*
   ? Dynamics: To what degree do the environment variables change during the learning?
   ? Complexity: Is the set of all possible solutions, search space, finite/countable?
   ? Uncertainty: does the information regarding the state contain noise? Are the actions performed noisy?
   ? Pre-acquired knowledge: Can some knowledge about the solutions be acquired before learning starts?
   ? Observability: Is the current/past states known to the learning algorithm?

? Type of data: Are the data provided discrete-valued, real-valued, and complex-structured or states and transitions?
? Feedback type: Should the learning algorithm respond as an immediate, on-demand, delayed or no-response feedback?
? Physical limitations: What is the processing capability or memory size of the system where the learning algorithm runs?

b. *Learning algorithm's characteristics*

? Internal parameter type: what type of parameters does the algorithm contain and how do they change?
? Input data: what kind of input data can the learning algorithm deal with and can it adapt to noisy data?
? Solution/Goal type: can the learning algorithm produce approximations in real valued functions?
? Dynamics: Can the solutions be changed during the environments execution or can the learning algorithm only change the solutions off-line?
? Parameter change: what parameters change in each phase of the learning cycle: do they change all at the same time or only a small subset?

Another important distinction in learning agents is whether the learning is done online or offline. Online learning means that the agent performs its tasks, and can learn or adapt after each event. Online learning is like "on-the-job" training and places severe requirement on the learning algorithm. It must be (a) fast and (b) very stable and fault-tolerant. Other hotly debated issues are whether supervised or unsupervised learning is best. Later we present the ISL and the AOFIS as examples of the unsupervised agent. The general challenges faced by designers of embedded-agents for such environment were discussed at a recent workshop on Ubiquitous Computing in Domestic Environments [Callaghan 01b].

4.4 Application Level Emergent behaviour

In pervasive computing systems, the embedded-agent host (frequently an appliance) has a network connection allowing the agents to have a view of their neighbours, thereby facilitating coordinated actions from groups of embedded-agents. The key difference to isolated appliances is that those participating in groups not only have their individual functionality (as designed by the manufacturer) but they also assume a group functionality that can be something that was not envisaged by the manufacturers. In fact, if there are only weak constraints on association of appliances, it is possible for the user to program unique coordinated actions (ie unique collective functionality) that was not envisaged by the different manufacturers offering the component appliances. This enables an application level emergent behaviour or functionality (something that whilst enabled by the system, was not specified by the system). This naturally gives rise to questions such as the balance between pre-specified functionality and emergent functionality, what or who is responsible for the association between devices and the programming of the basic behaviours. Later in this paper we discuss various approaches to this challenge. TOP provides an explicit means of directly harnessing user creativity to generate emergent applications whilst the ISL and AOFIS involve various degrees of user interaction using both supervised and unsupervised learning paradigms to generate emergent application level functionality.

4.5 Machine Level Emergent Behaviour

In the behaviour based approach to AI, the equivalent to reasoning and planning in traditional AI is produced by arranging for an agent to have a number of competing processes that are vying for control of the agent. The "sensory context" determines the degree to which any process influences the agent. Thus, as sensing is derived from what is effectively a non-deterministic world, the solutions from this process are equally non-deterministic and result in what is termed "Emergent Behaviour" (behaviours or solutions that emerged but were not explicitly programmed). Anything that affects the context can thus have a hand in this machine level "emergent behaviour". For example, the connections (associations) between devices critically affect the sensed data. Thus agent driven associations, or user driven associations, will be closely associated with emergent behaviour. Emergent behaviour is also sometimes described as emergent solutions. The freedom to make ad-hoc association is an important factor in this process, as without them it is difficult to see how emergent functionality could be achieved. At the University of Essex we are researching into what we term promiscuous association; the freedom for agents to form their own associations in as open a way as possible. This approach opens up the possibility of using formally specified ontologies of devices and groups of devices. It is important to understand that being autonomous and promiscuous (open to making associations with other artefacts) does not imply undirected or unsafe behaviour. Agents can have basic fixed rules built into them that prevent them taking specified actions deemed unsafe.

4.6 Multi-Agents

The underlying paradigm of all Essex agents is that they are associated with actuators (they are essentially control agents rather than information processing agents). In the underlying agent model, multi-agent operation is supported via three modes. In the first sensory and actuator parameters are simply made available to other agents. In the second mode agents make a "compressed" version of this information (or their internal state) available to the wider network. In a behaviour based agent, such as the ISL, the compressed data takes the form of which behaviours are active (and to what degree). The general philosophy we have adopted is that data from remote agents is simply treated in the same way as all other sensor data. As with any data, the processing agent decides for itself which information is relevant to any particular decision. Thus, multi-agent processing is implicit to this paradigm, which regards remote agents as simply more sensors (albeit more sophisticated sensors). We have found that receiving high level processed information from remote agents, such as "the iDorm is occupied" is more useful than being given the low level sensor information from the remote agent that gave rise to this higher-level characterisation. This compressed form both relieves agent processing overheads and reduces network loading. A third approach we have developed is the use of inter-agent communication languages. Standardised agent communication languages (e.g. KQML and FIPA) tend to be too big to use on embedded-computers (many tens of megabytes) and are not well matched in terms of functionality to them. We have generated research that has looked at the problem of developing a lightweight agent communication language and the interested reader is referred to our description of the Distributed Intelligent Building Agent Language (DIBAL) [Cayci 00]. Finally, in the home environment (rather than a general unconstrained pervasive environment), because the number of connected appliances is relatively tractable (no more than a few hundred) a widely adopted approach at a network level, is to fully connect all the appliances, relegating the issue of what appliance will collaborate with any other to the application level. This approach has been successfully applied by the University of Essex group [Duman 02a] [Duman 02b].

4.7 Knowledge in Rule Based Agents

One reason we have opted for fuzzy logic rather than neural networks is that the knowledge acquired by the agent is gathered in human linguistic terms. A typical rules set from the iDorm is presented in the figure 5. It is made up of simple, if somewhat large IF THEN ELSE rule sets. Such rules intrinsically well structured and are based on mathematical logic sets. Meta structures can also be used. For example, at the meta level rules sets can also be characterised according to context such as rules sets for Mr A relating to Context B (e.g. a bedroom). Thus, from such rule sets it is possible to perform meta functions such as deriving the closest rule-set for a new user, - Ms C - based upon rulesets from others users in the same context.

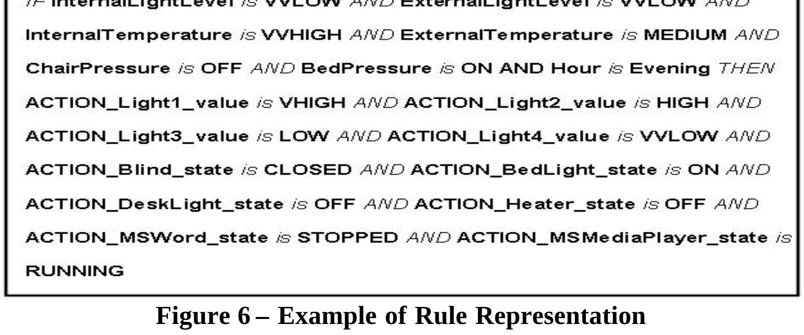

IF **InternalLightLevel** *is* **VVLOW** *AND* **ExternalLightLevel** *is* **VVLOW** *AND* **InternalTemperature** *is* **VVHIGH** *AND* **ExternalTemperature** *is* **MEDIUM** *AND* **ChairPressure** *is* **OFF** *AND* **BedPressure** *is* **ON AND Hour** *is* **Evening** *THEN* **ACTION_Light1_value** *is* **VHIGH** *AND* **ACTION_Light2_value** *is* **HIGH** *AND* **ACTION_Light3_value** *is* **LOW** *AND* **ACTION_Light4_value** *is* **VVLOW** *AND* **ACTION_Blind_state** *is* **CLOSED** *AND* **ACTION_BedLight_state** *is* **ON** *AND* **ACTION_DeskLight_state** *is* **OFF** *AND* **ACTION_Heater_state** *is* **OFF** *AND* **ACTION_MSWord_state** *is* **STOPPED** *AND* **ACTION_MSMediaPlayer_state** *is* **RUNNING**

