Towards Affective Pervasive Computing,

Emotion Detection in Intelligent Inhabited Environments.

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Abstract

Recent advances in neurology and psychology have demonstrated the importance of emotions in various aspects of our lives from learning to motivation and planning. It is clear now that our decisions are often assisted by how we feel and not the product of rationality alone as previously thought. In the face of these findings, a group of technologists have made some progress towards the integration of emotions and reasoning into their computing models.

The work presented in this thesis supports the idea that because emotions have a direct effect on our ability to make optimal decisions, pervasive systems relying on behavioural models could enhance their response to user actions through the incorporation of emotional information into their technologies. In accordance with this view, I have developed a computer system that operates based on the detection and classification of emotional classes, comprised of: 1) A novel method to detect emotions based on sensor validation, 2) an affective wearable that transmits the wearer's emotional state in real time, and 3) an affective agent that utilizes emotional inputs to operate a pervasive environment on behalf of the user.

I will present preliminary empirical evidence demonstrating that the inclusion of the emotional component of human decisions in interactive systems increases their accuracy and improves user comfort compared to applications not using emotional information. I suggest that areas such as medicine, sports science, and psychology could also benefit from models that describe the relationship between emotional states, ambient conditions, and behaviour in what could be the beginning of a new discipline called Affective Pervasive Computing.

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List of Abbreviations

AANNs	Autoassociative Neural Networks
AI	Artificial Intelligence
AIM	Affect Intensity Measure
AmI	Ambient Intelligence
ANNs	Artificial Neural Networks
ANS	Autonomic Nervous System
AOFIS	Adaptive Online Fuzzy Inference System
BVP	Blood Volume Pressure
CS	Change Speed (Signal Entropy)
DBI	Davies-Bouldin Index
DEA	Discretized Emotional Fuzzy Agent
DFA	Discriminant Function Analysis
EDA	Electrodermal Activity
EMG	Electromyogram
EQ	Emotional Intelligence
FCM	Fuzzy-C-Means
FLC	Fuzzy Logic Controller
FP	Fisher Projection
GA	Genetic Algorithm
GPSs	Global Positioning Systems
GSRe	Galvanic Skin Response
GSR	Gradient of Skin Resistance

HMMs	Hidden Markov Models
HR	Heart Rate
HTML	HyperText Markup Language
IAPS	International Affective Picture System
iDorm	Intelligent Dormitory
IEEE	Institute of Electrical and Electronic Engineers
IIE	Intelligent Inhabited Environments
ISTAG	European Community Information Society Technologies Advisory Group
KNN	k-Nearest Neighbor
MASs	Multi-Agent Systems
MET	Metabolic Equivalent
MSE	Mean Square Error
NEA	Non-emotional Fuzzy Agent
OCC	Ortony, Clore and Collins Cognitive Model
PC	Personal Computer
PDAs	Personal Digital Assistants
PP	Power Point
RESP	Respiration Rate
RFEA	Raw Fuzzified Emotional Fuzzy Agent
SC	Skin Conductance
SFDIA	Sensor Failure Detection, Isolation and Accommodation
SFFS	Sequential Floating Forward Search
SPRT	Sequential Probability Ratio Test
SR	Skin Resistance

SVMs	Support Vector Machines
TCP/IP	Transmission Control Protocol/ Internet Protocol
UML	Unified Modelling Language
UPnP	Universal Plug and Play
X-Vest	eXperimental Vital-sign-based Emotional State Transmitter

"I would show that justice and kindness are no mere abstract terms, no mere moral conceptions framed by the understanding, but true affections of the heart enlightened by reason, the natural outcome of our primitive affections; that by reason alone, unaided by conscience, we cannot establish any natural law, and that all natural right is a vain dream if it does not rest upon some instinctive need of the human heart" Jean-Jacques Rousseau

Introduction

Thesis Aim and Hypothesis

The aim of this thesis is to gather evidence to support the hypothesis that emotions provide pervasive environments with invaluable, irreplaceable information about user behaviour that no other natural or artificial variable can deliver. I wish to show that such a perspective on user's motivations could afford interactive systems with the tools to enhance behavioural modelling thereby improving comfort and efficiency inside intelligent environments.

In pursuit of this view, I suggest that agents which are delegated with the responsibility of controlling an inhabited space on behalf of the user should employ emotions as an essential part of their modelling of the user. Moreover, as a corollary to my main hypothesis, I want to demonstrate that pervasive systems that ignore emotional states are inevitably at a disadvantage with respect to those capable of assimilating affective data. In this context, I will argue that the use of physiological signals is the most adequate means to determine emotional changes inside real-life settings.

The experiments that will be presented throughout this thesis, along with the results and discussion thereon, will lead the reader progressively towards my aims by a) introducing the concepts of affective and pervasive computing, b) developing the design of a real-time physiological emotion detection system suitable for pervasive environments, c) describing the embodiment of this system into a wearable artefact, d) detailing the development of the concept of Affective Pervasive Computing through the implementation of two affective agents, and e) carrying out the analysis of how such affective agents compare to a non-emotional agent in terms of user satisfaction and room control.

Motivations

We all recognize or at least are aware that emotions play an important role in our personal and professional lives. Emotions are an essential part of social interaction and regulate most of the activities we humans regularly undertake from simple conversations to business deals or house renovations. In recent years new findings about how emotions influence our conduct have motivated a renewed attention from the public, the government, and the industry into the phenomena linked to affective interaction and individual emotions. The consequence of this growing interest has been that emotions have become a crucial element in the strategies and operation of areas like education, advertising, or product design.

Much of the credit for this revival of scientific interest in the emotions could be attributed to the creation of new brain scanning techniques permitting researchers from numerous scientific and humanistic areas to reveal strong evidence supporting the argument that, in contrast to those who think of affect as the natural adversary of reasoning, emotions and rational deliberation are two intertwined elements that constitute our decision-making abilities and which collectively determine other elements of our lives such as learning, motivation, memorization, interpersonal communication, and attention. Discoveries have even demonstrated that on many occasions the appropriateness of our judgement to act in response to a variety of external stimuli hinges not on rationality but on our affective capacities. I agree with this idea and believe that emotions influence our behaviour to such an extent that computer systems that involve human interaction are inherently impaired if they do not, at least partially, interact at an emotional level.

It is noteworthy that as industry progresses towards a technological paradigm in which common objects become increasingly more customised through the relationships they establish with us through continuous use, the importance of emotions shaping our thoughts becomes even more important. Emotions are spontaneous expressions of our states of mind and body conveying what we like and thereby mirroring our tastes and customs. Consequently, they represent an alternative source of information that could be used to enhance the interaction of computerized devices and their users.

The work presented in this thesis is motivated by the understanding that, despite the mounting evidence portraying emotions as an indispensable ally of rationality, the majority of computer scientists still deem emotions an unreliable and even damaging element in computer system design and operation. By doing so they neglect our own nature and overlook the fact that computers have historically been created in the image of men with the intention of replicating our own capabilities. Furthermore, the growing trend among leading software companies to use social science research to improve their interactive models has thus far largely been ignored by researchers in areas of computer science that rely on behavioural modelling, including pervasive environments. In terms of intelligent environments for instance, the belief that human behaviour could be reduced to measuring environmental settings and overt user behaviour has led to interactive systems which have only been able to offer a partial solution to the problem of poor user comfort and satisfaction.

The research presented in this thesis aims to contribute towards enabling scientists, through awareness and experimentation, to appreciate the value of emotions for computing systems, in particular those depending on real-life interactions with the user. In particular it can be seen as exploring what Rosalind Picard [Picard95] has called Type III Affective Computing, where the computer system can recognise emotions but not synthesise them, within the field of pervasive computing.

Main Achievements and Contributions

The work presented in this thesis comprises the following achievements and contributions:

- A novel method to detect emotional states in an innovative way using sensor validation techniques and physiological measures was developed and tested. This system is based on continuous real-time monitoring of online biosensors that provide an indication of changes in the Autonomic Nervous System (ANS) associated with emotional states. Using data describing the physiological patterns of an individual in a neutral emotional state, i.e., showing no significant emotional arousal, I am able to identify emotional changes using a signal processing module that measures the differences in physiological signals between a non-neutral emotional state and the neutral emotional state. A classification module then categorizes such differences sequentially until a recognizable pattern related to emotional valence (positive or negative) is found [Chapter 3].

- A major novelty of this research is the utilization of techniques employed in psychology and biomedical engineering to validate the ability of my emotion detection system to resist perturbations in bodily measures caused by low-to-moderate physical exertion and different levels of affect intensity. The results stemming from this robustness study showed that the aforementioned method was suitable to be employed in real-life environments demanding highly dynamic interactions [Chapter 4].

- Through the integration of my emotion detection system and wireless, portable biosensors, I was able to construct a wearable artefact called the X-Vest (eXperimental Vital-sign-based Emotional State Transmitter) to perform remote monitoring of emotional states. The development of the X-Vest was closely linked to studies of user-independence and generalization of the main detection methods [Chapter 5].

- One the most important achievements of this research project was the implementation of two affective agents capable of perceiving the emotional state of a subject inside pervasive environments. These agents were built upon an existing fuzzy agent featuring on-line adaptation and control of an inhabited space. The two affective agents differed in the way they processed emotional information. While one of them used the high-level output of my emotion detection system the other employed a raw indication of physiological change [Chapter 6].

- A comparison between the two affective and the non-affective agents confirmed that emotions can be integrated into existing interactive models and enhance their performance. Evidence founded on factual information and experimental results drew the following significant conclusions: The two affective agents performed better than the non-affective agent in terms of the efficiency of the model created to control the environment (the number of fuzzy rules that needed modification and those which were created but not used). The agent using high-level emotional information demonstrated improvements of more than 100% in terms of user comfort with respect to the other two agents [Chapter 7].

Publications Arising from this Work

Below is a list of publications that resulted from the various research investigations described in this thesis.

Patents

- UK patent application number 0611762.6: System for Real-time Analysis of Physiological Signals.

Journal Papers

- Leon, Enrique, Clarke, Graham, Callaghan, Victor, and Sepulveda, Francisco; "A User-independent Real-time Emotion Recognition System for Software Agents in Domestic Environments". To appear in: Engineering Applications of Artificial Intelligence, The International Journal of Intelligent Real-Time Automation, summer 2006.

- Leon, Enrique, Clarke, Graham, Callaghan, Victor, and Sepulveda, Francisco; “Real-time Detection of Emotional Changes for Inhabited Environments”, International Journal of Systems and Applications in Computer Graphics, 28 (5), pp. 635-642, 2004.

Conference Papers

- Leon, Enrique, Clarke, Graham, Sepulveda, Francisco, and Callaghan, Victor; "Real-time Physiological Emotion Detection Mechanisms: Effects of Exercise and Affect Intensity", Proceedings of the 27th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Shanghai, China, 2005.

- Leon, Enrique, Clarke, Graham, and Callaghan, Victor; "Towards a robust real-time emotion detection system for intelligent buildings". In: Proceedings of the 2005 IEE International Workshop on Intelligent Environments, Colchester, UK, 2005.

- Leon, Enrique, Clarke, Graham, Sepulveda, Francisco, and Callaghan, Victor; "Neural Network-Based Improvement in Class Separation of Physiological Signals for Emotion Classification". In: Proceedings of the 2004 IEEE Conference on Cybernetics and Intelligent Systems, Singapore, Singapore, 2004.

- Leon, Enrique, Clarke, Graham, Sepulveda, Francisco, and Callaghan, Victor; "Optimised Attribute Selection for Emotion Classification Using Physiological Signals". In: Proceedings of the 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, San Francisco, California, 2004.

Thesis Layout

This thesis has been organized into 9 chapters. The first two chapters concern a detailed exposition of the motivations, theories, and rationale underlying my work along with an analysis of existing technology and an introduction of some useful terms. The remaining chapters describe all the experimental work. Chapter 3 describes a novel method to detect emotions in real time using sensor validation techniques and bodily measures. Subsequent chapters offer evidence that such novel mechanism is suitable for utilization inside real-life environments thanks to its robustness to physical exertion and variable levels of affect intensity as well as its user-independent operability. Chapters 5 through 7 discuss the implementation of an affective software agent for intelligent environments and the results of real-life experiments aimed at investigating the effects of emotion information on pervasive systems. The last two chapters include a discussion on the work presented here and the concluding remarks along with further and future work.

Chapter 1 Affective Computing

This chapter provides an assessment of existing emotion recognition techniques with particularly emphasis not so much on technical details as on issues such as robustness and suitability for real-time operation involving ambulatory conditions. Two main conclusions are derived from this exhaustive literature survey. First, from the various parameters used in emotion detection, physiological signals were chosen over alternative options such as facial or speech expressions, this was based on issues involving the adverse effect of cameras and microphones on the natural behaviour of individuals and the fact that bodily signals are difficult to disguise and unrestrictive in terms of the location of the users or their current activity. Second, I realized that none of the existing emotion detection techniques concerned the utilization of emotions to improve human-machine interaction inside pervasive environments. In fact, I found that the operation of existing techniques of physiological emotion detection was generally based on the analysis of sensor readings acquired after a certain pre-specified period of time. This modus operandi reduces dynamism and potentially increases detection time. From the work in this chapter I concluded that: 1) *physiological affective computing could assist in real-life behavioural modelling*, and 2) *there* *was an absence of emotion detection systems purposely designed to operate inside pervasive environments*.

Chapter 2 Pervasive Computing

A general introduction to the field as it impacts on the design and development of intelligent inhabited environments. I discuss concepts like pervasive and ubiquitous computing and also ambient intelligence. I explain how various technical terms such as smart environments and intelligent environments relate to each other. This chapter also includes an outline of the underlying techniques employed in the design of pervasive systems highlighting the use of intelligent agents. To supplement this discussion and support my arguments in favour of the utilization of emotional information inside pervasive computing, several research initiatives concerned with intelligent environments are presented along with the solutions they have put forward to the problem of behavioural monitoring. It is argued that due to the complexity posed by the naturally-occurring fluctuations of the user's state of mind, existing pervasive systems struggle to accurately respond to activities inside real-life domestic environments. I suggest that an alternative view to the *problem of behavioural monitoring* could be based on the *recognition of affective states using physiological changes*.

Chapter 3 Real-time Detection of Emotional Changes based on Sensor Validation

This chapter describes how the implementation of my system for enabling emotion recognition is based on the utilization of signals stemming from the Autonomic Nervous System (ANS) and methods of sequential analysis previously proven to operate reliably even under the most demanding conditions. This innovative approach to detecting emotions is founded on the concept that the detection of emotional changes using physiological signals is similar to a real-time sensor validation process. This approach departs radically from traditional emotion detection in the sense that instead of looking for patterns of emotions on entire sets of physiological signals, I continuously analyse how sensors change over time and then relate sensor variations to emotional changes thereby potentially delivering quicker classification. Results from recognition trials on physiological data from a single subject confirmed a 100% recognition rate when detecting single-state changes from neutral to non-neutral emotional states.

Another important element of my emotion detection methodology is the introduction of cluster analysis with the intention of identifying a priori the physiological signals that provide the best separation between the different emotional states. Because only bodily parameters guaranteeing optimal identification of emotional classes are used in the classification modules, the detrimental effect of irrelevant or contradicting data is diminished.

Chapter 4 Assessing the Effects of Exercise and Affect Intensity on Real-time Physiological Emotion Detection

This chapter presents an analysis of the degree to which factors associated with real-life settings influence the operation of the emotion detection system introduced in the preceding chapter. Particular importance is given to the effects of bodily changes caused by variable levels of affect intensity and low-to-moderate physical exertion. Details of the procedure employed to elicit emotions in experimental subjects including a description of the measures used to evaluate affect intensity and physical fitness are given.

The experiments described in this chapter demonstrated that neither low-to-moderate physical stress nor affect intensity played an unfavourable role in the capacity of my emotion detection system to separate physiological patterns associated with positive, negative and neutral emotional classes. These conclusions are based on similarity studies involving the Wilcoxon test and clustering analysis derived from calculations of the Davies-Bouldin Index.

Chapter 5 Development of a Wearable User-independent Real-Time Emotion Detection System for Intelligent Inhabited Environments (IIE)

Two important developments aiming at achieving emotion detection of three emotional classes on groups of individuals inside real-life settings are discussed in this chapter. First, I explain why user independence is important and suggest a manner of achieving such functionality without obscuring the importance of emotional individuality. Second, I introduce the X-Vest (eXperimental Vital-sign-based Emotional State Transmitter), a wearable device enabling remote monitoring of emotional states independent of the wearer's activity and location inside a pervasive environment. Relevant information involving technical details on the X-vest implementation is provided.

Experimental evidence supports the claim that the collection of emotional data from eight subjects with different affect intensity levels was sufficient to provide my system with enough information to generalize even when data not included during training was presented. The enhanced generalization capabilities of the detection system were confirmed by recognizing emotional states on a subject whose physiological data was not included during training with 71.4%-80% recognition accuracy.

Chapter 6 Towards Affective Pervasive Computing: An Ambient Intelligent Affective Agent

One of the main implications of my initial hypothesis is that given that many of our actions originate directly from complex relations between our emotions and the environment, software agents capable of recognizing such relations would be capable of interpreting and predicting human actions more appropriately than agents that take no account of emotional state. To investigate this idea, I built two new affective agents based on the X-Vest and an existing fuzzy agent operating inside a test-bed for pervasive spaces called the iDorm2. I explain the implementation details of both affective agents and the functional differences between the two.

Chapter 7 Real-life Experimentation: Using An Affective Agent to Model Behaviour inside IIE

This contains the main experimental work of the thesis and focuses specifically on my main hypothesis and its corollaries. This chapter is the result and culmination of a concerted, purposeful integration of the methods described in all the previous chapters. The iDorm2 was used to perform real-life investigations comprised of a two-day learning phase in which three agents (two affective and one non-affective) monitored and learned the activities undertaken by a male subject. After this initial training the agents took control of the environment and operated the devices located inside iDorm2 on behalf of the user using the knowledge previously acquired. This latter phase encompassed 6 days in which the agents also performed on-line monitoring and adaptation. I obtained empirical evidence supporting my hypothesis about the significance, usefulness, and unique contribution of emotions in the context of human-machine interaction inside interactive environments.

Chapter 8 Discussion

The last chapter of this thesis concerns a general overview of the main findings discussed throughout the thesis and the significance of my experimental results. I suggest new ways to utilize and improve the components and methods of the X-Vest and manners to increase the applicability of my emotion detection system. Finally, I explain my immediate future work and discuss the contributions of this research project within a global perspective. I propose that the study and modelling of human behaviour and human-machine interaction should rely on emotions as an invaluable, unique source of information about the individual's rationale.

"Some have thought that the entrance to the secret garden of creativity was randomness; others quantum mechanics; others, emotions. In my book [Affective Computing] I talk about some links between emotion and creativity because I think emotions contribute significantly to human creativity, and could contribute to a new kind of machine creativity. The evidence seems to indicate that creativity involves emotions. Psychologists have even shown that being in a good mood can facilitate creativity, making it more likely you can solve a problem that requires a creative solution" Rosalind Picard.

Chapter 1

Affective Computing

1.1 The Inadequacy of Reason

The combination of cognitive and emotional components is a characteristic aspect of human thinking that is related to our evolution and development [Music01]. It was during the nineteen nineties, sometimes known as "decade of the brain"[1], 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. Some of the most influential work has been done by neurologists who have demonstrated that, for instance, emotions sometimes override reasoning in situations 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 [Damasio95]; even decisions about the most ordinary choices in our daily life are greatly affected by the incapacity to

[1] This term is commonly used by researchers after the US Presidential Proclamation 6158, July 17, 1990.

express emotions [Goleman97]. It has now become clear that emotional and the cognitive processes are two interrelated, cooperative, inter-dependent constituents of our being rather than separate, incompatible, independent elements. In fact, those researchers 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. A theory becomes indeterminate when it fails to deliver a unique prediction and inadequate when its predictions are erroneous [Elster89].

The inadequacy of reason applies not only to extreme situations where emotions, using Goleman's [Goleman97] words, "hijack" our body and mind 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 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. A computing system that only attended to external behaviour would have problem distinguishing the different emotional motivations underlying a given action and would be likely to develop erroneous conclusions and action plans.

Originally the view of computer scientists and in particular those working in artificial intelligence (AI), has been biased towards an interpretation of human behaviour solely as the product of rational thinking, a purely cognitive process, in which affective states can be ignored. This has 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 (see Appendix 1).

The rest of this chapter focuses on two main aspects of emotional analysis. Firstly, I will describe the development of some of the most influential views on emotions and outline the traditional mechanisms that have been employed to measure emotional states. Secondly, I will examine how the work of psychologists, sociologists, physiologists, etc. has motivated Computer Scientists to devise convenient, efficient tools to distinguishing emotional states in a new discipline which has been given the name Affective Computing.

1.2 Introduction to the Study of Emotions

Some of the earliest accounts of emotional episodes can be traced back to the first lasting impressions of human thought on written text by the Sumerians 5,000 years ago [Oatley04]. The afflictions of the heart, the anger towards the enemy or the traitor, the cherishing of friends and family or the longing for the loved one, they are all part of our present and past history. Despite their universality however, human emotions are not felt in the same way by everyone. We all have our own personal, unique subjective way of feeling, interpreting, and recognizing emotional episodes. That's what makes humanity so diverse and that is why precise elucidations of emotion are difficult to formulate: There are patterned emotional differences between individuals and societies based upon social and cultural factors. Such differences, personal to each individual, are nonetheless concealed by physical and behavioural expressions that are consistent among humans. This is the foundation of the study of emotions.

It was the Greek philosophers at Plato's Academy in ancient Athens who arguably were the first theorists carrying out a serious exploration about the nature of emotions. The ideas emanating from their endeavour included a description of emotions in terms of psychological, rhetorical, ethical, poetical, and political aspects that would have an impact onto emotional literature for centuries

[Fortenbaugh75]. But just like technology, the study of emotions has evolved since the Hellenic times and has followed many directions each concerning a different theory. Not surprisingly, these theories do not often agree with each other and there have been colourful debates, heated discussions, and passionate arguments in terms of finding a definition for “emotion”. Just to give you an idea about the variety of opinions among scientists and humanists, in 1981 Kleingina and Kleingina identified 92 definitions of emotion in books, dictionaries and some other sources [Plutchik94]. For example, for Peter Goldie emotions are “complex, episodic, dynamic, and structured” phenomena encompassing various elements that change over time and that form part of a narrative [Goldie00], for the British psychoanalyst John Bowlby emotions are phases of an individual’s appraisals of either “organismic states” or “environmental situations” [Bowlby82], for Andrew Ortony, emotions are positive or negative reactions to events, agents or objects linked to the way eliciting situations are construed [Ortony88].

Although the effort made by scientists to explain affective experience is commendable, many of their conclusions (cf. their emotional classification) derives from very particular studies that concern the view of the scientist involved alone. From time to time however, scientists have made extraordinary contributions to the analysis of emotions that survive to our days and that have influenced entire generations of theorists. Five major schools of emotional theory have been recognized [Plutchik94]: The evolutionary, the psychophysiological, the neurological, the psychodynamic, and the cognitive.

1.2.1 The Evolutionary Tradition

Twenty-three years after he had returned from a 5-year trip onboard the HMS Beagle as scientific observer, Charles Darwin published a book that would revolutionize the study of human beings for years to come. In "On the Origin of Species by Means of Natural Selection", Darwin described how his observations led him to the conclusion that the changes on the animals' corporeal characteristics including organs, body parts, and size and also their life styles, stemmed from their attempts to adapt to changes in the environment. Different anatomical structures such as wings, eyes or fins were the result of successful adaptations whereas those that did not succeed led to the demise of the group and therefore ceased to exist [Darwin1859].

Darwin's ideas of evolution incorporated a series of other postulates on different aspects of human life and biological science. One hypothesis that still influences scientists to this day is the acceptance that, like bodily structures, intelligence, reasoning ability, and memory, emotions could also be described as evolutionary processes. In "The Expression of the Emotions in Man and Animals", Darwin provides an in-depth exposition on how the study of postures, gestures, and facial expressions offered evidence of the fact that human emotions are not only similar among humans but similar with those of other animal species. These similarities could be explained in terms of the "functional" purpose of expressive behaviour. Thus, an emotional expression found across many species such as anger and its associated physical manifestations, e.g., making their hair stand up or expanding their chests, would have been used by our ancestors to appear bigger and more formidable in front of other beasts or rivals, thus avoiding attack and ensuring the survival of the species. Even though some of these behavioural expressions do not serve any particular purpose to modern humans, they remain as vestiges of early behavioural, physical, and emotional adaptations in our evolution.

Darwin also drew attention to other relevant aspects of animal emotions including emotion innateness and primitiveness as well as cross-species emotion recognition. It is particularly notable that his ideas about inherited, genetically embedded emotions raised a fundamental question about the degree to which emotions conform to reason. Some of the experiments carried out by Darwin demonstrated that our reactions towards some external situations, e.g., danger, seem to be instinctual rather than rational thus supporting the idea that some emotional expressions persist in ourselves even in the absence of a cognitive process.

1.2.2 The Psychophysiological Tradition

In 1884 William James suggested a revolutionary idea with regards to how to interpret the psychology of emotions. According to James, emotional states are produced as a result of physiological responses to situations that themselves elicit the emotion [Carlson98]. Thus, a human being first realises bodily reactions and then perceives emotions as a consequence of the activity response from muscles and internal organs. In James's words, "… we feel sorry because we cry, angry because we strike, afraid because we tremble…" and not the opposite (at the time James decided to narrow the scope of his findings to what he called "coarser emotions" which included grief, fear, rage, and love). A major point in James' argument was that emotions with strong physiological activation can be identified by specific patterns of bodily changes. Working separately, Carl Lange, a Danish physiologist, drew the same conclusions three years later and researchers started referring to James' proposal as the James-Lange Theory [Plutchik94].

It is worth mentioning that James never provided solid answers to questions raised by his conclusions such as which bodily changes are associated with which emotions and how individuals with physical impairment manifested emotional states. Plutchik even challenges the validity of James's suggestions as a theory in today's standards for it mainly concerns a chicken-and-egg question [Plutchik94]. In the 60's however some psychologists provided experimental evidence that James and Lange theory was not far from reality. Despite the controversy, it is undeniable that the James-Lang theory served as starting point of a strong movement within psychology concerned with investigating the autonomic changes that occur before, during, and after emotional events take place

1.2.3 The Neurological Tradition.

From 1915 to 1929, Walter Cannon, a Professor at Harvard University, worked on a new theory of emotions based on studies that strongly contradicted what James had said. Cannon's criticism of the psychophysiological approach was based on his own experimental observations and consisted mainly of the following arguments: 1) Some visceral symptoms associated with emotional episodes, are too weak or subtle to be recognizable by an individual, 2) Some emotional expressions seemed to be faster than their visible physiological response, 3) Artificial stimulation of internal organs associated with "coarse emotions" did not produce any affective response, and 4) More importantly the absence of visceral sensing did not inhibit emotional expressions. Cannon did not only challenge the James-Lange Theory but he even provided his own interpretation of the role of somatovisceral changes in emotional expressions.

Based on experiments on animals from which parts of the brain have been removed and also on reports from patients with partial body paralysis, Cannon concluded that an emotional state is the result of the effect of the lower brain centres, namely the hypothalamus and thalamus, on the higher cerebral structures which in turn activates bodily organs via the autonomic system. Thus, we perceive the external stimuli, feel the emotion, and then react. About the same time, a young scientist named Philip Bard influenced by Cannon's theories, provided empirical evidence on the neurological roots of affective states and the whole hypothesis was called the Cannon-Bard theory.

Cannon's work has been extremely influential in the development of theories about the neurological foundations of human emotions.

1.2.4 The Psychodynamic Tradition.

In 1895 two Viennese doctors, Joseph Breuer and Sigmund Freud published a book on some of the work they had developed to explain and treat cases of hysteria. In "Studies of Hysteria", Breuer and Freud described how the moderate to extreme physical impairment (mainly sensory-motor problems) shown by patients suffering from this illness were the result of traumatic events. They also offered accounts of patients that had been successfully treated using hypnosis and an intense, overt expression of repressed emotions. Freud called the latter abreaction or catharsis.

Having discovered that some patients could not be hypnotized, Freud decided to discard hypnosis as a medical tool and rather concentrate on developing a complex theory around his idea of emotional catharsis. This new method of investigation received the name of psychoanalysis and was based on the idea that not only hysteria but all neurotic symptoms were the result of repressed memories with strong emotional content. Although Freud never developed a theory of emotions per se, his concepts helped in building a particular view of how to interpret affective experiences. In psychoanalysis, emotions or affects are interpreted as the result of an unconscious process stemming from the perception of stimuli. In the same manner, the expression of an emotion could involve a number of behavioural phenomena including subjective feelings and physical expressions. Finally, emotions are rarely found in "pure" state and often include various motivational sources and a mixture of feelings or reactions.

It is noteworthy that in Freudian theory both emotions and physiological changes occur at the same time as the result of the unconscious assessment of a given situation. The sequence dilemma posed by the James-Lange and the Cannon-Bard theories is therefore eliminated.

1.2.5 The Cognitive Tradition.

Another major paradigm in emotional theory involves the analysis of emotional expression within the context of social relationships. The Austrian psychologist Fritz Heider published a study in 1958 in which he described the symbiotic relationship between cognitive processes, e.g., concepts about what ought to be, aspirations and goals, and how we feel our emotions [Heider58].

Therefore, we might feel angry or sad as the result of how our beliefs and knowledge influence the way we perceive someone's attitude and behaviour, i.e., our emotions are determined by what we know about the environment. But our emotions can also affect our perception of the environment. One example is when we exaggerate the qualities or defects of someone depending on whether we feel love or hate toward them.

Among Heider's most important contributions are the "attribution" and the "balance" theories that help describe how our emotions intervene in the way we interpret and interact with other people.

Some approaches to emotions that are also based on cognitive theory include Schachter's verbal labels, and Ortony, Clore and Collins (OCC) cognitive structures.

1.2.6 Traditional Approaches to the Evaluation of Emotional States

Despite there being little agreement among the various theories involved in the attempts to define emotions, they usually have a more-or-less consensual description of emotional symptoms or expressions. It has been agreed that emotions are characterised by the awareness of a given situation, overt expressions and behaviours, readiness to act, and physiological changes supplemented with subjective feelings [Carlson98, Plutchik94].

The acceptance that explicit physical and mental manifestations of many types accompany emotional states has encouraged researchers to propose methods for recognizing and measuring emotions as they are experienced. Self-reporting, techniques of behavioural rating, projective techniques for evaluating behaviour products, physiological parameters, and analysis of facial and vocal expressions have been employed to determine emotional states [Carlson98, Plutchik94, Andreassi95]. In the next section, we will find out that the need for flexible emotion detection has prompted Computer Science to employ mechanisms that involve minimal or no human intervention, namely, bodily measures and artificial intelligence methodologies.

1.3 An Overview of Affective Computing

The term *affective computing* was coined by Rosalind Picard in the mid 1990s to describe computer methods that are related to, derive from or influence emotions [Picard95], 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. Some computing systems are even capable of establishing an empathic connection with the user's personal feelings by incorporating a combination of both emotion detection and emotion synthesis (see for example Garzon02 and Morishima00 in Appendix 1).

It is notable that, far from being an exclusive ambition of Computer Scientists, the idea of being able to detect and exhibit emotions through electronic means promoted in the affective computing paradigm has captivated the imagination of researchers from different areas including medicine and psychology and represents a fertile research ground for many other social and technological fields.

1.3.1 Emotion Synthesis

Emotion synthesis is useful to develop ways to communicate with humans at a subjective level involving social participation, for example using robots or GUIs capable of displaying emotional traits. Some of the most relevant work in this area has been done by Cañamero, e.g., [Cañamero00] and Aylett [Aylett04], followed by Itoh et al. [Itoh04], Suzuki et al. [Suzuki98], and Mobahi and Ansari [Mobahi03]. The preferred approach to develop emotion simulation in Computer Science is through the use of cognitive methods, i.e., subjective observation of the environment.

1.3.2 Emotion Detection

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. Three main methods have been suggested in emotion detection: facial recognition, speech recognition, and a combination of the two (bimodal). Recently, greater attention has been paid to internal bodily signs associated with physiological changes.

1.3.2.1 ***Facial Emotion Detection***

Facial expressions have been recognized as one of the most convincing signs of emotional episodes across different ethnic and social groups [Ekman73, Ekman94]. In facial recognition, video cameras and image processing systems are combined with methods to identify the spatial and geometrical relationships between facial gestures and organs such as eyes, eyebrows, and mouth and the variation in location among them. Facial expressions could also be measured using muscle movement by means of sensors attached to the face in particular to the masseter (a muscle in the jaw involved with chewing) and forehead.

The methods employed to analyze facial expressions vary with most of the approaches operating based on a comparison between the user's current expression and a library of facial measures linked to various emotional episodes.

1.3.2.2 ***Speech and Bimodal Emotion Detection***

Utterances are also of great value for emotional recognition. Speech or vocal emotion detection is based on the idea that particular ways of intonation convey information about the current emotional state of the speaker.

The most common speech features used in emotion detection systems can be grouped into phonetic, e.g., pronunciation of vowels and consonants, and prosodic, e.g., voice's pitch signal, energy, power, signal amplitude, mean, standard deviation, and range. In general, one or several of these features are extracted from the user's voice and compared to those associated with known variations of speech caused by emotional changes. From this comparison an emotional state can be determined.

An enhancement to speech recognition can be done by integrating both visual and vocal clues into the detection mechanism in what has been called bimodal or multimodal emotion recognition. Although multi-input systems might be expected to perform better than single-input mechanism, the integration of independent and often contradictory information makes multimodal emotion detection difficult.

From the methods described above, facial recognition has achieved the best results with 88-89% detection accuracy [Avent94, Rosenblum96] followed by speech recognition (50-87.5%) [Nicholson00, Moriyama99], and bimodal recognition (72%-85%) [DeSilva99, Yoshitomi00].

1.3.2.3 *Physiological Emotion Detection*

The specific role physiological signals (in particular those measures stemming from the autonomic nervous system and the brain) play in emotional expression has been mainly investigated within two scientific areas. Physiological psychologists focus on the analysis of behavioural response to physiological stimuli. Psychophysiologists are more interested in the physiological responses produced by behavioural changes [Carlson98, Andreassi95, Green87, Carlson92]. The physiological measures usually employed include one or more of the following: Heart rate, blood volume, blood pressure, skin resistance or conductance level (Galvanic Skin Response, GSRe), electroencephalogram, papillary response, electrooculogram (eye movement), gastrointestinal motility, electromyogram (muscle activity), skin temperature, brain potentials, and respiration rate [Andreassi95].

There are various reasons why physiological signals have become an increasingly popular choice among scientists interested in emotion detection. One of the main arguments in favour of bodily signals is that, in addition to being one of the two most recommended techniques to measure behaviour under real-life condition [Mischel86], physiological concomitants of emotional states offer two advantages over its facial and speech counterparts. Firstly, facial and speech recognition are usually based on fixed models that require well-defined gestures or utterances that make real-time emotion detection difficult whereas physiological signals can be obtained during normal activity without the need for cumbersome equipment thus making data acquisition less intrusive. Secondly, there is a well-documented tendency of people to alter their behaviour when they become aware of the presence of video-cameras or microphones. Thus, whilst facial expressions and vocal utterances can be more easily disguised in the presence of multimedia systems, physiological measures are difficult to conceal or manipulate, and are thus a more reliable representation of inner feelings. Lastly, advances in medicine, biomedical engineering and computing enable us to use sensing devices that provide high standards of portability, comfort, and reliability in the measure of physiological parameters in real-life situations. Dynamism and realism are two desirable characteristics of the control of pervasive environments, so it seems sensible and justifiable for the purposes of this investigation that I have chosen bodily signals as the most suitable mechanism to enable the recognition of emotional states.

1.3.2.4 *Discussion of Relevant Affective Computing Research*

Until the early 1980's, efforts to determine the specific physiological concomitants of emotions achieved only modest success. However, in 1983 Ekman et al. were able to distinguish between anger, fear and sadness (using skin temperature) and between happiness, disgust, and surprise and anger, fear, and sadness (using heart rate). More recently, Levenson [Levenson92], Prkachin et al.[Prkachin99], and Keil et al.[Keil02] have made attempts to verify the somatovisceral manifestations associated with emotions aiming at evaluating various aspects of sentient states.

