Early version of paper published in the Special Issue of Pervasive and Mobile Computing Journal on ``Human Behaviour in Ubiquitous Environments", Elsevier B.V, Volume 6, Issue 4, 2010

Affective Computing inside Intelligent Inhabited Environments: Effects of emotional information on the performance of a Fuzzy Agent.

Enrique Leon, Graham Clarke, Faiyaz Doctor, Victor Callaghan.

Abstract

Emotions have been perhaps the most underrated human trait of all. They are often used to explain how people act or react as they do and yet in science they do not seem to serve any useful purpose for rational deliberation. At least that was the assumption of researchers from various areas who a few years ago started studying emotions and its relationship with rationality. It has now become evident that emotions play an important role in learning, memory, decision-making, interaction, and motivation. It has been even suggested that the lack of emotional intelligence, i.e., the capability to recognise and utilize emotions, could impair the relationships between humans and their environment. In this paper a study is presented demonstrating the effects of emotional information on the capacity of intelligent agents to adapt to user preferences inside domestic environments. Experiments were carried out over an 8-day period inside the i-Dorm2 which is a self-contained apartment used as a testbed for various software agents paradigms. Preliminary results suggest that an agent incorporating meaningful emotional data into its input array could model user behaviour in a more accurate way than non-emotional or raw-physiological emotional agents. Improved mapping of human activities is of great significance for pervasive computing for it leads to optimal user comfort and enhanced use of resources.

Introduction

In 325 BC, Alexander III of Macedonia found himself stranded on the top of the wall protecting the capital of the Mallians (modern Multan in Pakistan). The ladder he had used to climb up had broke and just three of his men had been able to follow him after he had taken the lead a few moments ago (he was aware of a growing apathy among his troops and wanted to set an example). But instead of jumping back among his comrades, the king leaped down into the citadel and confronted the enemy alone. A cautious, rational man would have not risked his life as Alexander did. Or at least that is what reasoning tells us. Nonetheless, this does not seem to be an act of utter irresponsibility or reckless audacity but rather a calculated action stemming from the Macedonian awareness of superior military skills and strong inner feelings[1].

Throughout history emotions have provided capable men and women with the fortitude needed to realize their dreams and ideas be it a decision sealing the fate of a country or a scientific endeavour. This combination of cognitive and emotional components is an ingrained part of human thinking and determines the course of our actions and development [1]. However, it is until the nineteen nineties, sometimes known as "decade of the brain"[2], that researchers from various disciplines provided strong evidence with respect to how emotions influence reasoning in our decisions and also our motivational and learning mechanisms. Neurologists demonstrated that, for instance, emotions sometimes override reasoning in situation demanding quick decisions and immediate actions. They also discovered that affective states are an important neurological regulator of the relationships of humans and their environment and that normal behaviour is greatly disturbed in the absence of such regulators[2-4]. Moreover, the ability to make optimal decisions is highly dependant on the human capacity to identify and utilize emotions, i.e., emotional intelligence [5]. It has now become clear that the emotional and the cognitive are two interrelated, cooperative, inter-dependant constituents of our being rather than separate, incompatible, independent elements.

In fact, those researchers still pursuing the path of a purely rational-choice approach in order to develop models of human interaction and/or inference are facing what is called an indeterminate, inadequate theory [6]. A theory becomes indeterminate when it fails to deliver a unique prediction and inadequate when the its predictions are erroneous.

The inadequacy of reason applies not only to extreme situations but also to simple, ordinary, everyday life events. For example, a person could choose to turn a light on because of difficulties seeing or because of

[1] This anecdote was likely taken from Ptolemy's accounts of Alexander's military campaign in India and has been cited by many historians throughout the years.
[2] This term is commonly used by researchers after the US Presidential Proclamation 6158, July 17, 1990.

anxiety caused by a darkening room, or switch the TV off because of an emotional episode caused by a TV show or simply out of boredom, or stop working due to stress, depression, or extreme happiness or just because it is time for a break. It is apparent that decisions stemming from routine behaviour could be relatively easy to predict or establish; those involving a emotional-bodily components probably not.

The view of computer scientists and in particular those working in artificial intelligence (AI), has always been pointing towards a skewed interpretation of rational thinking as a purely cognitive process leaving affective states aside. This has gradually changed and more computing research has been aimed at finding ways of incorporating emotions into artificial information processes. Numerous investigations have been undertaken in areas ranging from human-machine interfaces with emotional content to the development of artificial nervous systems capable of displaying signs of affect [7,8].

Affective Computing

The term affective computing was coined by Picard in the mid 90s to describe computer methods that are related to, derive from or affect emotions[9], and involves two areas: Emotion synthesis (simulation), used to artificially imitate some of the physical or behavioural characteristics associated with affective states, and emotion analysis (recognition) which is often employed in decision making for interactive systems. Emotion synthesis is useful to develop ways to communicate with humans at a subjective level involving social participation, for example using robots. Emotion detection on the other hand could be used to monitor the emotional state of a subject and then take actions based on the type of individual experience being felt. Some computing systems are even capable of displaying immediate reactions to people's feelings by incorporating a combination of both emotion detection and emotion synthesis.

Hitherto, the identification and classification of emotional changes has obtained mixed results ranging from 60-95.5% detection accuracy for facial recognition [10-15] to 50-87.5% for speech recognition [16, 17], and 72% in bimodal recognition (face and speech) [18]. In physiological emotion detection some of the best results have been achieved by Kim et al. [19] with 61.2% correct classification for 4 emotions, Nasoz et al. 50-90% for 5 emotions [20] and Picard et al. with 81% for 8 emotions [21]. Some of the recognition techniques employed in the above approaches include neural networks [10-16] and advanced statistical mechanisms [17-21].

Towards the integration of Affective and Pervasive Computing

The idea of being able to exhibit emotions through electronic means has captivated the imagination of many researchers in various computing areas including IIE and robotics. In fact, the creation of artificial entities capable of displaying affect and interacting with users at an affective level represents a fertile ground not only for computer science but also for medicine and psychology. Many other social and technological fields could also benefit from the detection, utilization, and eventual imitation of human feelings. The research presented in this paper however concentrates on investigating the potential of emotion recognition for pervasive computing and leaves emotion simulation as an open issue.