Figure 6 – Example of Rule Representation

5. Embedded-Agent Based Approaches

At the University of Essex we have developed a number of agents that can deal with the problems discussed above. The main approaches we have developed are based on fuzzy logic. Fuzzy logic is particularly appropriate as it can describe inexact (and analogue) parameters using human-readable linguistic rules, offering a framework for representing imprecise and uncertain knowledge. Thus it is well suited to develop control on the basis of inexact sensing and actuation which, when coupled to behaviour based agent architectures can deal with the non-determinism which sometimes characterises human behaviour. We believe this has similarities to the way people make decisions as it uses a mode of approximate reasoning, which allows it to deal with vague and incomplete information. We have shown that fuzzy logic can be applied well to pervasive computing environment [Hagras 02a] [Hagras 02b] [Hagras 02c] such as the iDorm [Holmes 02] [Pounds-Cornish 02] and have developed and tested two fuzzy-based embedded-agents in the iDorm namely the Incremental Synchronous learning Agent [Hagras 04] and the Adaptive Online Fuzzy Inference System Agent [Doctor 04] . These agents have been run on commercial and in-house produced hardware. The following photo shows a hardware networked agent platform produced at the University of Essex and used to manage the iDorm pervasive computing community.

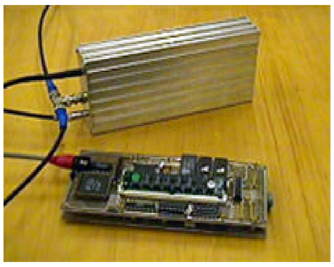


Figure 7 –Agent Prototype

5.1 The Incremental Synchronous Learning (ISL)[6] Agent

In general terms the ISL embedded-agent work is broadly situated within the behaviour based architecture work pioneered by Rodney Brooks at MIT, consisting of many simple co-operating sub-control units. Our approach differs to other work in that we use Fuzzy Logic based sub-control units, arrange them in a hierarchy (see following figure) and use a user driven technique to learn the fuzzy rules online and in real-time. It is well known that it is often difficult to determine parameters for fuzzy systems. In most fuzzy systems, the fuzzy rules were determined and tuned through trial and error by human operators. It normally takes many iterations to determine and tune them. As the number of input variables increases (Intelligent space agents develop large numbers of rules due to particularisation) the number of rules increases disproportionately, which can cause difficulty in matching and choosing between large numbers of rules. Thus the introduction of a mechanism to learn fuzzy rules was a significant advance. In the ISL agent we implement each behaviour as a fuzzy process and then use higher level fuzzy process to co-ordinate them. The resultant architecture takes the form of a hierarchical tree structure (see following figure). This approach has the following technical advantages:

? It simplifies the design of the embedded-agent, reducing the number of rules to be determined (in previous work we have given examples of rules reduction of two orders of magnitude via the use of hierarchies).

? It uses the benefits of fuzzy logic to deal with imprecision and uncertainty.

? It provides a flexible structure where new behaviours can be added (eg comfort behaviours) or modified easily.

? It utilises a continuous activation scheme for behaviour coordination which provides a smoother response than switched schema

The learning process involves the creation of user behaviours. This is done *interactively* using reinforcement where the controller takes actions and monitors these actions to see if they satisfy the user or not, until a degree of satisfaction is achieved. The behaviours, resident inside the agent, take

[6] A detailed account of this agent including the supporting theory and testing can be found in our published papers [Hagras 02a] [Hagras 02b] [Hagras 02c]

their input from sensors and appliances and adjust effector and appliance outputs (according to pre-determined, but settable, levels). The complexities of learning and negotiating satisfactory values for multiple users would depend upon having a reliable means of identifying different users.

5.1.1 Learning Architecture

It is clear that, in order for an appliance based agent to autonomously particularise its service to an individual, some form of learning is essential [Callaghan 01b]. In the ISL: learning takes the form of adapting the "usage" behaviour rule base, according to the users actions. To do this we utilise an evolutionary computing mechanism based on a novel hierarchical genetic algorithm (GA) technique which modifies the fuzzy controller rule-sets through interaction with the environment and user.

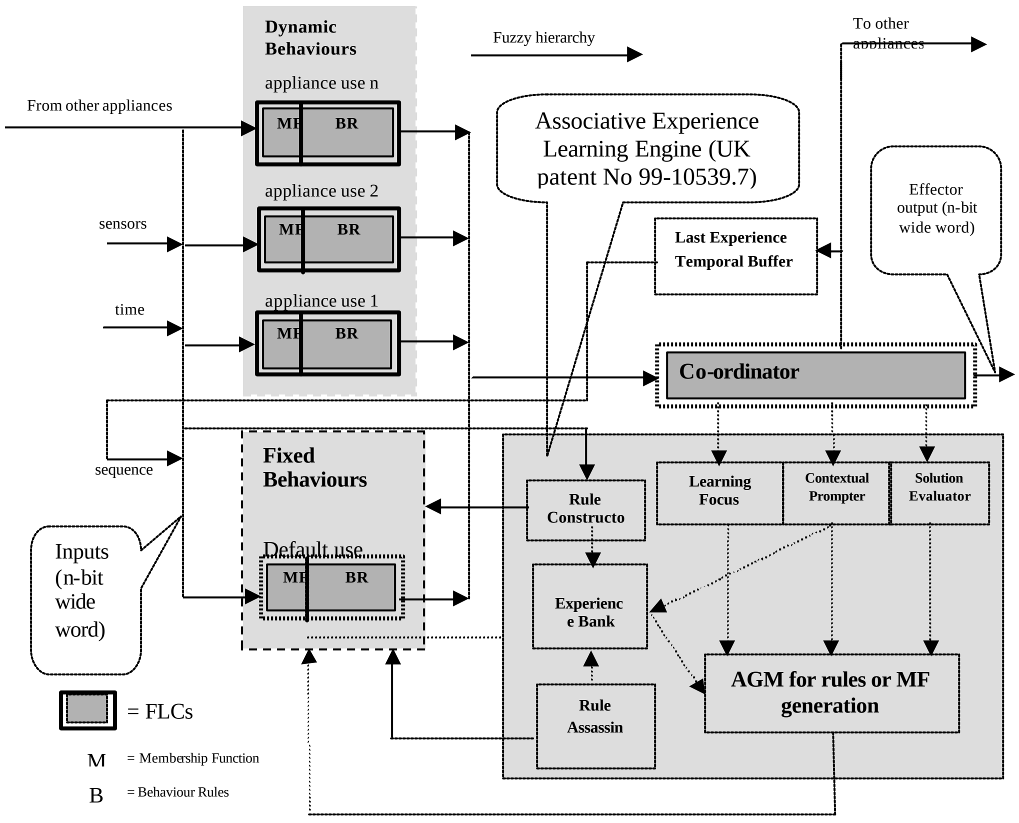


Figure 8- ISL Embedded-Agent Architecture

The hub of the GA learning architecture is what we refer to as an *Associative Experience Engine* [British patent 99-10539.7]. Briefly, each behaviour is a fuzzy logic controller (FLC) that has two parameters that can be modified; a *Rule Base* (RB) and its associated *Membership Functions* (MF). In our learning we modify the rule-base. The architecture, as adapted for pervasive computing embedded-agents, is given in the following figure. The behaviours receive their inputs from sensors and provide outputs to the actuators via the c*o-ordinator* that weights their effect. When the system fails to have the desired response (e.g. an occupant manually changes an effector setting), the learning cycle begins.