There has been a rather modest amount of computer science research into affective computing and the estimation of emotional episodes based on physiological signals. Picard et al.'s approach [Picard01] to detect anger, hate, grief, platonic love, romantic love, joy, reverence and the neutral state (no emotion) was based on the combination of two statistical methods, namely Sequential Floating Forward Search (SFFS) and Fisher Projection (FP). The SFFS is an attribute selection algorithm that performs a nonexhaustive search of the features that provide the best classification rate while FP is used to perform a discriminative projection (reduction of data dimensions) of those features based on their mean values thus decreasing the cost of classification. Picard et al. employed various statistical features calculated from the respiration, skin conductance, blood volume pressure (BVP) and electromyogram measured from the masseter (a muscle in the jaw involved with chewing) of a single individual collected over a period of 20 days. Each day's acquisition session resulted in 2001 samples per emotion per signal. The total number of samples collected by Picard was 40020 for each of the eight targeted emotions. The statistical features with the closest characteristics were selected by means of SFFS and then presented to the FP for classification. Despite its high level of correct classification (83%), Picard et al.'s method was limited in the sense that statistical features were calculated over one-day periods and local temporal variations (minutes, hours) were not taken into account, making real-time detection difficult. Kim et al. [Kim02, Kim04] suggested the utilization of a support vector machine (SVM) classifier using a shorter signal monitoring time than the one utilised by Picard et al. Using three physiological signals to classify four emotions, Kim's method achieved 61.2-78.4% correct classification. Nevertheless, the generalization of these results is questionable since the physiological data were collected from subjects whose ages ranged between five and eight years only. Nasoz et al. [Nasoz03a, Nasoz03b] conducted a study to detect various emotional states using three physiological measurements (skin galvanic response (GSRe), skin temperature, and heart rate). Instead of using statistical features, Nasoz et al. employed normalised signals and provided them to two separate classification methods: k-nearest neighbour (KNN) and Discriminant Function Analysis (DFA). KNN is a popular instance-based clustering algorithm used to group data according to the calculation of the sample's metric distance. DFA is a linear discriminant algorithm based on statistical pattern classification that employs covariance matrices to find the coefficients of the discriminant functions. The best results were achieved with the DFA method: 90% correct classification for fear, 87.5% for sadness, 78.58% for anger, 56.25% for surprise and 50% for frustration. Nasoz et al.'s approach is suitable for real-time detection since it does not require the collection of entire data sets before providing a hypothesis of the emotion experienced by the user. However, this method lacks the adaptability found in pattern detection mechanisms such as Artificial Neural Networks ANNs. For example ANNs can be retrained on-line if necessary, they are less prone to be affected by noisy or corrupted inputs, and have been designed to be multivariable, thus making them more suitable to be employed in highly interactive real-world applications that involve sensors.

Other researchers have focused on detection of very specific emotions for practical purposes. For example, Healey et al. [Healey98] detected user's mood using physiological and behavioural changes and then related those mood states to musical preferences. In another study, Healey [Healey00] developed a model for detecting stress (while a subject drove an automobile) based on physiological signals and statistical methods. Ark et al. [Ark99] implemented an adaptable computer environment based on physiological signals acquired through a computer mouse which include somatic activity (mouse movement), skin resistance, skin temperature, and heart rate. Fernandez [Fernandez97] utilized somatovisceral arousal to detect frustration in computer users based on galvanic skin response (GSRe) and blood volume pressure (BVP). Fernandez's approach employed statistical features in conjunction with Hidden Markov Models (HMMs) to identify the "frustration" that arises when humans interact with poorly interactive computer programs.

Appendix 1 demonstrating the state of the art in emotion detection is useful in highlighting two crucial issues. Firstly, although some approaches have been concerned with developing user-independent methods that operate in real time, little attention has been paid to the problem of emotion detection from an ambulatory subject who is carrying out activities that, at one given moment, might interfere with the detection process, e.g., moving away from the camera or microphone in the case of facial and speech emotion detection or performing physical exertion in the case of physiological emotion detection. The issue of robustness is a requirement of any satisfactory approach to the problem of integrating emotion detection mechanisms into highly interactive real-world spaces such as intelligent inhabited environments Secondly, none of the approaches above have been purposely designed to be employed inside real-life pervasive spaces with the intention of improving and facilitating interaction between an individual and the immediate environment.

1.4 Towards the Integration of Emotions into Pervasive Systems

I have mentioned that emotions are an essential element of human life and have a predominant role in the way we conduct our lives affecting our activities and delicately liaising between ourselves and the environment. In 1990, Salovey and Mayer developed a broad framework known as emotional intelligence (EQ) to describe how humans perceive and utilize their emotions [Salovey90]. The initial purpose of EQ theorists was to investigate the significance of emotions within the context of intelligence, paying special attention to adaptation and behaviour. However, health, personality, personal ambitions, motivations, and success have also been analysed from an EQ perspective.

The importance of emotions in the myriad mechanisms governing human conduct as portrayed by Salovey is one explanation why computer scientists investigating interactive systems have turned to emotions in an effort to improve the adaptability of software agents, increase the accuracy of decisions relating to human behaviour, and enhance human-machine interfaces. It is hoped that new more accurate, effective and flexible software applications with potential uses in social, medical and technological areas could be developed following the principles of affective computing, i.e., by including emotional information into the input parameters of artificial inference mechanisms.

Among all the areas that could benefit from the introduction of emotional information into interactive systems, pervasive computing is one of the best candidates. It seems to me that by allowing embedded computers to recognize and use emotional information, software agents of the type used inside interactive environments would be able to use this information to better adapt to what the user wants, increase the accuracy of decisions derived from what the user does, and facilitate mutual interaction. Actions taken by affective agents could ultimately be comparable to intelligent human activity, i.e., would be directed towards ensuring user's comfort. Affective agents could for example, be used to monitor the affective state of elderly or disabled people and adjust the ambience settings according to their stress levels and with the intention of providing comfort. In the same manner, the underlying relations between various environmental conditions and human behaviour important in a number of Humanistic areas could also be investigated using emotional information.

Because of their importance for understanding the purpose of the present work as well as setting the technical basis that would help to interpret later discussions, in the next chapter I will offer a general introduction into the main concepts of pervasive computing and related software paradigms. The ideas that will be presented next will allow not only readers from computer science but also the general reader to grasp the hypotheses, principles, repercussions, significance and contributions of this research endeavour and situate my effort within the area of pervasive computing. Chapter 2 will also provide a general view of the current trend in the area of intelligent inhabited environments so that I can make clear where my objectives, motivations, inspirations, and aspirations differ from those of other researchers working in similar areas.

"The clock, and the clockwork machine, are the metaphors of the past several hundred years of technology. Invisible technology needs a metaphor that reminds us of the value of invisibility, but does not make it visible. I propose childhood: playful, a building of foundations, constant learning, a bit mysterious and quickly forgotten by adults. Our computers should be like our childhood: an invisible foundation that is quickly forgotten but always with us, and effortlessly used throughout our lives" Mark Weiser

Chapter 2

Pervasive Computing

2.1 The Beginning

From the first stone tools to the invention of the computer, the development of technology seems to have served the single purpose of making human life better. Although this has had a different impact on peoples lives depending on what they do and where they live, it is undeniable that the utilization of technology has improved the living conditions of the whole of humankind over the centuries. The more evident effects of recent technological advances are in developed countries where the reduction in the price and size of electronic components has made it possible to rely on computers for everyday activities. Cell phones, Personal Digital Assistants (PDAs), MP3 players, notebooks, portable Global Positioning Systems (GPSs), and intelligent appliances are all computerized artefacts that have not only made our lives undoubtedly more comfortable but also become indispensable tools on which many people's existence and livelihood depend. Nonetheless, and despite the progress made on software and hardware interfaces, the interaction between humans and computers is still heavily dependent on the so-called desktop paradigm developed in the eighties at the legendary XEROX PARC. Any Personal Computer (PC) user would agree that this form of interaction involves a great deal of explicit physical and mental involvement that not infrequently leads to user disappointment and disenchantment. Nonetheless, as Mark Weiser suggests, this tortuous relationship is just part of a "transitional step" that will eventually culminate in the invisible integration of computers into the environment allowing the user to interact with them in a more natural, seamlessly way [Weiser91]. This prospect is known as Ubiquitous Computing and has since 1991, when it was first suggested by Weiser, been the inspiration of many scientists working in areas such as mobile technology, distributed and embedded systems, or human-machine interfaces [Abowd00].

2.1.1 Ubiquitous vs. Pervasive Computing

In Weiser's vision, users would interact transparently with ubiquitous computing systems without the need of an arduous cognitive process and with just the minimal amount of physical effort emphasising the use of our peripheral attention [Adelstein05]. However, in order to be capable of taking control of the majority of the cognitive tasks usually performed by the brain, ubiquitous computing systems would have to be able to learn specific user characteristics and behaviour permitting better responses to immediate and future demands. Pervasive computing is a concept in which applications and data are accessible anywhere and on any device "in a manner that is customized to the user and the task at hand" [Handbook05]. This definition seems to be useful to distance ourselves from the interminable discussion about the difference between pervasiveness and ubiquity. It seems evident that Pervasive Computing is an extension of the ubiquitous system paradigm where devices and services are not only "invisible" as Weiser suggested but go one step further and become "adaptive" to the user needs. This conceptual difference has been stressed by Max Goff in his book "Network Distributed Computing: Fitscapes and Fallacies" [Goff04]. For Goff, Pervasive Computing involves computing devices and services that are *available* everywhere in contrast to ubiquitous which involves technology that is *present* everywhere. Moreover, Goff portrays pervasive computing as the hitherto unfulfilled objective of the ubiquitous paradigm. It is notable that even at a semantic level there is a subtle but crucial difference between the two notions. According to the Oxford English Dictionary the word "ubiquitous" stems from the Latin word *ubique* meaning everywhere and it used to characterise those objects which are "present, appearing, or found everywhere". On the other hand "pervasive" is an adjective used to represent an object that is "spreading widely through or present everywhere **in something**". Thus, a computer system could be ubiquitous, i.e., found anywhere but not necessarily pervasive, i.e., be embedded in the environment. Let me illustrate this difference with an example. Let's say that you are travelling across Scotland, you have your PDA with you and need to find a hotel to spend the night. In a ubiquitous environment you would dial an 800 number, connect to the Internet and then search for suitable accommodation, i.e., the service is available but not seamlessly integrated with the environment. In a pervasive world, the moment you switch the PDA on, you would have access to a wireless network, and because the system detects your current position, it will automatically offer you a list of hotels offering en-suite rooms consistent with your previously expressed preferences. It's not unusual however to see in the literature authors avoiding controversy by using both concepts synonymously [Adelstein05, Handbook05, Satyanarayanan01, Moran01, Cook05] while some others prefer to add their share of debate by indistinctly using the term "context-aware" computing [Handbook05].

2.1.2 Pervasive Computing vs. Ambient Intelligence

There is yet another term that evolved from Weiser's ideas and that has recently been utilized among the European scientific community. Ambient Intelligence (AmI) is the result of integrating three important technologies: Ubiquitous Computing, Ubiquitous Communication, and Intelligent User Friendly Interfaces [ISTAG01]. The European Community Information Society Technologies Advisory Group (ISTAG), who originally coined the term, defines Ambient Intelligence as the computing scenario "…where the emphasis is on greater user-friendliness, more efficient services support, user-empowerment, and support for human interactions. People are surrounded by intelligent intuitive interfaces that are embedded in all kinds of objects and an environment that is capable of recognising and responding to the presence of different individuals in a seamless, unobtrusive and often invisible way".

Even though Pervasive Computing and Ambient Intelligence share common roots and they both seem to be "enhanced" versions of Weiser's ubiquitous paradigm (it has been even hinted that Ambient Intelligence is the European term given by Philips to IBM's Pervasive Computing [SWAMI05]), Callaghan et al. has suggested that Pervasive Computing is the result of a widespread deployment of basic AmI building blocks comprising a computer supplemented with a network interface and that can be "integrated into artefacts ranging from domestic appliances down to nano-scale devices" [Callaghan04].

Thus, for the purpose of this work and based on the above definitions, the term "pervasive" will be henceforth used to indicate the type of computing that arises from endowing context-aware ubiquitous devices with adaptive qualities that would resemble human intelligence. Context-awareness is the ability of a pervasive system to detect in which physical area the user is (indoors or outdoors), what actions have taken place and why, with or through which objects or persons, and when, and from where, these tasks are being generated [Adelstein05, Handbook05, Cook05]. Thus pervasive computing concerns the existence of a network of intercommunicated embedded computers incorporated in the environment, or as wearable devices, that are capable of monitoring internal (hardware and software) and external conditions and which, without being visible, could be manually or automatically customisable using knowledge acquired through interactions with the user. Using Callaghan's conceptualization, Ambient Intelligence (AmI) will be employed to designate the type of pervasive computing that is embedded inside closed inhabited environments as opposed to that found in open spaces (see Figure 2.1).

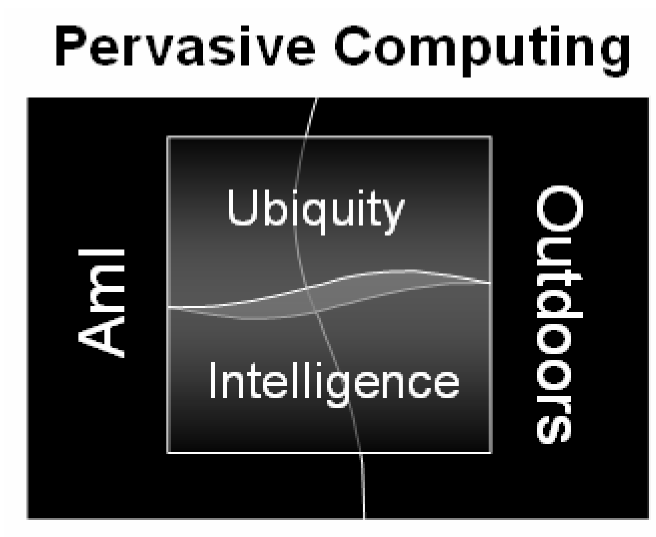


Figure 2.1. The domain of Pervasive Computing.

2.1.3 Intelligent/Adaptive vs. Perceptive/Non-adaptive Processes

It is important to remember that being mobile, context-aware, and automatic does not necessary mean that a given interactive environment or device conforms to the pervasive computing paradigm let alone that is "intelligent" [Cook05]. There is a subtle sometimes obscure difference between a system that is perceptive and responsive, i.e., one that measures a wide number of environmental variables and responds according to changes occurring on them, and one that is able to "learn", "infer" and "adapt". Callaghan et al. say "embedded intelligence can be regarded as the inclusion of some reasoning, planning and learning processes in an artefact that, if the person did it, we would regard as requiring intelligence" [Callaghan04]. I chose this definition of intelligence because it is useful mainly in three ways. First, it intrinsically associates intelligence with human aspects closely associated with emotions, i.e. goal generation, strategic planning, learning, memorization, intention and decision making. Second, we would normally regard someone as being intelligent only if he/she is capable of responding to varying situations (it is adaptive) using the knowledge acquired through past experience. Thus, in Callaghan's idea intelligence necessarily involves a level of adaptability. Finally, human emotions play an important role in what we could regard as an intelligent action, i.e., a human activity requiring intelligence inevitably involves an active participation of our emotional being to accurately identify and satisfy what we and others need.

For example, imagine that you are about to open your office door. You just arrived at work and are copiously sweating after having taken the stairs; you think "I need a cold drink". On your way there, you have decided to have a quiet morning (as from time to time you do) and catch up with some reading instead of working on the computer. You do not even want to turn all the ceiling lights on but just your desk lamp. The instant you open the door, the ceiling lights automatically activate and the coffee machine starts brewing a cup of coffee. You ignore the coffee and walk towards the book cabinet to pick up a book. As soon as you get near your desk the computer turns automatically on. Now you know you are going to have to wait a few minutes before the computer can be switched off. You finally sit down, activate the desk lamp and walk back to the main switch to turn the ceiling lights off. It is not difficult to see what's wrong in this picture. The computing system in your office was aware of your presence and responded to your movements on the basis of its pre-programmed functionalities but was incapable of knowing what you wanted based on your current behaviour and things that you had done in the past. Furthermore, this system did not only fail to learn from its own observations of your past behaviours, but it was unable to recognize key factors, e.g. your physical state and your mood, that would allow it to discriminate this behaviour from others. This limitation clearly resulted in user dissatisfaction and energy waste. In pervasive computing, hardware and software resources should be organized in a way that permits the environment to understand and learn from the individual characteristics of the users, their customs and preferences while minimising the use of energy resources.

2.2 Introduction to Pervasive Systems

Pervasive computing systems are complex applications that involve a myriad design and implementation issues. A quick look at the proceedings of the First IEEE International Conference on Pervasive computing will indicate the many and various areas researchers are currently working on: Middleware services, sensor networks, ubiquitous services, pervasive computing environments, context-aware computing, ad hoc networks (networks in which devices connect to each other without the need of intermediary non-mobile units [Handbook05]), location-aware systems, resource identification and naming, location based services, networking issues, philosophy of intelligent environments, mobile services, devices for pervasive computing, activity recognition, resource management, and system level design. Although an in-depth look into all these topics is beyond the scope of this thesis, there are some aspects relevant to our discussion.

2.2.1 Development Methods

Using two of the most desirable underlying characteristics of pervasive computing mentioned above (ubiquity and context-awareness) as developing guidelines, Banavar et al. recognize four main approaches to develop pervasive systems (listed in order of model maturity) [Adelstein05].

- Device-independent Views: These are representations of visual objects that allow information exchange between different hardware and software implementations. Instead of using "hard-wired" objects, the visual elements of an application are represented at a high-level easily translated by the host device at run time or by using specific encoded mechanisms devised at design time. Examples of this approach include various Mark-up languages (e.g. HTML, UML, etc.).
- Platform-independent controllers: This is related to the control flow of mobile interactive applications and involves aspects such as different input hardware, irregular data flow infrastructure, multiple visual displays, and dissimilar device platforms. One approach involves the use of generic graph representations also known as dataflow graphs.
- Host independent models: Based on a distribution of the data flow, the system's visual representation and the information being exchanged, mobile applications could be designed to rely heavily on a server (thin client), have a certain degree of autonomy with regards to the visual and logic implementation (thick client) or being completely independent (autonomous client).
- Source independent context data. This approach is based on the logical embodiment of the different data sources so that the response to a given query posed by an element of the pervasive system will be dealt with using only information about the data type leaving selection of the data source to the underlying infrastructure. In this manner, artefacts

including sensors and actuators could be operated indistinctly of their physical characteristics.

In reality, pervasive systems are often the result of a combination of these development techniques where they make use of visual representation of objects based on flexible data exchange operating on thin, heavy or autonomous clients and that obtain data from various “masked” sources.

2.2.2 Embedded Agents

Whatever the main development technique there is a common implementation predicament in the issue of the “intelligent” aspects of pervasive computing systems. It was mentioned before that in Pervasive Computing we would be assisted at all times and at any location by computerised devices. They will be in control of many activities we normally perform using our inference capacity. This cognitive “understudy” requires entities mimicking our behaviour to exhibit at least a certain degree of “human-like” intelligence. Therefore, there is a growing trend among scientists towards the utilization of embedded agent systems as the structural building blocks of pervasive systems. Agents can be defined as “autonomous, intelligent software entities that have the ability to perceive the environment, reason about what they observe, and act to change that environment to accomplish their goals”[Cook05].

2.2.2.1 *Intelligent Decision-Making*

The most logical choice to bestow “rationality” on agents is through the use of Artificial Intelligence (AI) mechanisms. There are three main aspects associated with computerised intelligent behaviour: learning, knowledge representation, and inference.

Machine learning

Broadly speaking, machine learning is the process through which an artificial entity acquires knowledge about a certain phenomenon. This can be done either by being taught using a "teacher" or by "first-hand" experience without the need of a "teacher".

- Supervised Learning

  Learning with teacher is called supervised and involves the utilization of input-output examples representing the phenomenon being modelled. Some supervised learning algorithms used in software agents include some types of Artificial Neural Networks (ANNs), decision trees, and instance-based methods such as nearest-neighbour. Some approaches to intelligent agents featuring supervised learning are [Brdiczka05, Rivera05, Sandhu04, Dodier94].

- Unsupervised Learning.

  Learning without a teacher is achieved using examples comprising just the input component of observations about the phenomenon being monitored and can be done 1) through reinforcement or 2) using unsupervised techniques. Reinforcement is a learning method in which the agent interacts with the environment and its actions are penalized or rewarded depending on how successful they are with respect to the goal but without necessarily knowing what the actual desired output is. Techniques to perform reinforcement learning include Q-learning and genetic algorithms. Examples of reinforcement in agents are [Mozer95]. In unsupervised learning there is no penalization and consequently no indication on whether actions taken by the agent are erroneous nor what the right output is. Various applications of agents using unsupervised techniques have been suggested [Claus98, Capera03, Messie04].

For a more detailed description of supervised and unsupervised methods see for example [Haykin99, Witten00, Winston92, Kaelbling96].

Knowledge representation

Closely linked to learning, knowledge representation is the method employed by the agent to record what has been learned. In some AI methodologies such as AANs knowledge is embedded as low-level data types in the structure of the network itself thus being not understandable in human terms while in some others such as fuzzy logic knowledge is constructed separately using high-level descriptions.

Inference, generalization and prediction

Inference (also called reasoning) is the process through which the knowledge that has been recorded is used to answer queries and draw new conclusions. Inference could be achieved by generalizing or predicting from current or past observations. Generalization is the ability to appropriately categorize unfamiliar patterns, based on information about the classification of familiar patterns [Haykin99, Winston92]. Through generalization an intelligent agent would be able to provide satisfactory outputs when unknown, corrupted or partial environmental data are present thus ensuring comfort and minimal costs. Prediction permits an agent establishing a hypothesis about what the next environmental conditions would look like. Note that when I say "environmental conditions" I am not only talking about ambience settings but also the actions taken by the individual interacting with the agent. Consequently, predictions made by the agent could be in relation to the next value of one or more variables, the next potential user activity or movement, or entire action plans comprising actions and ambience settings.

In pervasive systems, the decisions that derive from the agent's inference mechanisms are normally fed back into the learning system to further improve future interactions [Cook05]. Some inference algorithms for agents in pervasive computing include: Hidden Markov Models (HMMs), AANs, Fuzzy Logic, Genetic algorithms, Bayesian Classifiers, nearest neighbour techniques, and Support Vector Machines (SVMs).

2.2.2.2 *Operation*

Spaces equipped with pervasive systems would typically comprise a potentially vast number of variables related to artefacts and inhabitants distributed across a physical area. Although a single software agent could, in theory, be capable of handling all the complexity associated with a certain pervasive system, it is not uncommon to develop intelligent agents as part of a community of agents rather than in isolation. Multi-Agent Systems (MASs) involve several agents that are distributed, interconnected, control different aspects of the environment and cooperate towards the objective of the pervasive application they are part of in an intelligent proactive manner. MASs are usually characterized by agents displaying incomplete information and limited ability to resolve a problem, lack of global control, decentralized data, and asynchronous computation [Sycara98]. Thus, a MAS should include mechanisms that allow its agents to work together either by negotiating or by using centralized control.

MASs adduce several reasons why they are a popular choice to implement pervasive systems: 1) Capability to solve problems that might be too large, sensitive or demanding in terms of resources to be assigned to a single agent; 2) Reusability because MAS allow the use, interconnection, and interoperation of multiple existing legacy systems; 3) Increased scalability and flexibility since agents developed separately could be added at any time to increase the power and functionalities of the local system or be integrated into other societies of autonomous interacting agents; 4) Distribution of information sources and expertise; 5) Increased robustness and reliability since the failure of one or several agents does not render the overall system useless; 6) Faster operation and efficiency because of the use of asynchronous and parallel operation (provided that resources employed in agent coordination are kept minimal); and 7) Potentially lower costs since MASs could in some cases be more cost effective than their centralized counterparts [Sycara98, Weiss99].

Pervasive systems are often characterized in terms of some of the attributes inherited from MASs such as the capacity to include homogeneous or heterogeneous agents or the use of fine or coarse application granularity (how primitive agents are), hierarchical or democratic control (whether agents work independently or are centrally coordinated), interface autonomy (whether the agents cooperate to achieve a goal or work independently), and execution autonomy (how each agent is executed) [Sycara98, Weiss99].

2.2.3 Middleware

Underneath the structural implementation of the intelligent agent(s) lie the different software tools interfacing the various pervasive computing elements, the so-called Middleware. More formally defined, Middleware "is software that supports mediation between other software components, fostering interoperability between those components across heterogeneous platforms and varying resource levels" [Adelstein05]. Implementations of middleware often use messages, transaction servers, Remote Procedure Calls (small pieces of embedded code that intercommunicate different applications), web services or the combinations of two or more of these methods.

2.2.4 Intelligent Inhabited Environments (IIE)

Before moving on to discussing the applications of pervasive systems, let's just pay a quick visit at yet another concept that needs to be clarified. It is not surprising that because of the financial and practical implications, it is inside closed environments that research involving Pervasive Computing has flourished. Thus as we have seen it is not difficult to read or hear about "Smart", "Interactive", "Perceptual" or "Intelligent" offices, rooms, homes, or buildings. This of course does not mean that pervasive computing is bound to "roofed" spaces and it could, in theory, materialize anywhere, on any terrain and physical area the ultimate goal being a global pervasive system.

For my purpose however I will concentrate on the use of pervasive computing inside closed spaces and will henceforth employ the term "Intelligent Inhabited Environment" [Callaghan04] to denote the physical embodiment of Ambient Intelligence (AmI), i.e., pervasive computing confined to habitations and buildings rather than to open spaces. Although I will mainly be using the term Intelligent Inhabited Environments (IIEs) to refer to habitable buildings, IIEs in its broadest sense could include such living spaces as car, shopping malls, or even living organisms [Doctor05].

2.3 Pervasive Computing in Domestic Environments

If you were asked about the way you interact with computers, what would you say? "Well", you might say, "I use a PC at work 8 hours a day and I have a laptop computer at home that sometimes carry with me on the train". You might even say that you use computers on your mobile phone and PDA to keep in touch with you family and friends, or to organize office meetings. You could also enumerate some other pleasurable activities associated with popular wireless, mobile devices such as listening to music or playing videogames. The more adventurous could even tell about their intelligent offices. But, what about the rest of your daily activities? Why is a computer not opening the door and switching the radio on when you get home? Or washing the dishes? Or doing the shopping for you? One of the most exciting prospects of pervasive computing is the possibility of letting computerised devices take charge of our most habitual tasks in particular those we undertake at home. How many people in the past have envisioned an apartment in which every single object is operated automatically; a house in which artefacts ranging from lights to appliances recognize our needs and know what and when to do something without the need for our intervention, a place with its own intelligent way of understanding what we want? The increasing processing power of computer technology has now given the chance of endowing inanimate common household and personal objects the ability to possess a degree of autonomy and inference that has helped towards the realization of the "smart homes" paradigm.

2.3.1 The Importance of Ambient Intelligence

Why is Ambient Intelligence (AmI) so important? A few months ago while I was undertaking a preliminary analysis on emotional intensity, one of the subjects taking part in the study asked me, "Why are you studying Intelligent Environments? Isn't a bit frivolous to be spending valuable resources on trying to make domestic environments adaptive to the user's whims, changing moods and erratic behaviour while there are millions of people starving in Latin America and Africa?" At that moment my only answer was that my interest in intelligence environments did not stem from vanity but from a genuine desire to improve the living conditions of different kinds of people including the elderly, the sick, and the handicapped. However, I could also have replied with another question: What was the purpose of all those inventors and entrepreneurs behind the development of the electric freezer or stove? Were they looking towards their financial benefit or the praise of their contemporaries? Did they think that what they were doing was arrogant or only for the privileged at a moment when ice boxes and coal stoves were already available? Why were they making the effort to improve what was already there? A short answer could be that they were trying to make everyone's lives easier and more comfortable. A longer answer however might include the reasons why the electric freezer has saved the lives of many people by allowing decaying products to be preserved for longer periods of time under harsh weather conditions or how the electric stove has prevented the death by CO_2 asphyxiation of entire families.

Contrary to what many people think, AmI does not only involve entertaining but it has also to do with optimal comfort, safety, energy-consumption, and work efficiency. This is achieved by giving computers embedded in the environment the ability to manage, analyze, and control the ambience settings using adaptive inference methods. Furthermore, in AmI, domestic appliances and household services would possess the capacity to communicate with one another, cooperate, recognize and tackle deficiencies, work harmonically to avoid obstructions and potential conflicts, and ultimately satisfy user needs in the most effective manner. It is also suggested that future space habitation may be critically dependent on AmI technology.

2.3.2 Research Initiatives

The study of Ambient Intelligence has gained momentum in recent years and a lot of resources have been diverted into very large, often multidisciplinary research enterprises. I will divide the discussion of current projects concerning IIE into two areas: a) First, in this section I will outline the motivations and objectives of some of the most important working groups and research initiatives, and b) In the next section I will introduce the problem of modelling user activities inside IIE and how specific research projects have attempted to address this issue.

- Researchers at the Multi-agents Systems Lab of Massachusetts University at Amherst have been working since the late 1990's on a testbed for intelligent environments called the Intelligent Home (IHome). The objective of this research project is to improve efficiency at home by offloading some the activities currently performed by the users into intelligent multi-agent systems (MASs) with particular interest into resource coordination among intelligent artefacts as well as temporal chains of agent activities over shared resources. The IHome features a probabilistic task modelling framework known as TÆMS that distribute, organize, and evaluate the course of actions undertaken by the various agents that include the intelligent WaterHeater, CoffeeMaker, Heater, A/C, DishWasher and a robot that fetches items and moves physical objects from one location to another.

  For the purpose of practical analysis, the IHome has been realized as a simulated environment comprising a bedroom, a living room, a bathroom, and a kitchen, all joined by a common hallway. Using predefined user profiles and resource models the IHome is able to administer resources aiming at optimal operation and minimal waste.

- The Aware Home Research Initiative at Georgia Tech focuses on the design of a living laboratory to study the relationship between technology and inhabitants inside domestic environments. The main purpose of this multidisciplinary project is to employ ubiquitous computing to make the surroundings aware of the activities in the house and assist users in everyday situations [Kidd99, AHRI04].

Some of the current research taking place under the Aware Home initiative includes: the Digital Family Portrait which facilitates the contact of family members who live far away with a particular concern for independent elderly individuals; the Dude's Magic Box which provides grandparents a way to perform long-distance caring of their grandchildren; the Cook's Collage capable of displaying recent cooking activity along a kitchen countertop thus assisting retrospective memory recall; and the Gesture Pendant that recognizes gestures and translates them into commands for home appliances. Some other projects are related to more theoretical aspects of pervasive computing, such as user location services, activity recognition, rapid prototyping of home applications, methods to assist building applications that engage the acquisition and eventual retrieval of images about live experiences, studies on security and safe management of personal information, and the analysis of the impact of industry standards such as Universal Plug and Play (UPnP) on context aware infrastructure.

- The PlaceLab developed as part of the MIT's House_n project is a 1000 square foot live-laboratory located in Cambridge, MA, USA that is used to design and test ubiquitous computing algorithms and also for the study of human behaviour. The PlaceLab's interiors is comprised of 15 prefabricated cabinetry elements each one of them equipped with a micro controller, an addressable speaker system, and an array of 25 to 30 sensors. In addition, home appliances, furnishings, fixtures, and movable objects are also equipped with sensors to detect whether they are in use or moving. Sensors are also used to detect open-close events as well as internal conditions such as distributed temperature, humidity, lighting, barometric pressure, water flow, gas flow and electrical current. There are 17 cameras and 18 microphones located in various places in the PlaceLab plus 20 computers to process video and audio information. Wearable sensors appropriate for human movement detection are also featured in the PlaceLab [Intille04, Housen05].

The PlaceLab has been developed with the idea of undertaking long-term live experiments on single individuals for several days or weeks. Recently, experiments have been carried out to evaluate mechanisms for activity recognition, activity recall, and dietary reports.

- The HomeLab is an endeavour initiated by Philips Research and Development (R&D) with the purpose of re-creating a domestic environment in which people would have the opportunity to interact with technological prototypes. The cameras, microphones, and sensors installed inside the HomeLab provide a detailed view of how humans react to certain technology and gives Phillips R&D valuable information about whether to continue, discard or modify technological innovations [Homelab03].

  Some of the artefacts already being used and tested inside the Homelab include a bathroom mirror that displays the time, the weather, the news and the vital signs of the person whose image is being reflected and a stereo that plays music using voice commands. Some other multi-modal devices in the HomeLab are: Nebula, which is a multimedia system that can access a database of images and swirl those images on the ceiling above the bed in the master bedroom in accordance with body movements, and Pogo, a combination of manual toys and multimedia. The HomeLab is also the tesbed for the PHENOM project, which main objective is to create an inhabited environment that is capable of recognizing the identity, location, and motivations of its inhabitants and imitate a butler-like behaviour [Phillips06].

- The Intelligent Dormitory 1 and 2 (iDorm1 and 2) developed by the Intelligent Inhabited Environment Group (IIEG) at the University of Essex are two state-of-the-art testbeds for various agent paradigms and pervasive computing methodologies. The idea behind the iDorms is to give researchers the opportunity to explore new ways of interfacing technology with users inside domestic environments aiming at improving their living conditions. The iDorms main designing concept is the development of an optimal internal and external communication environment that would enable the user to manipulate and interact with the surrounding technology in a seamlessly, cross-platform manner [Pounds-Cornish02, Hagras02].

  Thanks to an uninterrupted, thorough monitoring of the users activities, the iDorms are not only responsive to user needs but also potentially capable of acquiring knowledge and displaying signs of intelligent behaviour. To this end, the iDorms are equipped with an array of embedded sensors and actuators that provide information about external and internal light and temperature levels as well as occupancy, and humidity indicators. They allow automatic and manual control of the internal ambience settings and also of the entertainment, office-work and energy systems. Remote cross platform access is achieved by using standardised technology such as UPnP and Transmission Control Protocol/ Internet Protocol (TCP/IP). Research endeavours involving the iDorms include the eGagdets initiative aimed at developing a conceptual and technological framework to assemble and control network-aware products in pervasive environments [Egadgets03] and the Careagent involving the integration of intelligent areas and robots [Careagents03].

Other projects that favour research on inhabited spaces other than domestic environments but deserve a special mention because of their leverage are:

- The Interactive Workspaces project at Stanford University started in 1999 as part of a novel study on the interaction between humans and large high-resolution displays located inside a lab. The initial purpose of the displays soon proved to be of better use within the context of pervasive systems and current research has been expanded to include the study of a wide range of wireless, multimodal I/O devices some of which have integrated into the environment in a seamlessly way. The main muscle of this project has been directed into using pervasive systems in workspaces with a special emphasis on task-oriented work such as brainstorming meetings and design reviews rather than entertainment, personal communication, or ambient information. The Interactive Workspaces group has developed a testbed for their analyses called the iRoom with special interests on Multi-device, multi-user applications, multimodal interaction, software tools for deploying ubiquitous computing environments, advanced visualization capabilities using wall-sized displays, and seamlessly integration of computing devices such as PDA's, scanners, digital cameras, etc.

- The Perception and Integration for Smart Spaces Project (PRIMA) from the Institut National De Recherche En Informatique Et En Automatique in France encompasses several research efforts concerned with technologies for the perception and recognition of human action in intelligent environments. The four main areas composing PRIMA are multi-modal observation and tracking of people, integration and control of perceptual processes, new forms of human-machine interaction, and recognition and learning guided by the context of interaction. There are various ongoing projects tackling different aspects along PRIMS main research lines. For example, the ECVision network links investigators studying different aspects of cognitive computer vision, FGNet concerns the study of mechanisms for face and gesture recognition, Imalab investigates a software development tool for computer vision, CAVIAR or Context Aware Vision using Image-based Active Recognition, CHIL or Computers In the Human Interaction Loop, DETECT for automatic broadcast analysis, FAME concerned with multicultural agent exchange and RAVI for multilingual interactive programming.