Pervasive or ubiquitous computing involves the integration of computers into the environment allowing the user to interact with them in a more natural way. It is argued that by allowing embedded computers to recognize and use emotional information, IIE software agents would be able to adapt better to what the user wants, increase the accuracy of decisions derived from what the user does, and facilitate mutual interaction. Actions taken by affective IIE agents would ultimately be comparable to those related to intelligent human activity, i.e., accurate fulfilment of immediate personal needs.

Methods

Experiments were carried out inside an experimental testbed for intelligent agents (iDorm2), to assess the degree to which emotional data could contribute towards improving the modelling of a user's behaviour inside an intelligent environment. An enhanced representation of the way the user interacts with the environment could lead to better agent adaptability and a reduced need for user intervention, more efficient use of resources, and ultimately increased comfort.

Real-time Emotion Detection

The first step towards the effective incorporation of affective and pervasive computing into IIE lies in the accurate identification of the emotional state of the individual being analysed. Towards this end, the combination of Autoassociative Neural Networks (AANNs) [22] and sequential analysis, proved to be effective to detect changes in physiological signals associated with emotional states (neutral and non-neutral) from a single individual with 100% recognition rate [23] and 85.2% on experiments involving three emotional categories, i.e., neutral, positive, and negative, on 8 subjects.

This approach to recognizing affective changes is based on a real-time continuous evaluation of 4-5 measures associated with the autonomic system and the brain which have been previously subjected to a clustering analysis. The calculation of the instantaneous Davies-Bouldin cluster separation Index (DBI)[24] is used to select the attribute(s) that contribute to the best separation of the emotional states involved.

The above methodology is based on the idea that the detection of emotional changes using physiological signals could be likened to a real-time sensor validation process in which emotional states could be detected by estimating the amount of deviation they demonstrate with respect to a neutrally-emotional state. Alterations in the autonomic system associated with emotional states are identified by providing a Sequential Probability Ratio Test (SPRT) [25] module with the continuous calculation of the difference between the actual sensor values and their AANN-estimated counterpart (residual henceforth).

Because the AANN is trained to mimic the input behaviour of the neutral state, the mean of the difference is be very close to zero (with a standard deviation similar to that of the noise introduced by the sensing device) when the physiological state of the subject is normal. When the sensor value chose by means of the DBI calculation drifts because of a change in the physiological status of the subject provoked by an emotional episode, the mean value of the residual deviates from zero. The SPRT value is consequently altered and the likelihood ratio displaced to either of the two solution spaces (neutral or non-neutral and positive or negative). Despite the fact that only one physiological measure is employed in the SPRT calculation, the relationship of all the parameters is needed for projecting the targeted variable into the AANN estimation space.

This way to detect emotional changes in real-time has been proved to be sufficiently robust to resist perturbations caused by various degrees of emotional intensity and bodily changes associated with physical activities such as exercise or household chores[26-27].

Experimental Vital-sign-based Emotional State Transmitter (X-Vest)

The X-Vest is a wearable artefact capable of communicating the wearer's emotional state in real time using wireless technology (see Figure 1). The X-Vest integrates a finger clip with built-in sensors providing 3 physiological signals, i.e., heart rate (HR), skin resistance (SR), blood volume pressure (BVP), and 2 estimated parameters, namely the gradient of the skin resistance (GSR) and the speed of the changes in the data (CS - a measure of the signal's' entropy). Bodily signals are sent to a PC computer using a bluetooth connection and then employed to identify neutral, positive, or negative emotions using the methodology described above. The emotion detection system is in turn embodied as a UPnP device allowing remote cross-platform access (see Figure 2).

The use of robust effective emotion detection in the X-Vest mechanism guarantees the accurate recognition of underway affective states under various dissimilar circumstances and user characteristics and also makes possible reliable real-life experimentation involving ambulatory conditions.

Figure 1. The X-Vest. Attire, sensing device, and transmitter.

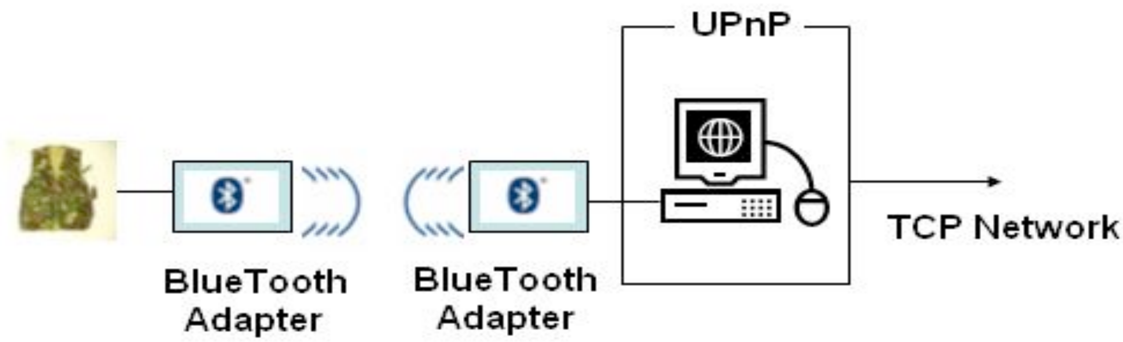


Figure 2. The X-Vest. Architecture.

Fuzzy Logic Agent

A fuzzy agent previously shown to possess improved adaptability to operating inside intelligent environments was used in this study [28,29]. This implementation of a Fuzzy Logic Controller (FLC) is based on the utilization of singleton fuzzification, max-product composition, product implication, and height defuzzification techniques to produce a model of the user's behaviour inside domestic environments, more specifically, the iDorms 1and 2. After an initial monitoring phase the fuzzy agent is able to extract fuzzy rules and membership functions from ambience information and then use such rules and functions to efficiently control the environment while guaranteeing users physical ease.

The agent's input vector comprises seven sensors: the internal and external light levels, internal and external temperature, chair pressure, couch pressure and time measured as a continuous input on an hourly scale. Artefacts subjected to agent control include four variable intensity spot lights, a desk lamp, and two PC-based applications namely a word processing and a media playing program. An important attribute of this particular agent is its improved capacity to adapt to changes in the environmental parameters being monitored. Thanks to this long-term learning functionality the fuzzy agent provides an enhanced depiction of the conditions inside the iDorms.

In the present study three different implementations of this fuzzy agent were compared: the original agent with no emotional information (NEA), an agent using an extra input involving discretized emotional values (1-Neutral, 2-Positive, 3-Negative) (DEA) and an agent with raw fuzzified emotional data added to the original input vector (4 Fuzzy sets stemming from the residual of the heart rate) (RFEA).