When a learning cycle is initiated, the most active behaviour (i.e. that most responsible for the agent behaviour) is provided to the *Learning Focus* from the *Co-ordinator* (the fuzzy engine which weights contributions to the outputs), which uses the information to point at the rule-set to be modified (i.e. learnt) or exchanged. Initially, the *Contextual Prompter* (which gets a characterisation of the situation, an experience, from the Co-ordinator) is used to make comparison to see whether there is a suitable behaviour rule set in the *Experience Bank*. If there is a suitable experience, it is used. When the past experiences do not satisfy the occupant's needs we use the best-fit experiences to reduce the search space by pointing to a better starting point, which is the experience with the largest fitness. We then fire an *Adaptive Genetic Mechanism (AGM*) using adaptive learning parameters to speed the search for new solutions. The AGM is constrained to produce new solutions in a certain range defined by the *Contextual Prompter* to avoid the AGM searching options where solutions are unlikely to be found. By using these mechanisms we narrow the AGM search space massively, thus improving its efficiency. After generating new solutions the system tests the new solution and gives it fitness through the *Solution Evaluator.* The AGM provides new options via operators such as crossover and mutation until a satisfactory solution is achieved.

The system then remains with this set of active rules (an experience) until the user's behaviour indicates a change of preference (e.g. has developed a new habit), signalled by a manual change to one of the effectors when the learning process described above is repeated. In the case of a new occupant in the room the *Contextual Prompter* gets and activates the most suitable rule base from the *Experience* Bank or if this proves unsuitable the system re-starts the learning cycle above. The *Solution Evaluator* assigns each stored rule base in the *Experience Bank* a fitness value. When the *Experience Bank* is full, we have to delete some experiences. To assist with this the *Rule Assassin* determines which rules are removed according to their importance (as set by the *Solution Evaluator*). The *Last Experience Temporal Buffer* feeds back to the inputs a compressed form of the n-1 state, thereby providing a mechanism to deal with temporal sequences.

5.2 Adaptive Online Fuzzy Inference System (AOFIS) Agent

Like the ISL agent, AOFIS is based on fuzzy logic. We utilise an unsupervised data-driven one-pass approach for extracting fuzzy rules and membership functions from data to learn a fuzzy logic controller (FLC) that will model the user's behaviours when using iDorm based devices. It differs from the ISL in that it not only learns controller rules, but it also learns membership functions (a significant advance on the ISL which has fixed membership functions). The data is collected by monitoring the user's use of the iDorm over a period of time. The learnt FLC provides an inference mechanism that produces output control responses based on the current state of the inputs. The AOFIS adaptive FLC will therefore control a pervasive computing community, such as the iDorm, on behalf of the user and will also allow the rules to be adapted online as the user's behaviour changes over time. This approach aims to realise the vision of Ambient Intelligence and support the aims of pervasive computing in the following ways:

? The agent is responsive to the particular needs and preferences of the user.

? The user is always in control and can override the agent at any time.

? The agent learns and controls its environment in a non-intrusive way (although the user may be aware of the high-tech interface, he is unaware of the agent's presence).

? The agent uses a simple one pass learning mechanism for learning the user's behaviours, and thus it is not computationally expensive.

? The agent's learnt behaviours can be adapted online as a result of changes in the user's behaviour.

? Learning is life-long in that agent behaviours can be adapted and extended over a long period of time as a result of changes in the pervasive computing environment.

AOFIS involves five phases: Monitoring the user's interactions and capturing input/output data associated with their actions; extraction of the fuzzy membership functions from the data; extraction of the fuzzy rules from the recorded data; the agent control and the life long learning and adaptation mechanism. The last two phases are control loops that once initiated receive inputs as either: monitored sensor changes that produce appropriate output control responses based on the set of learnt rules; or user action requests that cause the learnt rules to be adapted before an appropriate output control response is produced. The following diagram illustrates these five phases.

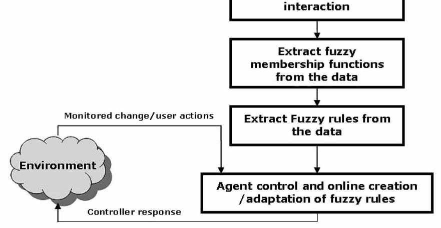

Capture data on user interaction
Extract fuzzy membership functions from the data
Monitored change/user actions
Extract Fuzzy rules from the data
Environment
Agent control and online creation /adaptation of fuzzy rules
Controller response

Figure 9 - Phases of AOFIS

The agent initially monitors the user's actions in the environment. Whenever the user changes actuator settings, the agent records a 'snapshot' of the current inputs (sensor states) and the outputs (actuator states with the new values of whichever actuators were adjusted by the user). These 'snapshots' are accumulated over a period of time so that the agent observes as much of the user's interactions within the environment as possible. AOFIS learns a descriptive model of the user's behaviours from the data accumulated by the agent. In our experiments in the iDorm we used 7 sensors for our inputs and 10 actuators for our outputs with a user spending up to 3 days in the iDorm. The fuzzy rules which are extracted represent local models that map a set of inputs to the set of outputs without the need for formulating any mathematical model. Individual rules can therefore be adapted online influencing only specific parts of the descriptive model learnt by the agent.

It is necessary to be able to categorise the accumulated user input/output data into a set of fuzzy membership functions which quantify the raw crisp values of the sensors and actuators into linguistic labels. AOFIS is based on learning the particularised behaviours of the user and therefore requires these membership functions be defined from the user's input/output data recorded by the agent. A Double Clustering approach combining Fuzzy-C-Means (FCM) and hierarchical clustering, is used for extracting fuzzy membership functions from the user data. This is simple and effective approach where the objective is to build models at a certain level of information granularity that can be quantified in terms of fuzzy sets.

Once the agent has extracted the membership functions and the set of rules from the user input/output data, it has then learnt the FLC that captures the human behaviour. The agent FLC can start controlling the pervasive computing community on behalf of the user. The agent starts to monitor the state of the pervasive community and affect actuators based on its learnt FLC that approximate the particularised preferences of the user. The following diagram illustrates the FLC which consists of a fuzzifier, rule base, fuzzy inference engine and defuzzifier.

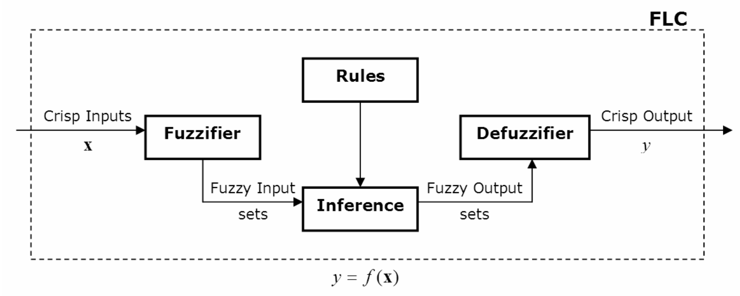


Figure 10 - AOFIS FLC.

In conformity with the non-intrusive aspect of intelligence [Doctor 04] whenever the user is not happy with the behaviour of the pervasive computing device or community, he can always override the agent's control responses by simply altering the manual control of the system. When this occurs the agent will adapt its rules online or add new rules based on the new user preferences. This process incorporates what we term 'learning inertia' where the agent delays adapting its learnt rules until the user preference for changing a particular set of actuator values has reoccurred a number of times. This prevents the agent adapting its rules in response to 'one off' user actions that don't reflect a marked change in the user's habitual behaviour (this "learning inertia" parameter is user settable). As rules are adapted it is sensible to preserve old rules so they can be recalled by the agent in the future if they are more appropriate than the current rules. Whenever the user overrides the agent's control outputs and overrides any of the controlled output devices, a snapshot of the state of the environment is recorded and passed to the rule adaptation routine. The AOFIS agent supports the notion of life long learning in that it adapts its rules as the state of the pervasive community and the user preferences vary over a significantly long period of time. Due to the flexibility of AOFIS, the initially learnt FLC can be easily extended to both adapt existing rules, as well as adding new rules. The fuzzy nature of the rules permits them to capture a wide range values for each input and output parameter. This allows the rules to continue to operate even if there is a gradual change in the environment. If however there is a significant change in the environment or the user's activity is no longer captured by the existing rules then the agent will automatically create new rules that satisfy the current conditions. The agent will therefore unobtrusively and incrementally extend its behaviours which can then be adapted to satisfy a pervasive device and community user.