2.4 The Problem of Behavioural Modelling inside Domestic Environments

The advantages of integrating technology into domestic environments are evident. So far however, the final leap into the so-called "smart home" has remained an unrealised aspiration shared by both manufacturers and researchers alike. This fascinating technology we've been promised for years seems to be part of a world only existing in the media and the achievements made by computer scientists have not had direct wide-spread repercussions in our homes.

There are various reasons why the tools, applications, and theory already being used in laboratories have not reached our homes. Such reasons are mainly related to unsolved issues concerning the sociological, psychological, economical and technological impact of AmI in our daily activities and also the software safety and ubiquity levels needed to guarantee our privacy [Callaghan07]. For example, 1) to what degree should devices be in control of our lives, 2) when should they stop being proactive and let the user choose what s/he wants; 3) where should a home pervasive computing system be placed and where not; 4) what is the potential impact of computerized home devices running out of control or their data becoming corrupt on the user's behaviour; 5) what do we expect in exchange for our money; 6) because many systems would need to be connected to a network, who could potentially be watching every move we make; 7) what would make people forget about their prejudices against technology.

Although many of the issues mentioned above are currently undergoing extensive analysis and their solution depends primarily on deepening the investigation, there is one problem that is beyond researchers control for it does not seem to follow any specific pattern, or abide by any rules, framework, or parameters and has thus far been a central obstacle for incorporating intelligent pervasive computing into our homes: that is, us humans. It is not that we are doing anything wrong, after all AmI is all about leaving technology do all the work without any major interventions from us apart from behaving naturally. But that's exactly where the problem begins.

For centuries, human behaviour has been the focus of countless studies from different theoretical, philosophical and historical perspectives but whatever the justification, it is no secret that the way we think and act is a highly complex phenomenon that is generally difficult to predict. It is usually only after a careful long-time observation and under very specific, controlled situations that theorists have been able to determine what actions we are likely to take in response to certain internal or external stimuli. In fact, behavioural assessment relies heavily on a very simple principle: the alteration of the internal and external conditions of the stimuli is followed by modifications in our behaviour.

No wonder AmI researchers have struggled to find the mechanisms that would accommodate our needs in the best way. Our home is our most intimate haven, a place where we can do as we please at the times we like; a space we are continuingly changing according to what and how we feel, to what we like or dislike. It is also a dynamic territory teeming with stimuli - our families, the television, the weather, our tastes and needs as they change over the days and weeks, months and years, these can all inflict change and conflict upon us. This natural fluctuation in our feelings and desires caused by the interaction with our environment leads to an incessant variation in how we behave that makes artificial modelling of real-life activities inside domestic environments very difficult.

It is evident however that no matter how complicated humans are, as Mischel puts it, “we can know people only by examining their behaviour, the things they say and do” [Mischel86]. Thus, the only way for AmI applications to understand and potentially anticipate human actions occurring in a natural milieu is by analysing the external conditions and the inner processes guiding our behaviour. We cannot expect to have “Intelligent” environments which are not capable first of all of understanding or at least recognising our motivations.

2.4.1 State of the Art in Behavioural Modelling inside IIE

Several attempts have been made to provide AmI systems with the ability to recognize, model and predict user behaviour or at least some of the particular activities that stem from it. Some of the most relevant work is outlined below.

- The Medical Automation Research Center (MARC) at Virginia University has embarked on a project to determine whether a web of motion sensors could help discovering behavioural patterns of elderly people inside an Intelligent Inhabited Environment called the SmartHouse. The SmartHouse comprises 8 rooms, namely, a bedroom, a bathroom, an office, a living room, a kitchen, and a laundry room/back door area, each one equipped with a motion detection sensor. Two more motion sensors have been installed at the front door and the shower. In addition, on/off switches are embedded in some of the kitchen appliances including a cabinet and a microwave oven. Activities are detected using an unsupervised clustering mechanism called the *mixture model approach* which is based on a probabilistically analysis of the how often and for how long motion sensors were active in each room [Barger05]. Preliminary results demonstrated appropriate recognition of patterns of sleep, changing clothes, bathroom/toilet use, leaving/returning home, and meal preparation. The main objective of MARC's project is to use AmI to detect anomalies in the behaviour of elder people and thus provide opportune information to relatives, caregivers, or health-care personnel about potentially perilous situations.

- The Managing and Adaptive Versatile Home (Mavhome) at the University of Texas at Arlington is an intelligent inhabited environment composed of a society of agents each one organized in four layers: Decision, Information, Communication, and Physical. Information about the environment is captured by the Physical layer though sensors and devices and transmitted over the network according to the Communication layer. The Information layer collects and records useful information about the ambience state and the behaviour of the inhabitant which is later used by the Decision layer to act upon the environment.

  Mavhome main attribute is its capacity to learn and forecast user behaviour using data mining and prediction methodologies. The Episode Discovery (ED) algorithm [Heierman04] recognizes sequential patterns and then employs the Minimum Description Length (MDL) principle to detect those that are repeatable enough (using frequency and length measures) to make predictions. User actions are predicted using the Active LeZi (ALZ) algorithm which is an extension of a text compression mechanism known as LZ78. According to this methodology, action sequences along with the context in which they happen are stored along with the probability of them occurring and then treated as Markov chain models to estimate the next probable activity. Learning is done using a reinforcement technique based on the Q-learning algorithm [Gopalratnam04].

- The Adaptive House is an initiative of the Department of Computer Science at the University of Colorado to develop a domestic environment that learns from the user activities and accommodates and anticipates user needs without requiring human intervention. The operation of the Adaptive House is based on a system called ACHE that has been designed to attempt finding a balance between the user desires and an optimal use of energy. Towards this end, the system has a penalization scheme that is used whenever ACHE actions fail to provide inhabitants with what they needed at the right moment [Mozer98].

  The Adaptive House encompasses a number of sensors and various residential comfort systems that include heating, ventilation, and air conditioning and provides automated control of the water heater and the interior light levels. In order to allow the various non-linear devices to interact and adapt to the user lifestyle ACHE utilizes ANNs to learn behavioural and usage patterns

- The ADA project currently underway at the Institute of Neuroinformatics of the Swiss Federal Institute of Technology has been focusing on the development of methods to effectively measure human activity inside intelligent inhabited environments. ADA was introduced during the 2002 Swiss national exhibition Expo as a 160-m^2 entertainment closed space in which a number of people could interact with the intelligent space using lights, sounds, and tactile artefacts.

Using Pavlov's classical conditioning, ADA's people has developed a learning robotic model called DAC to interact with individuals while acquiring, influencing and analysing their behaviour. In Pavlov's theory a neutral stimulus becomes a conditioned stimulus (CS) when it is associated with an unconditioned stimulus (US). In ADA, DAC would learn a Conditioned Response (e.g. moving to a corner of the room) provoked by the CS (e.g. turn a given set of lights on), when after several trials a CS was consistently associated with one of a number of US (combinations of light and sounds) [Eng04]. DAC consists of several artificial neurons that utilize an ad-hoc reinforcement technique to learn and eventually utilize the actions that have a greater impact on the behaviour of visitors to the exhibition. The idea behind ADA is to evaluate how the manipulation of visual, acoustic and tactile stimuli performed by DAC could provide a more accurate measure of human behaviour. One of the main postulates of ADA is that an intelligent environment is comparable to a robot in terms of perceptual and behavioural learning, and idea also put forward by Callaghan et al. [Callaghan04].

- Researchers at Milan Polytechnic are interested in ways to provide IIE the means to develop a course of actions (plan) aimed at achieving a given goal directly associated with the user needs. The pervasive system on this occasion is built on top an agent configuration called D-HTN (Distributed Hierarchical Task Network) and it is an example of a MAS featuring hierarchical control. Instead of having a community of independent agents with its own perception of the environment, D-HTN encompasses a global centralized planner that decomposes plan into tasks and resources among the elements of the system.

The different roles each agent plays are embedded into the agents themselves in the form of plan libraries that allow them to become aware at any moment of what their response to a given situation should be. The task of D-HTN is to select the appropriate route to a goal using predetermined index values assigned to each agent depending on how their functionalities fit into the overall goal plan. These indexes are associated to the performance, the cost, and the probability of success for the tasks in the plan decomposition [Amigoni05]. Learning about the tasks associated with user behaviour is achieved by updating agent libraries at the end of the day depending of which agents were relevant to successfully achieve a given purpose.

- One of the AmI endeavours taken on as part of the Intelligent Inhabited Environments (IIE) initiative at the University of Essex involves the development of a fuzzy-based agent that is able to recognize and learn user behaviour. The Incremental Synchronous Learning (ISL) agent comprises a number of sub-control units arranged in hierarchical fashion that utilizes a user-driven mechanism to learn fuzzy rules in real time using predetermined membership functions. Each sub-control unit is realized as a Fuzzy Logic Controller (FLC) and is in charge of monitoring a particular user behaviour be it dynamic or fixed.

  During learning behaviours are added to the model and then modified using a learning mechanism based on a hierarchical genetic algorithm (GA) that employs reinforcement to determine the optimal model. The effects of actions taken by the FLCs (behaviours) are evaluated by a coordinator that initiates a learning cycle should actuators outputs fail to satisfy the user (the occupant of the IIE performed a manual adjustment). One of the most important characteristics of the ISL is that its internal inference mechanisms (referred to as an Associative Experience Engine) are capable of using both contextual information and past observations to find a suitable behaviour and its associated set of fuzzy rules more efficiently. Furthermore, adaptation is carried out throughout the lifetime of the agent thus promoting life-long learning [Hagras02].

- In another project supported by the Swiss Institute of Neuroinformatics and undertaken in conjunction with National Science Foundation Engineering Research Center for Neuromorphic Engineering at the California Institute of Technology, Rutishauser et al. introduced a novel approach to a fuzzy-based intelligent building controller (IBC) that is suitable for AmI implementations. This multi-agent framework has been deployed in a commercial building with non-stationary components distributed across several rooms and that are organized in clusters which, depending on their functionality, might contain other clusters and elements. Such elements could include sensors, effectors, feedback devices, or a combination of these [Rutishauser05].

Conversely to D-HTN, Rutishauser's method employs distributed autonomous agents with non-centralized control. Four main types of agent that communicate using asynchronous message oriented middleware are included in this MAS model:1) A Bus agent managing communications with all sensors and actuators, 2) a Distribution agent in charge of task assignation, 3) a Structure agent that contains the information about the latest structure of the environment and its independent or clustered elements, and 4) a Control Agent encompassing one or more decision and learning units (DLUs) containing Fuzzy Logic Controllers (FLC) that supervise the operation of effectors.

FLCs are trained on-line using an unsupervised learning algorithm. Fuzzy rules are continually updated or modified using the feedback from the user actions and the status of environment. The knowledge about the user behaviour, new and pre-existing elements in the environment and their structural organization is represented using a principle similar to inductive logic and embedded in *maximal structure* fuzzy rules. Thanks to the *maximal structure* property the state space is covered as completely as possible at any particular time. It should be noted, however, that some simple actions, e.g. turning a light on, are taken at low level involving only the hardware layer. This means that some controls are directly linked to the appropriate effectors and the resulting actions are not recorded as part of the learning process.

- Yet another effort from the IIE Group at Essex University to address the problem of behavioural modelling inside IIEs involves a highly sophisticated Fuzzy Agent that utilizes a one-pass approach to learn user conduct. The Adaptive On-line Fuzzy Inference System Agent (AOFIS) is an intelligent mechanism that, conversely to the ISL, is not only able to learn rules for the FLC but also the membership functions associated with the environmental variables. After an initial monitoring phase in which the user interacts naturally with the environment, AOFIS's FLC learns a descriptive model of the user's behaviour based on the event-related data that has been accumulated. The latter is done using a combination of two mining algorithms namely Fuzzy-C-Means (FCM) and hierarchical clustering.

Once a preliminary behavioural model has been constructed, AOFIS initiates an automatic control of the environment on behalf of the user using the knowledge previously acquired. Because AOFIS actions are based on observations about the user and its interactions with the pervasive environment reflecting just a limited amount of time and thus not being definite or complete, the user is always in position to override AOFIS actions should they not satisfactory. In order to avoid the incorporation of one-off activities, AOFIS behavioural model is not immediately altered a result of user actions. Instead, AOFIS uses a method called "learning inertia" in which learned rules are modified until the user preference for changing a particular set of actuator values has re-occurred a number of times [Doctor05].

- The Pervasive Healthcare project developed at the Centre for Pervasive Healthcare of Aarhus University in Denmark focuses on an amalgamation of Tele-care and pervasive computing to provide patients suffering from diabetes-related foot ulcers with optimal treatment and medical support while avoiding unnecessary visits to hospital. The use of telecommunications, sensing devices, and embedded computers allows medical staff to perform uninterrupted remote monitoring and supervision of diabetic ulcers that reduces the risks of infections and limb amputations.

  The design of the Pervasive Healthcare system encompasses various modules that include videlolink conference accessible through the patient's TV, remote sensing of the ulcers conditions, and a database with information about the patients previous medical history as well as details about treatment and care and also sensor configuration and status. The use of technology to transfer a significant part of the treatment from the hospital to the patient's home enhances the dialogue between the doctor and the home care nurse improving cooperative care that in the end benefits the patient.

One of the main characteristics of Pervasive Healthcare is the inclusion in the system of not only physiological and medical data but also information about the patient's activities. By recognizing behaviour that could cause further damage to the open wounds, doctors and nurses can recommend the course of action that would guarantee the fastest healing process. Another important feature of Pervasive Healthcare is that information about the progress of a patient is shared not only by the medical staff but also by the patients themselves and their relatives.

2.5 The Use of Emotions to Improve Performance of IIE

Although the study of emotions and the findings on their significance have been useful to challenge the popular belief that emotions interfere with logic and rational thinking and has provided computer scientists with new ideas to improve intelligent models, there still is a tendency in pervasive computing research to belittle or overlook affective information (the above approaches are an example of this). For instance, in [Adelstein05] Adelstein et al. used Abowd and Mynnat's 5 Ws to highlight the types of context that could be utilized as the central part of pervasive computing applications: "Who", consisting of information about the user details, "What" with information about tasks being executed, "Where" involving the location of the system, "When" encompassing temporal information and "Why", with the motivations behind user actions. While Abowd and Mynnat recognize that inner motivations are one of the most important types of contextual information to determine, emotional information is only vaguely mentioned later in the text as something "one can also consider". It is my opinion that it is time to realize the real significance of our emotions and do not reject the possibility that the answer to the “Why” question might reside within the sentient phenomena.

I described in the previous chapter my reasons for believing that detecting human emotions could be of benefit in the area of pervasive systems and in particular Intelligent Inhabited Environment (IIE) applications. The rationale for this lies in a) the evidence that psychologists and neurologists have provided in relation to the impact of emotions on the ways we think and act, b) since IIE adequacy resides in its capacity to learn from the user, the more a pervasive system knows about the reasons that motivate user behaviour, the more sophisticated its knowledge and responses will be, c) those components of our behaviour with strong emotional components can only be recognized by detecting and classifying emotions.

Another idea emanating from psychology that strengthens the assumption that emotion detection and in particular physiological emotion detection is a useful option to improve the modelling of user behaviour inside IIE is that there are two main mechanisms appropriate to perform direct human behavioural assessment involving real-life life conditions. It is generally agreed by psychologists that these are 1) Verbal and non-verbal situational behaviour sampling, and 2) Physiological response of emotional reactions [Mischel86]. The former includes various self-report methodologies while the latter involves the analysis of bodily signals. If we compare these two methods with the design principles of AmI systems and current approaches in emotion detection, we can see that physiological emotion detection harmonizes perfectly with existing techniques of behaviour modelling inside IIE since bodily signals can be processed online using AI mechanisms that do not require human intervention and therefore represent a transparent, consistent source of information. In this regard, affective computing is consistent with other branches of computing and they complement each other in working towards a better understanding of human behaviour, which is especially important in pervasive environments.

In the next chapter I will begin to present the steps involved in developing a novel mechanism to recognize emotions in real time designed with IIE in mind. This complete method whose development and testing makes up the body of the thesis integrates bodily signals, artificial intelligence and sequential analysis into a robust mechanism and hardware realisation suitable to detect emotions in real time under circumstances involving typical human activities within an IIE. My assumption is that in accordance with Salovey's theory where EQ is divided into emotion recognition and the ability to utilize our emotions, any attempt by Computer Scientists to model human interaction in IIEs using emotions as one of their input parameters should, in principle, be founded on an accurate identification of affective states.

"Human emotions differed from those of animals in one critical respect: humans tended to apply new solutions to new problems and thus they touched off an evolution-like process for artefacts, the accelerating nature of which eventually produced the contemporary human society where innovations occur with inordinate speed" Masanao Toda

Chapter 3

Real-time Detection of Emotional Changes based on Sensor Validation

3.1 A Novel Approach to Dynamic Detection of Emotional Changes

The analysis presented in this chapter is directly aimed at addressing a twofold problem that by the end of the thesis will be integrated into one single initiative. First, I am concerned with developing a radically new approach to detecting emotional changes using sensor validation that improves on previous approaches and that provides the basis for a more flexible and efficient way of using physiological data in affective computing. Second, I would like to use this emotion detection system to dynamically recognize changes in affective states of subjects living in pervasive environments. The emotional information will subsequently be used as part of the input pattern of an intelligent agent in charge of controlling an Intelligent Inhabited Environment (IIE) thus supplementing knowledge about the user's activities. Because emotion produce changes in the way we behave, my hypothesis is that by providing an IIE agent with both the behavioural and the emotional information stemming from the subject, more effective modelling of the actions carried out inside the IIE could be achieved thus increasing the efficiency of the agent and the comfort of the user. The Japanese Psychologist Masanao Toda who developed innovative theories of emotions that have inspired scientists in various research areas [Inoue96, Peters99, Wehrle94] has argued that emotions are the most simple and optimised decision making system there is.

Therefore, inspired by the possibility of significant gains from the area of affective computing, in this chapter I present a preliminary analysis and feasibility study on a novel mechanism for the real-time detection of emotional changes based on the utilisation of physiological signals, Autoassociative Neural Networks (AANNs), sequential analysis and clustering analysis. In what is the first attempt to evaluate a system that effectively recognizes emotional changes inside IIE that I am aware of, I will show that the design of this mechanism makes it suitable for detecting variations in body signs attributable to emotional episodes when a subject's affective status changes from neutral to positive or negative. Evidence will be presented based on experimental results stemming from data previously employed in another emotion detection study at the MIT and that were afforded by Professor Rosalind Picard, Director of Affective Computing Research and Co-Director of Things That Think Consortium. Furthermore, the results support the view that the methodology presented in this chapter is appropriate for implementation inside Intelligent Inhabited Environments (IIE) where real-time behaviour-based controls are employed [Picard01]. It should be mentioned that the decision to utilize Picard's data squarely falls on three reasons: 1) when the present project was initiated, Picard's team had achieved the highest recognition rate using physiological signals, 2) data sets used by Picard involved a range of emotions collected over a period of 20 days thus encompassing variations in day-to-day conditions, and 3) the elicitation method employed by Picard belongs to a widely known class of emotional stimuli called emotional imagery and was based on thespian techniques.

3.2 An Alternative Approach to the Problem of Emotion Classification

One of the most likely reasons why computer scientists remain sceptical about emotions is that a great part of what has been said and written about affective states depends on the emotional theory involved. For instance, if you want to embark on a study of emotions and decide to start by determining the number of emotions there are, you will soon realize that researchers in the field identify from three to eleven emotions with most proposals including between five and nine [Plutchik94]. The reason for this confusion is that these approaches are grounded in particular scientific hypotheses concerning emotions that reflect the researcher's own interests and beliefs.

There is nonetheless a simple yet well-founded alternative to this dilemma. In 1957, Osgood et al. [Osgood57] suggested a statistically-based categorization of emotions based on tripartite dimensional interpretation of emotions stemming from factor analytic studies on semantic differential demonstrating that the variance in emotional assessment could be explained using three main dimensions. The first dimension involved the affective valence of the emotion which ranges from pleasant or positive to unpleasant or negative. The second dimension represented a measurement of the arousal level of an emotional episode and it is evaluated from calm or low arousal to excited or high arousal. A third dimension was given the name of "dominance" or "control" and symbolized whether we feel in control of or controlled by a given emotional category.

I have decided to concentrate on the emotional classes that stem from Osgood's first affective dimension, i.e. positive, negative and neutral, founded on the fact that this simple standard categorization of emotions would facilitate analysis and provide a greater degree of objectivity to my study by avoiding the use of subjective labels that have given rise to much discussion among psychologists. Furthermore, it is common to find in numerous psychological studies the utilization of a bipolar scale of emotions in which affects are clustered into two mayor groups: positive and negative. The validity of this approach will be tested empirically in Chapters 3, 4, 5, and within an intelligent inhabited environment in real time in Chapter 7.

3.3 The Use of Sensor Validation Techniques for Physiological Emotion Detection

3.3.1 Background

The novel methodology proposed here is based on the idea that the detection of emotional changes using physiological signals could be realized using techniques previously employed in real-time sensor validation processes where emotional states could be detected by estimating the amount of deviation they demonstrate with respect to a neutral emotional state. Sensor validation is commonly used in industrial processes to determine the moment in which a given sensor becomes corrupted, i.e., provides readings others than the ones expected under normal operating conditions. The main appeal of the use of sensor validation techniques to recognize emotional states is that there is no need to amass a great number of data samples before a decision can be made. Alterations in the autonomic system associated with emotional states could be identified by providing a classification module with the continuous calculation of the difference between an actual sensor value and its estimated counterpart [Leon04]. This real time responsiveness is an important characteristic required by interactive systems in order to facilitate the acquisition of information and improve the quality of decisions made by agents in pervasive computing and particularly in Intelligent Inhabited Environments (IIE).

3.3.2 Brief Introduction to Sensor Validation

Sensors are hardware devices that measure real-world variables and translate them into numerical values by analog or digital means. It would be a titanic endeavor to try to enumerate the different areas in our lives in which sensors play a pivotal role. In fact sensors have played a major role in the development of modern technology and some control systems that we take for granted such as the correct functioning of our cars, public lighting, electrical and power distribution, and even the correct temperature of our boiler would not be possible without sensors. However, because they are in contact with the physical elements, sensors suffer from continuous wearing that limits their optimal long-term performance. Therefore, the accurate detection of sensors failures is extremely important especially when they are used to monitor control processes upon which human lives depend.

When a sensor fails due to a harsh environment or because of degraded calibration, corrupted values are injected into the feedback loop of the control system leading to unnecessary or incorrect control actions [Lee94]. In order to avoid sensor failures, numerous methods to guarantee favorable sensor operation have been investigated. Since periodic sensor recalibration or replacement results in prohibitively high costs, alternative methods to detect and compensate sensor failures have been proposed. Such methods are based on Sensor Failure Detection, Isolation and Accommodation (SFDIA) [Napolitano98].

SFDIA can be realized using physical or analytical redundancy [Lee94, Napolitano98, Gribok00, Ibargüengoitia96]. Physical redundancy implies the utilization of two or more sensors that monitor the same physical variable, which inevitably results in increased cost [Napolitano98]. Analytical redundancy assumes that sensor readings describing a given system or phenomenon are the subject of complex interrelations and therefore the failure of a given sensor can be detected using the readings from the other sensors [Napolitano98, Gribok00, Ibargüengoitia96]. Hence, analytical redundancy is based on continuous monitoring of a set of sensor readings and the utilization of predictive or estimation techniques for determining the moment when a sensor value deviates from an ideal expected value estimated from combinations of the readings from other sensors in the system [Luo98].

What does sensor validation which is an engineering problem have to do with emotion detection and how did I come to liken these two seemingly incompatible procedures? To begin with, sensors are essential to acquire the information on which physiological emotion detection relies. Sensors are the means through which bodily changes reflecting emotions states are detected using some kind of remote devices or wearable artefacts. Furthermore, both processes can be resolved using techniques of pattern recognition. Such techniques, linked to machine learning, permit the identification and classification of data based on discernable common tendencies or attributes. Thus, it is not difficult to recognise that techniques utilized in one area might be employed to assist in the other. This is where my approach is different from those other researches in affective computing have taken in the past. Instead of looking for patterns of emotions within entire sets of physiological signals, I constantly analyse how sensors change over time and then relate sensor variations to emotional changes (see Figure 3.1). To use an analogy I could say that while other researchers concentrate on how the needle of the speedometer moves, I move closer to the wheel and analyze the variations in the raw data that the speed sensor is delivering.

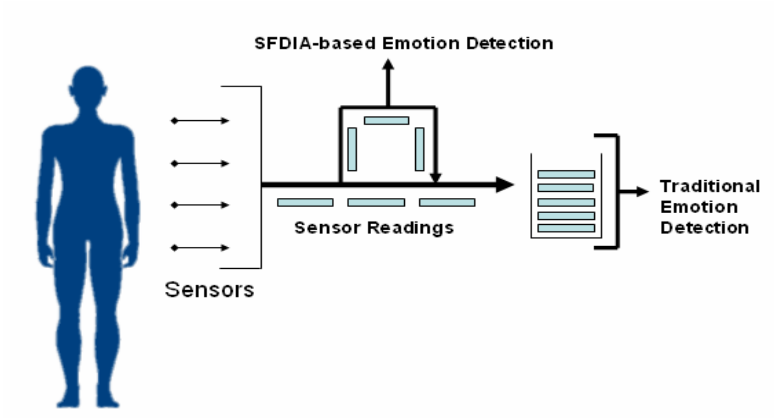


Figure 3.1. Diagrammatic representation of the role of sensor information in SFDIA-based and other emotion detection techniques.

An important characteristic of SFDIA techniques is that because they are commonly used to monitor extremely sensitive systems such as flight control, they are very reliable and quick to detect fluctuations in sensor readings thus potentially giving us a faster, more accurate, real-time indication of the moment an emotional change takes place.

Several approaches for analytical sensor validation have been proposed [Lee94, Napolitano98, Gribok00, Ibargüengoitia96, Luo98, Keeler96, Hines97, Böhme99, Himmelblau95, Lu01]. From these, the ones based on Autoassociative Neural Networks (AANNs) have been successfully used to monitor nuclear plants and other very demanding processes, and have shown to outperform related pattern recognition techniques [Hines97, Böhme99].

3.3.3 Autoassociative Neural Networks (AANN)

Autoassociative Neural Networks (AANNs) are a special type of back-propagation neural network (BPNN) designed with a specific architecture; they are trained to learn the identity function, i.e., outputs should equal inputs [Kramer98]. A most important characteristic of AANNs is that even in the presence of several abnormal or corrupted inputs they are still able to provide estimations for both faulty and healthy inputs. As a consequence, AANNs have been successfully utilised to perform SFDIA [Lu01].

In SFDIA, sensor readings are connected to the inputs of the AANN, and the output of the AANN produces estimated sensor values for each of its inputs. Failures are detected by calculating the error (**residual** henceforth) between each sensor value and its corresponding estimation [Hines97]. Figure 3.2 illustrates the design of an AANN.

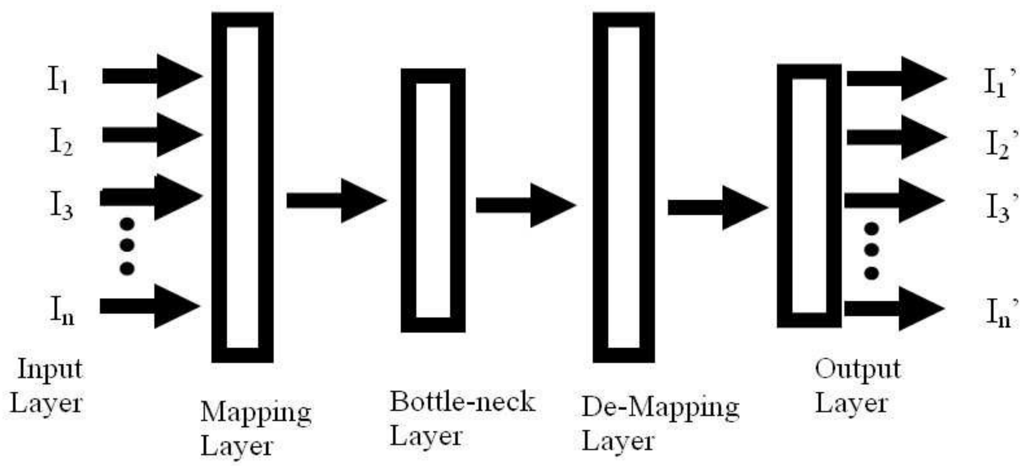


Figure 3.2. Architecture of an autoassociative neural network (After [Hines97]).

Another important attribute of AANNs is that they can be employed to perform noise filtering. Because input variations (due to sensor calibration, distortion, noise, etc.) are not correlated, AANN outputs, which are based on correlated data used for training, remain unchanged.

3.3.4 Introduction to Sequential Analysis

By means of calculating the residual, AANNs provide information about the changes that occur in the pattern of a sensor's output. However, in SFDIA a subsequent analysis is required in order categorize such changes in a meaningful way. One of the most frequently chosen approaches is to identify the changes in the residual provided by the AANN through the use of techniques from sequential analysis.

I mentioned that both sensor validation and emotion detection could be seen as problems of pattern recognition, i.e. the classification of groups of objects according to some ad-hoc requirements and based on their common characteristics [Fu68]. Several approaches to perform pattern recognition exist including some based on Artificial Intelligence techniques such as ANNs, Fuzzy Logic, or Genetic Algorithms and others based on statistical analysis. The latter are very popular because they were conceived to deal with variations in feature measurements and the effect of noise.

However many of these approaches rely on observation of fixed number of data samples. The selection of the appropriate number of samples on which the classification process will be based is not trivial. Too few samples could lead to erroneous conclusions while too many might increase the cost associated with time and resources. Furthermore, in some applications such as the control of airplanes, nuclear plants, or in medical diagnosis, the costs of lengthy data acquisition processes could be a matter of life or death.

Sequential analysis on the other hand offers a balance between an optimal number of samples without increasing the probability of misrecognition by "taking feature measurement sequentially and terminating the process (making a decision) when sufficient or desirable accuracy of classification has been achieved" [Fu68].

The theory of sequential analysis was formally described circa 1943 with the work of two military advisors: Abraham Wald in the U.S. and George Alfred Barnard in Britain. Wald's main contribution was the discovery of the "Sequential Probability Ratio Test" which has been used in innumerable practical applications which apart from sensor validation include detection of disease in fish stocks, milk bacteria grading, and psychological tests.

3.3.4.1 *Sequential Probability Ratio Test (SPRT)*

The main reason for the use of the Sequential Probability Ratio Test (SPRT) in this study is that it has been shown and it is still widely regarded to be an optimal classification technique to dynamically determine whether a given input pattern belongs to either of two categories [Cheng02]. The main advantage of the SPRT is that it requires a *minimal* number of measurements before being able to reach a conclusion about the two hypotheses being evaluated [Fu68, Tartakovsky01].

In SFDIA, the SPRT is continuously estimated using the residual value provided by an AANN and stopped when the value of the likelihood ratio reaches one of two predetermined mutually exclusive thresholds. Such boundaries are established based on the solution spaces related to two targeted classes and the Probability Distribution Function (PDF) of each variable. Considering that the measured parameter is a continuous function A(t) that should be categorized according to two stochastic processes $A_1(t)$ and $A_2(t)$, both possessing a normal distribution with means μ_1, μ_2 and standard deviation σ^2, the calculation of the SPRT at stage x is:

$$LOG(SPRT)_x = \frac{(\mu_1 - \mu_2)}{\sigma^2} \sum_{x=1} \left[A(t)_x - \frac{1}{2}(\mu_1 + \mu_2) \right] \quad (1)$$

and the decision boundaries are given by

If

$$LOG(SPRT) > LOG(e^{A_1}) \quad \text{then } A(t)= A_1(t)$$

If

$$LOG(SPRT) < LOG(e^{A_2}) \quad \text{then } A(t)= A_2(t)$$

Where e^{A_1} and e^{A_2} are related to the probability error of misclassifying A(t) into process A_1 and A_2 respectively and are given by

$$e^{A_1} = (1-\alpha)/\beta$$

$$e^{A_2} = \alpha/(1-\beta)$$

Where α and β are the desired confidence values to recognize $A_1(t)$ and $A_2(t)$ respectively. Alpha (α) and beta (β) are selected in such a way that the system will choose $A_1(t)$ with at least (1-α) probability and $A_2(t)$ will be selected with probability at least (1-β). Very small values of α and β increase confidence in the recognition results but would require more data samples before moving to any of the two solution spaces. In some cases the values of the confidence intervals could be obtained from experimental data previously acquired.

3.3.5 Clustering Analysis

A cluster or class separation analysis provides an insight into the amount of redundancy and scatter (inter- and intra-cluster separation) within a given data set as well as the attribute(s) (physiological signals in our case) that contribute to an optimal separation of two or more classes. The Davies-Bouldin Index (DBI) [Davies79] has been successfully utilised in studies that involve pattern recognition of physiological signals, where lower DBI indexes reflect a better class separation [Sepulveda04].

The DBI is calculated according to:

$$DBI = \frac{1}{n}\sum_{i=1}^{n} MAX\left[R_{ij}\right]$$

where n is the number of clusters and the cluster similarity is given by

$$R_{ij} = \frac{S_n(k_i) + S_n(k_j)}{d(k_i, k_j)}$$

with the intra-cluster scatter or average dispersion of cluster k_i as

$$S_n(k_i) = \left\{ \frac{1}{E_i} \sum_{m=1}^{E_i} \left\| x_m - z_i \right\|^2 \right\}^{1/2}$$

where z_i is the centroid the cluster k_i, E_i is the number of elements in cluster k_i, and the distance between cluster k_i and k_j is given by

$$d(k_i, k_j) = \left\{ \left\| k_i - k_j \right\|^2 \right\}^{1/2}$$

Hence the ratio is small if the clusters are compact and far from each other. That is why DBI with small values represent optimal clustering.

3.4 System Design

The operating principle underlying the proposed system is that emotional changes could be detected using SFDIA by estimating the amount of deviation physiological sensors (biosensors) demonstrate with respect to a neutral emotional state. More specifically, an AANN trained with physiological data associated with the neutral emotional state of an individual would respond to changes in the emotional state of the subject by projecting the residual into a transformed solution space (i.e. a space that differs to that of the original training data). This difference will be picked up by a SPRT module using the statistical characteristics (the mean and standard deviation) of data describing the neutral and non-neutral emotional state.

With the intention of improving the probability of accurate detection of an emotional change, my contribution to SFDIA techniques is that physiological signals fed into the SPRT module are pre-selected using a DBI-based cluster analysis. A clustering index evaluation is useful to detect the signal(s) that would most contribute to the optimal separation of the neutral and non-neutral emotional states. This needs to be done a priori to ensure that only the features with the best potential class separation are used.

Emotion detection is achieved based on idea that since the AANN is trained to mimic the input behaviour, i.e. bodily patterns associated with the neutral emotional state, the mean of the residual would be very close to zero under normal circumstances with a standard deviation similar to that of the noise introduced by the sensing device. When the sensor values drift because of a change in the physiological status related to an emotional episode, the mean value of the residual will deviate from zero. The SPRT value would be then altered and the likelihood ratio is displaced to either of the two solution spaces (neutral or non-neutral).

The overall architecture of the proposed emotion detection system is comprised of biosensors, a signal processing module containing a pre-trained AANN and a classification module where residuals are classified into neutral or non-neutral by means of a SPRT calculation (see Figure 3.3).

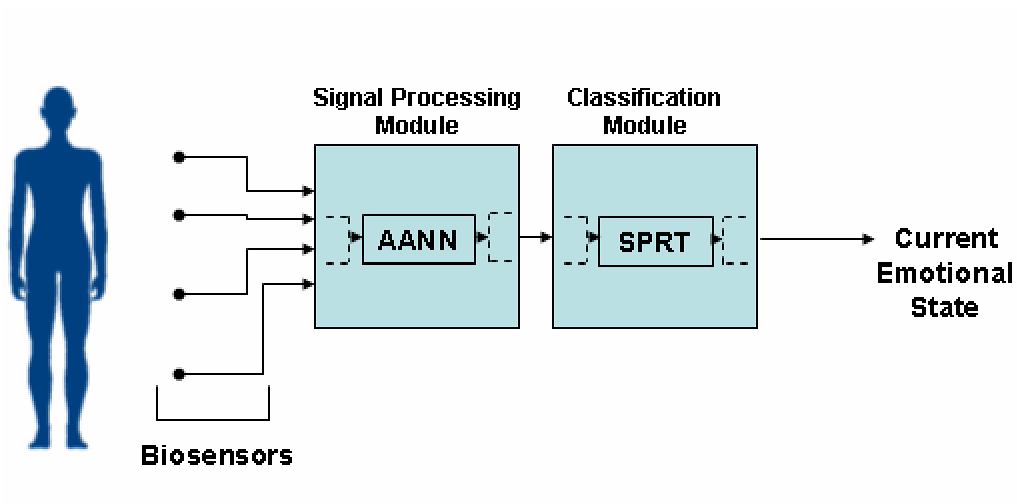


Figure 3.3. Emotional changes are detected by performing a sequential analysis on the residual provided by an AANN trained with data from the neutral emotional state.