Experimental Procedure

A male subject aged 27 who was assessed as of low emotionally intensity (based on the Affect Intensity Measure score[30]) lived inside the iDorm2 for 8 days while being equipped with the X-Vest (see Figure 3). The first two days were used to collect ambience and emotional data to train the three fuzzy agents. In the remaining 6 days the subject performed a range of activities inside the iDorm2 comparable to those commonly undertaken in everyday life e.g., studying, eating, resting, exercising, etc. A crucial element in the present study is that the participant was asked to behave as naturally as possible and not to alter his normal behaviour or his response to unforeseen circumstances such as unexpected changes in the weather or his physical state e.g., in the event of feeling unwell.

In order for a comparison to be as accurate as possible, the three fuzzy agents were exposed to similar temperature and light conditions over the whole period of experimentation. Because of the restrictions imposed by the use of the actuators (they could only be operated by one agent at a time) parallel operation of the agents was not possible. Therefore, it was decided that each agent would be used at a pseudo randomly selected time slot on the same day for the 6-day controlling period (the monitoring phase was the same for all the agents). The various time slots were chosen based on the times of the day in which more activity is likely to take place under normal conditions i.e., Morning or Breakfast time (8-10 AM), Midday or Lunch time (1-3PM), and Evening or Dinner time (6-8:20 PM). The random time slot assignation was made with the condition that all the agents would end up having the same exposure time. Thus, each agent was employed twice in the morning (1st and 2nd Session of 120 min. (7200 sec.) each), afternoon (1st and 2nd Session of 120 min. (7200 sec.) each) and evening (1st and 2nd Session of 140 min. (8400 sec.) each). Table 1 and 2 illustrate the order in which the three agents were used and the ambience conditions on the 6-day controlling phase.

Figure 3. Experiments inside the i-Dorm2.

		Agent Type		
Day/Time Slot		NEA	DEA	RFEA
Day 1	8-10 AM			
	1-3 PM			
	6-8:20 PM			
Day 2	8-10 AM			
	1-3 PM			
	6-8:20 PM			
Day 3	8-10 AM			
	1-3 PM			
	6-8:20 PM			
Day 4	8-10 AM			
	1-3 PM			
	6-8:20 PM			
Day 5	8-10 AM			
	1-3 PM			
	6-8:20 PM			
Day 6	8-10 AM			
	1-3 PM			
	6-8:20 PM			

Table 1. Assignation of experimental time slots.

	Ambience Conditions (Averaged Values)	
	Light	Temperature

Time Slot			Internal	External	Internal	External
8-10AM	1st Session	NEA	126.67	89.57	27.41	20.64
		DEA	133.98	90.39	27.56	20.88
		RFEA	142.59	88.37	27.68	20.73
	2nd Session	NEA	241.75	92.33	27.23	24.52
		DEA	232.58	92.46	27.09	21.87
		RFEA	319.27	92.55	27.75	26.46
1-3PM	1st Session	NEA	133.81	88.93	27.87	23.41
		DEA	314.65	93.15	28.63	22.19
		RFEA	246.61	93.02	28.51	27.70
	2nd Session	NEA	328.03	93.19	29.30	30.09
		DEA	223.10	92.02	28.03	23.13
		RFEA	81.95	58.30	23.95	19.97
6-8:20PM	1st Session	NEA	41.04	79.01	27.99	21.36
		DEA	103.18	89.16	28.25	24.14
		RFEA	73.12	86.68	28.48	21.32
	2nd Session	NEA	95.35	89.46	25.48	19.91
		DEA	63.50	87.46	26.27	22.80
		RFEA	72.53	86.99	26.35	19.52

Table 2. Light and temperature levels for the 6-day experimentation period.

Results

Agents' performance was evaluated according to two key categories: Interaction Model, and User Comfort. These two parameters are related to the agent's direct interaction with the user and provide a clear indication on whether a particular agent struggled to accommodate and/or adapt to user behaviour. Two categories previously employed to examine the performance of various intelligent agents paradigms are also presented [28, 29], namely the Progress Function and Model Stability. These two categories are mainly included in this paper with the intention of providing other researchers investigating affective computing in IIE with the basis to perform accurate comparisons between the present and other approaches.

Interaction Model

Interaction model refers to how effective an agent was to modelling user activities inside the iDorm2 after the two data collection days and during the 6-day controlling period. This could be evaluated by examining the number of initial and new rules that required an adaptation after they were created and also how many of these initial and new rules were actually used by the agent, i.e., the usefulness of the rules.

Table 3 shows that in terms of the suitability of the initial FLC model, the agent with raw fuzzified emotional data (RFEA) displayed greater accuracy since only 5.6% of the initial rules were adapted. In contrast 9.5% and 17.4% of the initial rules generated by (DEA) and the non-emotional agent (NEA) respectively, were modified. The advantage of RFEA's preliminary model is also confirmed by the greater number of initial rules that were fired: 40.3% against 39.1% of DEA and 27.2% of NEA.

The quality of the rules generated during the 6-day controlling phase seems to have clearly favoured DEA since only 3.4% of these were altered in opposition to 40.9% for NEA and 55.8 % for RFEA. The accuracy of the new rules was also superior for DEA since 92.4% of these were actually utilised followed by NEA 88.3% and 82.8% from RFEA. The higher number of fired rules and the number of rules used in less than 6 occasions suggest that DEA was able to adequately identify the subtleties in the user's behaviour and adjust the model accordingly.

In general terms, the interaction model generated by DEA seemed to possess improved consistency and accuracy in comparison to the other two since only 4.9% of its rules needed an adaptation while 79.2% of them were fired against 34.6% and 72.1% of NEA and 47.9% and 76.2% for RFEA respectively.