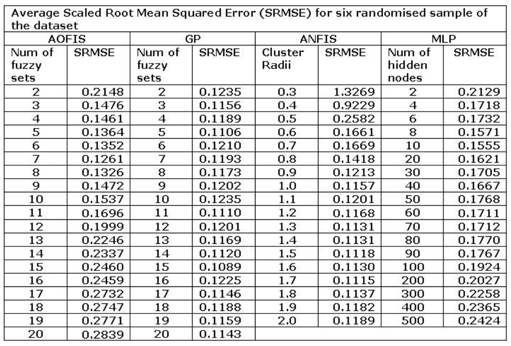
5.3 Benchmarking and Comparative Performance

We have also implemented other soft computing agents namely Genetic Programming (GP), the Adaptive-Neuro Fuzzy Inference System (ANFIS) and the Multi-Layer Perceptron Neural Network.

The dataset obtained from the iDorm during the AOFIS monitoring phase comprised of 408 instances and was randomised into six samples. Each sample was then split into a training and test set consisting of 272 and 136 instances respectively. The performance error for each technique was obtained on the test instances as the Root Mean Squared Error which was also scaled to account for the different ranges of the output parameters.

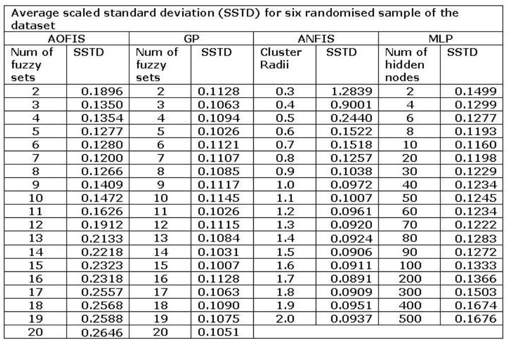
Figure 11 -User Gathering Experimental data in the iDorm

The GP used a population of 200 individuals evolving them over 200 generations. The GP evolved both the rules and the fuzzy sets. Each individual was represented as a tree composed of 'and' and 'or' operators as the internal nodes and triangular and trapezoidal membership functions as terminal nodes. The parameters of the membership functions were also evolved in parallel with the structure. The search started with a randomly generated set of rules and parameters, which were then optimised by means of genetic operators. The GP based approach for optimising an FLC was tested with different numbers of fuzzy sets. In ANFIS subtractive clustering was used to generate an initial TSK-type fuzzy inference system. Back propagation was used to learn the premise parameters while least square estimation was used to determine the consequent parameters.


Average Scaled Root Mean Squared Error (SRMSE) for six randomised sample of the dataset

AOFIS		GP		ANFIS		MLP	
Num of fuzzy sets	SRMSE	Num of fuzzy sets	SRMSE	Cluster Radii	SRMSE	Num of hidden nodes	SRMSE
2	0.2148	2	0.1235	0.3	1.3269	2	0.2129
3	0.1476	3	0.1156	0.4	0.9229	4	0.1718
4	0.1461	4	0.1189	0.5	0.2582	6	0.1732
5	0.1364	5	0.1106	0.6	0.1661	8	0.1571
6	0.1352	6	0.1210	0.7	0.1669	10	0.1555
7	0.1261	7	0.1193	0.8	0.1418	20	0.1621
8	0.1326	8	0.1173	0.9	0.1213	30	0.1705
9	0.1472	9	0.1202	1.0	0.1157	40	0.1667
10	0.1537	10	0.1235	1.1	0.1201	50	0.1768
11	0.1696	11	0.1110	1.2	0.1168	60	0.1711
12	0.1999	12	0.1201	1.3	0.1131	70	0.1712
13	0.2246	13	0.1169	1.4	0.1131	80	0.1770
14	0.2337	14	0.1120	1.5	0.1118	90	0.1767
15	0.2460	15	0.1089	1.6	0.1130	100	0.1924
16	0.2459	16	0.1225	1.7	0.1115	200	0.2027
17	0.2732	17	0.1146	1.8	0.1137	300	0.2258
18	0.2747	18	0.1188	1.9	0.1182	400	0.2365
19	0.2771	19	0.1159	2.0	0.1189	500	0.2424
20	0.2839	20	0.1143				

Table 2 - Average Scaled RMSE


Average scaled standard deviation (SSTD) for six randomised sample of the dataset

AOFIS		GP		ANFIS		MLP	
Num of fuzzy sets	SSTD	Num of fuzzy sets	SSTD	Cluster Radii	SSTD	Num of hidden nodes	SSTD
2	0.1896	2	0.1128	0.3	1.2839	2	0.1499
3	0.1350	3	0.1063	0.4	0.9001	4	0.1299
4	0.1354	4	0.1094	0.5	0.2440	6	0.1277
5	0.1277	5	0.1026	0.6	0.1522	8	0.1193
6	0.1280	6	0.1121	0.7	0.1518	10	0.1160
7	0.1200	7	0.1107	0.8	0.1257	20	0.1198
8	0.1266	8	0.1085	0.9	0.1038	30	0.1229
9	0.1409	9	0.1117	1.0	0.0972	40	0.1234
10	0.1472	10	0.1145	1.1	0.1007	50	0.1245
11	0.1626	11	0.1026	1.2	0.0961	60	0.1234
12	0.1912	12	0.1115	1.3	0.0920	70	0.1222
13	0.2133	13	0.1084	1.4	0.0924	80	0.1283
14	0.2218	14	0.1031	1.5	0.0906	90	0.1272
15	0.2323	15	0.1007	1.6	0.0911	100	0.1333
16	0.2318	16	0.1128	1.7	0.0891	200	0.1366
17	0.2557	17	0.1063	1.8	0.0909	300	0.1503
18	0.2568	18	0.1090	1.9	0.0951	400	0.1674
19	0.2588	19	0.1075	2.0	0.0937	500	0.1676
20	0.2646	20	0.1051				

Table 3 - Average Scaled STD

An iteration of the learning procedure consisted of two parts where the first part propagated the input patterns and estimated optimal consequent parameters through an iterative least squares procedure. The second part used back propagation to modify the antecedent membership functions.

We tested ANFIS with a range of different cluster radii values. The Multi-Layer Perceptron (MLP) back-propagation Neural Network was tested with different numbers of hidden nodes in a single hidden layer. We tested the AOFIS with different number of fuzzy sets and the membership function overlap threshold was set to 0.5 as this gave both a sufficient degree of overlap while allowing the system to distinguish between the ranges covered by each fuzzy set. Tables 1 and 2 illustrate the scaled Root Mean Squared Error (RMSE) and scaled Standard Deviation (STD) for each technique averaged over the six randomised samples, and corresponding to the values of the variable parameter tested for each approach. The results above show that the optimum number of fuzzy sets for AOFIS was 7 and on average AOFIS produced 186 rules. The GP in comparison gave a marginally lower error for 7 fuzzy sets. Both ANFIS and the MLP on average gave a higher error than AOFIS. The ANFIS only learns a Multi-Input Single Output (MISO) FLC and had to be run repeatedly for each output parameter. The FLC produced was therefore only representative of an MISO system. Another restriction with ANFIS were that it generates TSK FLCs, where the consequent parameters are represented as either linear or constant values, rather than linguistic variables as is the case with Mamdani FLCs. These linguistic variables are very important to understanding the human behaviour. It should be noted that the AOFIS generates Multi-Input, Multi-Output (MIMO) Mamdani FLCs representing rules in a more descriptive human-readable which is advantageous for pervasive computing communities or other ambient intelligent systems, as they deal with people whose behaviours are more easily described in such linguistic terms. The iterative nature of the GP makes it highly computationally intensive and this also applies to both ANFIS and the MLP which are also iterative based approaches. AOFIS is far less computationally intensive due to the one-pass procedure it employs, and is therefore more favourable for an embedded agent Both ANFIS and the GP based approach cannot easily be adapted online as this would require their internal structures to be re-learnt if either new rules were to be added or existing rules were adapted. So the AOFIS method is unique in that it can learn a good model of the user's behaviour which can then be adapted online in a life long mode, in a non intrusive manner, unlike other methods which need to repeat a time consuming learning cycles to adapt the user's behaviour. Hence, in summary, the AOFIS agent proved to be the best for online learning and adaptation, moreover it is was computationally less intensive and better suited to online learning than the other approaches compared. Finally, at the outset of our work it wasn't clear how long, if at all) it would take for such learning in this type of environment to reach a steady state. Our initial results see Figure 12) indicate this is possible within a day although we would need to conduct experiences over much longer periods to catch other cycles , such as annual climate related variations.