3.5 System Attainability: Preliminary Assessment

3.5.1 Dataset Description

In order to evaluate the performance of the above system, experiments employing real-life physiological data were conducted. It is worth noting that the task of pattern recognition in emotion detection requires physiological data that possess adequate characteristics if successful results are expected. Thus, instead of collecting new data, physiological information from one of the most successful emotion recognition experiment, i.e. Picard et al. [Picard01], was employed. Picard's data set comprised four normalized physiological signals, namely, electromyogram (MYOGRAM) obtained from the masseter, blood volume pressure (BVP), skin conductance (SC) and respiration rate (RESP) collected from a single individual over a period of 20 days, resulting in 2001 samples per day per emotion [Healey02]. The MYOGRAM has been used in experiments involving facial and physiological emotion detection [see for example Picard01, Prendinger06, and Ang04], while BVP, SC, and RESP are often employed on their own or as part of multimodal setups [see for example KimJ05, Yoo05, Healey00, and Ark99].

The entirety of the physiological data, 320160 samples, (2001 per day per emotion) was split into two groups. Group 1 contained data related to a neutral emotional state (Neutral_dataset) whereas group 2, called the Non-neutral_dataset, included the information concerning the remaining emotions (i.e., anger, grief, hate, joy, platonic love, romantic love and reverence).

3.5.2 The Signal Processing Module: AANN Architecture and Training

An AANN was trained to memorize the input mapping of the four physiological signals provided in Healey's data (Neutral_dataset). Emotional changes would be detected by continuously analysing the residual between the actual input values and the estimations provided by an AANN trained to memorize *neutral* emotion data.

Training of the AANN was performed utilizing the MATLAB implementation of the Levenberg-Marquardt algorithm in combination with Bayesian regularization [Hagan94, Foresee97] providing enhanced generalization. Training data comprised 2001 samples obtained from a 20-point moving average of the total 40020 neutral-emotion samples originally provided by Healey et al. The purpose of using averaged data is to 1) smooth sensor signals, and 2) enhance MATLAB's performance while not compromising overall performance.

In order to increase convergence speed, data provided to the AANN was scaled to fall in the range between 0 and 1. This is useful to reduce weight values and increase algorithm performance. The structure and architecture of the AANN employed for training is depicted in Figure 3.4 and Table 3.1.

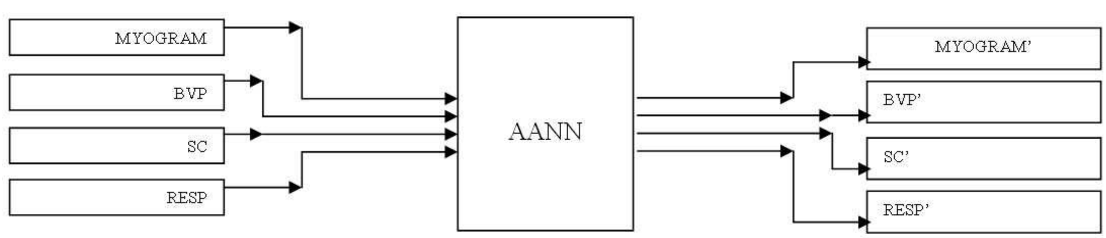


Figure 3.4. Training of the AANN employed to detect emotional changes.

Layer	Number of Neurons	Transfer functions
Input	12	Linear
Mapping	18	Logarithmic sigmoidal
Bottle-neck	4	Logarithmic sigmoidal
De-mapping	18	Logarithmic sigmoidal
Output	12	Linear

Table 3.1. Characteristics of the AANN for emotion detection.

3.5.3 Statistical Feature Selection

In order to identify the physiological signals that would provide the best separation of neutral and non-neutral emotional states in the classification module (SPRT) both the Neutral and Non-neutral datasets were provided to the pre-trained AANN. The instantaneous Davies-Bouldin cluster separation Index (DBI) was then calculated using the 15 combinations of residual values for the four AANN inputs. Instantaneous estimation of DBI implies the utilization of individual singal values instead of statistical features obtained from the whole data set or a multi-frame data segment.

Results from my a priori analysis showed that the signal with the lowest DBI was that of the electromyogram, with a value of 7.57. This value was better than for other signals used either individually or in combination. Thus, the electromyogram parameters were used as main features subsequently. (see Table 3.2 for a summary of the results).

Attribute combination	DBI Index
MYOGRAM	**7.59**
BVP	**451.73**
SC	**17.67**
RESP	**59.88**
MYOGRAM ,BVP	**13.47**
MYOGRAM ,SC	**13.88**
MYOGRAM, RESP	**20.28**
BVP,SC	**21.37**
BVP, RESP	**71.18**
SC, RESP	**24.94**
MYOGRAM, BVP, SC	**16.21**
MYOGRAM, BVP, RESP	**23.40**
MYOGRAM, SC, RESP	**19.08**
BVP, SC, RESP	**27.60**
MYOGRAM, BVP, SC, RESP	**20.87**

Table 3.2. DBI Indexes for the total number of signal combinations.

3.5.4 The Classification Module

With the intention of determining whether a given set of physiological measurements belonged to a neutral or a non-neutral emotional estate, the SPRT-based decision module would be provided with the residual between the actual electromyogram value and the value estimated by AANN for each of the data samples. Since the AANN was trained to mimic the input behaviour, the mean of the residual would be very close to zero with a standard deviation similar to that of the noise introduced by the sensing device. When the electromyogram value drifts because of a change in the physiological status of the subject, the mean value of the residual deviates from zero. The SPRT value is then altered and the likelihood ratio is displaced to either of the two solution spaces. It is worth mentioning that even though MYOGRAM is the only measurement employed by the decision module, the relationship with the other three parameters is needed for projecting the targeted variable into the AANN estimation model.

For the purpose of guaranteeing an accurate detection of emotion states without compromising system response, a standard significance value of 0.05 for both alpha (α) and beta (β) was chosen thus proving a 99.5% confidence in the SPRT results (this value for α and beta β is similar to that typically used in statistical analysis). Note that Picard's data were already normalized and therefore justified the utilization of Eq. (1) in the SPRT operation (other Probability Density Functions -PDFs require reformulation of this equation in accordance with the characteristics of the signal being monitored). For my purposes $A_1(t)$ is the hypothesis that the behaviour of the MYOGRAM was related to the neutral emotion state whereas $A_2(t)$ would be the hypothesis that the MYOGRAM signal represents a non-neutral state.

3.6 The Feasibility of Real-Time Physiological Emotion Detection based on Sensor Validation

Both the signal processing module containing the pre-trained AANN and the SPRT-based classification module were assembled into a single coordinated system (see Figure 3.5). This system was tested using Healey's data for the seven non-neutral emotional states. The assumption was that the AANN residual would only be altered as a consequence of any emotional state other than neutral and the SPRT will eventually classify such state within the non-neutral category.

Neutral data was scaled to fall between a range from 0 to 1 using the minimal and maximal values of the Neutral-dataset. Data was provided to the AANN in a manner that resembled real-time data acquisition, i.e., data from the neutral states was not subjected to any previous filtering nor statistical pre-processing and was sampled at the original rate utilised during data acquisition (20hz). Remember that the utilization of averaged neutral data during AANN training is just a manner of improving learning convergence speed by removing data outliers and does not affect the estimation properties of the AANN. In fact the operation of the AANN inherently involves a filtering process which does not have any adverse effect on the overall input mapping and actually improves the separation of the memorized and un-memorized data.

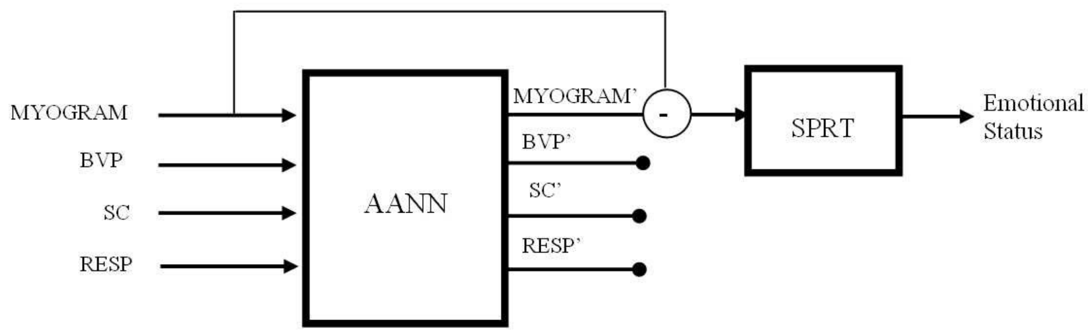


Figure 3.5. AANN estimations are compared to actual electromyogram values and the difference between the two (i.e., the residual) was utilized to detect emotional changes.

There were two major outcomes from this experiment. First, it was found that, based on the available information, the electromyogram (EMG) was the physiological measure with the most significant properties to participate in emotional pattern recognition when two emotional states are involved (neutral and non-neutral). As already mentioned the EMG gave better class separation on its own than the other signals alone or in combinations (which included EMG as well). However, it has to be said that Healey's experimental data was obtained from a single subject and generalization of these results should thus be avoided.

Second, it was concluded that the likelihood ratio provided by the SPRT module was sufficient to detect variations in physiological signals provoked by non-neutral emotional episodes. Table 3.3 shows the accuracy provided by the SPRT module when detecting variations in physiological signals provoked by emotional episodes. Non-neutral emotional states were accurately detected in the entirety of cases using just a few data samples. Table 3.3 also depicts the number of data samples needed by the classification module in order to establish a solution hypothesis. For example, in the case of the anger state days 1 and 5, the SPRT value moved beyond the non-emotional threshold once 6 and 8 data samples were provided. In the same manner the likelihood ratio had to be estimated using 575 data samples before the decision module had enough information to establish a verdict for the reverence state in day 7.

	Number of samples before detection						
	Anger	Grief	Hate	Joy	Love	Platonic	Reverence
Day							
1	6	2	1	4	12	3	1
2	1	2	12	1	1	2	10
3	1	1	3	1	6	11	9
4	3	2	2	5	3	5	5
5	8	2	2	2	7	3	6
6	3	8	2	4	1	3	81
7	3	2	2	29	6	18	575
8	1	4	1	1	5	7	10
9	5	2	5	9	1	1	1
10	1	1	1	2	2	1	1
11	2	1	3	11	8	6	1
12	1	1	1	1	1	1	1
13	1	1	1	5	1	14	1
14	12	2	14	1	1	3	1
15	1	5	2	8	13	8	5
16	1	4	9	1	4	2	1
17	2	1	1	14	3	1	1
18	3	2	10	11	10	1	1
19	9	1	1	1	5	1	4
20	1	3	10	3	1	5	1
Detection rate	100%	100%	100%	100%	100%	100%	100%

Table 3.3. Number of data samples analysed by the decision module before detecting changes in emotional status.

The discrepancy in the number of samples employed by the SPRT to detect emotional changes could be attributed to the fact that Healey's data lacked markers indicating when emotional episodes actually start or finish during data acquisition. As a consequence, the number of data samples required before a noticeable physiological change was identified was variable. However the AANN memorized the information of the neutral state accurately and responded to data from the non-neutral states almost immediately.

3.7 Towards Real-Time Emotion Detection in IIE

I have demonstrated that the utilization of clustering analysis (based on the calculation of the Davies-Bouldin Index) is a valuable mechanism providing better insight into the intrinsic characteristics of data employed in pattern detection. Using combinations of four physiological signals, I found that for this particular dataset the electromyogram contributed to the best cluster separation when neutral and non-neutral states are involved.

Using physiological data previously employed in other studies and based on experimental evidence, I have shown that the SPRT provides an optimal mechanism to dynamically distinguish between two possible pattern classes when it is employed in combination with an Autoassociative Neural Network (AANN). Due to its memorizing properties, input variations attributed to emotional changes were accurately detected by an AANN trained with data from a neutral emotional state. I suggest that because of the ability of AANNs to resist input perturbations caused by sensor malfunctioning or distortion, and because similar approaches have been employed in online validation mechanisms, my proposed methodology is appropriate for implementation in real-time decision making systems like the ones used for intelligent agents inside IIE. Real-time operation and resilience to sensor failures is useful to develop agents which are capable of establishing a symbiotic relationship with the user, i.e., every time the agent modifies the ambience of the room(s) the emotional state of the user is analysed, determined and subsequently used to respond to the user actions. The development of this type of symbiotic mechanism is one of the main purposes of this thesis since dynamic, immediate emotional response is the element I have suggested as a potential improvement in the behavioural modelling of agents operating in highly interactive real-world applications such as IIEs.

However, real-life scenarios involving human beings pose challenges to software applications that often go beyond resilience to sensor failures or real-time operation. Because of the variability in bodily characteristics and also the already discussed peculiarity of human emotions, IIE agents need to undergo a series of tests in their quest for reliable real-time recognition of emotions inside domestic environments. Therefore in the next chapter I will analyse whether the system proposed here and more particularly the operation of the AANN is in any manner affected by variations in levels of affect intensity, i.e. the intensity with which people react to emotional stimuli, or by the physical changes caused by exercise. These two issues, affect intensity and physical exertion, have a latent effect on the physiological concomitants of emotional episodes and might represent a problem for the operation of any physiological emotion detection system.

"Certainly you can forgive me for speaking so frankly, for saying
What I ought not to have said, yet now I can never unsay it
There are moments in life, when the heart is so full of emotion
That if by chance it be shaken, or into its depths like a pebble
Drops some careless word, it overflows, and its secret,
Spilt on the ground like water, can never be gathered together" Henry Wadsworth Longfellow

Chapter 4

Assessing the Effects of Exercise and Affect Intensity on Real-time Physiological Emotion Detection

4.1 The Volatility of Emotions inside Real-Life Environments

Emotions are intricate events involving an unpredictable interaction between mind and body that is easily disturbed and/or altered by the environment. It is evident that we continue learning about our emotions and the different things they affect and become affected by. The American academic Dolf Zillmann has suggested that when the body is in a state of physical arousal, due to exercise or a past emotional episode for example, the expression of an emotion such as anger or anxiety is greatly intensified in the face of a new triggering stimulus [Berkowitz93]. This also works the other way around and that's why as the physical arousal subsides so the intensity of the emotion does. In this context, issues such as our physical fitness and the intensity with which we react to stimuli could play a role in the way our emotional states and their physiological concomitants vary. For instance, the scene in a movie of a baby crying could provoke no reaction at all in some of us and yet be the cause of much happiness or anguish in others. If on top of that we add unusual physical distress because of taking exercise for the first time in months then we have a recipe for bodily and, according to Zillmann, also emotional mayhem. Hence, in this chapter I present an analysis of physiological signals employed in real-time emotion detection in the context of Intelligent Inhabited Environments (IIE) to see if reliable indicators of changes in emotional state can be determined despite differences in the affect intensity or level of exercise of the subject. Two studies were performed to investigate whether physical exertion has a significant effect on the way this emotion detection system handles bodily signals stemming from emotional episodes with subjects having different degrees of affect intensity: 1) A statistical analysis using the Wilcoxon Test, and 2) A cluster analysis using the Davies-Bouldin Index. Preliminary results demonstrated that the heart rate and skin resistance consistently showed similar changes in the face of emotional stimuli regardless of low-to-moderate physical exertion whereas blood volume pressure did not show a significant change. It was also found that neither physical stress nor affect intensity played a detrimental role in the separation of neutral and non-neutral emotional states provided by the AANN in our emotion detection methodology.

4.2 The Problem of Realistic Real-Time Physiological Emotion Detection

Real-time processing is a key attribute in many applications that depend on interactions with the environment. Because their operation relies on precise, timely decisions, real-time systems are among the most challenging developments attempted by computer scientists. They have to be able to accommodate real-world stimuli occurring at predictable time intervals (periodic) or at irregular time intervals usually as interruption actions (aperiodic). Because each type of stimuli, rooted in interactions with the environment possesses particular characteristics, is not static and occurs at a different time, a real-time system should be able to invoke the most appropriate process or function to respond to a given situation or in an extreme case compensate for or recover from unforeseen circumstances. The latter is not trivial and becomes specially complicated for affective detection systems where it is suggested that emotions should be dynamically detected, classified, and utilised using instantaneous responses from the autonomic system.

In the previous chapter I provided preliminary evidence to support the hypothesis that the method of categorizing emotions based on AANNs and sequential analysis (SPRT) was adequate to detect changes in the autonomic response of a subject in real time. These changes were later categorized as belonging to either a neutral or a non-neutral emotional state. The main appeal of this methodology is that, contrary to other approaches suggested in the past, it does not require a great number of data samples to be gathered before a decision can be made. This is an important characteristic of interactive systems taking actions based on user's current behaviour. Furthermore, because the ultimate purpose of this system is to equip an ordinary domestic environment with emotion recognition systems relating behaviour and affective states, real-time processing would facilitate the acquisition of information about the user. I argue and later test experimentally the hypothesis that such a system will potentially improve the quality and promptness of the decisions made by IIE agents.

Realistic scenarios, however, imply individuals becoming involved in all sorts of activities some of which are directly related to changes in the physiological signals of the subject being analysed that do not correspond to emotional states. Such bodily changes if not included during system design could eventually jeopardize real-time performance and detection accuracy. Two of the potentially most influential factors in emotion detection studies inside pervasive environments are the change in the physiological state of the user due to physical activity, and the variation of affect intensity across individuals. Thus, in addition to the level of reliability AANN-based SFDIA provides, real-time emotion detection demands an extra improved level of robustness to ensure that exercise and the various levels of affect intensity, do not interfere with the emotion detection mechanism and consequently the IIE agent's performance.

4.3 Two Factors Affecting the Study of Physiological Affective Computing

A major omission of research into emotional states is that researchers often forget to verify whether subjects actually experienced the targeted emotional states at the measured level of intensity during experimentation. In many experiments, researchers assume that participants react to emotional stimuli in a similar manner neglecting the influence of the subjects own personal interpretation which sometimes means that the intended emotional states never occur. The assumption that individual responses to emotional stimuli are similar for all the participants and that the simple presentation of such stimuli suffices to elicit emotional states could lead to the acquisition of flawed or biased experimental data. One way of correcting this problem is by the use of self-reports collected after a given stimulus has been provided or by selecting experimental subjects whose emotional responsiveness would make it more likely that the targeted emotions actually took place [Prkachin99].

Another important assumption often found in emotional experimentation and in particular in physiological emotion detection is that situations causing physical arousal that are not linked to emotional episodes, e.g. exercise, can be ignored during data analysis and pattern recognition. The introduction of noise or the potential upheaval of physiological signals due to unforeseen physical stress like exertion or the emotional augmentation caused by prior exercising could make emotion detection more difficult and thus skew the classification results.

For instance, the effects of exercise on physiological arousal have been widely studied and reported over a long period and there is evidence of bio-energetic, muscle, pulmonary, cardiovascular, neural, and hormonal variations during exercise [Birch05]. Even at very low-intensity, exercise provokes bodily changes such as increase in heart rate and reduction in respiratory rate.

In terms of the physiology of emotions it has been argued that physiological arousal fluctuates in accord with the type of emotional stimuli that it is being provided (the stronger the stimulus the higher the physical activation) [Ekman83, Levenson91, Cunningham04, Gross01, Gross98]. Because these bodily variations also depend on the intensity with which we respond to a given emotional stimulus, it is argued that subjects with intense emotional reactions are likely to experience intensified physiological activations.

For robust emotion recognition within IIEs I need a mechanism that will be able to identify emotional state independently of the affect intensity or level of exercise of the subject involved. To this end I am focusing on analysing the extent to which physical exertion and affect intensity alter the physiological signals employed by my emotion detection model. Should the disturbances provoked by physical activities or affect intensity make the AANN-based classification of emotional state unreliable or uncertain, then appropriate compensation techniques would have to be developed for detection systems using bodily parameters and AANN. Such compensation techniques would have to be implemented to perform real-time filtering and/or normalization of the physiological data so that the changes introduced by affect intensity and/or physical exertion would be reduced or eliminated.

4.4 Towards Robust Physiological Emotion Detection

4.4.1 Sensing Interface and Physiological Signals

Acquisition equipment included 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 online estimated parameters, namely the gradient of the skin resistance (GSR) and the speed of the changes in the data (CS - a measure of the signals' entropy).

Physiological data is originally acquired at 24 samples per second and pre-filtered using a 4-order built-in lowpass Bessel filter that eliminates high-frequency noise. Note that the device's sampling rate is affected by the characteristics of the hardware employed in data acquisition, e.g., processor speed. Thus, the resulting number of recorded samples usually varies between 15.6 and 15.8 per second for a 450Mhz Pentium III PC computer. It is also worth mentioning that the type or pre-processing employed by the acquisition equipment could influence the way signals are measured and processed. For example, a change in the parameters of the Bessel filter or the utilization of another type of filter could affect the level of noise introduced in the signal and provide totally different sensor readings.

According to the manufacturer's guidelines, the finger sensor:

- Could be attached to any finger on either hand;

- Should be positioned so that the fingertip rests on the sensor's touching pad;
- Should not be strapped too tightly (just firm enough to avoid the finger clip to slip off or move around the finger).

One of the main appeals of this against other sensing equipment is that it has the characteristics needed to potentially become wireless, thus possessing the flexibility needed if the detection methodology were to be migrated from a lab-controlled environment to a real-life situation inside an occupied environment.

4.4.1.1 *Skin Resistance (SR)*

Skin Resistance (SR) is one of the measures employed in psychology and related areas to evaluate Electrodermal Activity (EDA) associated with various human activities. EDA comprises a stable baseline level called *tonic* level and momentary fluctuations that appear after stimulation known as *phasic* responses. Some times also called Galvanic Skin Response, SR refers to such momentary fluctuations in the resistance values of the skin and it is measured by passing a small current between two electrodes located on the skin surface (known as the Fere Effect). A related measure known as Skin Potential Response does not require the use of external electrical current and instead relies on the use the body's internally generated electricity [Healey00].

The phenomena associated with EDA and psychology have been studied by scientists for more than a century. There is evidence that EDA alterations are related to brain and sympathetic activity. Changes in the autonomic nervous system caused by situations including emotional arousal are linked to sweat gland activity which in turn provokes changes in SR. In fact there is evidence that sweating in fingers and palms is stronger in cases of psychological and sensory stimuli than in those associated with thermoregulatory aspects [Andreassi95]. In addition to psychological studies, SR is a popular measure employed in areas of biology, medicine (including clinical diagnosis and disease research), law enforcement, cosmetic research, and sports performance.

SR is expressed in Ohms or K-Ohms (KΩ) and can be determined using a galvanometer, a device capable of providing a measure of electrical resistance. The amplitude of SR usually depends on the size of the electrodes and typically varies from 5 to 25 K-Ohms with visible changes sometimes noticeable after just a few tenths of second (0.2 – 0.5) of being exposed to eliciting stimuli. Experimental evidence has related SR to numerous psychological phenomena including: verbal learning [Andreassi67], detection of positive and negative emotional responses [Ekman83, Healey00, Levenson91], and motivation [Pecchinenda96].

Resistance-based EDA could be measured using one or various of the following features: the value of the baseline value during a given period of time, number of changes over the same period of time, amplitude, latency (time between a given stimulus and the onset on SR response), rise time (time between onset of SR and peak of SR), and recovery half-time (difference between time of SR peak and 50% of recovery to pre-stimulus baseline) [Healey00]. For the purpose of my analysis, I employed SR raw amplitude values.

4.4.1.2 *Blood Volume Pressure (BVP)*

Blood Volume Pressure (BVP) is measured using a technique called a photo plethysmography. This type of quantification involves photoelectric transducers that measure the extent of light reflected by the skin. Blood irrigated though blood vessels modifies the amount of blood present in a given tissue which by the effect of vasoconstriction and vasodilatation modifies the amount of light reflected to the photoelectric sensor [Andreassi95, Healey00]. A plethysmography change comprises two measurable elements: 1) an engorgement of a body area described simply as blood volume, and 2) a rapid component known as pulse volume or pulse amplitude.

BVP changes take place as a function of metabolic requirements commonly affected by the behaviour of an individual [Andreassi95]. Sexual response, orientating reflex and speed of habituation have been investigated using BVP measurements.

Although in principle photo sensors could be used in any area of the body, peripheral locations such as the fingers are recommended for the study of emotional states [Healey00]. In this respect a finger clip provides an ideal acquisition location for measuring emotional changes.

4.4.1.3 *Heart Rate (HR)*

Cardiac activity has been related to a number of psychological phenomena including emotional states [Sinha92]. Heart rate is the number of times the heart contracts to pump blood to other parts of the body (Heart beats) per unit of time, being beats per minute (bpm) the most common choice. A healthy human heart normally operates at 72 bpm at rest. HR can be calculated by using an electronic counter that estimates an average of the plethysmography's pulse amplitudes.

4.4.1.4 *Gradient of Skin Resistance (GSR)*

Gradient of SR is a measure of the amount of the change (delta values) happening in the skin resistance signal from one sample to the other. The sequence of delta values is useful to measure instantaneous alteration of an individual's emotional estate. High arousal dermal activity is linked to low values of SR whereas low arousal levels have the opposite effect. GSR is expressed in K-Ohms.

4.4.1.5 *Signal Entropy (CS)*

Entropy is a term used in many areas with different meanings and it is generally employed to denote changes occurring in the state of a process. For example entropy is useful to describe the amount of disorganized energy in bioenergetic phenomena related to chemical reactions [Birch05] while in communications entropy refers to degrees on randomness in signals and is directly associated with noise and bandwidth.

In our case signal entropy reflects how fast physiological signals are changing and it is expressed in Hz (samples per second). Transient or time-varying signal changes could give evidence of a shifting emotional state. This type of entropy measure has been successfully used in neuroscience to measure brain activity [Bezerianos03].

4.4.2 International Affective Picture System (IAPS)

The International Affective Picture System (IAPS) is a set of colour photographs encompassing a wide range of different themes and topics and which are standard, “emotionally-evocative” and internationally accessible [Lang01]. The IAPS was developed at the Center for the Study of Emotion and Attention at Florida University to offer investigators in the area of emotions and attention a set of normative emotional stimuli useful for experimental investigations. The IAPS relies on a dimensional interpretation of emotional judgements founded on Osgood et al.’s semantic differential approach.

The IAPS has been used as an emotional elicitation mechanism in numerous experiments. Codispoti el al. used pictures from the IAPS and physiological signals to demonstrate that brief periods of emotional stimulation are sufficient to "engage the motivational systems that mediate emotion" in a way comparable to those effects from more prolonged exposition time [Codispoti01]. Keil et al. used hemodynamic and electrophysiological analysis to provide evidence that IAPS's neutral and non-neutral pictures stimulate the brain in a different way [Keil02]. Smith et al. used the IAPS to elicit emotions in subjects before and after they were asked to perform an exercise routine. Smith et al. obtained preliminary evidence that light exercise did not influence emotional responsiveness [Smith02]. For a copy of IAPS pictures visit http://www.phhp.ufl.edu/csea/IAPSinfo.pdf.

Note that alternative methods of emotion elicitation based on emotional imagery exist such as video clips, sounds, and acting techniques. These approaches might have different advantages depending on the experimental procedure and the type of participants employed in a given study. You might want to read the work of Picard [Picard01] and [Nasoz03b] to see the utilization of these other techniques.

4.4.3 Stimuli

Seven slide shows containing 21 photographs each (7 pleasant, 7 neutral, and 7 unpleasant) were assembled using a selection of images from the International Affective Picture System (IAPS). Pleasant pictures included babies, landscapes, enjoyable activities, food, and erotic couples; unpleasant pictures consisted of scenes of attacking animals, situations of personal attack and war and also mutilated bodies (see Figure 4.1). Picture selection was based on the premise that the average valence content should be similar in each category for each picture set. IAPS picture numbers and valence values are detailed in Appendix 3 and are an extension on the work of

[Smith02]. The order of the stimuli was pseudo-randomised, i.e., manually done, with the restriction that no more than three pictures in the same affective category would be displayed consecutively.

Figure 4.1. Examples from IAPS. a) Neutral picture; b) Pleasant picture; c) Unpleasant picture [Lang01].

4.4.4 Participants

Thirty-nine individuals responded to an advertisement and agreed to complete the Affect Intensity Measure (AIM) questionnaire [Larsen 86] (See Appendix 2). The AIM scale has been widely employed in psychological studies and has been shown to possess sufficient reliability and validity [Prkachin99] to evaluate affect intensity. From the initial 39 subjects, 6 women and 3 men aged 26 – 48 years took part in experimental sessions. Five were considered highly emotionally intense (scored more than 0.5 standard deviations above the mean AIM value [Prkachin99]) and the remaining four were in the medium- and low-emotional intensity scale (see Table 4.1). As AIM scores increase so does the intensity with which an individual reacts to emotions and consequently his/her physiological response or affect intensity.

Highest AIM Score	Lowest AIM Score	Standard Deviation	Mean	High-Intensity Threshold
5. 35	2. 375	0. 60	3. 77	4. 07

Table 4.1. Summary of Results from The AIM Questionnaire.

4.4.5 Determination of VO_2Max Values and Exercise Routine

Participants in this study were required to complete a small exercise routine to evaluate how physical exertion affects the recognition of physiological responses associated with emotional states. In order to set up an exercise program that would produce comparable physical response from each individual it is necessary to evaluate his or her physical fitness and then use it as common parameter.

Cardiorespiratory endurance is considered to be one of the most important components of physical fitness. The maximum oxygen uptake value (VO_2max) or peak VO_2 is regarded as the most convincing measure of functional capacity of the cardiorespiratory system [Heyward98]. VO_2max can be expressed as an absolute or relative value. An absolute measure depends on body size and therefore is different for each subject. It is used to evaluate energy cost for non-weight-bearing activities such as leg or arm cycle ergometer. A relative value can be used to compare VO_2max values among individuals with different body sizes and it is employed to measure energy costs of weight-bearing activities such as running, dancing, and bench stepping. For the purpose of simplicity and low cost a stationary bicycle (see Figure 4.2) was used in experimental sessions involving physical activity and therefore an absolute VO_2max value was utilized.

Figure 4.2. Stationary bicycle employed in exercise routine.

VO_2max is usually calculated using maximal or submaximal graded exercise tests (GXTs). However, VO_2max can also be calculated without a GXT using the equations described in [Jackson90]. The correlation value of the described model with actual VO_2max measurements is 0.78 with a standard error of 5.6 ml/kg-min which is an error suitable for this kind of studies in which VO_2Max is used only as a reference parameter and not as the main targeted variable.

Female: $VO_2Max = 56.363 + 1.921\,(PA\text{-}R) - 0.381\,(age) - 0.754\,(BMI)$

Male: $VO_2Max = 67.350 + 1.921\,(PA\text{-}R) - 0.381\,(age) - 0.754\,(BMI)$

Where

PA-R is the score from the NASA Physical Activity Rating questionnaire (PA-R) developed at the Johnson Space Center (see Apendix A).

BMI is the Body Mass Index (BMI = Weight in kilograms / $[\text{Height in meters}]^{2}$).

Based on each individual's VO_2max values, a suitable exercise routine can be prescribed as follows.

1. Calculate target VO_2 based on the desired exercise intensity (low: up to 40% of VO_2max; moderate: 60-70% of VO_2max; high: 85% of VO_2max). For example:

   For a VO_2max=35ml /kg-min, a moderate exercise program would be from 21 to 24.5 ml /kg min.

2. Convert target VO_2 to metabolic equivalents MET (1MET = VO_2 / (3.5 ml/kg-min)).

3. Find a target MET (metabolic equivalents) value (see Table 4.2). For example:

   A low intensity exercise program (40% VO_2max) for a subject with VO_2max=35ml /kg-min would involve 4 METs (bicycling at <10 mph at leisure)

In his analysis of post-exercise response to the IAPS, Smith et al. [Smith02] employed two different exercise routines: cycling for 25 min at 40% VO_2max and then at 70% VO_2max. Since the purpose of this study was to analyse physical exertion under conditions that would resemble daily-life activities inside IIE, it was sufficient to use a low-to-moderate intensity exercise routine (up to 60% VO_2Max) rather than more demanding one.

Activity, Description	METs	ml/kg-min
Bicycling, BMX or mountain	8.5	29.75
Bicycling, general, <10 mph, leisure	4.0	14
Bicycling, 10-11.9 mph, leisure, slow, light effort	6.0	21
Bicycling, 12-13.9 mph, leisure, moderate effort	8.0	28
Bicycling, 14-15.9mph, racing or leisure, fast, vigorous effort	10.0	35
Bicycling, 16-19 mph, racing/not drafting or >19 mph drafting, very fast, racing general	12.0	42
Bicycling, >20mph, racing not drafting	16.0	56
Home Activities (Average)	3.6	12.6

Table 4.2. Compendium of physical activities [Ainsworth93].

Thus, based on the mean VO_2Max score (see Table 4.3) and on previous studies involving the analysis of bodily measures after being stimulated by IAPS pictures and physical stress [Smith03], participants were required to cycle for 25 minutes on a stationary "exercise" bicycle at no more than 10 mph (4.0 MET), equivalent to 27-57% of their theoretical VO_2Max value. It is notable that the physical load stemming from this exercise routine is very similar to the one associated with the average physical load of household activities (see last row of Table 4.2).

	Highest VO_2Max Value (METs)	Lowest VO_2Max Value (METs)	Mean	Standard Deviation
	14. 6	6. 97	9. 47	2. 38
Percentage of VO_2Max value required by Bicycling at less than 10 mph (4.0 MET)	27.4	57.4	42	
Percentage of VO_2Max value required by Home Activities (3.6 MET)	24.6	51.6	38	

Table 4.3. VO_2Max Values for Nine Subjects.

At this point it is important to mention that there has been evidence that various levels of exercise function as regulators of emotional responses such as stress and aggression among others. Thus, there is a question on whether my exercise routine could in some way taint the effects that affective pictures have on the experimental subjects. In this regard Smith et al. in 2003 carried out a study to complement his previous effort to examine the effects of low-to-moderate exercise on emotional response [Smith03]. They used various bodily responses to measure the effect neutral, positive, and negative pictures had on the emotional response of subjects at resting conditions and during physical exertion. Their conclusions were that “very low intensity and low intensity exercise induced activity had no effect on startle responses and corrugator supercilii responses during the viewing of pictures designed to evoke pleasant, neutral and unpleasant emotions”. In short, light exercise does not seem to alter emotional response as indicated by two valid measures of emotional responsiveness, i.e., corrugator supercilii EMG (activity in a muscle located in the medial forehead shown to be active in response to unpleasant stimuli) and the acoustic startle eyeblink as assessed by activity in the muscles of the eyelid (orbicularis oculi). Because the level of physical stress caused by my exercise routine did not pass the moderate-intensity level, I can feel justified in assuming that the emotional eliciting effects of the IAPS pictures before and after exercise remained similar.

4.4.6 Experimental Procedure

Seven Power-point (PP) slide shows (each one including a different IAPS picture set) were utilised to elicit emotions on participants while their physiological data was recorded. Before each slide show, subjects were instructed to stare at the centre of the screen and avoid explorative eye movements. Pictures were presented on a 17-in CRT monitor with a frame refresh rate of 75 Hz located at least 1.5 meters in front of the subject. With the exception of slide show 1, all the other presentations were designed to automatically display each picture for 6000 ms with blank intervals of 35000 ms.