Category		NEA	DEA	RFEA
Total Number of rules		**539**	**768**	**1345**
Number of **initial** *rules (controlling phase)*		*143*	*189*	*211*
Number of **new** *rules generated during controlling phase*		*396*	*579*	*1134*
Total Number of rules Adapted during controlling phase		**187**	**38**	**645**
	% of Total	34.6	4.9	47.9
Number of **initial** *rules adapted during controlling phase*		*25*	*18*	*12*
	% of Total	4.6	2.3	0.9
	% of Initial	17.4	9.5	5.6
	% of Total Adapted	13.4	47.4	1.9
Number of **new** *rules adapted during controlling phase*		162	20	633
	% of Total	30.0	2.6	47.0
	% of New	40.9	3.4	55.8
	% of Total Adapted	86.6	52.6	98.1
Total Number of Rules that Fired		**389**	**609**	**1025**
	% of Total	72.1	79.2	76.2
Number of **initial** *rules that fired*		*39*	*74*	*85*
	% of Total	7.2	9.6	6.3
	% of Initial	27.2	39.1	40.3
	% of Total Fired	10.1	12.2	8.3
Number of **new** *rules that fired*		*350*	*535*	*940*
	% of Total	64.9	69.6	69.8
	% of New	88.3	92.4	82.8
	% of Total Fired	89.9	87.8	91.7
Total number of rules that fired less than 6 times		**160**	**276**	**395**
	% of Total	29.6	35.9	29.3
	% of Total Fired	41.1	45.3	38.5

Table 3. Number of fuzzy rules. Initial generation, newly produced, and actually used (fired).

User Comfort

Enhanced user comfort is one of the most important objectives of researchers in the area of IIE agents. User comfort could be evaluated by analysing the number of times the user had to interact with the system in order to adjust the settings inside the iDorm2. Manual adjustments mean that the agent failed to configure the ambience to what the user expected under normal conditions and comparable weather conditions.

Experiments indicated the superiority of DEA with only 10 user interventions for the entire 6 sessions (RFEA and NEA were overridden 16 and 21 times, an increase of 60 and 110 % respectively) (see Table 5). DEA was especially efficient in the morning and afternoon sessions while NEA performed slightly better in the midday sessions.

		Number of User Interactions		
Time Slot		NEA	DEA	RFEA
8-10AM	1st Session	4	1	2
	2nd Session	1	1	5
1-3PM	1st Session	1	6	2
	2nd Session	3	2	5
6-8:20PM	1st Session	3	0	3
	2nd Session	9	0	4
Total		21	10	21

Table 5. Number of user interventions on 6 days of experimentation.

Progress Function (Learning curve)

The progress function or learning curve reflects the number of new rules generated over time and it is a good indicator of how effectively the agents were able to learn from changes in the environment. It is expected that after the initial generation of rules, the number of new rules would progressively diminish. Table 4 depicts the number of new rules created on each experimental session.

		Number of New Rules		
Time Slot		NEA	DEA	RFEA
8-10AM	1st Session	156	145	504
	2nd Session	12	0	0
1-3PM	1st Session	0	8	0
	2nd Session	0	0	108
6-8:20PM	1st Session	116	180	396
	2nd Session	112	246	126
Total		396	579	1134

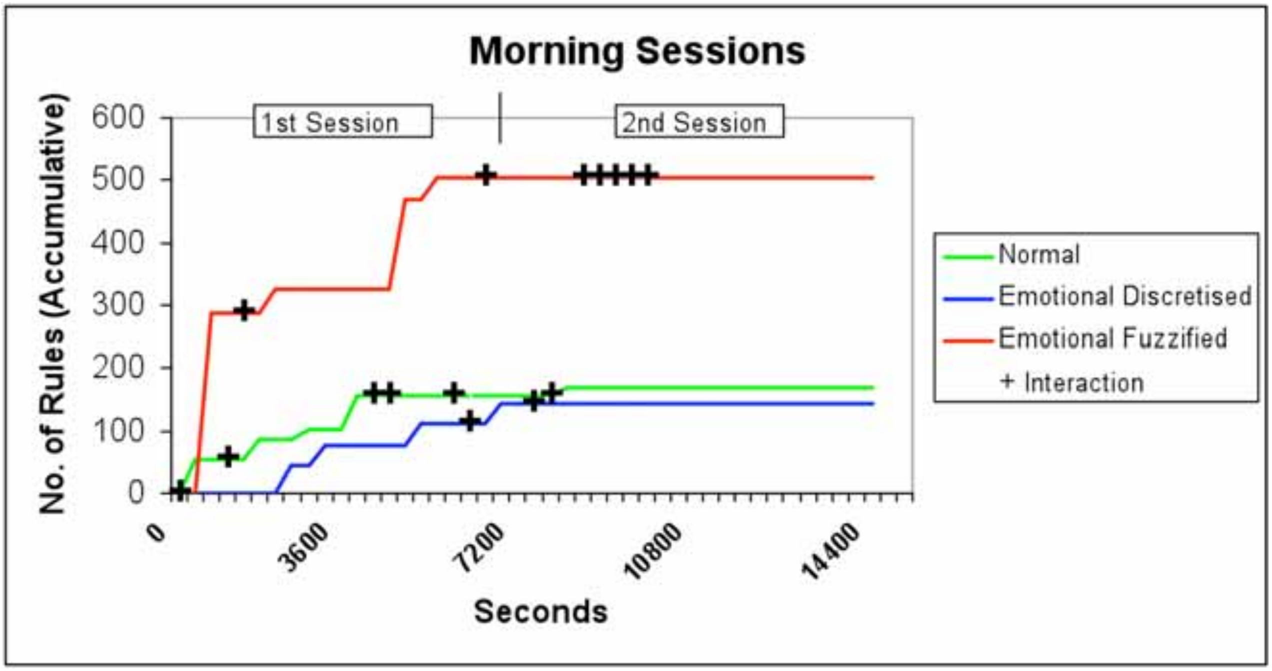
Table 4. Number of new rules per session.

It can be seen that on the morning experiments, the DEA did not need to make any further modifications to its interaction model after the first session. NEA on the other hand, performed a much better modelling in the midday sessions with no new rules created in either of the two sessions. A more in depth analysis on the results from the morning and midday sessions demonstrate that up to the beginning of the evening experiments, DEA had achieved the best performance of the three agents with only 152 new rules being created. This tendency changed in the evening when all the agents had problems modelling user’s behaviour each one of them having constructed more than 300 hundred new rules (RFEA was the worst case with 522 added rules).