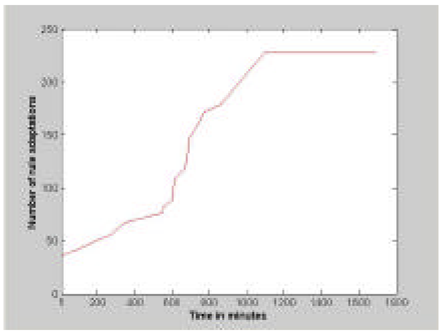


Figure 12 - Typical Learning Rate of FLC based Agent

6.0 An End-User Programming Based Approach

6.1 Discussion

Whilst autonomous agents may appeal to many people, their acceptance is not universal. Some lay-people distrust autonomous agents and prefer to exercise direct control over what is being learnt, when it is being learnt and to whom (or what) the information is communicated. These concerns are particularly acute when such technology is in the private space of our homes. Often, end-users are given very little, if any, choice in setting-up system to their likings, but rather, they are required to "surrender their rights" and "put-up-with" whatever is provided [Chin 04].

Moreover, there are other reasons advanced in support of a more human driven involvement, such as exploiting the creative talents of people by providing them with the means to become "designers of their own "pervasive computing spaces", whilst at the same time, shielding them from unnecessary technical details. To explore this aspect of our inhabited intelligent environment work we have recently opened up a complementary strand of research which we refer to as Task Oriented Programming (TOP) based a combination of Programming-By-Example (PBE) (sometimes referred to as Programming-By-Demonstration - PBD), pioneered by Smith in the mid-seventies [Smith 77], Learning-From-the User (LFU), the paradigm Essex University has been developing for many years and ontologies (the latter mainly drawn from research work on the semantic web) [Berners-Lee].
It is based on a vision to put the *user at the centre of the system programming experience* by exchanging *implicit* autonomous learning for *explicit* user driven teaching.. In this approach a user defines a community of coordinating pervasive devices and then "programs" it by physically operating the system to mimic the required behaviour ie "programming-by-example" [Chin 05].

6.2 Programming-By-Example

Programming-by-example (PBE) was introduced by Smith in the mid-seventies, where the algorithms for the system functionalities were not described abstractly but rather demonstrated in concrete examples [Smith77]. Henry Lieberman later described PBE is "a software agent that records the interactions between the user and a conventional direct-manipulation interface and writes a program that corresponds to the user's actions", where "the agent can then generalise the program so that it can work in other simulations similar to, but not necessarily exactly the same as, the example on which it is taught" [Lieberman01]. Thus, PBE reduces the gap between the user interactions and the delivered program functionality by merging the two tasks. The main area of PBE work has focused on graphical user interfaces running on PCs. For instance PBE has been applied to computer application development [Myers90], [Halbert93]; Computer-Aided Design (CAD) system [PBDCAD]; children's programs [Stagecast], [AgentSheets] [ToonTalk].and World Wide Web related technologies [Sugiura98], [Bauer 00], [McDaniel01], [Lieberman99], [Blackwell01]. The underlying principles in PBE are generic and transportable to the pervasive computing world. In addition to the underlying scientific principle PBE shares the same motivation of empowering lay-end-users to utilise what would otherwise be prohibitively complex technology. However, to-date PBE has not been applied to programming tangible physical objects, nor any other aspect of pervasive computing. Thus TOP is the first application of PBE to this area.

6.3 Task-Oriented-Programming (TOP)

TOP was proposed and developed by Chin in 2003 as a means to address the issues of privacy and creativity in iSpaces [Chin04b]. In the TOP approach, the system is explicitly put into a learning mode and taught (by demonstration) how to behave by the lay end-user. For example the TV or sitting room light could be made to react to an incoming call on the telephone. Thus the telephone, TV and light coordinate their actions to form a new meta (virtual) appliance. The vision goes beyond linking only conventional appliances. For instance if a network capability is added to an appliance, it becomes possible to allow its functional units to be shared with others. Thus in this notion, the audio amplifier in a TV could be made use of by the HiFi system, or vice versa. Consequently, "virtual appliances" could be created by establishing logical connections between the sub-functions of appliances, creating replicas of traditional appliances, or inventing altogether new appliances. This *decomposition* of traditional appliances into their atomic functionalities (either physically or logically) and later allowing users to re-compose "virtual appliances" (nuclear functions) by simply reconnecting these basic atomic functionalities together is the paradigm we called: "the *decomposed appliance*" model. The key to creating "virtual appliances" from decomposed functions is that of making connections between sub-functions so that a closed set of interconnected functions becomes a global set of functions (ie, it becomes a "community", or a collective of coordinating devices with a meta functionality. To facilitate this it is necessary to have some standard way of describing the functionality of the devices and connections; thus, for TOP, we have devised an ontology, dComp (see next section). Clearly, this concept of "*community*" is not limited to decomposed appliances, but relates to any set of coordinated pervasive entities, whatever their functional or physical level (eg it could also relate to nano-scale or even macro-scale building-to-building environments). In general, a richer the pool of sub-functions will lead to greater combinations or permutations for the user to create new virtual appliances.

As TOP has the notion of working with communities the system supports setting up communities (if they don't already exist). Then, by selecting any community that the user wishes to program, a set of coordinated actions are taught to the system by simply using the home networked devices in a role-play mode, supported by some on-screen activities An action causes an appliance to generate an associated event, and this event is then used to generate appropriate rules (based on a "snapshot" of the environment state). To be more general, coordinating actions (ie. tasks) are performed by a community (ie. one or more devices). A device can be involved in more than one community (ie. performing one or more actions). The designers (user) interface with TOP is via an editor called "TOPeditor". This editor provides a means for: (1) setting up / amending communities and (2) holding teaching sessions so that tasks can also be taught (via the editor) as well as via physical usage of networked devices.

The TOP architecture, shown in Figure 6, has two distinct modules; a "Top Editor" (to program the systems) and a "TOP Engine" (to execute the user generated rules). The TOP Editor has two main components. The first component, a "TOP community set-up assistant", allows the user to set up groups (communities) of devices that can communicate and coordinate their actions to produce some desired meta function (or virtual appliance). The second component, the TOP Engine is a process that runs inside each and every networked device and executes the taught rules It has three main components; a "TOP event handler" that monitors connected devices, forming a rules based on a users interaction with the networked devices (interactions generating "events" managed by an underlying UPnP middleware). User interactions can be direct (eg activating a control) or indirect activating a telephone by dialling in from another phone). The second component, a "Rule Manager", manages the addition and removal of rules from memory. This includes removing dormant rules to make space for newer rules, and checking for duplication or conflicts. The third module, "the Local Rule cache" acts as a temporary rule buffer whilst rules are being built by the user (ie while the user is still designing and experimenting with creating community functionality). To facilitate the information to be used within and beyond the community, data needs to be standardised so that it can be understood by all other parties in the network. For this aspect of work, the semantics in the TOP dComp ontology supports information interoperability between applications, providing a common machine "understanding" knowledge framework.