Experiments were carried out over a four-day period. Upon arrival on day one subjects were asked to complete two questionnaires associated with their physical activities and one consent form, and immediately after shown slide show 1. Slide show 1 was not used as part of the data collection process because this was a preliminary viewing session intended to give participants the opportunity to opt out from the experiment should they consider picture content unacceptable. In each of the subsequent days subjects viewed 2 slide shows separated by interval periods of 25 minutes in semi-recumbent position on day 2, 25 minutes cycling on the stationary bicycle followed by 25 minutes in semi-recumbent position on day 3, and finally 25 minutes of cycling on the stationary bicycle on day 4 (see Figure 4.2). Warm-up and cool-down periods were provided before and after each exercise routine. The warm-up period involved a gradual increase on the exercise intensity to prepare the body for the low intensity exercise. During cool-down subject continued exercising for an additional 2 minutes at a very low intensity rate. For a summary of the three-day tasks see Appendix 2. In all cases there was evidence of increased HR activity as a result of the exercise routine with a difference of up to 25 bmp (beats per minute) with respect to resting conditions.

Before the finger clip was attached to the individual's body during physiological data acquisition, subjects were asked to thoroughly wash and dry their hands to avoid excessive hand moisture. Participants were also instructed to avoid any abrupt body or hand movement while the acquisition artefact was attached. Physiological data was recorded at 15-16 samples per second on a 450-Mhz Pentium PC computer while the subject watched pictures on the screen.

4.5 Dataset Description

Data collection sessions produced 6 data sets per subject (one per slide show on days 2, 3, and 4). These files were named Pre25minRest (Slide show 2), Post25minRest (Slide show 3), PreExercise-1 (Slide show 4), Post25minExercise25minRest (Slide show 5), PreExercise-2 (Slide show 6), and Post25minExercise (Slide show 7). From the original 9 volunteers, only 5 completed the exercise routine on day 4. In addition, the information from one subject was lost due an error in the data storage procedure resulting in 42 usable files. The number of samples on each data set involved between 12123 and 18993 data samples which were later reduced to between 1871 and 2627 after the elimination of samples corresponding to the 35 sec. inter-slide periods. A further division on the data was made in accordance with the emotional content of the pictures they related to (neutral, positive, and negative). Additionally, emotional information was identified with a class number (1-neutral, 2-non-neutral) and assembled into 2 groups: BeforeExerciseOnly included neutral and non-neutral data collected throughout the viewing of slide show presentations 2, 3, and 4; and BeforeandAfterExercise involved neutral and non-neutral information from data colleted during the presentation of slideshows 2, 3, 4, and 5.

4.6 Similarity Test of Emotional Data Before and After Exercise

The Wilcoxon Two-sided Rank Sum Test provides a way to determine whether two independent data sets associated with a given parameter could actually be seen as two contributing parts of the same population instead of separate individual groups, i.e., how similar two datasets are. Assuming that $\mu 1$ and $\mu 2$ are the mean values of the parameter contained in data set 1 and 2 respectively, the Wilcoxon test will estimate the probability P that the hypothesis H0 that $\mu 1$ equals $\mu 2$ is true, i.e., the two data sets possess a high degree of similarity [Brown77]. The Wilxoxon Test is estimated by calculating the differences between two paired observations and rank such differences from smallest to largest by absolute value. All the ranks associated with positive differences are added together to form the so called “test statistic”. Finally, the probability (P) value related to the test statistic is obtained from a look-up table.

A series of Wilcoxon tests were performed to evaluate the extent of physiological changes provoked by physical exertion and determine whether light exercise could disturb bodily signals in such a way that these changes might have an potential effect on the estimations provided by the AANN. More specifically, if the bodily signals measured before and after exercise possessed radically different characteristics then I would have to be very cautious in the selection of AANN’s training data. That is, if the two data sets showed similar patterns that would mean that the utilization of information either before or after exercise would not have a major effect on AANN’s performance. Furthermore, similar signal behaviour before and after exercise, would permit my emotion detection system to operate on subjects at resting conditions and generalize for situations of light physical exertion and viceversa. On the other hand, should the two datasets demonstrate striking differences, I would have to either 1) use the two datasets to train the AANN thus including all possible data variations but with potential adverse consequences in generalization and converging time, or 2) normalize and/or filter the data to compensate for such differences which would otherwise constitute a major impairment of the robustness and generalization attributes of the AANN.

Results showed that the hypothesis that data obtained before (PreExercise-1 and PreExercise-2) and after exercise (Post25minExercise25minRest and Post25minExercise) possessed a high degree of similarity (H_0) was consistently false for HR and SC and true for BVP with a confidence factor of 0.05 (see Table 4.4 (a) and (b)). The changes in HR and SC associated with H_0=FALSE however were also present during trials in which no exercise was involved (Pre25minRest, Post25minRest, and PreExercise-1) (see Table 4.4 (c)). In those cases where the averaged valued was not close to either 0 or 1, a not conclusive note was used (N/C).

	Subject 2*	Subject 3*	Subject 5	Subject 6	Subject 8
	P/H_0	P/H_0	P/H_0	P/H_0	P/H_0
GSR	7.26E-01/ TRUE	0.9058/ TRUE	7.69E-04/ FALSE	6.81E-09/ FALSE	1.00E-08/ FALSE
HR	0/ FALSE	0/ FALSE	1.12E-253/ FALSE	0/ FALSE	0/ FALSE
BVP	0.842/ TRUE	0.7552/ TRUE	0.4856/ TRUE	0.4776/ TRUE	3.17E-01/ TRUE
SR	0/ FALSE	0/ FALSE	0/ FALSE	0/ FALSE	0/ FALSE
CS	6.15E-11/ FALSE	6.21E-01/ TRUE	1.71E-65/ FALSE	0.0025/ FALSE	2.60E-06/ FALSE

a)

	Subject 2*	Subject 3*	Subject 5	Subject 6	Subject 8
	P/H_0	P/H_0	P/H_0	P/H_0	P/H_0
GSR	8.25E-06/ FALSE	0.002/ FALSE	0.19/ TRUE	0.14/ TRUE	4.50E-07/ FALSE
HR	0/ FALSE	0/ FALSE	5.30E-176/ FALSE	0/ FALSE	0/ FALSE
BVP	0.52/ TRUE	0.54/ TRUE	0.8/ TRUE	0.1588/ TRUE	8.20E-01/ TRUE
SR	0/ FALSE	0/ FALSE	0/ FALSE	0/ FALSE	0/ FALSE
CS	9.20E-19/ FALSE	5.36E-08/ FALSE	2.80E-13/ FALSE	0.0122/ FALSE	1.85E-01/ FALSE

b)

	Subject 2*	Subject 3*	Subject 5	Subject 6	Subject 8
	P/H_0	P/H_0	P/H_0	P/H_0	P/H_0
GSR	0.06/ N/C	0.01/ N/C	0.28/ FALSE	0.18/ N/C	0.29/ N/C
HR	3.00E-04/ FALSE	0/ FALSE	0/ FALSE	6.00E-247/ FALSE	5.89E-07/ FALSE
BVP	0.34/ TRUE	0.28/ TRUE	0.54/ TRUE	0.41/ TRUE	0.70/ TRUE
SR	2.86E-09/ FALSE	0/ FALSE	1.03E-19/ FALSE	0/ FALSE	6.33E-04/ FALSE
CS	0.33/ FALSE	0.10/ N/C	0.01/ N/C	0.02/ N/C	1.53E-04/ FALSE

c)

Table 4.4. Results of the Wilcoxon Test Between a) Preexercise-2 And Post25minexercise; b) Preexercise-1 And Post25minexercise25minrest; c) Pre25minrest, Post25minrest, And Preexercise-1 (Averaged Value) (* Denotes Highly Emotional Subjects).

4.7 Class Separation Test of Emotional Data Before and After Exercise

As previously stated a cluster or class separation analysis provides an insight into the amount of inter- and intra-cluster separation within a given data set and indicates the signal(s) that contribute to an optimal separation of two or more classes. The DBI was used to assess the classification index of the various monitored physiological signals before and after physical exertion and taking into account the various levels of affect intensity. Remember that lower DBI indexes reflect a better class separation.

Preliminary results obtained from a clustering analysis on data from the original 8 subjects who took part in the first 3 days of experimentation and depicted in Table 4.5 showed that there was no significant difference in the lowest DBI values of physiological data before and after exercise in subjects with different degrees of affect intensity. Furthermore, bodily signals involving physical exertion demonstrated improved class separation on two occasions (See subjects 4 and 5 in Table 4.5).

	BeforeExercise		AfterExercise	
	Minimal Value	Mean	Minimal Value	Mean
Subject 1*	6. 96 (CS)	81. 37	7. 37 (CS)	111. 85
Subject 2*	9. 51(CS)	63. 41	14. 90(HR)	316. 92
Subject 3*	13. 02(GSR)	85. 07	16. 18(HR)	163. 56
Subject 4*	7. 21(CS)	71. 71	6. 18(CS)	82. 26
Subject 5	7. 30(HR)	85. 47	7. 08(HR)	125. 13
Subject 6	5. 32(HR)	97. 12	5. 92(HR)	153. 88
Subject 7	10. 83(HR)	157. 31	13. 24(CS)	387. 04
Subject 8	6. 15(HR)	172. 87	8. 50(HR)	294. 49

Table 4.5. DBI Values for Raw Data from 5 Physiological Signals (* Denotes Highly Emotional Individuals).

Similar tests were performed to evaluate whether AANN estimations would suffer from the consequences of physical exertion and degrees of affect intensity. Thus, I trained an AANN for each of the 8 individuals using raw physiological data from their neutral emotional state before exercise and then provided data before and after exercise.

	BeforeExercise		AfterExercise	
	Minimal Value	Mean	Minimal Value	Mean
Subject 1*	5.79 (CS)	14.70	7.23 (CS)	18.07
Subject 2*	6.78 (BVP)	17.92	10.79 (CS)	27.84
Subject 3*	5.71 (BVP)	34.87	9.39 (GSR)	24.14
Subject 4*	6.09 (CS)	23.33	5.83 (CS)	73.94
Subject 5	3.59 (HR)	11.73	5.48 (HR)	38.87
Subject 6	4.39 (GSR)	42.24	5.71 (CS)	95.73
Subject 7	5.59 (CS)	93.42	9.32 (CS)	95.09
Subject 8	5.66 (HR)	32.89	7.04 (HR)	97.57

Table 4.6. DBI Values for AANN Estimations from 5 Physiological Signals (* Denotes Highly Emotional Individuals).

Results in Table 4.6 demonstrate that AANN estimations possessed an enhanced class separation when compared to the original raw data both before and after exercise thus evidencing the filtering properties of the AANN. Moreover, the DBI values obtained from AANN estimations after exercise showed little difference with respect to those stemming from data before exercise, thus confirming the idea that neither exercise nor affect intensity affect AANN performance in a significant manner.

It is worth mentioning that Tables 4.5 and 4.6 consistently demonstrate an increase in DBI values before and after exercise in all but one participant (subject 4). This phenomenon could be related to the effect of exercise on the physical state of the participants which provoked an augmented overlapping in the physiological signals used to distinguish between neutral and non-neutral emotional states. It should also be noted that although it might have been an interesting, illustrative example of how physiological signals behave after light physical exertion, a comparison between DBI values obtained immediately after exercise and following 25 minutes of rest is not possible since the two datasets corresponding to these situations were acquired on different days.

4.8 Physiological Emotion Detection for Real-Life Scenarios

The analysis presented in this chapter supports the view that systems relying on physiological measures to recognize emotions in real-time and involving realistic situations should be able to operate reliably independent of the level of physical effort and different degrees of affect intensity of the person. Two different experiments were undertaken to investigate the potential effects of low-to-moderate effort exercise and affect intensity on 5 physiological signals employed in real-time emotion detection. The results from the Wilcoxon test demonstrated that there was a change in HR and SC in all the trials whereas BVP remained very similar. This is true when comparing data before and after the low-to-moderate exercise routine but was also true for data when no exercise was involved. It could then be inferred that any changes caused by various degrees of affect intensity and different levels (from low to moderate) of physical activity would not interfere with the operation of the AANN.

In order to verify these conclusions, a series of DBI-based clustering tests were performed using raw-physiological data acquired before and after exercise. Apart from being an indicator of whether the properties of bodily signals employed in emotion detection are altered by the effects of physical exertion, the estimation of the DB index is an important part of my methodology for it is used to determine the physiological signal(s) that provide the best class separation during the emotion detection process. Evidence from DBI values calculated on raw data showed that in terms of the effects of physical exertion and affect intensity on physiological signals, these do not seem to be contributing to a deteriorated class separation before and after low-to-moderate exercise.

Furthermore results from a second class separation study, demonstrated that the ability of the AANN to separate the physiological residual associated with neutral and non-neutral emotions (Chapter 3), did not show a negative effect as a result of physiological variations. Because the attributes of enhanced class separation found in AANN estimations were not influenced as a result of bodily alterations induced by various levels of affect intensity and physical activity, it could be inferred that the operation of the SPRT (based on AANN outputs) would also remain unaffected. These experimental results indicate that no special adjustments are required to real-time data acquisition systems classifying emotions based on bodily data in order to account for differences in levels of physical activity or varying affect intensity. In terms of systems utilizing AANN, the findings presented above suggest that the use of data acquired before exercise for the purpose of AANN training should also be valid for the detection of emotions after physical exertion.

In these experiments I have intentionally not considered situations where participants are involved in high-intensity physical exertion and whether or how this might make a difference to emotion detection. The main justification for this is that, although I do not rule out the possibility that the subject would undertake more vigorous activities inside an IIE, my main concern was the potential bodily disturbances provoked by everyday domestic activities. As explained in Section 2.4.5, I likened the physical effort involved in this type of household activities with that of a low-to-moderate intensity exercise and those were the bases on which my physical exercise routine was designed. In general it is the case that exercise demanding maximum VO_2Max levels are rarely undertaken at home and are normally carried out under specialized supervision. Therefore, since the

AANN is able to accommodate for physiological changes caused by light physical exertion (from low to moderate), that should be sufficient to account for most of the activities likely to take place inside an IIE.

Another important point that should be mentioned is the distinction between the effects exercise has on the detection capabilities of my emotion detection system and those that might affect emotional responsiveness. I mentioned that there have been numerous efforts aimed at analysing the consequences of exercise on emotional responsiveness with evidence that low-to-moderate intensity levels of physical activity do not alter the reactions to emotional stimuli similarly to resting conditions [Smith03]. My discussion does not concern how low-to-moderate physical activity changes the perception of emotional stimuli but only how the physical arousal that derives from such physical activity might disturb the performance of my emotion detection system.

In summary, the analysis presented in this chapter indicates that the AANN-based emotion detection system should be able to withstand the consequences of such factors as low-to-moderate intensity physical activity and affect intensity. This is of great relevance for my purposes since the analysis of real-life situations occurring inside an IIE does not hinge on the assumption that all individuals are identical, they react differently to emotional stimuli and might or might not include light exercise and other physically demanding routines as part of their normal activities.

In the next chapter I will complement this study to evaluate the design of my emotion detection system with respect to two crucial operational parameters. Firstly, I will measure the generalization capability of the AANN to estimate physiological signals from a subject that was not part of the initial training model. The results stemming from this analysis will help me determine the degree to which this system is capable of performing user-independent emotion recognition. Secondly, experiments will be performed under circumstances mimicking real-time real-life IIE operation. The purpose of such simulation is to establish the parameters needed to perform remote acquisition of physiological data and subsequent emotion detection from a subject undertaking real-life, genuine daily activities inside an IIE.

"Emotions and the feelings are not a luxury, they are a means of communicating our states of mind to others. But they are also a way of guiding our own judgments and decisions. Emotions bring the body into the loop of reason" Antonio Damasio

Chapter 5

Development of a Wearable User-Independent Real-Time Emotion Detection System for Intelligent Inhabited Environment (IIE)

5.1 The Relevance of Multi-User, Room-Based Emotion Detection

In November 2005, the British Government announced a pilot programme to teach emotional literacy in fifty secondary schools in England [BBC05]. The purpose of this plan is to assess the benefits of lessons aimed at assisting pupils of secondary education in expressing their emotions. This scheme had shown its efficacy in helping young children of primary school level improve their behaviour by reducing violence and encouraging "self-awareness, friendships, empathy and self-motivation". This extraordinary effort by the Department for Education and Skills highlights the importance of emotional intelligence as a "vital skill" in modern society. It also gives a hint about the future of affective computing where applications involving emotions inside IIE would not be limited to in-lab experimental sessions relevant to a few investigators but could also be of importance for a wider audience involving different ages, social backgrounds, fitness levels, affect intensity, and behaviours. In this context, the possibility of employing affective systems, emotion detection in particular, on a varied set of individuals appears exciting but it brings us back to one aspect of emotions I have tried to emphasize in previous chapters i.e. that despite measurable similarities, they are *personal* experiences. No two persons live and express their inner feelings in exactly the same way nor do they feel identical emotions about similar matters.

It is important therefore for physiological emotion detection mechanisms to be not only capable of handling external factors affecting bodily signals but also of operating on different subjects and catering for their individual responses to emotional stimuli. The specific aim of this chapter is to present convincing evidence that the emotion detection methodology presented so far is not only a system that resists noise introduced by exercise and affect intensity but could also account for psychological subtleties caused by individual differences in emotional expression thus providing user-independent operation.

Moreover, physiological emotion detection systems designed for IIE should be able to perform remote monitoring of the subjects emotional state. In "New Technologies for Ambient Intelligence", Alcañiz and Rey state that "…One of the purposes of the [ambient intelligence] system can be to track the user's emotional state and to react accordingly. One of the ways to detect modifications in the emotional state can be recording physiological signals, for example, heart rate, galvanic skin response, temperature, electromyography, etc. Biosensors can be attached to the user's body and this data can be analysed while he/she is inside the ubiquitous computing system or room…" [Alcañiz05]. So, in section 3.9.1, I will describe a system I have developed to fulfil these conditions.

5.2 Assessing User-Independence in Physiological Emotion Detection

Two main conclusions stem from consideration of the work presented in the two preceding chapters. First, using off-line analysis, it is suggested that Autoassociative Neural Networks (AANNs) and sequential analysis could be employed in real-time analysis under real-life conditions to guarantee accurate classification of changes in emotional response. This methodology has shown better results than other approaches in two-class separation trials. Second, experimental evidence regarding affect intensity and exercise suggests that the detection of affective states employing AANNs is sufficiently robust to resist bodily variations provoked by factors other than emotional states. Thus, in this chapter, I intend to test not robustness but generalization abilities thus assessing the user independence of the emotion detection system.

The way to assess user independence in this particular case is by extracting and utilizing knowledge from a sample population and then use such knowledge to identify emotional changes on a totally new set of physiological data stemming from an individual that was not part of the original group. This will show that my methodology does not necessarily need to learn the specific bodily/emotional characteristics of a subject in order to deliver emotion detection for her/him. Note that this idea does not contradict my postulate about the individuality of the sentient experience. That is, the fact that I use data from several subjects in an attempt to detect emotions on a new subject, does not mean that I consider all individuals to be identical but instead that I expect the AANN and SPRT to pick up similarities and differences in the physiological signals of a sample population and then use that knowledge to generalize for another sample.

A major contribution of this chapter towards my initial objectives and hypothesis is that if this system, that embodies the operating principles of the methodology introduced in Chapter 3, can offer additional advantages for multi-user, reliable recognition of positive and negative emotions then it can form the basis of a wearable interface supplementing an affective agent that recognizes emotions in real-time from any given subject living inside an IIE.

5.3 An Experimental Multi-user System for Detecting Positive and Negative Emotions

In Chapter 3, the combination of Autoassociative Neural Networks (AANNs) and sequential analysis, namely the Sequential Probability Ratio Test (SPRT), proved to be effective in detecting changes in 4 physiological signals, more specifically the electromyogram obtained from the masseter, blood volume pressure, skin conductance and respiration rate associated with emotional states from a single individual. The recognition rate on that occasion was 100% for a single state change. This 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, Sensor Failure Detection, Identification and Accommodation (SFDIA) in which emotional states could be detected by estimating the amount of deviation they demonstrate with respect to a neutrally-emotional state. In Chapter 4, I demonstrated that the underlying methodology described above was able to resist perturbations due to bodily changes provoked by light-to-moderate exercise and also to various degrees of affect intensity [Leon05a]. Based on the calculation of the DBI index and the Wilcoxon test, it was demonstrated that neither physical activity nor affect intensity play an important role in the associative and generalization properties of the AANN trained with neutral data [Leon05b]. It was concluded that the use of physiological signals from individuals with variable affect intensity collected under resting conditions or after physical activity should not affect classification performance.

In the present chapter I extended the detection model outlined in Chapter 3 in various ways: First, instead of using data from a single subject, emotional information used to train the AANN was acquired from several individuals. Second, the number of bodily signals involved in the analysis was also increased by one and the recognition module modified to recognize not only neutral and non-neutral emotional states but also valence-based positive and negative emotional classes. Finally, in addition to real-time performance and robustness the user-independence capacity of this new and improved system was tested by presenting the AANN with never previously seen real-time physiological data.

In general terms the new improved real-time physiological emotion detection system, operates as follows. Data from five physiological signals is collected: 1) the heart rate (HR), 2) the skin resistance (SR), 3) the blood volume pressure (BVP), 4) the gradient of the skin resistance (GSR), and 5) the speed of the changes in the data (Signals' entropy) (CS)). An AANN is subsequently trained with physiological data associated with the neutral emotional state of each individual. Such AANN will respond to changes in the emotional status of the subject by projecting the residual into a transformed solution space (i.e. a space that differs to that of the original training data). Alterations in the Autonomic Nervous System (ANS) associated with emotional states are then identified by providing a SPRT-based classification module with the continuous calculation of the residual between an actual sensor value and its AANN-estimated counterpart.

The model then uses cluster analysis to determine the physiological signals that provide the best separation between neutral and non-neutral and also positive and negative emotional states. Residuals from each of these pre-determined bodily measures are provided to two individual SPRT modules: one concerning neutral and non-neutral states (status SPRT module henceforth) and another for classifying positive and negative emotions (valence SPRT module henceforth). These two classification modules operate sequentially (i.e., I continuously monitor physiological signals until an emotional episode provokes an alteration in the subject's bodily state, changing from neutral to non-neutral). Once an emotional change has been detected I classify that alteration as belonging to a positive or negative emotional class. The design of the new improved system is shown in Figures 5.1 and 5.2.

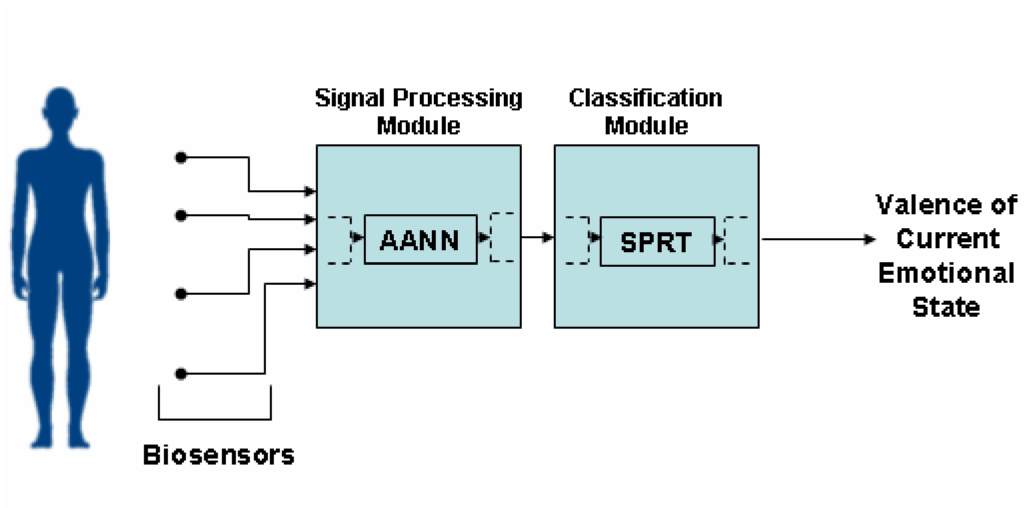


Figure 5.1. General diagrammatic representation of the new improved emotion detection system.

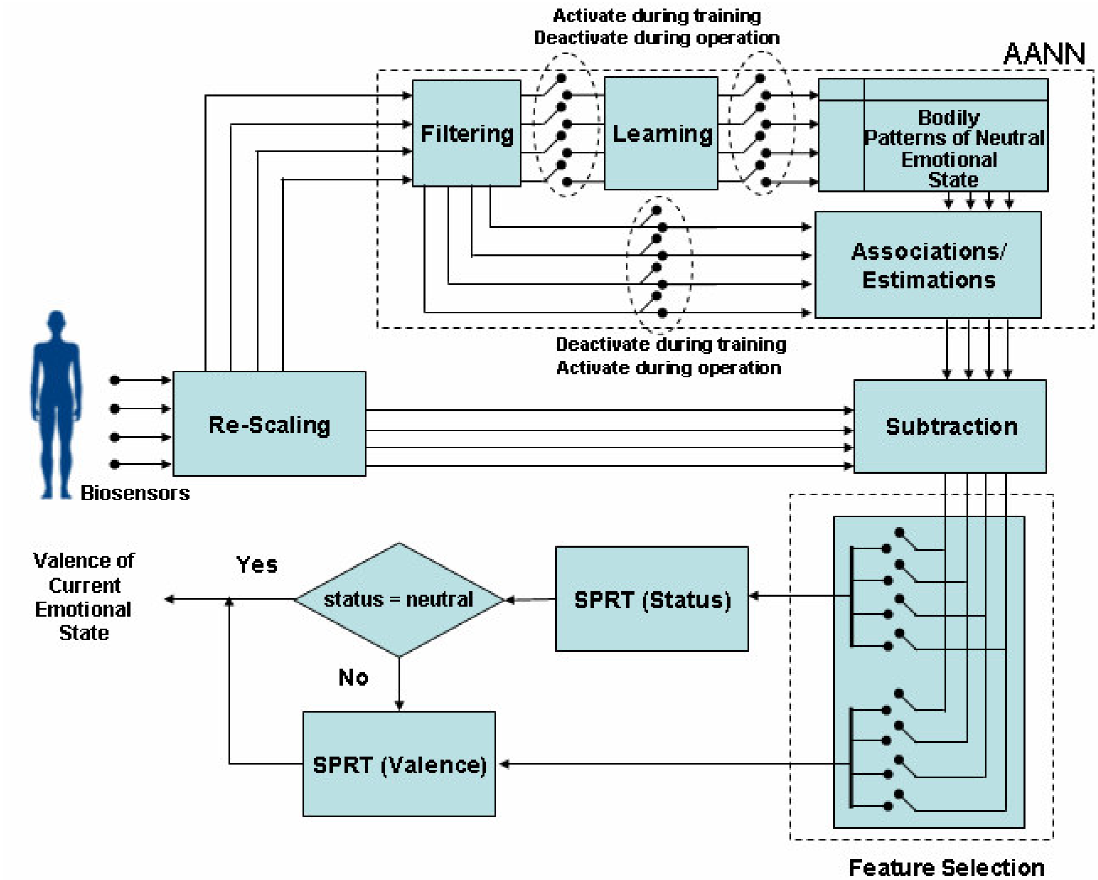


Figure 5.2. Detailed diagrammatic representation of the emotion detection system showing the AANN training and feature selection processes.

5.4 Dataset Description

Using the same physiological information employed in Chapter 4's robustness analysis, AANN training data comprised information from 3 emotional categories (Neutral, Positive, and Negative) collected from 8 individuals (5 women and 3 men) aged 26-36 and grouped according to whether they were acquired before or after physical activity. I have mentioned that the tripartite emotional classification used here is rooted in the valence dimension of the three dimensional view recognized by theorists in emotional assessment (the other two dimensions being arousal and dominance) [Lang01].

The proportion of data samples was approximately ¾ before exercise and ¼ after exercise. Based on their responses to the Affect Intensity Measure (AIM) questionnaire [Larsen86] four of the subjects were considered to have high affect intensity (scored more than 0.5 standard deviations above the mean AIM value [Prkachin99]) and the remaining four were on the medium and low affect intensity scale.

The original datasets were categorized according to the emotional class they belonged to (neutral, positive or negative) using time labels, i.e., both the presentation of the stimuli and the data acquisition process were coordinated using the same clock.

5.5 The Signal Processing Module: AANN Architecture and Training

Training data comprised the entirety of the neutral data from the eight individuals before physical activity totalling 18788 records. In order to reduce weight values and increase algorithm performance, data provided to the AANN was scaled to fall in the range between 0 and 1 using the maximal and minimal value of each physiological signal.

Training of the AANN was performed by means of the MATLAB implementation of the Levenberg-Marquardt algorithm in combination with Bayesian regularization [Hagan94, Foresee97] which as previously mentioned provides enhanced generalization.

5.6 Statistical Feature Selection

With the purpose of selecting the physiological signals that provide the best class separation, the trained AANN was provided with a dataset containing both neutral and non-neutral data from the eight individuals. The resulting residual calculation was then subjected to a clustering analysis.

5.6.1 Neutral and Non-Neutral Emotions

The calculation of the Davies-Bouldin Index (DBI) evidenced that the Heart Rate (HR) was the best signal to distinguish between neutral and non-neutral data with 14.35 followed by Change Speed (CS) with 21.42. The HR was therefore utilized in the continuous calculations provided by status SPRT module to detect the moment in which an emotional change occurs.

5.6.2 Positive and Negative Emotions

In the same manner, the CS was shown to be optimal for classifying positive and negative emotions with a DBI of 14.76 followed by the HR with 21.36. The calculation of the CS residual was eventually employed in the valence SPRT module to determine whether the emotional episode that gave rise to the emotional change could be catalogued as possessing a positive or negative emotional valence.

5.7 The Classification Module

It has been mentioned that the formulation of the SPRT is based on the Probability Density Function (PDF) of each variable involved in the classification process. In order to safely assume that the residual values used in the SPRT calculation stem from a normal distribution and to justify the utilization of Eq. (1) in Chapter 3, it is necessary to assess the normality of the data. In the case of the experiments presented in Chapter 3 such verification was not necessary since the data provided by Dr. Picard had already been normalized. However, because in this study I am using an entirely new data set on the SPRT, normality tests are useful. These can be done using what is referred to as a normality test using a normal probability plot. In a normality graph, the closest data points are to the straight line, the better the normality. Figure 5.3 shows that the assumption of normality in the HR and CS after the elimination of the noise introduced by the sensing device is reasonable.

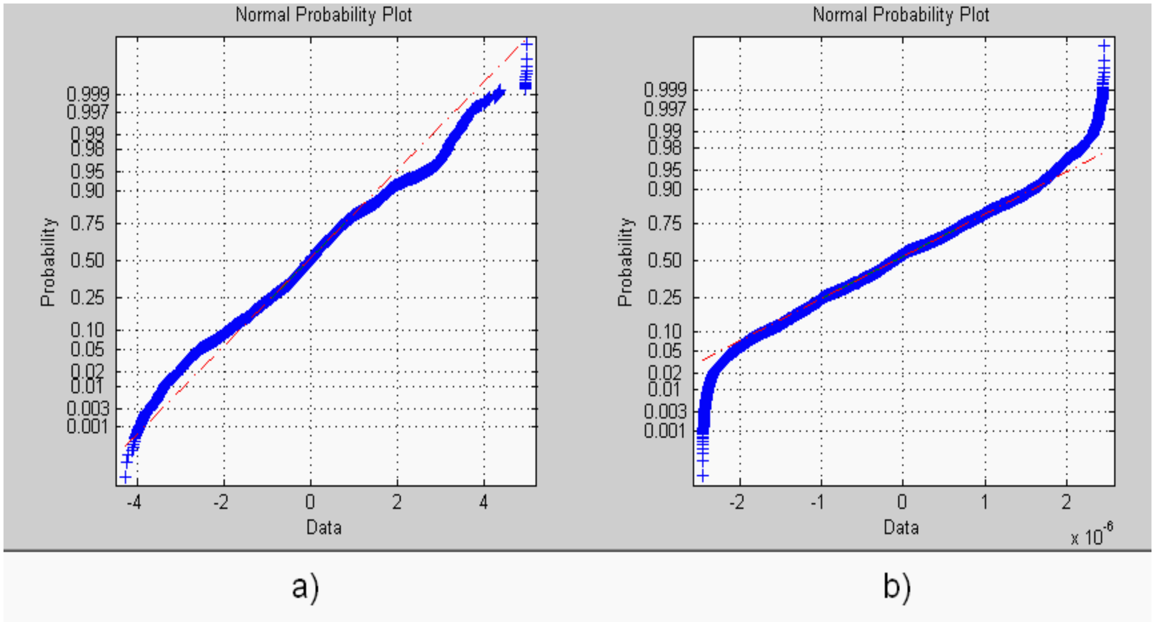


Figure 5.3. Normality test for the residuals produced by the AANN for a) HR and b) CS.

For the purpose of guaranteeing an accurate detection of emotion states without compromising system response, a standard significance value of 0.05 for both alpha (α) and beta (β) was chosen thus providing a 99.5% confidence in the SPRT results (this value for α and beta β is similar to that employed in other experiments involving sequential analysis [Li99, Poloniecki04, Johnstone98]). Note however that changes in alpha and beta values alter the probability of misrecognition and might affect the sensitivity of the emotion detection system to emotional changes. Smaller alpha values might provoke neutral emotional states to being classified as positive or negative while greater alpha values would have the opposite effect. Therefore it would be desirable that future implementations of the SPRT involved repeated significance tests to find the most favourable alpha and beta values. One example of such studies involving variable values for alpha and beta (including values of 0.05) is [Spiegelhalter03].

The mean (μ_1, μ_2) and variance (σ^2) values associated with the normal distribution of the residual were estimated from the AANN results to the entire dataset and were different for the SPRT implementation used for detecting affective status and that for emotional valence.

The operating principle of the classification module is similar to that of the initial system presented in Chapter 3. Since the AANN is trained to mimic the input behaviour, i.e. bodily patterns associated with the neutral emotional state, the mean of the residual should remain very close to zero under normal circumstances. When the sensor values drift because of an alteration in the subject's physiological status related to an emotional episode, the mean value of the residuals (HR for emotional status and CS for emotional valence) deviates from zero. The SPRT values are then altered and the likelihood ratio is displaced first into the neutral and non-neutral and then into the positive and negative solution spaces (Figure 5.4).

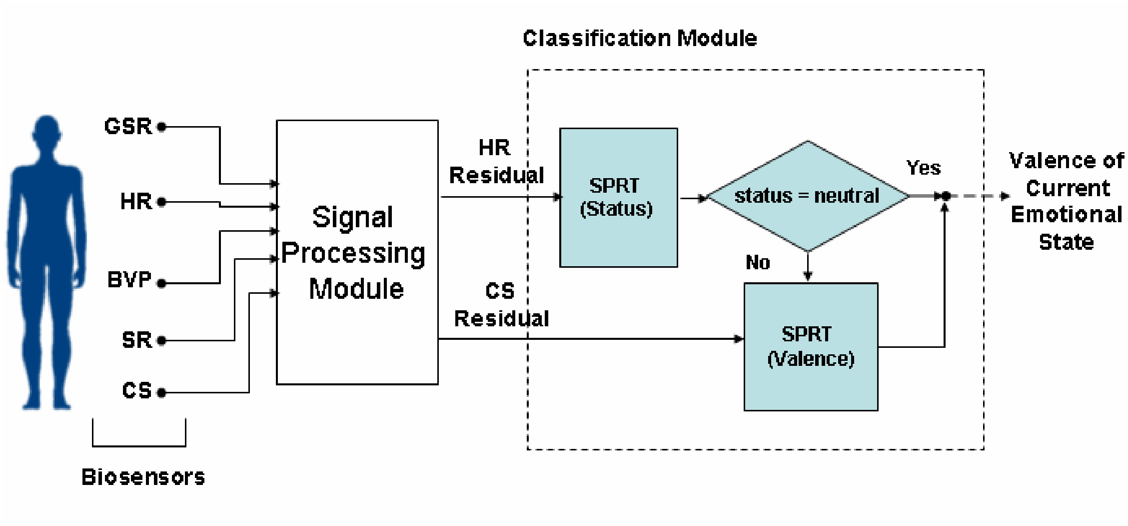


Figure 5.4. Classification of emotion classes. HR is the heart rate, SR is the skin resistance, BVP is the blood volume pressure, GSR is the gradient of the skin resistance and CS is the speed of the changes in the data (Signals' entropy).