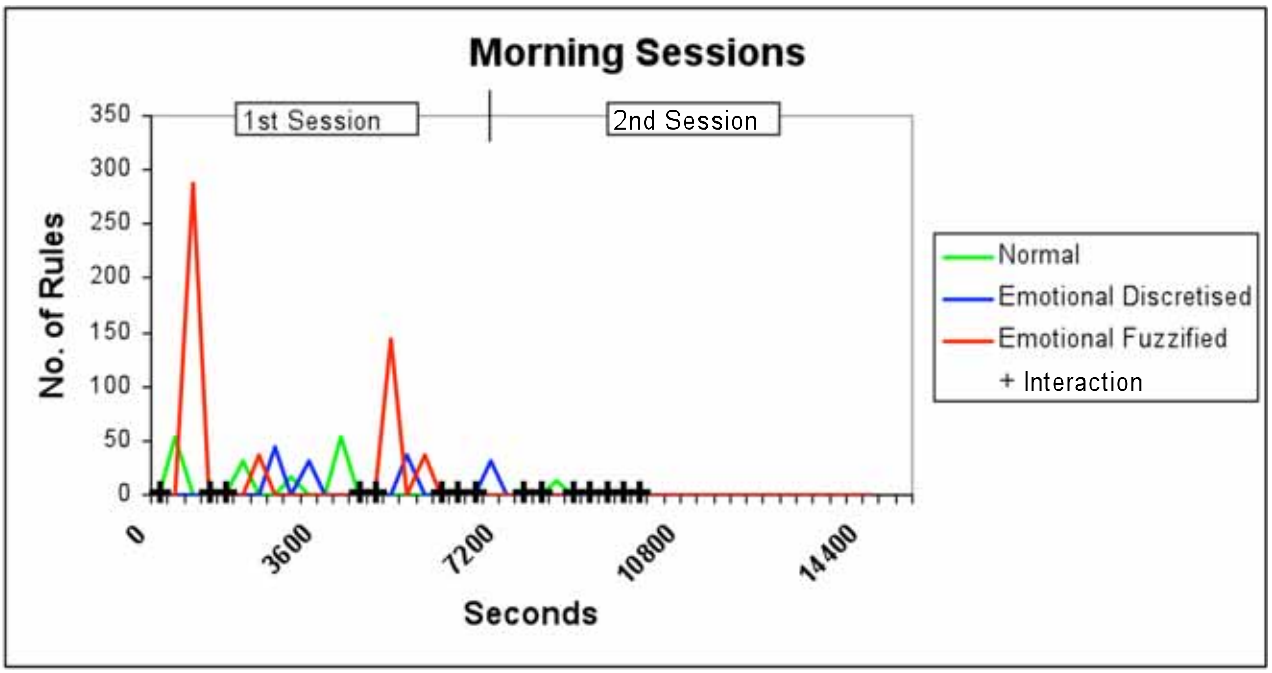
It is worth noting that the DEA was the only agent in which a second session produced more rules than the previous one (see the 1st and 2nd sessions of the 6-8:20 slot). This could be attributed to the fact that the subject felt sick on the first evening session and rested most of the time on the couch thus completely changing his normal activities.

Model Stability

Stability is a measure of how fast the agent was able to formulate an optimum interaction model that maximised the information collected from the environment including ambience variations caused by user’s behaviour and/or weather conditions. It is argued that this optimal interaction model would improve over time requiring only a small number of major adaptations. Figures 4-6 illustrate the number of new rules over time generated by each agent in each experimental session.

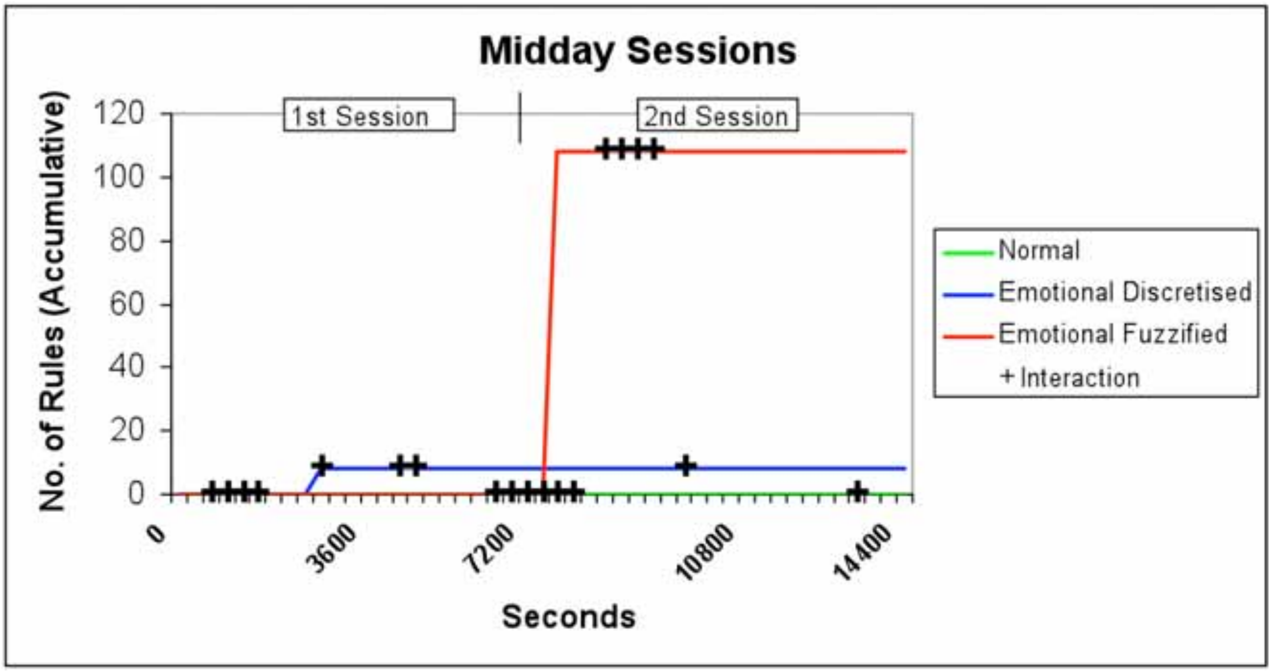


a)