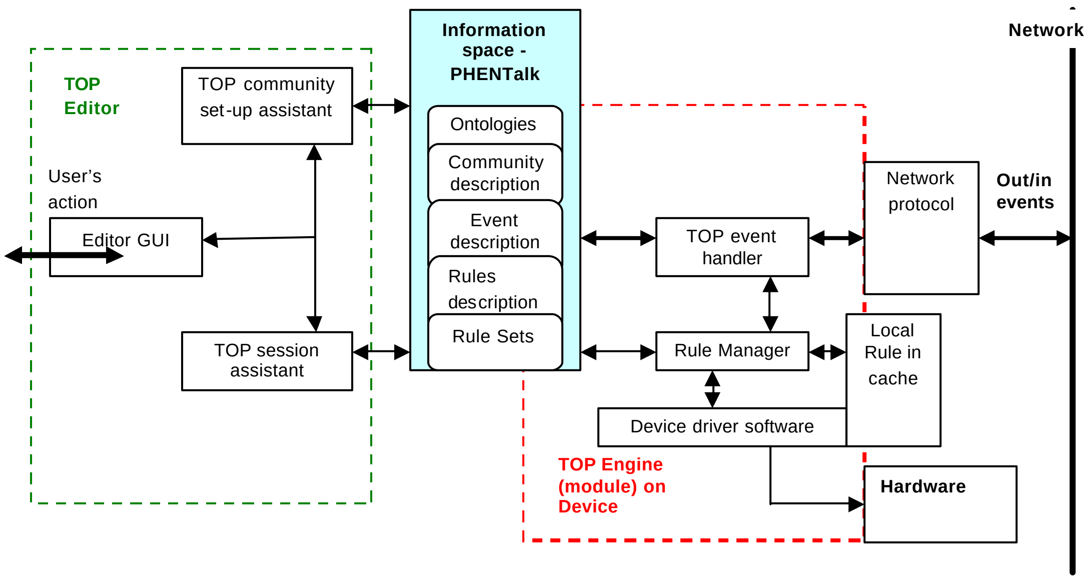


Figure 13 - The TOP Architecture

6.4 The dComp Ontology

TOP leverages Ontology semantics as the core vocabulary for its information space, generating ontology-based rule sets when a user demonstrates her/his desired tasks to the system in a "teaching" session. As explained in the previous section, these rule-sets are then interpreted and executed by a back-end execution engine; the "TOP Engine". (TOPengine). As Ontology allows information to be conceptually specified in an explicit way by providing definitions associated with names of entities in a universe of discourse (eg. classes, relations, functions, or other objects)that are both a machine and human useable format. Thus, in more practical terms, ontology describes things such as what a device names mean, and provide formal axioms that constrain the form and interpretation of these terms. Most ontology tools support descriptions of behaviour based on rules, hence an ontology based approach is well suited the challenges TOP faces.

We have chosen to base dComp around the OWL language as it is more expressive than RDF or RDF-S (ie provides additional formal semantic vocabularies allowing us to embed more information into our ontology) and. is widely used (especially for the semantic Web) with numerous supporting tools such as Jena [HP Jena] and inference engines such as RACER [Haarslev and Moller 01], F-OWL [Zou 04], Construct [Network Inference]. In order to realise our vision, a set of explicitly well-defined vocabularies (ie. an ontology) is needed to model, not just the basic concept of decomposed devices but also, the communities they form, the services they provide, the rules and policies they follow, the resultant actions that they take, and of course the people who inhabit the environment along with their individual preferences; dComp provides these properties. Wherever possible we have sought to build on existing work. The SOUPA ontology (from Ubicomp) is aimed at pervasive computing but lacks support for key TOP mechanisms such as community, decomposed functions and coordinating actions (to produce higher level meta functionality) [Soupa]. In addition, the current SOUPA standard has only limited support for the concept of pervasive home UPnP-based devices (with TOP depends on). However, SOUPA has a well defined method of supporting notions of Action, Person, Policy and Time which dComp has adopted. Thus most of the innovation in dComp relates to the ontology of decomposition and community; hence the name "Decomposed Community Programming" (dComp).

The following is a summarised walk-through of the full dComp specification which is described more fully online[2] and in other papers [Chin 04b]. To avoid any confusion in terminology, henceforth we refer the dComp Ontology as "the ontology" whereas the documents that describe a certain concept of entities (e.g. device, services, community etc) that exist in the dComp environment are referred to as "ontology documents". Ontology also describes a set properties and relationships that are associated with these concepts, along with the restrictions they may have. The current version (v.1.1)of the dComp ontology consists of 10 classes (see figure 14).

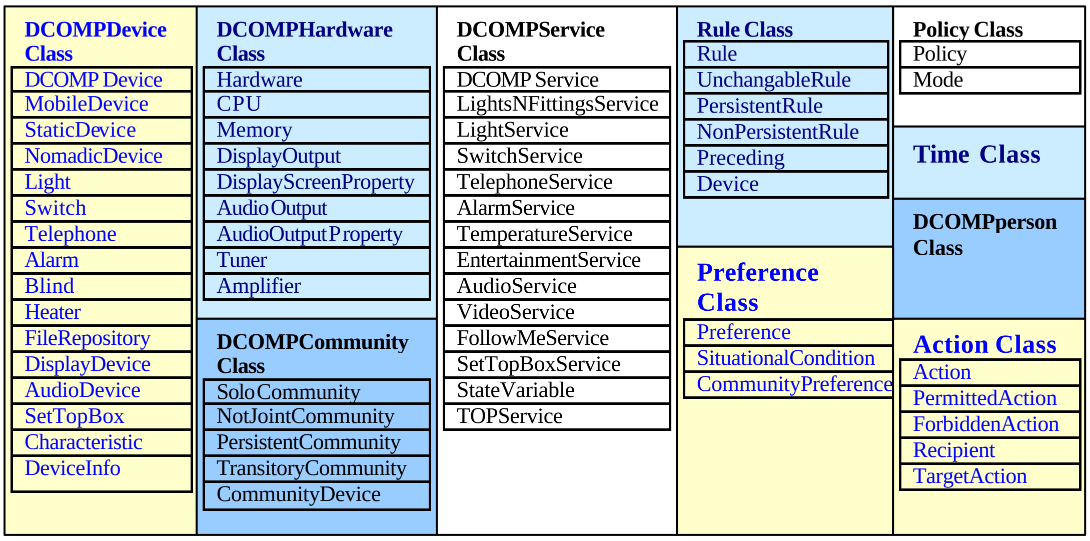


Figure 14. dComp ontology (v.1.1)

6.4.1 The Device Class

The main class called "DCOMPDevice" provides a generic description of any devices. Currently DCOMPDevice has 10 sub-classes including both nuclear (traditional appliances) and atomic (decomposed) devices and remains the subject of ongoing development. The roles of most sub-classes are obvious from their names. Those which might not be obvious include "DeviceInfo" which is for individuals that share some UPnP descriptions, "DeviceInfo" for devices sharing some UPnP descriptions, "Characteristic" for different mobility characteristics, Relationships are defined by using the OWL object property[5] and are: (1) hasDeviceInfo (2) hasHardwareProperty (3) hasDCOMPService (4) hasCharacteristic. The main elements of a typical DCOMPDevice expression is shown in figure 15.:

6.4.2 Hardware Class

The abstract class, DCOMPHardware, generalises all hardware that exists in a DCOMPDevice and, in the current version,, has 8 sub-classes along with associated properties: CPU, Memory, DisplayOutput, DisplayInput, AudioOutput, AudioInput, Amplifier and Tuner. In order for the DCOMPDevices to work together, every DCOMPDevice on the dComp network offers services. These services are modelled by a class called "DCOMPService" which currently contains three sub-classes, namely TOPService, LightsAndFittingsService and EntertainmentService. Each contains sub-services, for example, the EntertainmentService class includes AudioService, VideoService, FileRepositoryService, SetTopBoxService and FollowMeService. The LightsAndFittingsService and EntertainmentService are mutually distinct (ie in mathematical terms, they do not belong to a same set). These characteristics are