5.8 Analysis of Validation for Intra-Group Generalization

In order to test the learning and classification performance of the system, data from the 8 volunteers originally monitored and that was not used during training (i.e. after physical exertion) was provided to the signal processing module (the pre-trained AANN) and SPRT-based classification modules (See Table 5.1, 5.2, and 5.3).

	Individual Recognition Rates per Category			
	Positive	Neutral	Negative	Recognition Rate (%)
Subject 1*	57% (4/7)	100% (7/7)	100% (7/7)	85.7
Subject 2*	42.8% (3/7)	100% (7/7)	100% (7/7)	80.9
Subject 3*	71.4% (5/7)	100% (7/7)	100% (7/7)	90.4
Subject 4*	57% (4/7)	100% (7/7)	100% (7/7)	85.7
Subject 5	42.8% (3/7)	100% (7/7)	100% (7/7)	80.9
Subject 6	71.4% (5/7)	85.7% (6/7)	100% (7/7)	85.7
Subject 7	71.4% (5/7)	85.7% (6/7)	100% (7/7)	85.7
Subject 8	42.8% (3/7)	100% (7/7)	100% (7/7)	80.9

Table 5.1. Individual recognition results for 21 emotional episodes on 8 subjects (* Denotes Highly Emotional Individuals).

		Recognition Results per Category		
		Positive	Neutral	Negative
Subject 1*	Positive	4	3	0
	Neutral	0	7	0
	Negative	0	0	7
Subject 2*	Positive	3	4	0
	Neutral	0	7	0
	Negative	0	0	7
Subject 3*	Positive	5	0	2
	Neutral	0	7	0
	Negative	0	0	7
Subject 4*	Positive	4	1	2
	Neutral	0	7	0
	Negative	0	0	7
Subject 5	Positive	3	4	0
	Neutral	0	7	0
	Negative	0	0	7
Subject 6	Positive	5	0	2
	Neutral	0	6	1
	Negative	0	0	7
Subject 7	Positive	5	2	0
	Neutral	0	6	1
	Negative	0	0	7
Subject 8	Positive	3	4	0
	Neutral	0	7	0
	Negative	0	0	7

Table 5.2. Confusion Table for recognition results of 21 emotional episodes on 8 subjects (* Denotes Highly Emotional Individuals).

Overall recognition rates (%)					
Highly-Emotionally Intense Subjects		Medium- and low- Emotionally Intense Subjects		Overall Results	
Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
85.71	3.36	83.3	2.38	84.52	3.14

Table 5.3. Overall recognition results of 21 emotional episodes on 8 subjects (* Denotes Highly Emotional Individuals).

Results in Tables 3.1, 3.2, and 3.3 demonstrate that the trained AANN was capable of appropriately learning and acquiring the relationships between sensors associated with the emotional episodes and that were embedded in the training physiological data. The residual between the neutral and the positive and negative emotional was sufficient for the status and valence SPRT modules to differentiate between the various emotional categories with an 84.52% of efficacy.

It is notable that it appears that it was more difficult for experimental subjects to respond positively to pictures associated with a positive mood. Tables 5.1 and 5.2 demonstrate that there was more difficulty in eliciting the targeted positive emotion than in correctly eliciting the negative emotions with recognition rates for positive emotions much lower than those obtained from identifying neutral and negative emotional states. This phenomenon is in line with results from psychological studies showing that some positive emotions do not have as strong physiological components as negative emotions do [Ito98, Levenson91].

5.9 The ground truth about physiological changes

There is a more fundamental question in the argument of whether a given physiological change could authentically be attributed to an emotional state and not be the result of unstable operation of the equipment being used to measure such physical change. The question about the ground truth of physiological data has been asked in the past and it is recognized to be an important, critical issue. In this respect, it could be said that there is substantial evidence supporting the argument that emotional episodes often involve unique correlations among physiological signals which are different and could be distinguished from those linked to noise or other elements such as exercise [Picard97, Prkachin99, Smith03, Levenson92, Lang79]. It is reasonable then to assume that the utilization of a multivariable mechanism such as an Autoassociative Neural Network is a good option to try to address the problem of the origin of physiological changes because, as previously mentioned, the operation of an AANN is based on the relations developed among the inputs and non-correlated data is continuously discarded.

5.10 Analysis of Validation for Extra-Group Generalization

An *entirely new* set of physiological data was collected from a physically fit and high- affect intensity female aged 46 with the intention of determining whether the detection system was capable of generalizing from the original dataset and recognizing emotional states for any subject. Following the same pre-study requirements described in Chapter 4, emotional states were elicited using 21 pictures from the International Affective Picture Systems (IAPS) which were presented on the screen for 6000 ms with 35000 ms inter-slide blanks while the volunteer remained in a semi-recumbent position with the finger clip attached to her body. The selection of the IAPS pictures (7 neutral, 7 positive and 7 negative) was based on their high arousal and valence values in order to guarantee an optimal response from the participant. The subject was instructed to avoid exploratory eye movement while the pictures were on the screen. At the moment of the projection the subject confirmed that she was in a neutral emotional state because of a previous personal meditation session. Table 5.4 shows the results obtained after the collected data were provided to the trained AANN in a continuous fashion thus resembling real-time operation.

Verbal self-reports after the presentation evidenced that some of the pictures did not evoke the targeted emotions in this particular subject. In order to identify data relating to the failed stimuli, the original dataset (which was initially acquired uninterruptedly) was divided according to the various emotion categories they belonged to (7 datasets per emotional category). Subsequently, I conducted a series of Wilcoxon similarity tests on the 7 data sets within the positive and negative emotional episodes. This cross comparison is useful to discover those datasets that behave as "outliers" within the same affective category. The identification of failed stimuli using both subject accounts and mathematical tools instead of an entirely subjective discrimination enhances the validity to the results and provides more veracity to the analysis. After the elimination of physiological data from unsuccessful emotional stimuli, I reassembled the remaining datasets and provided them as a single continuous data stream to the AANN. Results are depicted in Table 5.4.

It can be seen from Table 5.4 that the emotional system was able to recognize the majority of the emotional episodes with 71.42% accuracy for the entire set of 21 emotional episodes and 80% if data from the failed stimuli is not considered. Emotional changes (neutral and non-neutral) were recognized in ten out of 14 occasions while a positive emotion was erroneously labelled as neutral 4 times and a neutral as negative in 2 instances. The recognition rates shown in Tables 3.1, 3.2, 3.3, and 3.4 demonstrate that the performance of the method described here is comparable to the best results achieved through off-line analysis of statistical features.

Emotional Stimuli (Original set)	Detection Output	Emotional Stimuli (Revised set)	Detection Output
Neutral	Neutral	Neutral	Neutral
Positive	Neutral	Neutral	Neutral
Positive	Neutral	Neutral	Neutral
Neutral	Neutral	Neutral	Negative
Neutral	Neutral	Negative	Negative
Negative	Negative	Positive	Positive
Neutral	Negative	Negative	Negative
Negative	Negative	Negative	Negative
Positive	Positive	Neutral	Neutral
Negative	Negative	Negative	Negative
Negative	Negative	Positive	Neutral
Neutral	Neutral	Negative	Negative
Negative	Negative	Neutral	Negative
Positive	Neutral	Neutral	Neutral
Positive	Neutral	Positive	Positive
Negative	Negative		
Neutral	Negative		
Neutral	Neutral		
Positive	Positive		
Negative	Negative		
Positive	Positive		
Overall recognition rate: 71.42%		Overall recognition rate: 80%	

Table 5.4. Recognition results for the original 21 emotional episodes and after the elimination of data corresponding to failed stimuli.

It is important to mention that the fact that some emotional episodes were not recognized by this system or were attributed to a conflicting category, could be related to the personal reaction to the pictures' emotional content rather than to the performance of the classification system itself. For instance, the fact that an emotional episode was recognized by the system as a negative one when the actual stimulus was neutral, does not entail an error in the system but instead the detection of the subject's actual reaction to that particular stimulus. Because the parameters used in the two SPRT modules (means and variances) to distinguish the different emotional states were based on the residual values from the entire group of 8 original volunteers they would remain valid for a population with similar emotional characteristics. Furthermore, the use of small alpha (α) and beta (β) values in the SPRT module, guarantees the accuracy of the verdict provided by the system regardless of the uncertainty introduced by personal interpretation of the stimuli. In other words, the fact that in both experiments some participants were of high emotional intensity makes it more likely that the intended emotional states actually occurred, and because the system was trained to detect and classify the physiological response associated with such emotional states, the validity of the results presented above should remain valid.

It is worth noting that one prerequisite for the optimal operation of the AANN is the 0-to-1 rescaling of real-time data using the subject's individual maximal and minimal recorded values for each physiological signal during experimentation. In fact, the use of maximal and minimal values other than the ones related to the subject being examined could lead to very poor AANN estimations and consequently low recognition rates. In this regard, although an initial collection of data with the sole purpose of determining maximal and minimal physiological values could seem as a limitation of the system, it actually is a normal tuning or pre-training process used in many agent configurations.

5.10.1 The X-Vest - A User-Independent Real-time Emotion Recognition Wearable System

As pointed out by Alcañiz and Rey [Alcañiz05], one requirement for realistic emotion detection inside pervasive environments is the utilization of wearable artefacts capable of interpreting signals coming from the autonomic nervous system and translating them into useful classes of emotional expressions. The obvious choice is to employ sensors that either by being in direct contact with the user or using remote sensing could provide uninterrupted measure of physiological signals. In accord with this approach, I have developed a wearable artefact which I called the eXperimental Vital-sign-based Emotional State Transmitter or X-Vest. The X-Vest is capable of capturing and communicating the wearer's emotional state in real time using wireless technology.

5.10.1.1 *Remote Real-Time Emotion Detection*

The X-Vest has been designed to work in conjunction with the real-time emotion methodology described in the thesis so far. The sensing interface along with batteries and transmitters is embedded into a hunting jacket (see Figure 5.5). Once sensors are initiated they continuously transmit the user's current physiological information onto a PC computer where bodily signals are classified dynamically using AANN residuals. Both the signal processing and the classification module are parts of a single software application (located on the PC) and operate in "listening mode" i.e., their operation begins as soon as the signals from the sensing device are received.

The main characteristics that make my emotion detection mechanism suitable for the study of emotions inside IIE include:

- 100% recognition rate in detection of changes in the neutral emotional state of a single individual when her physiological data was used to train the AANN.

- Robustness against physiological changes caused by physical exertion.

- Guaranteed performance for different degrees of affect intensity.

- Around 84.52% of recognition rate on 3 emotional categories for 8 individuals whose physiological information was included during AANN training.

* At least 71.4% recognition rate in the detection of 3 emotional categories on generalization trials.

Figure 5.5. The X-Vest. Jacket, sensing device, and transmitter.

5.10.1.2 *Architecture*

The X-Vest integrates the finger sensor used in the earlier experiments to deliver three physiological signals, i.e., heart rate (HR), skin resistance (SR) and blood volume pressure (BVP) (see Figure 5.6). These physiological signals, along with the skin resistance gradient (GSR) and the signal's entropy expressed as the speed of the changes in the data (CS), are sent to a PC using a Bluetooth connection where they are used to feed the signal processing module. The emotion detection system runs as a Universal Plug and Play device on a PC allowing remote cross-platform access (see Figure 5.6).

Note that the combination of the X-Vest and a sufficiently robust user-independent emotion detection mechanism makes it possible to carry out experiments where a subject is free to move and act normally while their emotional state and its dynamics are being monitored and used by an IIE agent.

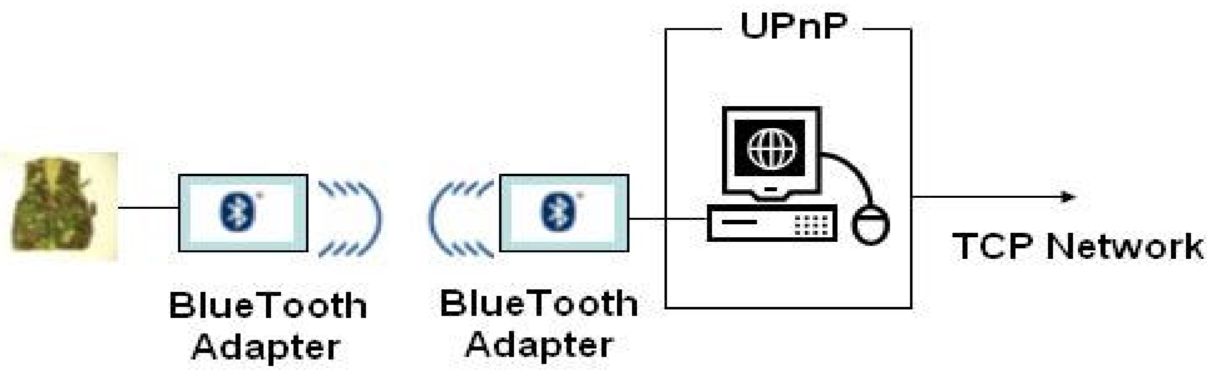


Figure 5.6. The X-Vest. Architecture.

5.11 A Multi-User, Real-Time, Robust Emotion Detection System for Intelligent Inhabited Environments

This work demonstrates that realistic user-independent real-time detection of emotional states in pervasive computing is feasible. It has been shown that the collection of emotional data from eight subjects with different affect intensity levels was sufficient to provide an AANN with enough information to generalise in the presence of data not included during training. The enhanced generalization capabilities of this system were confirmed by recognizing emotional states on a totally new subject, whose physiological data was not part of the original training set, in real-time with a 71.4% accuracy based on the original categorization of the emotional stimuli and 80% after the elimination of invocative or contradictory stimuli.

It is important that the AANN was not only able to generalize within the population whose data was used during training (from a resting to a non resting condition) but was also capable of detecting emotional changes on a subject whose data was not included during training, with a recognition rate similar to the ones obtained by other methodologies using off-line analysis. Thus, it seems plausible to suggest that my system was capable of identifying and learning bodily variations associated with emotional states, and moreover that this knowledge could also be applicable to a wider population of subjects.

Furthermore, these latest results confirm that the use of a pre-trained AANN in conjunction with a SPRT-based decision module provides a mechanism that can reliably distinguish emotional states with high recognition rates. For the purpose of this analysis it has been shown that emotion detection could be done in principle for any subject, independently of whether information about his/her bodily signals was previously used to train the system, as long as his/her maximal and minimal physiological response is known. The combination of this recognition system along with portable sensing equipment would provide me with the mechanisms I need to integrate emotional states into decision systems in pervasive computing and utilize both emotional and behavioural information to assist the user in his/her daily activities with special attention to comfort.

For this purpose, I will describe in the next chapter how the X-Vest was integrated into an existing IIE agent allowing the detection mechanism presented above to be deployed and operate on a subject who is able to move freely and comfortably inside an IIE. Consistent with my initial hypothesis, it is argued that a potentially significant insight into the interrelation between emotions, environment and user actions could be achieved using affective software agents. It is worth noting that the embodiment of the emotion detection system in an affective agent preserves the advantages associated with the agent's attributes of robustness, adaptability, scalability, and immediate, accurate response to changes in the environment.

"Emotions face both in and out: they reflect facts about the subject, but refer also to something outside, to which they typically are responses. In this respect they offer both an analogy and a contrast with sensory perception" Ronald De Sousa

Chapter 6

Towards Affective Pervasive Computing: An Ambient Intelligent Affective Agent

6.1 Emotions and The Home of The Future

A generic description of the ideal home of the future might be that of a sympathetic environment. That is, a space that responds to us and pleases us with sets of natural and artificial entities that are in some ways sensitive to our interests, tastes, and preferences. If you were to look closer at such an environment you would find that the unremarkable surface of this apparently normal environment incorporates a "latent" society of sensors and effectors ready to be triggered in response to situational clues. These devices which have been constructed to learn from the user's previous moods and its behaviours, complement their emotional repertoire by knowing what they want. The home is therefore one of the centres of behavioural changes caused by emotional states and therefore an invaluable source of information for embedded artefacts. In studies investigating the sources and effects of stress and coping mechanisms for commercial and military pilots, researchers have made two important discoveries with regards to home-based stressors. They found that while the most stressful situations were home-related issues [Fiedler00], the most effective ways to cope with stress were also associated with home life [Sloan86]. Fiedler et al. found that, for example, one of the most stressful domestic factors for helicopter pilots at two American bases was the "build up of tasks, duties, and things to do", and that at the same time one of the two most helpful factors in dealing with stress was a "smooth and stable home life"! We are all aware of these tensions and it is difficult in general to accurately identify and point out the exact source and effects of our feelings of happiness or anger among other perhaps more subtle emotions. For instance, while we all recognise that financial problems, work difficulties, or personal losses are great sources of negative emotions it is not clear whether other circumstances such as weather and pollution also negatively affect our behaviour and emotional states when we are at home [Berkowitz93] thus colouring our interaction with the environment and influencing our decisions. In this sense then, affective pervasive computing provides the means though which our emotions might become an integral, dynamic part of ambient intelligence thus endowing inanimate household objects with the capacity to interpret our state of mind, understand our behaviour, be empathetic towards our motivations, be efficiently proactive, helpful and economic at the same time, and ultimately satisfy our needs in a futuristic, fulfilling, diligent way.

In this chapter I will outline the design of a software agent that includes emotion recognition capabilities based on the methods and systems described in previous chapters of this thesis. The objective of such agent is to become a research tool to determine the degree to which the incorporation of emotional information from the user is of value to decision making in ambient intelligence. It is also relevant to deciding whether my system is the appropriate mechanism for affective pervasive computing by enabling me to perform comparative testing between my affective and other agents.

6.2 Affective Computing for Ambient Intelligence

From my initial aims stem two of the main ideas around which this thesis revolves. The first one concerns the widely accepted fact that some of the most important attributes of pervasive computing systems, namely adaptability, context awareness, and intelligence, hinge on continuous interactions with the user. From these interactions, intelligent systems are able to develop their behavioural models which can ultimately lead not only to increased accuracy of the user current needs but also to opportune anticipation of future requests. However because emotional states exert an enormous effect on human behaviour, I have suggested that models stemming from human-machine interaction are incomplete if they do not take into account our emotions. In fact, the utilization of emotional information could not only "complement" pervasive systems but be a decisive requirement to guarantee improved performance. My second major postulate is that emotions could be efficiently integrated into pervasive systems by means of effective physiological emotion detection. I argue that signals related to the body are not only a more reliable way to detect emotions but they have also been suggested as one of the two most adequate mechanisms to the study of behaviour in real-life scenarios.

Since domestic environments are the crucible of many of our strongest emotions and actions, it is reasonable to believe that IIE are a good place to investigate the benefits of affective information on pervasive computing. In passing, I would like to say that until as recently as January 2005, emotion detection inside IIE had only been seen as a promising prospect for investigators in pervasive computing [Alcañiz05]. Although it is true that the majority of research initiatives concerned with pervasive systems have in some way envisioned the need for incorporating emotional states detectable through physiological data into their applications (see for example Phillips' Home Lab vision statement [Homelab03]), none to date had made concrete steps towards the utilization of emotions (expressed as bodily signals) to test the theory that emotions could indeed be of crucial importance for interactive systems. As far as I am aware no one to date has designed and implemented a real-time physiological emotion detection mechanism to gauge user comfort inside IIE. In this regard the experiments presented here are at the forefront in the study of integrating affective computing and ambient intelligence systems.

6.3 Recognition of Emotional Changes Inside Intelligent Inhabited Environments (IIE)

As is argued by EQ theory, being capable of recognizing and effectively using our emotions is a key element in our lives. Some of the advantages associated with the aptitude to interpret emotions include better communication, less stress and empathy towards other people's feelings. When we translate this into software agents, we might find many potentially beneficial applications other than Intelligent Inhabited Environments (IIE) could be found in areas such as medicine, psychology, and sport science.

In Medicine for instance, affective IIE agents could be an enormous boost for the services Tele-care systems can offer. Because stress levels and negative emotions have been widely recognized as influential detriments to the immune system, the opportune identification of such affective states could provide medical staff with means to continuously monitor the patients' physical and mental well-being thus avoiding unnecessary visits to the clinic. Perhaps the most propitious medium for the development of devices rendering the immediate changes in the emotional conditions of an individual is still that of psychological analysis. Although psychologists have been for a long time developing methods to measure emotions, equipment providing affective information at the sophistication and intimacy level a IIE emotional agent can open a new way of exploring human psyche. A corollary of the latter could be the study of adverse feelings (e.g. fear and anger) for athletes inside domestic environments, something that has been proven to be a major obstacle for maximal competition performance.

The dynamism of living environments however necessitates of reliable ways to obtain emotional information without putting extra pressure on the subject being studied and without dramatically disturbing his/her activities. I have mentioned that facial and speech emotion detection could provide remote detection without the need of putting any sensing device on the users but it is also a known fact that cameras and microphones are very likely to alter human behaviour and moreover, the number of cameras and microphones needed to closely monitor user actions in ambulatory conditions might be enormous. That is the reason why one of the most active areas in affective computing has been the design of artefacts to remotely measure bodily signals associated with emotional states. Such portable devices can accompany the users at all moments independent of their location and current activity.

In previous chapters, I outlined a novel real-time mechanism for analysing physiological signals and deriving an accurate characterisation of emotional state in terms of three categories – neutral, positive and negative. Such mechanism was later implemented as a wearable artefact called the X-Vest designed for comfort by maximizing user's freedom of movement. The purpose of this portable device is to measure the physiological concomitants of emotional episodes under real-life conditions without greatly interfering with the user's regular activities. In the following sections I will complete the development of an overall intelligent system that detects emotions inside IIE by developing two new IIE agents from an existing IIE agent using the emotional information provided by the X-Vest.

6.4 An IIE Fuzzy Logic Agent with Emotion Detection

Because my main intention is not to analyse agent design but instead the impact of emotions on room control and behaviour modelling inside IIE, I need to use an established intelligent agent that has already been used successfully within such environments. Thus, I am going to use a fuzzy agent that has already been shown to possess improved adaptability for operating inside intelligent environments [Doctor05].

This implementation of a Fuzzy Logic Controller (FLC) is based on the utilization of the Adaptive Online Fuzzy Inference System (AOFIS) outlined in Chapter 2 to produce a model of the user's behaviour inside domestic environments, more specifically, the iDorm2. The iDorm2 is an experimental testbed for intelligent agents developed at the University of Essex comprised of a self-contained apartment containing a kitchen, two bedrooms, a living room, and a bathroom. After an initial training phase the fuzzy agent is able to extract fuzzy rules and membership functions from ambient information and then use such rules and functions to efficiently control the environment during an adaptation phase while guaranteeing user's comfort.

6.4.1 Agent Implementation

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. The environment contains artefacts subject to agent control which include four variable intensity spot lights, a desk lamp, and two PC-based applications namely a word processing and a media playing program. This original input vector will be supplemented by the X-Vest. An important attribute of this particular agent is its capacity to adapt its control algorithms (control model) to respond to the user's changing use of the environment based on a continuous sensing of user actions and the state of that environment. Thanks to this long-term learning functionality the fuzzy agent provides an enhanced depiction of the state and user behaviour inside the iDorm2.

An interesting research question concerning the incorporation of new sensor-based emotional information relates to the forms in which this information is made available. As an initial foray into this question it was decided that the emotional information would be provided in two different forms. One in which the categorisation of the emotional state was discretized into one of three emotional valence values (neutral, positive, and negative). The other in which a raw calculation of the bodily differences between these three emotional categories was provided for the fuzzy system to deal with as it would a normal sensor value indicating environmental changes. Such raw calculation would be taken from the residual values associated with a given physiological signal. Note that under normal conditions the value of the residual would be close to zero (with a given standard deviation) and would only be altered as a result of an emotional change. Based on a three-class cluster analysis the heart rate (HR) was the physiological signal that provided the best separation between neutral, positive, and negative with a DBI of 21.78 followed by CS with 28.74.

Including the original agent there are thus three different implementations of this fuzzy agent: 1) the original agent with no emotional information (NEA), 2) an agent using an extra input value involving discretized emotional values as provided by the SPRT-based classification module (1-

Neutral, 2-Positive, 3-Negative) (DEA), and 3) an agent with raw fuzzified emotional data added to the original input vector (3 Fuzzy sets stemming from the AANN residual of the HR using the output of the signal processing module) (RFEA) (see Figure 6.1).

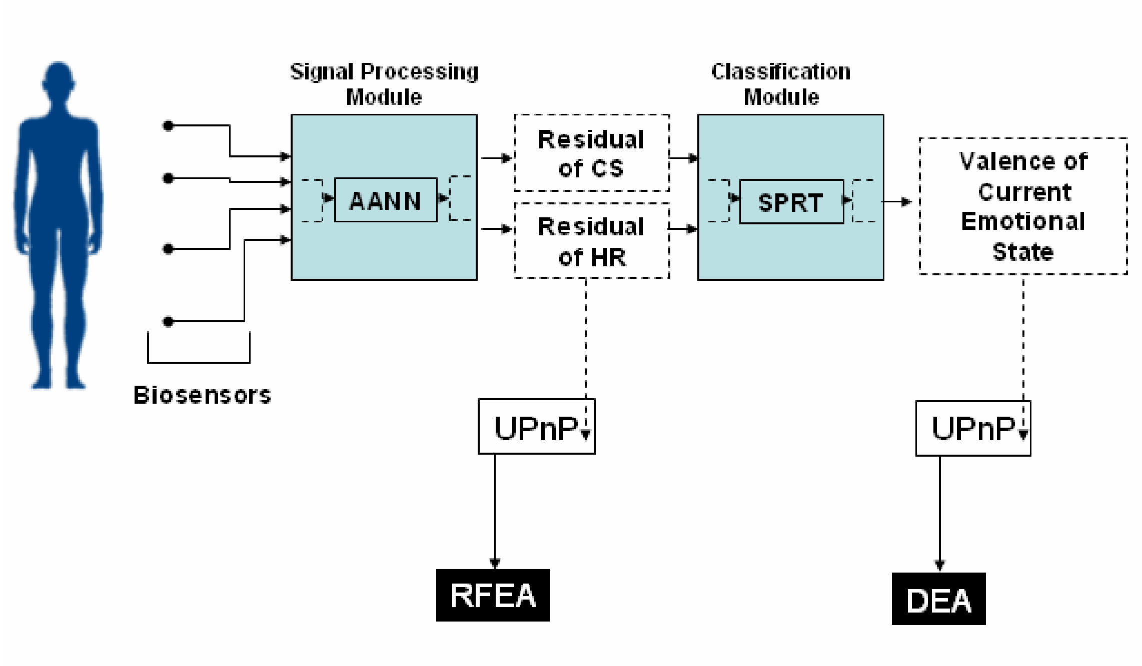


Figure 6.1. Inputs to affective IIE agents where HR is the heart rate and CS is the signal entropy.

Figure 6.1 draws attention to a crucial difference between DEA and RFEA: While DEA uses the HR to detect emotional changes and then the CS to classify the previously detected emotional change, RFEA employs the HR to provide one-pass classification of emotional categories. These two configurations entail particular attributes.

Firstly, my separation of the emotion detection procedure into two separate processes was from the beginning envisaged as a flexible design providing modularity and scalability to any potential agent implementation. For instance, I could modify or increase the number and type of emotional categories detected by DEA simply by reconfiguring the second SPRT module (valence) or adding new SPRT modules capable of recognizing other emotional categories. Moreover, this could be done without affecting the detection of emotional changes (status SPRT), without the need for AANN retraining, and independent of the agent architecture.

On the other hand, the use of the HR in RFEA is both efficient and practical. It is efficient because the HR alone provides information to perform one-pass emotional detection thus reducing computational costs. It is practical because emotional information is masked as a regular sensor. A shortcoming of this approach is that any future changes in the number of targeted emotional categories would imply alterations in the agent's internal configuration.

6.4.2 A Real-Case Introduction to Fuzzy Logic Controllers (FLCs)

It is important to mention that in order to remain congruous with the aforementioned objective of this investigation, i.e., evaluating the advantages of affective information for pervasive systems, I haven't modified the underlying functioning mechanisms of the original non-emotional fuzzy agent. All that was done was to increment the input vector to accommodate the two different types of emotional information (discrete and raw fuzzified). In that respect, the three agents were seen and treated as black boxes, i.e., I changed the input set and analysed the effects on the tangible operation of the IIE without great concern about the internal inference strategy (part of which in fact remained as intellectual property of agent designer). However and for the purpose of properly interpreting some of the discussions that will be presented later, it is convenient at this point to afford a brief explanation of what a Fuzzy Logic Controller is and how it works. Let's start by describing the idea behind Fuzzy Logic.

Fuzzy Logic is an inference methodology that arises from the necessity to construe the impreciseness and vagueness of real-life problems using a language similar to the one used in human intuition. Built on the concept of Fuzzy sets, Fuzzy logic extends the boolean class membership of traditional (also known as crisps) sets (a given element belongs to a class or category or not) to allow degrees of membership (an element belongs to class up to a certain degree). These so-called membership functions could be simple linear or singleton (one value) relations or gaussian or sigmoidal models (See Figure 6.2). The membership values that result from the utilization of a membership function are the "fuzzified" equivalent of the input dataset.

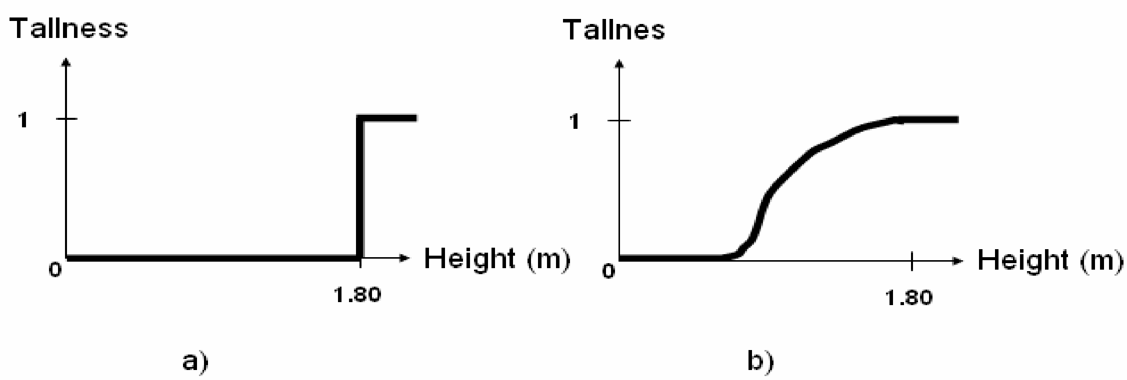


Figure 6.2. Membership representation of a) a Crisp set and) a Fuzzy set.

Fuzzy Logic Controllers (FLCs) use Fuzzy Logic and Fuzzy sets to interact with the environment using associations between inputs and outputs expressed as linguistic IF-THEN rules with membership functions as subjects and fuzzy logic operations as verbs [Bezdek81]. FLCs have been widely used in automatic control because of their characteristic of robustness to noise and changes in input parameters [Ordoñez97]. The operation of a FLC normally encompasses 5 stages: 1) Identification of input and output variables as well as their associated membership functions; 2) Fuzzification of input data using membership functions; 3) Translation of fuzzified data into linguistic terms (fuzzy rules); 4) Application of these rules using input data, and 5) Production of crisp control actions or defuzzication. I will illustrate these operating phases by describing in brief how they are realized in the case of my IIE agents. For a more detailed explanation see [Bezdek81].

- Determination of membership functions and Fuzzification

The number of input and output variables was determined according to the quantity of sensors and actuators located inside the iDorm2. It has been said that these comprised 7 inputs for the Non-emotional Fuzzy Agent (NEA) and 8 for the Discretized Emotional Fuzzy Agent (DEA) and Raw Fuzzified Emotional FuzzyAffective Agent (RFEA) plus 6 outputs in all cases. Membership functions are automatically generated by the Adaptive Online Fuzzy Inference System (AOFIS) using data acquired during the training phase of predetermined duration. After an initial categorization of input and output parameters using high-level definitions, e.g., VERY LOW, LOW, MEDIUM, HIGH, and VERY HIGH in the case of the light and temperature levels, or ON and OFF for the pressure sensors, AOFIS performs two concatenated clustering techniques to determine the centres of the various memberships functions that would best model the available data. These centres are subsequently used to estimate the parameters of the gaussian and singleton functions used to fuzzify (apply membership functions onto real-life data) incoming environmental data.

- Rule extraction

In AOFIS the extracted membership functions and input and output data, $x = (x_1,..., x_n)^T$, and $y = (y_1,..., y_k)$, are combined to produce a set of multi-input, multi-output set of rules of the type:

$$IF\ x_1 \text{ is } A_1^{(l)}\ and \ldots and\ x_n \text{ is } A_n^{(l)}, THEN\ y_1 \text{ is } B_1^{(l)}\ and \ldots and\ y_k \text{ is } B_k^{(l)}$$

Where l is the index of the rules and M is the number of rules (l=1,2,…,M). There are V_i fuzzy sets $A_s^q\ q=1,\ldots,V_i$ defined for each input x_s where s=(1…n) with n=7 for NEA and n=8 for RFEA and DEA. There are W fuzzy sets $B_c^h, h=1,\ldots,W,$ defined for each output y_c where c=(1…k) and k= 6 for my purposes.

Using the combination of input/output pairs and the available membership functions, AOFIS creates an initial set of rules containing all the possible combinations of variables and membership functions. In a subsequent step, these rules are refined and compacted by the elimination of those parts of the rules that are associated with low membership values.

Because each input/output pair can potentially result in one fuzzy rule created, the refined rule set is subjected to a process in which rules are merged together depending the similarities of their IF statement and also on the weighted value of their fuzzified components. An example of a rule generated this way is:

```
IF
      InternalLightLevel is LOW and ExternalLightLevel is HIGH and
      InternalTemperature is VLOW and ExternalTemperature is LOW and
      ChairPressure is OFF and BedPressure is OFF and Hour is Morning
THEN
```

```
ACTION_Light1_value is VLOW and ACTION_Light2_value is VLOW and
ACTION_DeskLight_state is OFF and ACTION_MSWord_state is STOPPED and
ACTION_MSMediaPlayer_state is STOPPED
```

The premise before the “THEN” statement is called the “antecedent” and the one after is referred to as the “consequent”. The antecedent involves fuzzifying the inputs and applying fuzzy operator whereas the consequent specifies the fuzzy set that will be modified to the degree specified by the antecedent. Output membership functions are singleton fuzzy sets, i.e. they only have one value within the entire solution space at which they are valid.

- Defuzzification and Control

The process of deriving membership functions and rules from sample data is in fact the mechanism through which the agent captures the behaviour of a subject living inside the iDorm2. However, because fuzzy rules implications produce values which are related to fuzzy sets (the degree to which the output value is the answer we look for), such values need to be converted back into crisps values so that they could be applied onto real-world applications. Thus, once AOFIS has extracted membership functions and rules from the training data, control is achieved in the following manner: 1) Data about the current environmental and emotional conditions is collected from sensors; 2) Sensing data is fuzzified and then provided to all the rules which are executed in parallel; 3) The utilization of the AND operator in the rules means that the maximum values of each individual component in the antecedent of the rules will be multiplied (a procedure called max-product composition) to obtain single membership value for the consequent; 4) These outputs are then combined together and later converted into crisps values using the x-coordinate of the point of maximum height; 5) The resulting defuzzified values are associated with real operational values for each of the actuators.

Remember that this implementation of a FLC features on-line adaptation and life-long learning in which rules can be modified, discarded and created to accommodate changes in the user behaviour. There are two main operational guidelines involved in this adaptation process. We have on one side the adaptation of existing rules which is done by capturing a snapshot of the environment whenever the user overrides the agent. The values of the sensors and actuators are used to produce a new rule that is compared to the existing rule that was overridden by the user. If the maximal membership value of components in the antecedent from the new rules is greater then the old rule is replaced. On the other side we have what it is called “learning inertia” in which a rules are adapted only after the user preferences have reoccurred several times (a variable parameter).

6.4.3 Affective Agent Operation- Fuzzified vs. Discretized

There are three main differences in the design and operation of the Raw Fuzzified Emotional (RFE) and the Discretized Emotional (DE) agents: 1) In terms of how emotional information is processed; 2) The number of emotional categories the agents can accommodate; and 3) In the manner they respond to changes in physiological data.