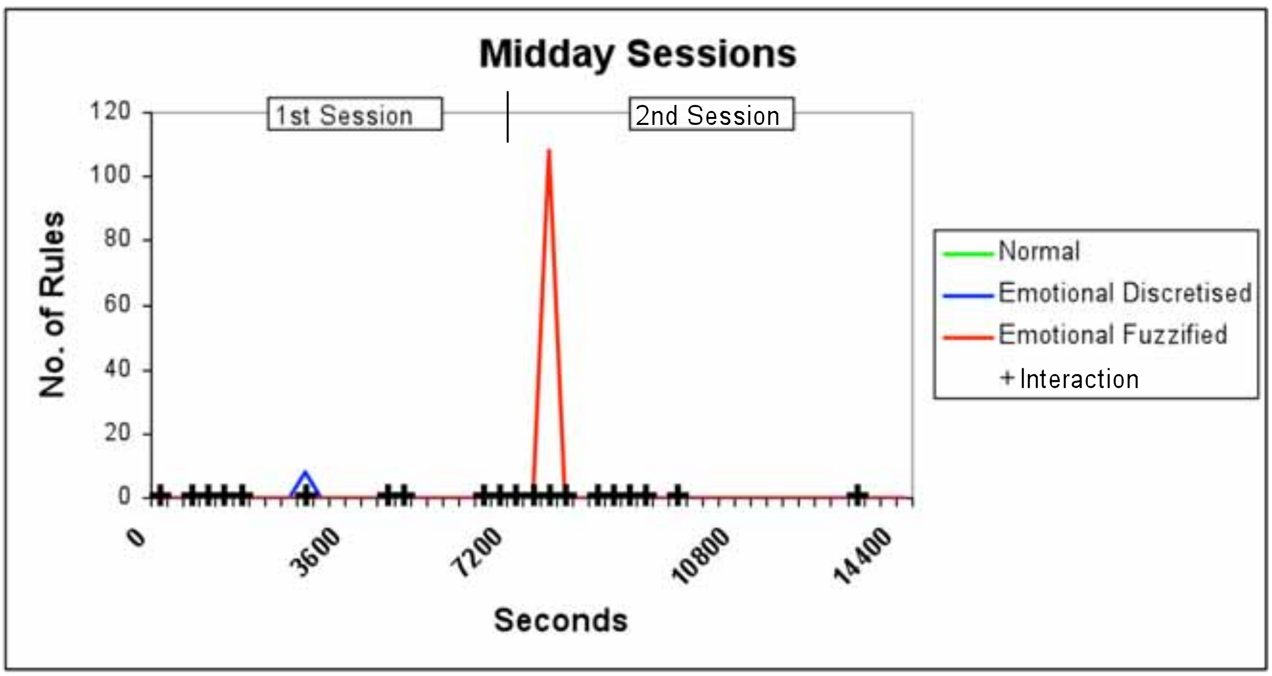


b)

Figure 1. Model stability over time in the morning sessions expressed in new rules per second. a) accumulative and b) instantaneous values.

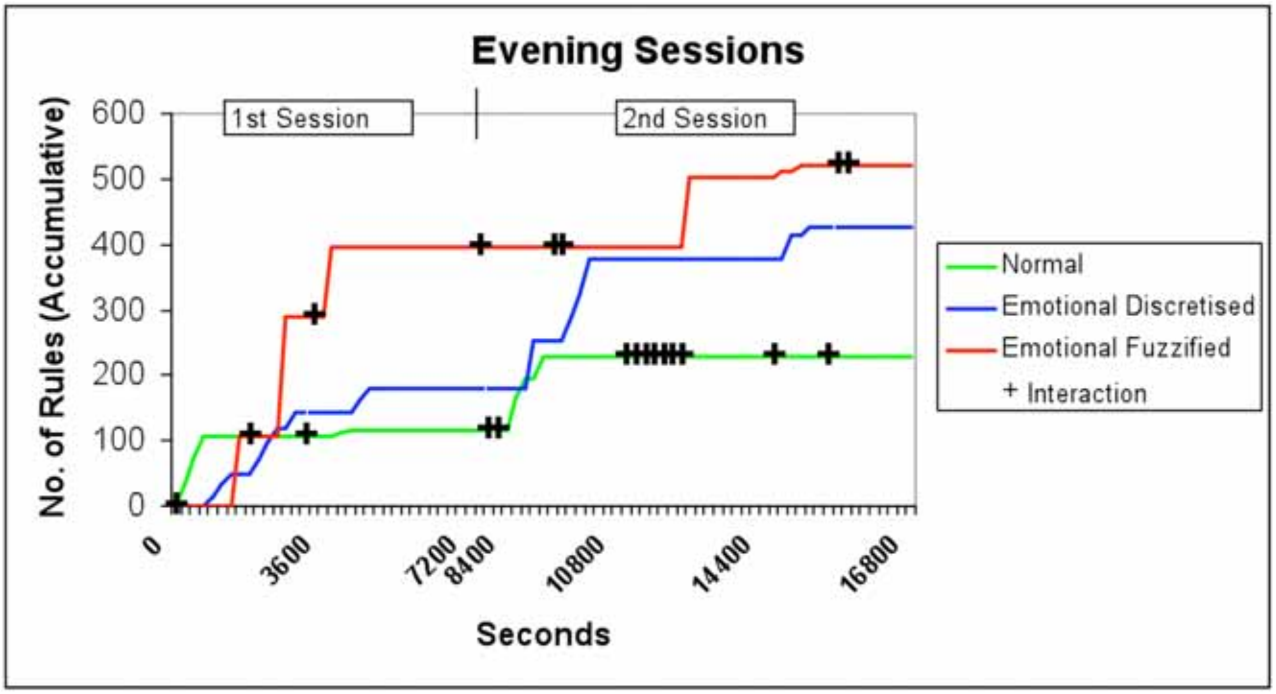


a)