[2] dComp ontology can be retrieved from : http://iieg.essex.ac.uk/dcomp/ont/dev/2004/05/
[5] object property denotes relations between instances of two classes. See owl:ObjectProperty
[6] SymmetricProperty denotes: If a property, P, is tagged as symmetric then for any x and y: P(x,y) iff P(y,x)

modelled by declaring the classes to be disjointWith[7] each other. Every service in the dComp environment is identified by a property called "serviceID" and a class called "StateVariable" (to represent UPnP values). The StateVariable class has three properties, namely: "name", "value" and "evented". The relationship between a DCOMPService and the StateVariable is linked by an object property called "hasStateVariable". The relationship between a DCOMPDevice and DCOMPService is coupled by an object property called: hasDCOMPService.

```
<device:AudioDevice rdf:ID="TestDevice12">
<device:hasDeviceInfo>
<device:DeviceInfo>
<device:friendlyName>TestDevice12</device:friendlyName>
<device:DeviceUUID>0</device:DeviceUUID>
<device:DeviceType>urn:schemas-upnp-
org:TestDevice12:1</device:DeviceType>
<device:DeviceModelURL>http://TestDevice12URL/</device:Devi
ceModelURL>
<device:DeviceModelNumber
rdf:datatype="&xsd;double">0.0</device:DeviceModelNumber>
</device:DeviceInfo>
</device:hasDeviceInfo>
<hw:componentOf>
<hw:RAM rdf:about="#JCTestMemory2"/>
</hw:componentOf>
<serv:hasDCOMPService>
<!-- can have more than 1 service -->
<serv:AudioService rdf:about="#JCAudioService01"/>
</serv:hasDCOMPService>
<!-- 2nd service -->
<serv:hasDCOMPService>
<serv:AudioService rdf:about="#JCAudioService02"/>
</serv:hasDCOMPService>
<!-- 3rd service –>
<serv:hasDCOMPService>
<serv:AudioService rdf:about="#JCAudioService03"/>
</serv:hasDCOMPService>
```

Figure 15 - Typical Display Device Expression

```
<com:TransitoryCommunity rdf:ID="JCTV">
 <com:communityID>Tran-JCTV</com:communityID>
 <com:communityName>JC TV</com:communityName>
 <com:communityDescription>The first JC testing
TV</com:communityDescription>
 <com:timeStamp rdf:datatype="&xsd;dateTime">2004-09-
06T19:43:08+01:00</com:timeStamp>
 <com:hasOwner>
  <person:Person rdf:about="#JC"/>
</com:hasOwner>
<com:hasCommunityDevice>
 <com:CommunityDevice rdf:about="#JCMonitor CRT17"/>
</com:hasCommunityDevice>
<com:hasCommunityDevice>
<com:CommunityDevice rdf:about="#JC AudioMMS223"/>
</com:hasCommunityDevice>
<com:hasCommunityDevice>
 <com:CommunityDevice rdf:about="#JC :NetGem442"/>
</com:hasCommunityDevice>
</com:TransitoryCommunity>
```

Figure 16 - Typical TV community definition

6.4.2 Community Class

As dComp needs to support the notion of community (a collective), there is a class called DCOMPCommunity. In the current implementation we model three types of communities namely: (1) SoloCommunity (for those devices not yet part of a community) (2) PersistentCommunity (for communities with a degree of permanency) (3) TransitoryCommunity (for communities with a short lifetime). A DCOMPDevice can join one or more communities (a community must have at least one device). Relationship between a DCOMPDevice and a DCOMPCommunity, is desrbed using an object TransitiveProperty[8] called "inTheCommunityOf". A class called "CommunityDevice" is introduced to represent all the devices in a community. These devices are identified by their deviceUUID identification. The relationship between a Community and CommunityDevice is linked by another object TransitiveProperty called "hasCommunityDevice". Communities in dComp are formed by a user; thus, each community has an owner. The properties of Communities are: community ID, communityName, communityDescription and timestamp. The relationship between a community and its owner is linked by an object type property, called "hasOwner". An example of the main elements in a dComp TV community is given in figure 16.

6.4.3 Rules Class

Rules are needed in TOP for coordinating community actions and are supported by a class called "Rules" which models three types of rules: (1) UnchangeableRules (rules that can not be changed), (2) PersistentRules (rules that infrequently change) and (3) NonPersistentRules (rules that frequently change). These rules are mutually distinct and are declared to be complementOf[9] each other. Rules have properties: ruleID and ruleDescription and an object property called "hasRuleOwner" to link to the owner. (Note: the rule and community owners may be different people). A class called "Preceding" is used to represent a set of triggers that cause the coordinating actions to be executed. The devices in the Preceding class are identified by their deviceUUID, and the service they offer. Finally an object property called "hasAction" binds the relationship between Rules and Actions. The main elements of a Rule Definition is given in figure 17.

[7]disjointWith asserts that the class extensions of the two class descriptions involved have no individuals in common.

[8] TransitiveProperty denotes if a device X is in the community of C and the community C is a member of Community P then the device X is also a member of community P

[9] complementOf denotes all individuals from the domain of discourse that do not belong to a certain class

```
<NonPersistentRules rdf:ID="Rule1">
 <rule:ruleID rdf:datatype="&xsd;int">00001</rule:ruleID>
  <rule:ruleDescription>Test Rule 1</rule:ruleDescription>
  <com:communityID>Tran-JCTV</com:communityID>
 <rule:hasRuleOwner>
   <person:Person rdf:about="#JC"/>
  </rule:hasRuleOwner>
<rule:hasPreceding>
  <!-- can have more than 1 device -->
   <rule:Device>
   <dComp:DeviceUUID>uuid:Telephone01</dComp:DeviceUUID>
    <serv:hasDCOMPService>
    <!-- a device can provide more than 1 service -->
     <serv:TelephoneService>
      <serv:serviceID>Telephone</serv:serviceID>
       <serv:hasStateVariable>
                <!-- a service can have more than 1 value of state variable-->
                  <serv:name>state variable 1</serv:name>
                  <serv:value>RINGING</serv:value>
      </serv:hasStateVariable>
     </serv:TelephoneService>
    </serv:hasDCOMPService>
   </rule:Device>
</rule:hasPreceding>
<rule:hasAction>
 <act:PermittedAction rdf:about="#TestAction"/>
</rule:hasAction>
</NonPersistentRules>
```

Figure 17 - Main elements of Rule Definition

```
<owl:Class rdf:ID="SituationalCondition">
 <rdfs:label>SituationalCondition</rdfs:label>
 </owl:Class>
 <SituationalCondition rdf:ID="DuringTheWorkdays"/>
 <Situational Condition rdf:ID="DuringTheWeekends"/>
 <SituationalCondition rdf:ID="WhileOutOfTown"/>
 <SituationalCondition rdf:ID="WorkingFromHome"/>
 <SituationalCondition rdf:ID="FriendsVisiting"/>
 <SituationalCondition rdf:ID="FamilyVisiting"/>
 <SituationalCondition rdf:ID="OnHoliday"/>
 <SituationalCondition rdf:ID="WhenComeHomeFromWork"/>
 <SituationalCondition rdf:ID="WhenComeHomeFromSchool"/>
 <SituationalCondition rdf:ID="WhenAtMyOffice"/>
 <SituationalCondition rdf:ID="WhenDining"/>
 <SituationalCondition rdf:ID="WhenHavingLunch"/>
 <SituationalCondition rdf:ID="WhenHavingBreakfast"/>
 <SituationalCondition rdf:ID="WhenEating"/>
 <SituationalCondition rdf:ID="WhenPlayingComputerGames"/>
 <SituationalCondition rdf:ID="WhenWatchingTV"/>
 <SituationalCondition rdf:ID="AtNight"/>
 <SituationalCondition rdf:ID="InTheMorning"/>
 <SituationalCondition rdf:ID="AtLunchTime"/>
 <SituationalCondition rdf:ID="AtTeaTime"/>
 <SituationalCondition rdf:ID="Alone"/>
 <SituationalCondition rdf:ID="WhenAlarmGoesOff"/>
 <SituationalCondition rdf:ID="WhenSmokeAlarmGoesOff"/>
```