The first difference is rooted in the membership functions that are employed to fuzzify physiological data. While RFE utilizes gaussian membership functions, DE employs singleton models which in reality represent rigid crisp sets. The reason for this lies in the type of emotional information DEA and RFEA can handle. On one side the combined outputs of DEA’s SPRT modules only permit four possible discrete values: 1 for neutral, 2 for positive, 3 for negative and 0 a change that has been detected but no decision had been made at the moment of sampling, whereas on the other side RFEA operates on the continuous non-linear value of the HR residual. The centres of RFEA's three gaussian fuzzy sets are calculated based on the mean residual value of each of three emotional categories calculated from the data employed for AANN training (see Figure 6.3)

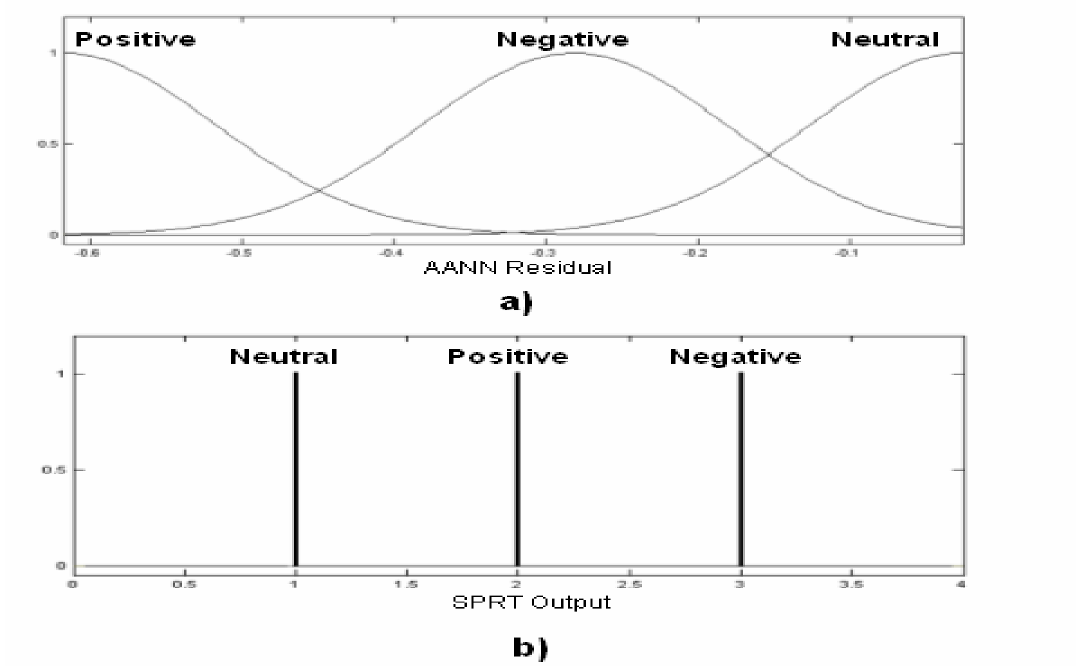


Figure 6.3. Effects of Fuzzification for a) RFEA and b) DEA.

This first difference promotes a more profound dissimilarity in the interpretation of emotions that the two emotional agents can cater for. Because Gaussian functions permit different degrees of membership, RFEA allows the combination (overlapping) of various degrees of positive, negative, and neutral emotions. In contrast DEA accommodates the entire emotional spectrum into 3 single categories along Osgoods' valence dimension. If we consider that according to Plutchick most of emotional classes "exist at points along implicit intensity dimensions" and they blend into one another, then it could be inferred that RFEA is capable of recognizing many of the emotions that are often described in subjective terms. In other words RFEA is capable of measuring variable degrees of negativity, positiveness, and neutrality in a given emotional state. We will later see whether this is of any benefit in terms of user satisfaction.

The third difference is related to the way physiological data is processed. RFEA has been designed to evaluate the value of the HR residual estimated from AANN calculation which is a raw indication of how emotional changes are drifting from the neutral emotional state. Because the residual is calculated in real-time, any change would be immediately picked up by RFEA thus potentially allowing more rapid detection of emotional changes (expressed as bodily signals). However this type of operation could also render RFEA sensible to momentary bodily alterations caused by factors such as small changes in the position of the sensors or physiological peaks stemming from the sensing device and that could not reflect a durable emotional change. Moreover, because the agents are designed to record a "snapshot" of the iDorm2 state whenever a change in the inputs occurs, the RFEA model is potentially prone to produce a great number of rules some of which do not reflect actual emotional states but just unrelated transitory bodily changes. On the other hand, DEA is a more stable mechanism that would only report an emotional change after analysing physiological signals from various sequential samples. That is, DEA would report an emotional state change only when there is a very high probability that such a change took place even if this means delaying its decision for a few miliseconds.

6.5 The iDorm2: A Pervasive Environment Featuring Affective Agents

By integrating a reliable emotion detection mechanism using the wearable X-Vest into an existing IIE agent I have made it possible to use the iDorm2 for experiments incorporating data acquired on the emotional states of a subject undertaking real-life activities. I have implemented three different versions of an IIE agent: 1) An AOFIS-based fuzzy logic-based control agent not furnished with emotion based information related to the user's physiological state, 2) the same control agent with an augmented input span using raw emotion information based upon user's physiological changes (residual), and 3) the original Adaptive Online Fuzzy Inference (AOFIS) agent featuring high-level emotion detection based upon the real-time analysis of the user's physiological state using the method described earlier in the thesis. The development of the three agents required close collaboration with the agent designer and required about two month's work including implementation and testing inside the iDorm2. The aim of the next chapter is to present the results of an experiment carried out to test the hypothesis that an intelligent agent that incorporates emotional information into its inference mechanisms is better able to learn from user actions inside IIE and consequently more capable of providing satisfaction than an agent that ignores emotional information. A secondary hypothesis of this analysis will be that meaningful emotional data is more effective than raw emotional data in distinguishing emotional valence and therefore is a more effective way of recognizing user behaviour.

"We have to put emotion back into the brain and integrate it with cognitive systems. We shouldn't study emotion or cognition in isolation, but should study both as aspects of the mind in its brain"
Joseph Ledoux

Chapter 7

Real-life experimentation: Using An Affective Agent to Model Behaviour inside IIE

7.1 Affective Pervasive Computing: A Potential Insight into Human Behaviour

My rationale for believing in the potential benefits of emotion recognition for pervasive computing and IIE in particular is that I am convinced that affective computing could become the corner stone of an evolving process in the way computer applications interpret the world. The culmination of such process of integration between the rational and the affective would result in the development of software systems with exceptional adaptive attributes.

In this chapter I will concentrate on one only aspect of affective computing for pervasive environments. I will report on experiments to see if data from the emotion detection system I have developed could help to improve the way ambient intelligent systems identify, measure, and utilize knowledge about user's behaviour inside IIEs. A short-term longitudinal experiment involving one individual was carried out inside the previously introduced iDorm2. Because as pointed out it is a self-contained domestic environment equipped with many ambient sensors, the iDorm2 is an ideal environment to perform real-life pervasive computing experimentation.

There are a lot of unsolved issues and questions associated with emotion detection and its application to ambient pervasive computing. Hence, the work presented here will be an attempt to answer a number of these basic questions. The questions explicitly addressed by this study are:- Is emotion detection useful i.e. does it improve the way pervasive systems model user behaviour inside IIEs? Could emotion detection enhance adaptability and increase the agent's capability to adjust the environment to reflect user's habitual behaviour and increase their comfort? As a subsidiary to these questions the question of how emotion detection information should be included in pervasive systems is raised, Should it be based on the raw physiological signals or on high-level (pre-processed) categories as in the output from the X-Vest? Other questions related to this issue involve the emotional categories I am detecting – positive, negative and neutral - and whether these are sufficient to improve user comfort?

7.2 Assessing the Impact of Emotions on Ambient Intelligence

7.2.1 Pre-experimental Considerations

First of all it should be said that the type of experiments that will be discussed in the upcoming sections could only be made possible thanks to a collaborative, concerted effort from various parts including the iDorm2 technical staff and the IIE fuzzy agent designer. This of course also means that some decisions with regards to the best way to obtain the information needed for my purposes had to be agreed upon by all the team.

7.2.1.1 *Training and Adaptation Phase*

Because the Fuzzy Logic Controller (FLC) requires a training period in which it records and learns user actions, experiments involving behavioural analysis usually last from a few days to entire weeks. Based on previous similar experiments carried out by the agent designer [Doctor04], it was agreed that two days of training data acquisition would suffice to provide the agents with a reliable initial model of user activities inside the iDorm2. In the same manner, the duration of the adaptation phase was set to 6 days accounting for 2 days per agent. During the adaptation phase the agent controls the iDorm2 on behalf of the user and makes adjustments to the behavioural model acquired during training based on new or altered actions. Although 2 days of actual operation might seem a rather short period in terms of duration, it does nevertheless expose the agent to a sufficiently varied set of situations (under normal circumstances) to provide the agent with enough information about the user behaviour.

7.2.1.2 *Experimental Setting and Participants*

The eventual experimental setting involved the analysis of a subject living inside the iDorm2 for 8 days during the summer of 2005. The participant was instructed on how to use the iDorm2's graphic interface (GI) (see Figure 7.1).

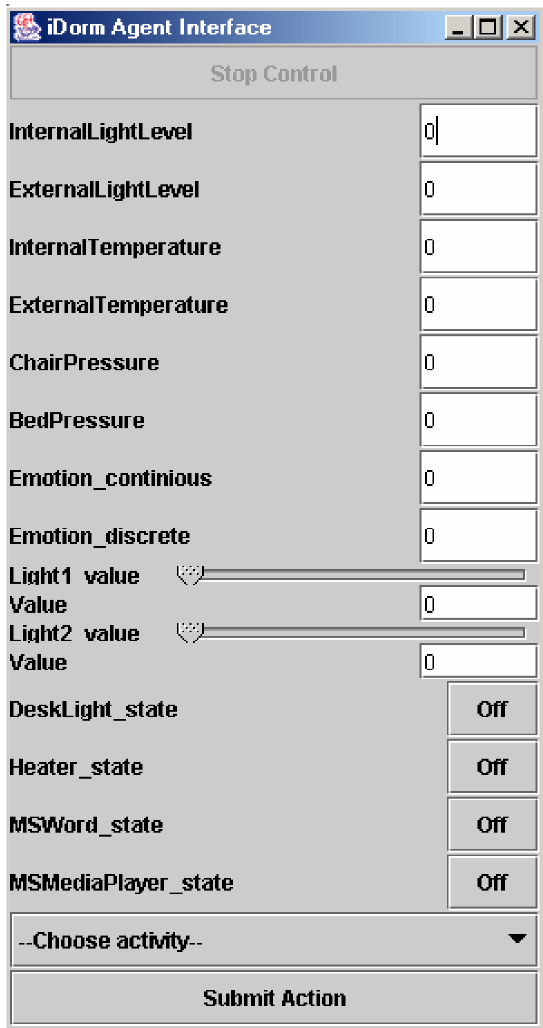


Figure 7.1. GUI of the iDorm2's Agent.

This type of experiment known as longitudinal studies "in which information is collected concurrently on one or many individuals over a time span long enough to encompass a detectable change in development status" [Wall70] have been proved to be an efficient (and sometimes the only) way to study variables associated with social, mental and biological aspects of human development. The history of longitudinal studies date back to 1759, they have been used to study child development, post-war psychological traumas, attitude changes, adjustment to aging and retirement, cognitive and intellectual development, creativity, heart diseases, emotional development, stress and social behaviour among many other topics [Young91]. Particularly interesting examples are those studies employing physiological signals as one of the measures to evaluate real-life intra-familiar life.

There is an argument against longitudinal studies related to the fact that experimental subjects are often chosen in terms of their cooperativeness and availability which makes them unrepresentative and raises doubts about generalization. However, "intensive small-sample" longitudinal studies are sufficiently adequate in many areas including those associated with personal traits and physiological functions. The American Academic C. B. Hindley says about small-sample, intensive longitudinal studies: "The ultimate aim is naturally to produce generalizable findings, but reliance is placed not so much on having a strictly representative sample, which may be impossible to attain, as on the possibility of replicating important findings. This is the normal procedure in scientific inquiry, in which it is by no means assumed that any one investigation will produce conclusive matters". This study accords with such scientific aims. This experiment will involve methods and produce initial evidence to test my hypothesis about the relation of emotion detection and the adaptability of pervasive systems. In this context, the duration of my experiment and the number of subjects involved is directly related to the time needed to collect the numbers of samples required to show the effect I am investigating.

7.2.1.3 *Preparation and System Set-up*

A few days before the commencement of the study, the nature of the study was explained to the subject and then, after signing a consent form, he was measured for physical fitness (he had already being classified as being of low-moderate emotional intensity). He was then asked to perform a series of tasks, the first one being to remain in a semi-recumbent position for 20 minutes while wearing the X-Vest. He was then asked to exercise for 20 minutes on a stationary bicycle at less that 10 mph without the X-vest on and finally rest in semi-recumbent position for 20 more minutes with the X-Vest put back on. The purpose of this procedure was to 1) measure the typical maximal and minimal values of the 5 physiological measures employed by the detection system, and 2) evaluate whether the subject experienced any discomfort from wearing the X-Vest. The estimation of typical values from the sensing device is a requirement mentioned in Chapter 5. This set of values is used to normalize physiological data coming into the system. It should be mentioned that I decided to measure peak physiological values prior to moving into the iDorm2 to be consistent with the way I had conducted the recognition experiments outlined in Chapter 5. However, the estimation of the peak physiological measurements could have also been done inside the iDorm2 under normal living conditions before the beginning of the training phase.

7.2.1.4 *Natural Living Conditions and Affective Assessment*

From the outset, one of the most fundamental principles of my investigation was that any experiments inside the iDorm2 would be undertaken in a way that would minimize as much as possible the disruption of the subject's regular activities thus permitting me to reproduce real-life behaviour in its natural milieu. I therefore decided not to ask the experimental subject to do anything he would not normally do during his stay in the iDorm2. Thus the subject did not log everything that he did or every emotion that he felt (which by itself is extremely difficult anyway). It is true, that although this approach entails advantages in terms of studying normally-occurring emotions, it also raises the question about whether emotional changes detected by the recognition system were in accordance with the user's own emotional perceptions and actions.

As I mentioned earlier Prkachin has suggested that there are two ways to be certain that an emotional change occurred. One is through the use of self-reports and the other by ensuring that the experimental subject is of very high affect intensity. Although self-reports are the most favoured way to verify the occurrence of an emotional episode, they are also extremely impractical. I could not ask the experimental subject to fill in a self-report every given number of minutes or whenever he thought appropriate for this implies a high-level of awareness that not all people have and which becomes a difficult task when one is immersed in other activities rather than meditation for example. It was known that the subject did not posses high affect intensity so that option was not a viable verification argument (although I had proved that affect intensity does not affect the performance of my detection mechanism).

Thus, it was then decided that emotions (as detected by the system) and actual events would be compared and related using two mechanisms. First of all, the investigator would record a diary of the user activities inside the iDorm2 based on observations. Second, at the end of each experimental session both the user and the researcher would analyse the way emotions fluctuated and would verify the occurrence of emotions in relation to certain activities. This post-analysis would not only be useful to identify technical or procedural anomalies of the detection system but would give the experimental subject the opportunity to ventilate personal problems or dramatic emotion-related situations.

Another important characteristic of my experiments is that I wanted living conditions to resemble those a human normally confronts and that often involve a non-localized set of actions performed either in any of the rooms composing our home or at external non-domestic locations. Nonetheless, I also needed a setting that would allow adequate parameterisation of my measurements in a proper, controlled way. Hence, I did want to find a balance between the subject not feeling like a prisoner inside the iDorm2 and a chaotic environment with the subject leaving the room every often. I therefore, decided to ask the participant to stay inside the iDorm2 at very specific, predetermined times of the day. In order to maximize data acquisition, these various time slots were chosen based on the time periods in which more activity is likely to take place under normal living conditions i.e., Morning or Breakfast time (8-10 AM), Afternoon or Lunch time (1-3PM), and Evening or Dinner time (6-8:20 PM).

7.2.2 Results of Emotional Activity and Situational Clues During Training

The routine undertaken by the subject inside the iDorm during training remained very much the same for the entire duration of the experiments. Note that the training phase is extremely important for it is there that the agents build the initial FLC model that will determine the later operation of the agents. Daily routine normally commenced around 8.00 AM with the subject reading and responding to e-mail messages for a maximum of an hour and then moving on to perform some work-related activities. This was done until the end of the morning session (10 AM) and continued for the totality of the afternoon session (1-3PM). The evening sessions usually had the user involved in leisure activities such as watching TV and playing videogames (except for one evening on the fourth day in which the subject felt unwell and remained lying on the couch most of the time). There was no specified time for eating and the user was allowed to feed whenever he felt like it. Most of the time meals comprised a quick snack eaten while in front of the computer during the morning and afternoon sessions or sitting on the couch in the evening sessions.

According to the diary I recorded and also in accord with the subject's after-session verbal reports, mornings were rather relaxed and quiet periods that mainly concerned planning the rest of the day's activities. Afternoon and evening sessions were the most dynamic times, involving various work-related and entertaining activities. In relation to how user emotions oscillated during training, Figure 7.2 shows the results of both the DEA's SPRT-based Classification module and also the AANN residual calculations used by RFEA. In order to determine any possible relation in the way these two parameters represented emotional changes I calculated the correlation between the two sets of samples acquired during the 2-day training phase. Results demonstrated the existence of a strong negative correlation with a value of -0.876 indicating that when one of the measures moves down the other moves up. More specifically, when DEA measures an emotional change from neutral to positive for instance (meaning a shift from 1 to 2), the AANN HR residual value goes down, and vice versa.

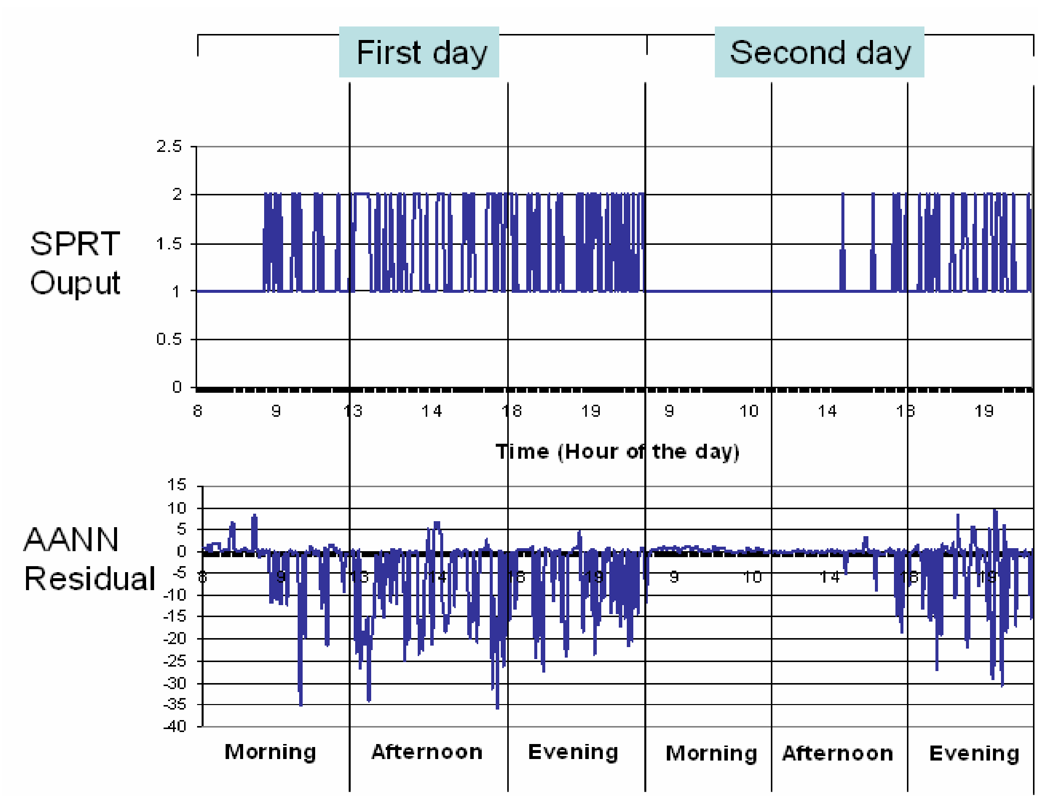


Figure 7.2. Emotional response during the two-day training phase. Expressed as DEA's emotional categories (SPRT Output) and RFEA's physiological data (HR residual).

There is a number of interesting situations that could be inferred from Figure 7.2 (since high-level emotions are easier to understand than psychological measures I will concentrate on the results from the DEA). In the first place, it seems that according to DEA, the emotional state of the subject remained in the neutral-positive range (1 and 2 values) during the entire 2-day training phase. This situation was corroborated by the subject who confirmed that he had not felt negatively in any moment and had not had to deal with any adverse event while in the training phase.

Another notable peculiarity that stems from Figure 7.2 is the number of emotional changes that occurred across the different time slots. There seems to be a relationship between those periods of apparent inactivity and the number of emotions that were detected. This was confirmed not only by the classification module but also by the occurrences of maximum peaks in measured HR residuals which were just a few in some cases, and numerous in others (changes in HR residual mean a deviation from the neutral emotional state). A reasonable explanation could be found in the type of activities that were performed at each given time of the day and how they affected the subject's inner state. Using the user's own account to rate the emotional content associated with each different activity, we will find that reading emails was not a very emotional-eliciting activity apart from the odd email from friends and family which some times might provoke a sudden rush of joy. Working on the other hand is an activity that involves a lot of affective interaction, in particular when attempting challenging activities that might result or not in the desired successful outcome. Even more provocative are videogames and TV watching (especially the former); they carry an enormous emotional load that is released in brief outbursts (anyone familiar with playing videogames or watching sitcoms would agree with this). If we look carefully and associate the activity of the user with the time of the day we will see that as the day progressed and moved from less to more highly emotional charged activities (morning to evening) the number of emotional changes (neutral-to-positive and positive-to-neutral) detected by the system also increased (see Table 7.1). As a "sidebar" discussion I could comment that the relationship between certain creative activities, e.g., playing videogames or working, and the emotional response they provoke could be interesting from a psychological or social point of view.

	Emotional Changes (neutral-to-positive and positive-to-neutral)	
Time Slot	Day 1	Day 2
Morning	18	0
Afternoon	32	4
Evening	45	34

Table 7.1. Total number of emotional changes during the training phase as detected by DEA.

Something that caught my attention on these results was the discrepancy in the number of emotional changes that took place on the first and second day. According to the participant's own assessment this was probably caused by two factors arising from day 1: 1) an augmented number of work-related tasks caused by the adjustment into the new environment (moving into the iDorm2), and 2) a slightly increase in the subject's arousal due to the excitement caused by the experiments.

I was also interested in analysing how environment affected the emotional states during the training period. The estimation of the correlation value between the various climatic parameters seemed to indicate that the variation in the external and internal lighting and temperature conditions did not have a direct effect on emotional fluctuations with a maximal negative correlation of -0.156 between the DEA emotional output and the internal light level. This result however could also be seen as a slim but still existing relation between the amount of light inside the iDorm2 and the subject's emotions (when the light diminished the emotion changed from neutral to positive and vice versa).

7.2.3 Initial Model

It has been mentioned that the agent training phase is crucial because from the initial acquisition of data depends the adequacy of the user's behavioural model that will subsequently be utilized during the adaptation phase. Therefore it is worth having a look at the rules that were created after the two-day training to examine whether emotions made a difference on how such rules were created. Remember that the three agents, Non-emotional Agent (NEA), Raw Fuzzified Emotional FuzzyAffective Agent (RFEA) and Discretized Emotional Fuzzy Agent (DEA), used exactly the same basic environmental information (internal and external light and temperature levels, chair pressure, couch pressure, and time) and the same methodologies to generate their rules. Any difference in the content and number of such initial rules would be attributable to the emotional input in both DEA and RFEA.

The first major visible difference among the three agents was in the total number of rules generated from the information acquired over the two-day training period. We can see in Table 7.2 that the two affective agents produced a greater number of rules than the non-affective agent (NEA) with the RFEA being the most prolific one. This phenomenon could be related to the difference in the number of inputs used by the agents (one more in the case of DEA and RFEA), a factor already under investigation by other researchers [Duman06].

	Total Number of Rules					
	Day 1			Day 2		
	NEA	DEA	RFEA	NEA	DEA	RFEA
Morning	36	43	49	22	19	23
Afternoon	41	49	56	7	15	21
Evening	20	33	28	17	30	34
Total	97	125	133	46	64	78

Table 7.2. Total number of rules included in the initial fuzzy model generated from two-day training data.

Another more crucial difference was found in the way rules were constructed. This difference revealed a clear indication that emotional detection indeed altered the way agents perceived actions inside the iDorm2. Let's examine an example. Below are in Table 7.3 a group of rules created by the NEA and DEA from information collected around the same time in the morning of Day 1.

		NEA		DEA			
		Rule 20	Rule 21	Rule 20	Rule 21	Rule 22	Rule 23
IF	`InternalLightLevel`	VHIGH	LOW	VHIGH	MEDIUM	LOW	LOW
	`ExternalLightLevel`	VHIGH	VHIGH	VHIGH	VHIGH	VHIGH	VHIGH
	`InternalTemperature`	LOW	LOW	LOW	LOW	LOW	LOW
	`ExternalTemperature`	**MEDIUM**	**VLOW**	**MEDIUM**	**LOW**	**LOW**	**VLOW**
	`ChairPressure`	ON	OFF	ON	ON	ON	OFF
	`CouchPressure`	OFF	OFF	OFF	OFF	OFF	OFF
	`Hour`	MORN	MORN	MORN	MORN	MORN	MORN
	`Emotion_Discrete`	-	-	**POSITIVE**	**NEUTRAL**	**NEUTRAL**	**NEUTRAL**
THEN							
	`Light1_value`	VLOW	HIGH	VLOW	VLOW	VLOW	HIGH
	`Light2_value`	VLOW	VLOW	VLOW	VLOW	VLOW	VLOW
	`DeskLight_state`	**OFF**	**ON**	**OFF**	**OFF**	**ON**	**ON**
	`MSWord_state`	RUNNING	RUNNING	**RUNNING**	**STOPPED**	**RUNNING**	**RUNNING**
	`MSMediaPlayer_state`	STOPPED	STOPPED	**STOPPED**	**RUNNING**	**STOPPED**	**STOPPED**

Table 7.3. Comparison of rules created by NEA and DEA in the Morning of Day 1.

If you look at rule 20 in both the NEA and DEA cases and NEA's rule 21 and DEA's rule 23, you will see that environmental conditions expressed in the antecedent and also the settings of the actuators in the consequent are exactly the same the only difference being the extra emotional input in the case of DEA. However, the rules that followed changed radically with DEA picking up the emotional changes that occurred that morning (see Figure 7.2). In DEA's rule 21 we can see that a change in the emotional state of the subject was also accompanied by a specific action (activation of the MSWord application). This action on the actuators could not have been discovered by NEA for it was only diagnosed because of its relation with an alteration of the subject's emotional state. NEA's Rule 21 seems to be associated with a later state where the internal light level is moved from VeryHigh (VHIGH) to LOW. NEA's rule 22 also seems to indicate the gradual change in lighting conditions finally expressed in rule 23. Let's look at another example with rules that were created in the same time frame during the evening sessions of Day 1 (Table 7.4).

If you look at NEA's rules 96 and 97 and compare them to DEA's rules 124 and 126 you will notice that they are almost identical (apart of course from the DEA's extra input). But in between rules 124 and 126, DEA created another rule that reflected an emotional change. This emotional alteration (from positive to neutral) embedded in rule 125 seemed to have preceded the change in the couch pressure sensor that was later detected by the two agents. This subtle behavioural clue could have only been found by the inclusion of the emotional information in DEA's input vector. Furthermore, because the operation of the agents will be the same during the adaptation phase I would expect DEA and RFEA to create more rules than NEA to account for those situations directly linked to affective modulations provided by the extra emotion-based input.

		NEA		DEA		
		Rule 96	Rule 97	Rule 124	Rule 125	Rule 126
IF	InternalLightLevel	VLOW	VLOW	VLOW	VLOW	VLOW
	ExternalLightLevel	VLOW	VLOW	VLOW	VLOW	VLOW
	InternalTemperature	LOW	LOW	LOW	LOW	LOW
	ExternalTemperature	MEDIUM	MEDIUM	MEDIUM	MEDIUM	MEDIUM
	ChairPressure	OFF	OFF	OFF	OFF	OFF
	CouchPressure	**ON**	**OFF**	**ON**	**ON**	**OFF**
	Hour	NIGHT	NIGHT	NIGHT	NIGHT	NIGHT
	Emotion_Discrete	-	-	**POSITIVE**	**NEUTRAL**	**NEUTRAL**
THEN						
	Light1_value	VHIGH	VHIGH	VHIGH	VHIGH	VHIGH
	Light2_value	VLOW	VLOW	VLOW	VLOW	VLOW
	DeskLight_state	OFF	OFF	OFF	OFF	OFF
	MSWord_state	STOPPED	STOPPED	STOPPED	STOPPED	STOPPED
	MSMediaPlayer_state	STOPPED	STOPPED	STOPPED	STOPPED	STOPPED

Table 7.4. Comparison of rules created by NEA and DEA in the Evening of Day 1.

The changes that DEA was able to detect and which were imperceptible to NEA are extremely important primarily for two reasons. Firstly they show that some user actions were accompanied by a change in his emotional state, and secondly they enrich the behavioural model that the agents utilize to interact with the user and operate the environment which in turn could leads to more efficient, friendly, satisfactory operation.

7.2.4 Putting the Affective Agent to Test: Experimental Procedure during Adaptation Phase

As outlined above, the participant lived inside the iDorm2 at specific times for a total of eight days while wearing the X-Vest (see Figure 7.3). The first two days were used to collect ambience and emotional data to train the three fuzzy agents while the remaining six days (the adaptation phase) were used to adjust the behavioural model of the agent. Similar to the training phase, the adaptation phase involved the subject performing a range of activities inside the iDorm2 comparable to those commonly undertaken in everyday life e.g., studying, eating, resting, exercising, etc. It is opportune to emphasize once again that the crucial element in this study is that the participant was asked to behave as naturally as possible at all times and was encouraged 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 the 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, I decided that each agent would be used at a pseudo randomly selected time slot on the same day for the 6-day adaptation period (remember that the training phase was the same for all the agents). 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 (1^{st} and 2^{nd} Session of 120 min. (7200 sec.) each), afternoon (1^{st} and 2^{nd} Session of 120 min. (7200 sec.) each) and evening (1^{st} and 2^{nd} Session of 140 min. (8400 sec.) each). Table 7.5 and 7.6 illustrate the order in which the three agents were used and the ambience conditions on the 6-day controlling phase.

Figure 7.3. Experiments inside the iDorm2 with the subject wearing the X-Vest.

		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 7.5. Assignation of experimental time slots.

			Ambient Conditions (Averaged Values)			
Time Slot			Light		Temperature	
			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 7.6. Light and temperature levels for the 6-day experimentation period.

7.3 Performance Analysis

My main objective was to evaluate the agents performance according to two key categories of behavioural modelling: an Interaction Model, and a User Comfort Model. 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. Comparative results on these two parameters would shed light on whether the inclusion of information about the emotional component of the human decision-making process and which is reflected in how we behave, could actually improve the quality of the modelling of user activities that the IIE agents generate. Two other categories employed to examine the performance of various intelligent agents paradigms in other research are also presented [Doctor04], 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 IIEs with the basis to perform comparisons between the present and other approaches.

The Interaction Model refers to how effective an agent was at modelling user activities inside the iDorm2 during the 6-day period in which the rules developed during the two data training period were applied. One way that this could be evaluated is by examining the number of initial rules and comparing that to the number of new rules that had to be created. This might involve the modification of old rules plus the development of completely new rules. The number of original rules that were unused and the frequency of rules utilization would also provide us with important data on the key issue here - the usefulness and quality of the rules.

Enhanced User Comfort is one of the most important objectives of researchers in the area of IIE agents. The User Comfort Model involves analysing the number of times the user has to interact with the system in order to *override* the settings chosen by the agent inside the iDorm2. Overriding means that the agent failed to configure the environment to whatever the user wanted at that time and is a response to the agent making changes that the user doesn't want or agree with.

7.3.1 Interaction Model

Adaptation of original rules: Table 7.7 shows that in terms of the suitability of the initial FLC model, the agent with raw fuzzified emotional data (RFEA) seemed to have reflected the actions the user took inside the iDorm2 in a better way during the 2-day training phase since only 5.6% of the initial rules needed subsequent adaptations. In contrast 9.5% and 17.4% of the initial rules generated by (DEA) and the non-emotional agent (NEA) respectively, were modified. In the same manner, we should also note that of the RFEA's initial rules 40.3% were fired compared to 39.1% for the DEA and 27.2% for the NEA, thus indicating that a greater number of initial rules were indeed used.

Category		NEA	DEA	RFEA
Total Number of rules		**539**	**768**	**1345**
Number of **initial** *rules (Training phase)*		*143*	*189*	*211*
Number of **initial** *rules adapted during adaptation phase*		*25*	*18*	*12*
	% of Initial	17.4	9.5	5.6
Number of **initial** *rules that fired*		*39*	*74*	*85*
	% of Initial	27.2	39.1	40.3

Table 7.7. Adaptation of original rules.

Adaptation of new rules: The *quality* of the rules generated during the 6-day adaptation 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 (see Table 7.8). 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.

Category		NEA	DEA	RFEA
Total Number of rules		**539**	**768**	**1345**
Number of **new** *rules generated during adaptation phase*		*396*	*579*	*1134*
Number of **new** *rules adapted during adaptation phase*		162	20	633
	% of New	40.9	3.4	55.8
Number of **new** *rules that fired*		*350*	*535*	*940*
	% of New	88.3	92.4	82.8

Table 7.8. Adaptation of new rules.

7.3.1.1 *Discussion on Interaction Model*

In general terms, the overall interaction model generated by DEA (including both the training and adaptation phases) 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 (see Table 7.9). Moreover the overall higher number of fired rules and the number of rules used on less than 6 occasions suggest that DEA was better at adequately identifying the clues in the user's behaviour and adjust the model accordingly especially during the adaptation phase. It is expected that this improved capacity to identify little variations in the user's behaviour and that was evidenced when I discussed the initial model, would give an advantage to recognize user needs more aptly.

These results should be considered with the following factors in mind: 1) As already mentioned more inputs mean more rules, that and not deficient agent operation is the reason why DEA and RFEA created more rules than NEA; 2) The fact that RFEA produced many more rules than the other two agents could be attributed to the intrinsic noisy nature of the AANN residuals (see Figure 7.2). However, it should also be said that the interpolation provided by gaussian fuzzy sets inherently implies a filtering in the input signals since close sensor or residual values would produce similar rules. Furthermore, the agents are designed to eliminate duplicated or inconsistent rules and thus many rules that were generated as a consequence of the noise are continuously discarded; 3) It is notable that the effect of noise in raw physiological did not seem to be factor during the creation of the initial model since RFEA was the agent that performed better with less initial rules being modified and more of them having been used. We could infer then that the noise in AANN residual did not dramatically influence rule creation and in fact raw AANN data could have provided an enhanced level of granularity (level of detail in information) since 40.3% of the initial rules were used in the adaptation phase (as opposed to 27.2 and 39.1 from NEA and DEA respectively). Therefore, the conclusion might be that although RFEA created the best initial model this was insufficient to provide enough information for modelling changes in user actions or that such changes exceeded RFEA inference capacity. This could also be related to why during adaptation phase a large amount of new RFEA rules were created but not used; 4) The DEA seems to have captured user actions in a better way than RFEA and NEA since fewer of its rules needed modification (only 4.9% as opposed to 34.6 and 47.9 respectively). One could suggest that the reason why so many RFEA rules needed alteration lies in the aforementioned variability of AANN raw data which provoked the RFEA to produce many inaccurate rules that needed later modifications. However, the NEA did not have the extra emotional input and yet almost a third of its rules were modified (see Table 7.9).

Category	NEA	DEA	RFEA
Total Number of rules	**539**	**768**	**1345**
Number of **initial** *rules (training phase)*	*143*	*189*	*211*
Number of **new** *rules generated during adaptation phase*	*396*	*579*	*1134*
Total Number of rules Adapted during Adaptation phase	**187**	**38**	**645**
% of Total	34.6	4.9	47.9
Total Number of Rules that Fired	**389**	**609**	**1025**
% of Total	72.1	79.2	76.2
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 7.9. Comparative table of Interaction Models.