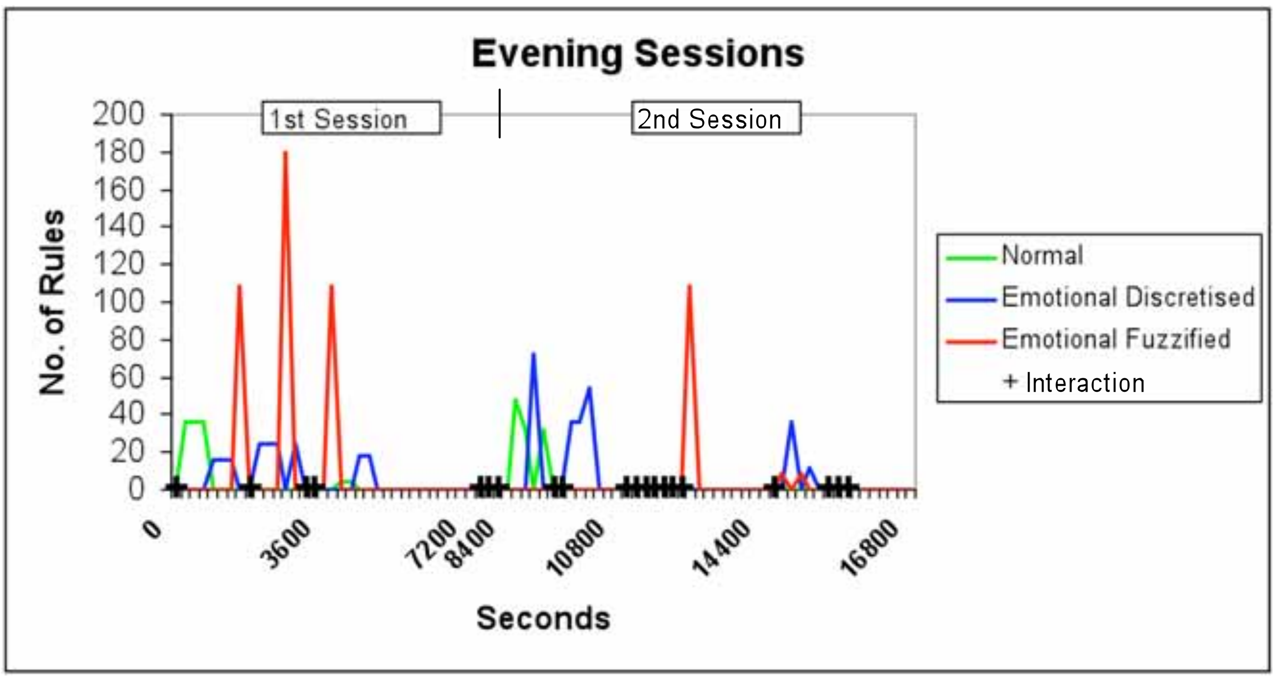


b)

Figure 2. Model stability over time in the midday sessions expressed in new rules per second. a) accumulative and b) instantaneous values.



a)



b)

Figure 3. Model stability over time in the morning sessions expressed in new rules per second. a) accumulative and b) instantaneous values.

Despite the large number of rules generated by RFAE in the morning sessions, it is evident that its interaction model captured ambience subtleties in a more efficient way than the other two agents with the last rule being created at 9:23 (5505 sec.) on the first part of that experimental session (see Figure 3). In the same manner NEA showed an improved performance during the evening sessions having made the last update to the model 8572 sec. after the beginning of the session (see Figure 5). Although the three agents performed similarly in the midday sessions, DEA and RFEA needed 8 and 108 new rules respectively thus leaving NEA as the best model on that particular time slot (see Figure 4).

Overall Performance

Results in Table 6 demonstrate a clear advantage of DEA in the categories related to the efficiency and quality of the rules encompassed in the Fuzzy Controller, while NEA seemed to have an improved performance in the learning capacity and stability of the model.

	Overall Performance		
Category	NEA	DEA	RFEA
Interaction Model (% of Adapted rules from Total)	34.6	**4.9**	47.9
Interaction Model (% of Fired rules from Total)	72.1	**79.2**	76.2
User Comfort (No. of user interactions)	21	**10**	21
Progress Function (No. of New Rules)	**396**	579	1134
Model Stability (Averaged Time of last generated rule (in sec))	**5896**	8110	9224

Table 6. Category winners.

Discussion

The fewer number of times the user had to override agent’s decisions along with a diminished need for rule alteration suggests that, despite its slower learning curve, DEA was able to establish a better representation of how the user behaved inside the iDorm2. The reason for this could be that, just as the user responds to changes in the environment, emotions prompt individuals to act according to stimuli stemming from the various activities undertaken inside the IIE. The reactions to such stimuli are not easily recorded by a non-emotional agent since they depend on modifications on the user’s psychological and physical perception of his/her surroundings. The lack of interaction at a more personal level inhibits the symbiotic relationship between a non-emotional agent and the user and neglects important information about why and when certain events usually occur.

Results shown in Table 6, also suggest that the NEA possesses a greater capability in terms of learning speed and model stability. This apparent advantage however is not definite and could be the result of a smaller number of sensors being used in order to generate fuzzy rules and membership functions rather than a poor performance by the two emotional agents. The utilization of fewer input variables inherently means more stability for the FLC since less event combinations are possible. Thus, rather than attributing poor learning curves to uncertainties introduced by the inclusion of emotional data, it is safer to assume that a greater number of sensors seems to have a direct linear effect on the agent’s learning speed. This is an important characteristic that should be taken into account when comparing different implementations of IIE agents.

If an increase in the number of input sensors seems to be associated with longer learning periods, it does not seem to have a direct effect on whether the agent is capable of learning from the user. For example, if only the two emotional agents with the same number of input sensors were compared, the superiority of the DEA is still manifest thus indicating that not only the quantity but also the quality of the information determines the agent’s performance.

The poor performance of RFEA reveals that the sole addition of extra sensing information stemming from the user’s physiological state into the agent’s input vector does not guarantee improved modelling of user’s activities. It is the inclusion of meaningful emotional data that provides a valuable insight not only into the current activities but also into the relationship between ambience conditions and the user’s state of mind.

Conclusions

The experimental results suggest that the utilization of emotional data truly improves the performance of IIE software agents particularly in those categories involving the modelling of user activities. Emotion provides the agents with a more accurate depiction of why and when the user undertakes certain activities at certain times. It is manifest that the distant observation of an individual without the care of knowing their motivations does not suffice to endow software agents with an accurate representation of the events taking place inside IIE.

Although the findings presented here have been narrowed to a particular type of agent and are rather modest with regards to the number of subjects employed and the extent of the experiments, they provide encouraging evidence of the importance and influence of emotions into human decision-making and information processing. The intention of this work is mainly to contribute to a better understanding of emotions in the context of pervasive computing and towards the eventual amalgamation of affective computing and artificial intelligence.

Acknowledgments

We are pleased to acknowledge the EU IST Disappearing Computer funding program which has provided support for the iDorm2 (intelligent dormitory). Enrique Leon also appreciates the support of the Mexican National Council for Science and Technology (CONACYT). We are indebted to Robin Dowling and Malcolm Lear for their invaluable support in the implementation of the X-Vest. We also express our gratitude to Dr. Francisco Sepulveda for his invaluable contributions to our work.