Figure 18 - Main elements of a Situated Condition.

```
<act:PermittedAction rdf:ID="TestAction">
 <act:actionName> Test action</act:actionName>
  <act:hasRecipient>
device:DeviceUUID>UUID:PHLAudioMMS223</device:DeviceUUID>
   <serv:serviceID>AudioMMS223</serv:serviceID>
  </act:hasRecipient>
 <act:hasTargetAction>
  <act:actionName>Mute</act:actionName>
  <act:ta rgetValue>Mute</act:targetValue>
 </act:hasTargetAction>
</act:PermittedAction>
```

Figure 19 - Main elements of an Action (muting the TV)

6.4.3 Action, Person, Policy and Time Class

Wherever possible we have sought to build on existing ontology work. SOUPA provides a suitable DCOMPperson, Policy and Time ontology and thus these have been adopted in dComp [7]. The Action ontology document has, to some extent, been influenced by the SOUPA Action ontology. The class "Action" represents the set of actions defined by the rules. As with SOUPA, we have two types of actions, namely: PermittedAction and ForbiddenAction class. The Action class in dComp is the union of these two action classes; every coordinating action has its target devices. A class called "Recipient" models target devices, which represents a set of target devices where actions take place. The members of Recipient are identified by their deviceUUID and the serviceID. Actions for the recipient are called "TargetAction" which has two properties namely actionName (the name of the action) and targetValue (the value for the action to be taken). A typical statement "when the phone rings, mute the TV" could be expressed as in Figure 19.

6.4.4 Preference Class

As the name implies, DCOMPPreference describes the preferences a person has within any given set of options. In dComp, preferences are referred as "situated preferences", which is similar to Vastenburg's "situated profile" concept where he uses situation as a framework for user profile so that the values of the profile are relative to situations [Vastenburg 04]. The "Preference" class represents a set of situated preferences of a person for his community. This Preference class has a subclass called "CommunityPreference" and an associated property called "communityID". To model "person A prefers X, depending on the situation conditions of Y", another class called "SituatedConditions" is defined which represents the set of situated conditions that the person's preferences depended on. Although a person is allowed to define his own "SituatedConditions", dComp explicitly defines a list

[7] For further information refer to their site at: http://pervasive.semanticweb.org/soupa-2004-06.html

of pre-set situated conditions so that it forms a default template that a person can use. The Preference class has a close relationship to the Person class. To bind this relationship, an object property called "hasPreference" is used, which links the domain of Person to the range of Preference. The relationship between the Preference class and SituationConditions class is linked by another object property called: "hasCondition". The main elements of a Situated Condition are given in figure 18.

6.5 dComp Performance

To assess the performance of dComp we compared two sets of device descriptions; the first description was structured in typical xml-based "all-in-one" format, while the second was decomposed into smaller segments (i.e. broken up into hardware and service information), each segment being "linked" back to the device. Both descriptions were written in OWL. For each set, we used 2 different quantities of devices in the test (3 and 32). A common query with five conditions was used for the test, with each test being run fifty times. The test was conducted using a WindowsXP, 2.08 GHz, 512 RAM machine. Four sets of tests were completed: (1) 3 device descriptions in "all-in-one" format (2) 3 device descriptions in "decomposed" format (3) 32 device descriptions in "all-in-one" format and (4) 32 device descriptions in "decomposed" format.

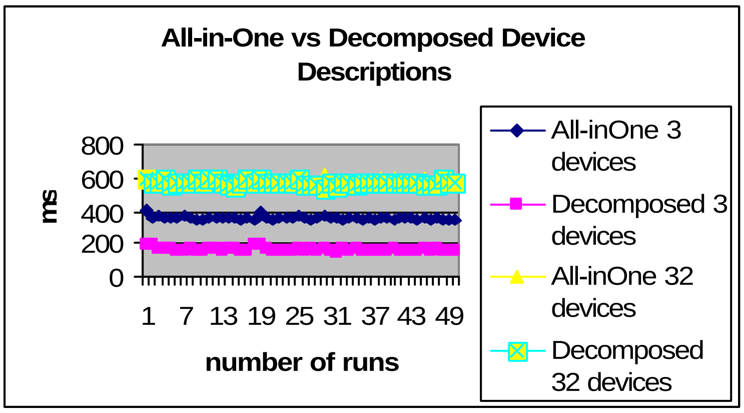


Figure 20. A typical dComp performance test

A representative example of our tests is provided in figure 20. As can be seen we found that the decomposed device description out-performed the compact devices description for smaller domains with fewer devices. On average, queries took half the time that "all-in-one" format descriptions took. Although we had been concerned that decomposed descriptions might not fair as well for larger domains, because of increased link following, we found that this was not the case, as the system performed as well as the "all-in-one" descriptions, whilst bringing the advantages of decomposition described earlier. This we attribute to additional link-processing being counterbalanced by the processing benefits of smaller, better focused descriptions. For larger domains we found that the performance of decomposed versus the compact descriptions remained roughly the same. Both TOP and dComp represent new directions in our research and t hold great promise for solving the problems of providing user creativity and privacy.

7.0 Summary

Both the ISL and AOFIS provide life-long learning and adaptation for pervasive devices and communities. Both techniques were evaluated by arranging for users to live and use the iDorm for periods of up to five days. Both techniques performed well in handling human behaviour (with all the uncertainties involved), and in dealing with complex sensors, actuators and control. The agents operated in a non-intrusive implicit manner allowing the user to continue operating the pervasive computing device or community in a normal way while the agents learn controllers that satisfy the users required behaviour.

In contrast the TOP approach deliberately seeks to involve the user in the learning phase, providing explicit control of what and when the agent learns. In support of TOP we devised the ontology dComp which directly supports the concept of community, and collectives of decomposed devices, together with coordinating actions to create meta-group functionalities. We were motivated to produce such an ontology to serve our longer terms research goals which aim to explore the development of end-user tools to allow lay-people to "program" groups of coordinated pervasive computing devices, so as to become designers of their own environments. In dComp, the notion of decomposition extends to device descriptions which are decomposed to map to separate sub-capabilities, each linked to other related descriptions. Thus, decomposed device descriptions do not necessary have to reside in the same place, a consequence of dComp's roots being in the semantic web ontology, which firewall the physical location of data servers, facilitating information retrieval via a hyperlink. dComp device descriptions can be shared or reasoned about by other applications on the network, while queries can be directed to a specific service rather than the whole device.

Contrasting these two approaches will allow us to evaluate the arguments for and against increased agent autonomy and determine when and where each is appropriate. In all the approaches, the underlying science is based on methods that are practical to implement in embedded-computers.

7.1 Future Directions

Our work is taking a number of directions. First we are continuing to try to develop and experiment with new types of autonomous intelligent embedded-agents. For example we have projects underway looking at new Type-2 Fuzzy logic based agents and new types of neuro-Fuzzy agents. We are also mindful of the role that mood and emotions play in making decisions and have begun a project that is seeking to enrich the decision space of agents by adding sensed data on emotions. We have also embarked on two projects concerned with investigating developing agents at a nano-scale; one project is looking at nano agents in fluids, the other as part of smart surfaces. Our end-user programming work (TOP and ontologies) is at an early stage but the initial results as report in this paper are encouraging. We anticipate future systems will require a mix of both autonomous-agent approaches (perhaps dominating low levels) and end-user programming methods (perhaps dominating higher levels). We hope our work will go some way to resolving where and when either method is most appropriate, perhaps exploring the notion of the end user determining the levels of autonomy that the communities of devices use. Finally, to gather more realistic and meaningful results for all our research into pervasive environments, we need better data and so, with SRIF support, we have embarked on the construction of a new purpose built test-bed for pervasive computing and iSpace work called the iDorm-2. The iDorm-2 is a full size domestic flat built from scratch to facilitate experimentation with pervasive computing technology. Apart from being equipped with the latest pervasive computing appliances, and having been constructed to facilitate easy experimentation, the major advantage of the iDorm-2 is that we will be able to get much longer periods of experimentation as people will be able to stay in the environment for weeks and months. Thus we look forward to being able to report more interesting and useful results when this facility comes on line in January 05.

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