References

[1] Graham Music, “Affect and Emotion”, Ideas in Psychoanalysis, Icon Books Ltd, Duxford Cambridge, 2001.
[2] A. Damasio Descartes' Error: Emotion, Reason, and the Human Brain. New York, NY: Avon Books, 1995.
[3] De Sousa, Ronald. The Rationality of Emotion. Cambridge, MA: MIT Press, 1987.
[4] J. Ledoux The emotional brain. London, United Kingdom: Weidenfeld & Nicholson, The Orion Publishing Group Ltd, 1998.
[5] D. Goleman Emotional Intelligence. Why it can matter more than IQ. New York, NY: Bantam Books, 1995.
[6] Jon Elster, “Solomonic Judgments. Studies in the limitations of rationality”, Cambridge University Press, Cambridge, UK, 1989.
[7] Ark W, Dryer DC, Lu DJ. The Emotion Mouse. In: Proceedings of Human Computer Interaction 1999, Edinburgh, Scotland, 1999.
[8] Christine L. Lisetti, “Emotion Generation for Artificial Agents via a Hybrid Architecture”, *Proceedings of the Autonomous Agents Workshop on Emotion-Based Agent Architecture (EBAA'99)*, (Seattle, WA, May 1999).
[9] R. Picard Affective Computing. Technical Report No. 321, Media Laboratory Perceptual Computing Section, M.I.T, 1995.
[10] R. R. Avent, T. Chong, and J. A. Neal, “Machine Vision Recognition of Facial Affect Using Backpropagation Neural Networks,” in Proc. 16th Annual International Conference of the IEEE, Engineering Advances: New Opportunities for Biomedical Engineers, 1994, pp. 1364 -1365.
[11] M. Rosenblum, Y. Yacoob, and L. Davis, “Human Emotion Recognition from Motion Using a Radial Basis Function Network Architecture,” in Proc. 1994 Workshop on Motion of Nonrigid and Articulated Objects, Austin, TX, pp. 43-49.
[12] Yafei Sun, Nicu Sebe, Michael S. Lew, Theo Gevers, “Authentic Emotion Detection in Real-Time Video”, Computer Vision in Human-Computer Interaction, ECCV 2004 Workshop on HCI, Prague, Czech Republic, May 16, 2004. Proceedings
[13] M.S. Bartlett, G. Littlewort, I. Fasel, and J.R. Movellan, “ Real time face detection and expression recognition: Development and application to human-computer interaction”. In CVPR Workshop on Computer Vision and Pattern Recognition for Human-Computer Interaction. 2003.
[14] K. Anderson & P. McOwan, "Real-time Emotion Recognition using Biologically Inspired Models" in 4th International Conference on Audio and Video Based Biometric Person Authentication, Surrey pp. 119-127, 2003.
[15] De Silva, L.C. Suen Chun Hui, Real-time facial feature extraction and emotion recognition: Information, Communications and Signal Processing, 2003 and the Fourth Pacific Rim Conference on

Multimedia. Proceedings of the 2003 Joint Conference of the Fourth International Conference on Publication Date: 15-18 Dec. 2003.
[16] J. Nicholson, K. Takahashi, and R. Nakatsu, "Emotion Recognition in Speech Using Neural Networks," Neural Computing & Applications, vol. 9, no. 4, pp. 290-296, 2000.
[17] M. Tsuyoshi and O. Shinji, "Emotion Recognition and Synthesis System on Speech," in Proc. 1999 IEEE International Conference on Multimedia Computing and Systems, Firenze, Italy, pp. 840-844.
[18] L. C. De Silva and P. C. Ng, "Bimodal Emotion Recognition," in Proc. 1999 International Conference on Face and Gesture Recognition, Grenoble, France, pp. 332-335.
[19] Kim KH, Bang SW, Kim SR. Development of person-independent emotion recognition systems based on multiple physiological signals. In: Proceedings of the Second Joint EMBS/BMES Conference, Houston, TX, 2002. p. 50-51.
[20] Nasoz F, Lisetti CL, Alvarez K, Finkelstein N. Emotion recognition from Physiological Signals for User Modelling of Affect. In: Proceedings of the 3rd Workshop on Affective and Attitude user Modelling, Pittsburgh, PA, 2003.
[21] Picard R, Vyzaz E, Healey J. Toward Machine Emotional Intelligence: Analysis of Affective Physiological State. IEEE Transactions on Pattern Analysis and Machine Intelligence 2001, 23 (10): 1175-1191.
[22] Kramer MA. Autoassociative Neural Networks. Computers and Chemical Engineering 1992; 16(4): 313-328.
[23] Leon, E, Clarke, G., Callaghan, V., Sepulveda, F., "Real-time detection of Emotional Changes for Inhabited Environments," Journal of Computers & Graphics, Special Issue on Pervasive Computing and Ambient Intelligence – Mobility, Ubiquity and Wearables, vol. 5, no. 23, pp. 635-642, October 2004.
[24] D. J. Davies and D. Bouldin, "A Cluster Separation Measure," IEEE Trans. Pattern Recognition and Machine Intelligence, vol. PAMI-1, no.2, April 1979.
[25] Fu KS. Sequential Methods in Pattern Recognition and Machine Learning. New York, NY: Academic Press, 1968.
[26] Leon, E., Clarke, G., Sepulveda, F., Callaghan, V.; "Optimised Attribute Selection for Physiological Emotion Detection". In: Proceedings of the 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, San Francisco, California, 2004.
[27] Leon, E., Clarke, G., Sepulveda, F., Callaghan, V.; "Real-time Physiological Emotion Detection Mechanisms: Effects of Exercise and Affect Intensity". In: Proceedings of the 27th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Shanghai, China, 2005(In print).
[28] Doctor, F., Hagras,H.A.K.,Callaghan,V., Lopez, A., "An Adaptive Fuzzy Learning Mechanism for Intelligent Agents in Ubiquitous Computing Environments", Proceedings of the 2004 World Automation Conference, Seville, Spain.
[29] Doctor, F., Hagras,H.A.K., Callaghan,V., "An Intelligent Fuzzy Agent Approach to Realising Ambient Intelligence in Intelligent Inhabited Environments", IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans
[30] R. J. Larsen, E. Diener, and R. A. Emmons, "Affect Intensity and Reactions to Daily Life Events," Personality and Social Psychology, vol. 51, no. 4, pp. 803-814, 1986.