7.3.2 User Comfort

The experiment indicated the superiority of the DEA based agent with only 10 user interventions for the entire 6 sessions while the RFEA and NEA were overridden 21 and 21 times respectively, an increase of 110 % in both cases (see Table 7.10). It is notable that the DEA agent was especially efficient in the morning and afternoon sessions while NEA performed slightly better in the afternoon sessions. This seemed rather peculiar especially if we consider that in a session-per-session comparison, DEA outperformed the other two in all but the first afternoon session. Thus, I decided to inspect the data that was collected during that day in an attempt to find a clue for this unusual situation. What I found was that during the hours of the first DEA's afternoon session there had been a number of emotional changes much greater that the one obtained during the two-day training period (56 against 34). This also seemed to coincide with a particularly busy day for the subject. If on top of this we consider that this session was the first one for the DEA after training, it does not seem strange that a number of manual adjustments by the user were in order and caused an outlier in DEA's consistently improved user satisfaction.

		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 7.10. Number of user interventions on 6 days of experimentation.

7.3.3 Progress Function (Learning Curve)

The progress function or learning curve which has been used by other researchers [Doctor04] 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 indicating that the rule base was generally adequate to the behaviour of the user. Table 7.11 depicts the number of new rules created on each experimental session.

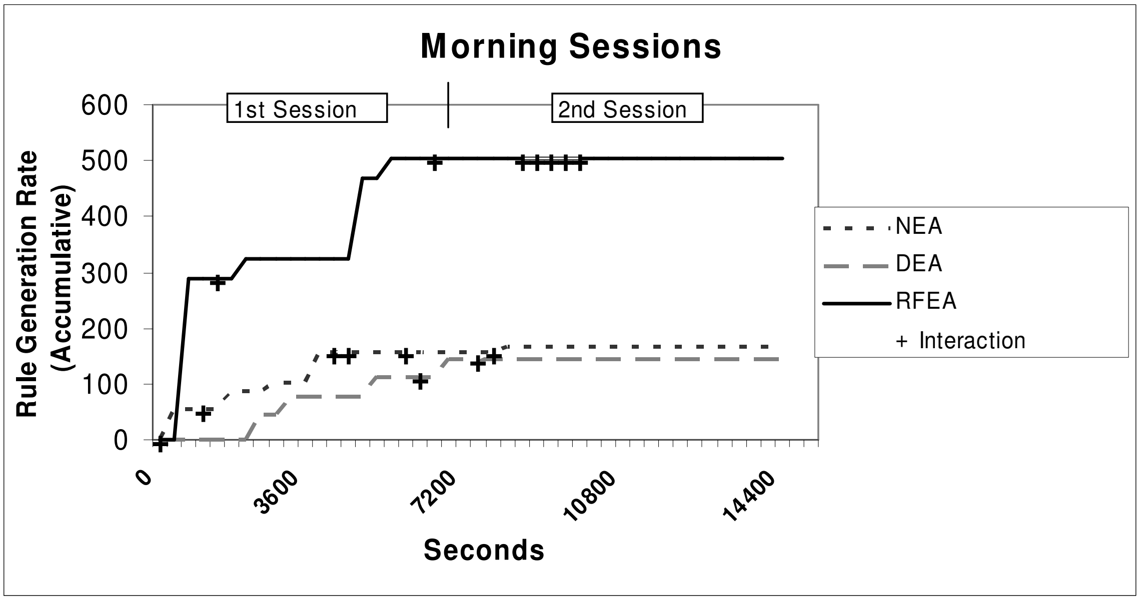
		Number of New Rules		
Time Slot		NEA	DEA	RFEA
8-10AM	1st Session	156	145	504
	2nd Session	12	0	0
1-3PM	1st Session	0	8	0
	2nd Session	0	0	108
6-8:20PM	1st Session	116	180	396
	2nd Session	112	246	126
Total		396	579	1134

Table 7.11. Number of new rules per session.

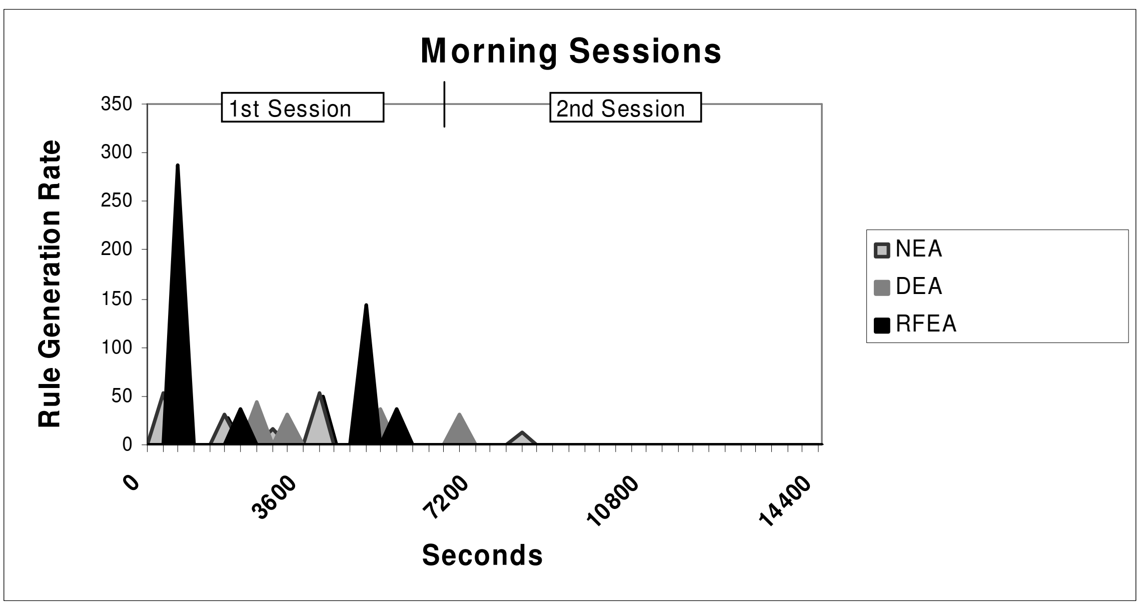
It can be seen that on the morning experiments, the DEA did not need to make any further modifications to its interaction model after the first session. NEA on the other hand, performed a much better modelling in the afternoon sessions with no new rules created in either of the two sessions. A more in depth analysis on the results from the morning and afternoon sessions demonstrated 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 apparent problems to modelling user's behaviour each one of them having constructed more than 200 new rules (RFEA was the worst case with 522 new added rules). This could be attributed to the eclectic and varied set of activities the user engaged in during the evening sessions. Remember that I mentioned that the subject used this time to entertain himself playing different videogames and watching TV. Nonetheless, and perhaps naturally, these activities did not follow a predetermined order. According to the diary I recorded, the switch between being immersed in a challenging racing car videogame and watching a comedy movie was rather unpredictable and hinged on the user's mood. 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. A solution for this and the unpredictable order in activities might be to increase the controlling period so that behavioural changes provoked by illness could be observed and learned by the agent

7.3.4 Model Stability

Model Stability is closely related to the progress function and it measures not only the number of rules created over time but how quickly this number becomes stabilized. This is an indication of the agent's promptness in achieving an interaction model that maximises the information collected from the environment based on surrounding variations caused by user's behaviour and/or weather conditions. The argument is that this interaction model should improve rapidly over time requiring fewer and fewer adaptations as time goes by. Figures 7.4-7.6 illustrate the accumulative number of new rules over time (Rule Generation Rate) and also the peak values generated by each agent in each experimental session. The crosses in Figures 7.4a, 7.5a, and 7.6a indicate the moment when an interaction occurred.

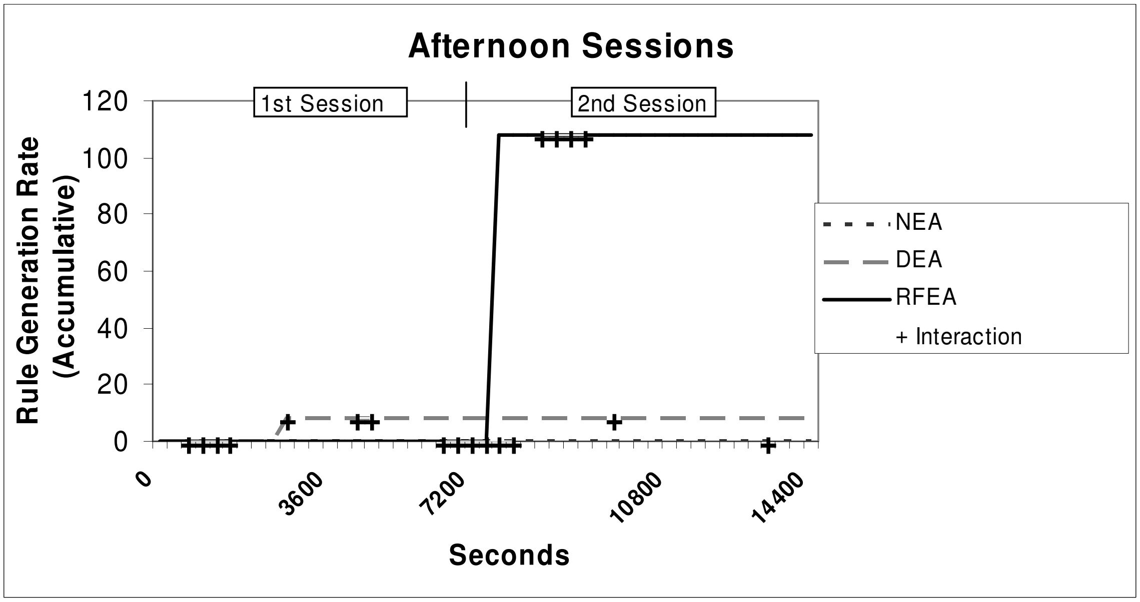


a)

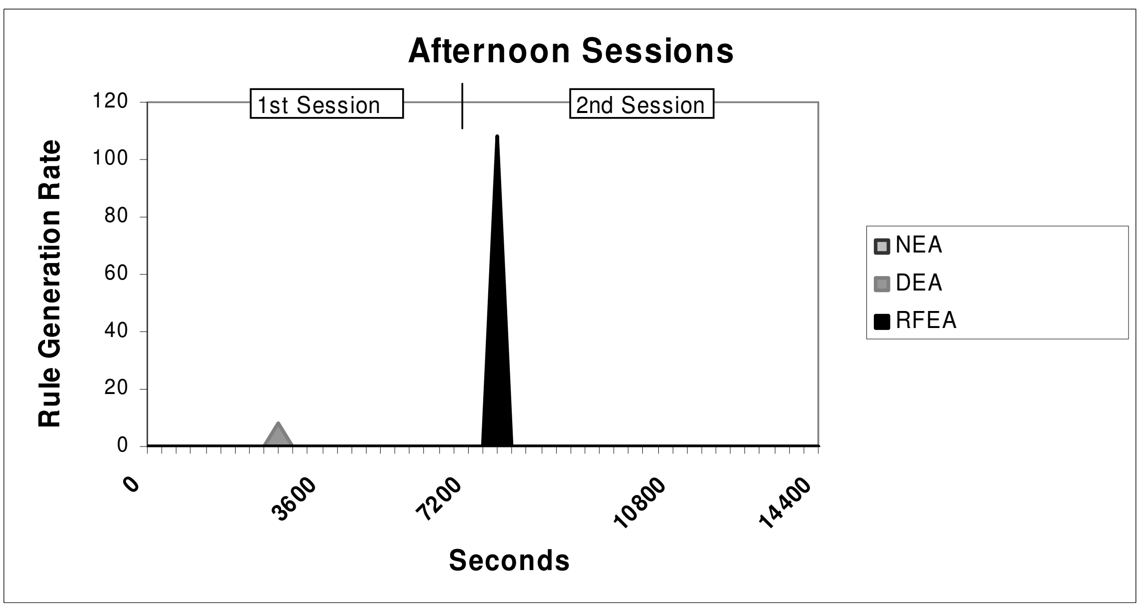


b)

Figure 7.4. Model stability over time in the morning sessions expressed in new rules per second. a) accumulative and b) peak values.

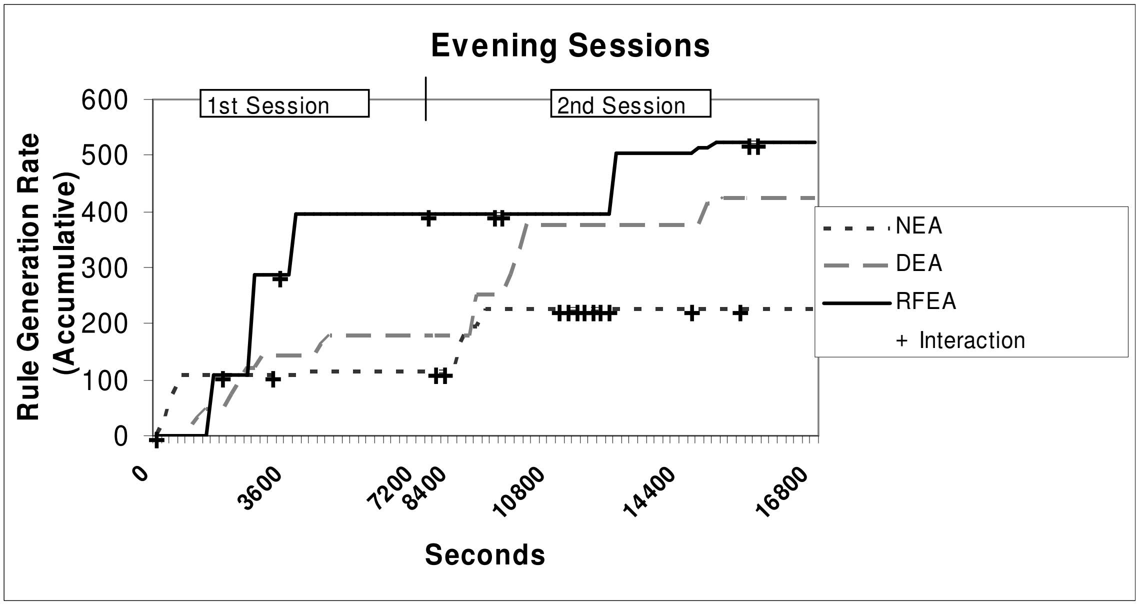


a)

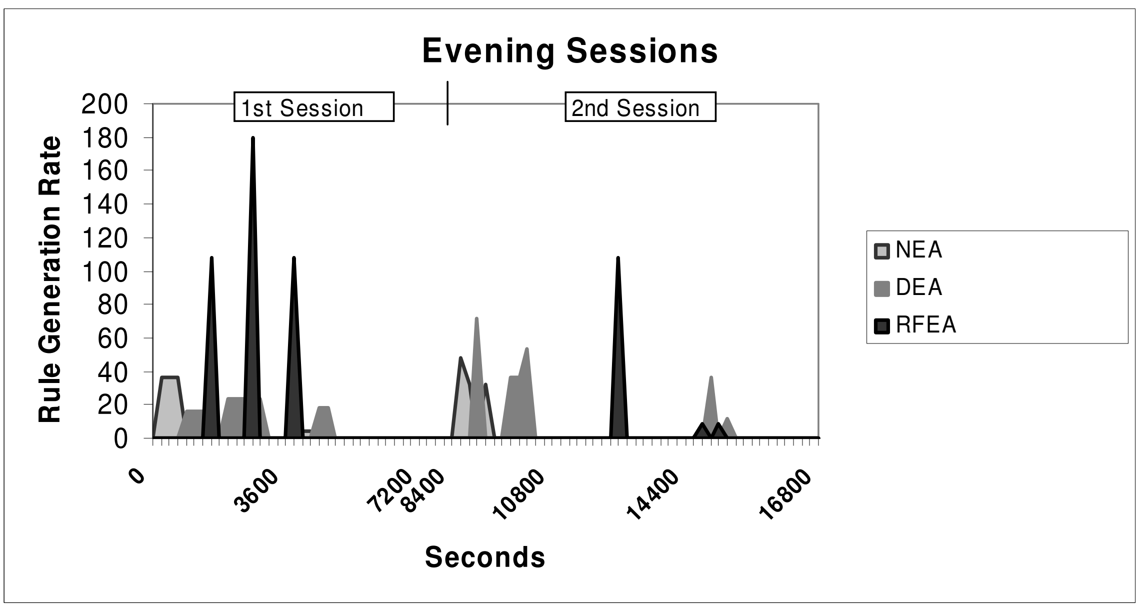


b)

Figure 7.5. Model stability over time in the afternoon sessions expressed in new rules per second. a) accumulative and b) peak values.



a)



b)

Figure 7.6. Model stability over time in the morning sessions expressed in new rules per second. a) accumulative and b) peak values.

Despite the large number of rules generated by RFEA in the morning sessions, it is evident that this agent reached a stable interaction model much quicker that 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 7.4). A closer look at this results suggests that this apparent advantage of RFEA could be related to the massive number of rules created during the first part of the morning sessions (much greater than the ones created in any other day by any other agent (see Table 7.11 above). It is logical to suppose that because RFEA created so many rules in the beginning fewer rules needed to be created as time progressed.

In the same manner NEA showed an enhanced performance during the evening sessions having made the last update to the model 8572 sec. after the beginning of the session (see Figure 7.6). NEA was also the best model during the afternoon sessions since not a single rule was needed in contrast to 8 and 108 new rules by DEA and RFEA respectively (see Figure 7.5). The fact that apart from the morning sessions, NEA showed an indisputable predominance in the model stability category could be attributed to the extra emotion input both RFEA and DEA possess. It is argued that the extra emotional input would increase the time needed to capture the different parameter combinations stemming from the user's activities (remember more inputs, more rules). In the case of RFEA this was conspicuous by the high numbers of rules being created.

7.3.5 Overall Performance

Results in Table 7.12 demonstrate a clear advantage to DEA in the categories that most concern us and that are 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.

DEA's supremacy in the first two categories could be attributed to its ability to pick up changes in the user's behaviour associated with emotional changes. The reduced number of rules that required a change along with the bigger number of rules that were utilized reveals a greater accuracy in those rules which in turn had an effect on the fewer occasions the user had to override agent's decision about the ambient settings. Note that these results concern the overall experiment for it has been shown that RFEA was better in creating the initial model. In the next section I will attempt to explain why the RFEA which was theoretically able to recognize the same subtleties did not perform as well in the final results especially in regards to user comfort.

With respect to NEA prominence in the category of rapidity to create a behavioural model, I mentioned that this could be linked to a smaller number of inputs. More inputs in the DEA and RFEA models intrinsically mean more possible parameter combinations leading to more time to establish a behavioural 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 7.12. Category winners.

7.4 Comparisons between Two Emotional and One Non-emotional Agent

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 the changes provoked by the effect of emotions on our decisions, are more likely to be captured by an emotional agent than by one not aware of emotional changes. We've seen that when rules are generated DEA is able to recognize the moment when an emotional change takes place and by doing this revealing user actions that otherwise would have remained undetected (for example the change in emotions that preceded the shutdown of MSWord).

Remember 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 an IIE. The reactions to such stimuli are not easily recorded by a non-emotional agent since they depend on modifications of the user's psychological and physical perception of his/her surroundings The lack of interaction at a more personal level associated with NEA inhibits the symbiotic relationship between a non-emotional agent and the user and neglects important information about why and when certain events usually occur. DEA and RFEA on the other hand are capable of discovering not only otherwise imperceptible relationships between environment and user actions but also small clues that could potentially help the agents predict the subject's future actions (just as in the case of the couch sensor). The knowledge that at certain time an individual undertakes a given action and that such action is preceded by changes in the environmental conditions is a useful tool for agents operating inside intelligent environments and it is one of the main premises of pervasive environments.

7.4.1 Emotional vs Non-Emotional

Results shown in Table 7.12, suggest that in general 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 fewer 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 (see Duman06).

In terms of user satisfaction, DEA was much better than NEA with nearly 110% less interventions by the user. This advantage alone signifies a success of my experiments in terms of finding an agent that improves on another one. One might suggest that DEA performed better than NEA because of its increased granularity thanks to a greater number of inputs which potentially provides a more detailed depiction of user activities. However, the other agent with the same granularity attributes as DEA - the RFEA - performed equally poorly as NEA in terms of the need for user intervention. Thus a greater number of sensors means more granularity and more rules but that does not necessarily imply better user comfort.

For instance, let's forget for a second that DEA contained emotional information. In pervasive computing we are always looking for ways to enhance the way intelligent agents operate. In this regard, the selection of the inputs on which such agents base their decision is crucial. This task however is not easy: Some sensors would indeed improve agent performance but some others could in fact have the opposite effect and disturb operation by inserting noise, increasing operation time, and complicating decision making. Thus, the fact that I was able to find a sensed input that improved the user satisfaction provided by an already tried and tested agent is commendable.

7.4.2 Fuzzified vs Discretized

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, as I mentioned, not only the quantity but also the quality of the information determines the agent's performance.

But, why did RFEA not perform as well as DEA if both agents had the extra emotional information with RFEA's physiological and DEA's emotional changes having a strong correlation indicating similar behaviour? Based on the results from the initial model the effect of variability in AANN residual can be discarded as a viable reason. The answer however could lie in another element associated with AANN residuals, extra granularity. As I mentioned in the previous chapter RFEA is designed to react to instantaneous changes in physiological changes. I anticipated that this attribute of RFEA could potentially increase the number or rules created during training and operation. This hypothesis turned out to be true and RFEA was the agent that created the greater number of rules (1345) of the three available models (see Table 7.9). RFEA's capacity for rule creation seemed to work to developing an enhanced initial behavioural model but did not perform as well during the adaptation phase since many rules did not seem to reflect durable changes with only 76% actually being utilised. Thus, the extra granularity achieved by RFEA's through the use of AANN residuals could have in reality been a destabilizing factor rather than making control more accurate. In other words, too much detail in the information about a particular activity could have led to erroneous RFEA actions during the 6-day adaptation phase especially at moment of deciding which rules to use. There could be another explanation to RFEA's "confusion" related to the fuzzification of HR residual values. The intrinsic overlapping of gaussian fuzzy sets caused by close HR mean residual values could have blurred the distinction between the three emotional categories and provoked conflicting control actions. A remedy for this could be to intensify AANN training thus increasing memorization and broadening the distance between the residual values describing the different emotional classes. Excessive memorization on the other hand could render the AANN incapable of recognizing emotions other than neutral. Hence we have to be careful when choosing between a low level of overlapping in fuzzy sets and good AANN performance. The use of singleton fuzzy sets is a straightforward solution for this dilemma since overlapping in this kind of fuzzyfication is non-existent.

One could also argue that perhaps RFEA was picking up many more subtleties stemming from a wider range of possible emotional states than the other two agents and therefore it struggled to satisfy users in a better manner. Furthermore because of this enhanced "resolution" or granularity, one might expect RFEA to come up with a better modelling in the long term. However, from my preliminary empirical evidence, this does not seem to be case and RFEA's second sessions witnessed a greater number of user interventions than the ones that took place during each of the first session. Indeed the opposite of what one might expect (see Table 7.10). Thus another conclusion that I could make is that the detection of combinations of various degrees of positive, negative, and neutral emotional states played against RFEA and was a detriment rather than an advantage in the agent's operation at least during the crucial adaptation phase.

The modest display of RFEA particularly in the category of user comfort reveals that the sole addition of an extra sensor providing information stemming from the user's physiological state into the agent's input vector does not guarantee improved modelling of user's activities (or user comfort). 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 ambient conditions and the user's state of mind

7.5 Affective Pervasive Computing: Initial Evidence of the Importance of Emotions inside Ambient Intelligence

My experimental results suggest that the utilization of emotional data improves the performance of IIE software agents particularly in those categories involving the modelling of user activities (user comfort and interaction model). This was evidenced by the DEA having created a behavioural model that required less adaptations over the experimentation period than the other two models and that provided greater user comfort with a diminished need for manual override. I suggest that emotions provide the agents with more clues about why and when the user undertakes certain activities at certain times as was shown by the difference in the rules generated by DEA and NEA (see Tables 7.3 and 7.4). For instance, the fact that DEA detected an emotional change (from positive to neutral) when Word was shut down and the Media Player was switched on could be indicate a relationship between the need for leisure activity and a decrease in emotional valence. This type of relationships is crucial to model human behaviour and gain insight into user rationale. I am aware of the fact that additional inputs mean additional rules, however emotion detection introduces a new dimension of information that another light or temperature sensor could never provide. It is apparent therefore that observing an individual without knowing their motivations is not sufficient to endow software agents with an accurate representation of the events taking place inside an IIE. In fact, I would say that the evidence demonstrates that emotions provide valuable information allowing finer discrimination and consequently better behaviour representation.

Before we conclude let's revisit the questions that I posed at the beginning of this chapter:

- "Is emotion detection useful i.e. does it improve the way pervasive systems model user behaviour inside IIEs?" Yes, I found that the model created by DEA using behavioural and emotional information did require a lot less modifications than the one from a non-emotional agent based on behavioural data only.

- "Could emotion detection enhance adaptability and increase the agent's capability to adjust the environment to reflect users habitual behaviour and increase their comfort?" Yes, there is evidence that during the time DEA was in charge of controlling the iDorm2, fewer manual interventions were required thus indicating that the user was pleased with the way the DEA controlled the environment.

- "How should emotion detection information be included in pervasive systems? Should it be based on the raw physiological signals or on high-level (pre-processed) categories as in the output from the X-Vest?" Results from the total number of rules created indicate that the raw fuzzified data increased the number of rules generated and this had a direct (negative) effect on the agent's performance. This was inferred from the fact that RFEA was the agent that needed the greater number of adaptations to its behavioural model (see Table 7.9). In this respect DEA's high-level emotional categories provided by the AANN/SPRT mechanism worked better.

- "Other questions related to this issue involve the emotional categories I am detecting – positive, negative and neutral and whether these are sufficient to improve user comfort?". Because they are based on Gaussian functions, RFEA's fuzzy sets are capable of representing combinations of various degrees of three basic emotions: positive, negative, and neutral. However this capacity to accommodate a greater number of combined emotional categories did not seem to improve RFEA's performance and in fact seems to have caused more confusion in the agent possibly due to fuzzy sets overlapping. Crisp valence-based tripartite emotional classification on the other hand seems adequate to produce a better model of the user activities and also greater comfort than the RFEA and the NEA based on the measures I have described earlier. I therefore suggest that the use of gaussian fuzzy sets in which function overlapping provides arithmetic blending of emotions, e.g. 10% negative and 90% neutral, is not the most adequate way of integrating emotions into IIE agents since it could lead to deficient operation in the long term. Instead I support the idea that the use of emotional states should be founded on discrete separation using singleton or crisp fuzzy sets and therefore avoiding emotional overlapping. Whether the three categories I employ will be sufficiently subtle to allow further refinement of the system or whether there will be some need to try and produce a finer categorisation of emotions is discussed in the conclusion.

The findings presented here provide encouraging preliminary evidence of the importance and influence of emotions into human decision-making and information processing. The intention of this work is to contribute to a better understanding of the impact of emotions in the context of designing pervasive computing agents and towards the eventual integration of affective computing and artificial intelligence. I hope that other researchers will be able to build upon these empirical results and create applications that rely on emotional states to experiment further on the way we behave inside pervasive environments.

"If your emotional abilities aren't in hand, if you don't have self-awareness, if you are not able to manage your distressing emotions, if you can't have empathy and have effective relationships, then no matter how smart you are, you are not going to get very far" Daniel Goleman

Chapter 8

General Discussion

This investigation aims at developing better techniques of human-machine interaction inside intelligent inhabited environments (IIE) by including information on the emotional state of the user. My hypothesis was that computer systems that could make use of emotional information in order to establish the relationship between affective states and environmental conditions would be better able to satisfy users needs thereby increasing comfort and efficiency.

From this initial hypothesis I have developed a robust generic system for identifying emotional valence in real time using physiological signals. This has been used to develop a wearable which has allowed the technique to be used in conjunction with an established intelligent agent and tested within an IIE setting. The results achieved show that thanks to the inclusion of emotional information the agent produced better decisions in particular with respect to user comfort. I have thus produced a proof of concept wearable and affective agents and successfully tested the original hypothesis.

8.1 Main Findings

The main contribution of my work to the area of affective computing is the development of a reliable and robust system for detecting emotions in real time using sensor validation techniques applied to physiological responses. The operating principle of such physiological emotion detection system can be summarized as follows: Thanks to the ability of Autoassociative Neural Networks (AANNs) to mimic the input behaviour of training data, in this case bodily patterns associated with the neutral emotional state, the mean of the difference between an AANN-estimated value and the actual sensors readings (residual) should be very close to zero for situations of neutral emotionality with a standard deviation similar to that of the noise introduced by the sensing device. When the sensor values drift because of a change in the physiological status related to an emotional episode, the mean value of the residual deviates from zero. The Sequential Probability Ratio Test (SPRT) values in my classification modules are then altered and the likelihood ratios are displaced to either of the two solution spaces, neutral or non-neutral and positive or negative.

Empirical evidence stemming from various experimental setups involving the emotion detection system outlined above supports the following conclusions:

- Initial off-line experiments based on physiological data from a single subject demonstrated **100%** recognition rate when distinguishing in real time any given emotional change (positive or negative) in the neutral emotional state of a single subject. These results were superior to those obtained by other researchers in similar circumstances using physiological signals [Chapter 3].

- Further experiments aimed at detecting positive and negative emotions in real time involving 8 subjects were carried out using a non-intrusive sensing device. Results demonstrated **84.52%** recognition in validation trials (using data from the initial 8 participants that was not included during training) and **71.4-80%** in generalization trials (data from an entirely new dataset) [Chapter 5].

- Cluster and similarity analyses using the Davies-Bouldin Index and the Wilcoxon test respectively, evidenced the fact that: 1) Neither individual levels of affect intensity nor low-to-moderate physical exertion seemed to have an effect on the enhanced class separation found in AANN estimations, and 2) The physiological changes provoked by low-to-moderate intensity exercise remained similar before and after physical activity thus rendering unnecessary the utilization of additional filters on the physiological data employed in my detection system [Chapter 4].

In summary, the achievements of my novel sensor validation-based emotion detection system are:

Detection rate of a single emotional state including two emotional classes (neutral and non neutral)	100%
Detection rate of a multiple emotional states including three emotional classes (neutral, positive, and negative) in intra-group trials	84.52%
Detection rate of a multiple emotional states including three emotional classes (neutral, positive, and negative) in extra-group trials	72-80%
Real-time operability	Yes
Wearability	Yes
User-independence	Yes
Robustness - Ambient/ Activity Mobility	Yes

It should be said that the recognition rates discussed above are applicable to the conditions, equipment, and methods described in Chapters 3 through 7. Other sensing devices or sequential methods might provide different results in terms of AANN training length, portability, noise, and detection time.

Two comments on my emotion detection system are in order. First, note that user independence does not imply that all targeted users would experience emotions in the same way but rather that existing similarities are identified and then generalized among a sample population. Nevertheless, I recognize that individual dissimilarities are important and they are the cause of the discrepancies between the 100% recognition rate achieved in experiments using one individual (Chapter 3) and those relating to a group of people (Chapter 5). Despite such differences, similar recognition rates to the ones obtained in the generalization trials could be expected on wider populations provided that: 1) Comparable alpha and beta values are utilized in the SPRT configuration, 2) The targeted individual(s) do not suffer from any medical or mental condition, and 3) The same physiological measures with similar signal characteristics are used. Second, it was noted from my experiments that there could mismatches and even conflicts between what the system detects and what the user is “supposed” to feel, i.e., the expected reaction to a given emotional stimulus. Such mismatches are squarely linked to the subjective aspects of emotional interpretation i.e., a sad picture does not necessarily inspire sadness in everybody and may even be the cause of happiness to some. The use of self-reports is a manner of verifying whether a given emotional stimulus achieves its objectives but they require a high level of self-awareness. Thus, I rely on a combination of consistent statistical measures used in the classification modules including small α and β values and intensive AANN training to guarantee reliable emotion detection as accurately as possible.

Another contribution of the research associated with this thesis is the implementation of an affective agent based on a prototype wearable device called the X-Vest (eXperimental Vital-sign-based Emotional State Transmitter). The X-Vest comprises my physiological emotion detection system, a sensing interface and an UPnP control point permitting cross-platform access to the emotional state of the wearer. The X-Vest supplements the information used by an IIE Fuzzy-Agent by providing continuous valence measure of the wearer’s emotional state.

A third important purpose of my work was to investigate the benefits of emotion detection for behavioural modelling and user comfort inside IIE. Therefore, with the intention of gathering evidence to sustain my hypothesis that the identification of the emotional component associated with behaviour could improve the performance of interactive systems currently used in pervasive environments, my emotion detection system was utilized in experiments involving real-life situations inside an IIE, namely the iDorm2. Three different fuzzy agents were built for this purpose: 1) An agent that did not include any emotional information (NEA), 2) One incorporating data on valence-based emotional states featuring neutral, positive and negative emotional states (DEA), and 3) Another agent employing the residual calculation on the raw physiological data (RFEA) as provided by the AANN. Preliminary results indicated that agents that utilize emotional information in order to model and respond to behaviour inside IIE provide a more comfortable interaction than agents that don't use information about user's emotional state.

More specifically, comparisons between these three agents produced the following results:

- The behavioural model obtained while **DEA** was in operation, seemed to reflect user behaviour in a more faithful way, since fewer on-line adaptations of the total number of rules were required, **4.9%** against **34.6%** for **NEA** and **47.9%** for **RFEA**.

- Fewer manual interventions overriding agent's decisions were made during the experimental phase supervised by **DEA** (10 against 21 for **NEA** and **RFEA).** Hence I argue that these results indicate that users are happier with the way the DEA operated within the iDorm2 than they are with the other two agents. I suggest that this is a reflection of DEA's improved identification of user needs and habits.

- The tripartite discrete emotional classification used in DEA provided better results for the overall experiment than the one based on gaussian fuzzy sets using AANN residuals as demonstrated by the reduced number of rules that required modifications and the user comfort performance. Moreover, the fact that RFEA´s gaussian fuzzy sets accommodate a large number of combinations of the three emotional classes suggests that the use of many (ill-defined) affective states as opposed to the tripartite valence-based classification is to the detriment of the agent using this approach to emotion detection. I suggest that emotional information based on discrete values is more adequate than raw data indicating physiological changes for implementation inside pervasive environments.

- Examination of fuzzy rules suggested that DEA detected subtleties in user behaviour that NEA was unable to recognize. Such subtleties involved actions that were associated with measurable changes in the user's affective state. The significance of this advantage of DEA over NEA is reflected in the creation of a more accurate behavioural model that led to increased user comfort.

These empirical observations stemming from experimental evidence strengthen the theory that affective agents and more specifically those using high-level emotional classification, possess a greater capacity to assimilate information about the environmental and emotional conditions motivating user actions. In fact the two emotional agents outperformed or at least equalled NEA in the two categories that most interest us. DEA was better that NEA and RFEA in terms of the overall rule adaptation rate and user comfort, while RFEA on the other hand was better than both the DEA and NEA in the quality of rules created during the initial model and obtained similar results to NEA in user comfort. I would expect that usage would bring further improvements in terms of the user comfort DEA provides.

The argument concerning the potential effect of granularity on the enhanced performance of the two emotional agents can be discarded since, as I argued above, it is not the number of inputs what determines agent performance but the quality of the information that such inputs provide in terms of a better, more detailed modelling of user actions.

In conclusion, experimental evidence supports my original hypothesis that the information emotions provide to IIE agents with regards to the user's motivations is unique and could have not been provided by any other environmental sensor. Moreover, I have collected preliminary evidence to demonstrate that affective agents and, in particular those employing valence-based emotional classes are better able to model user actions and ultimately provide augmented satisfaction and comfort.

8.2 Discernible Concerns

I have mentioned that physiological signals entail some crucial advantages over some alternative methods of emotion detection such as facial or speech recognition. Such advantages are mainly associated with the issues of flexibility (bodily signals can be acquired and analysed even when people cover their faces or keep quiet) and accuracy (people are likely to behave in a more natural way using wearable sensors than when they are aware of the existence of cameras or microphones). Physiological emotion detection however, involves some disadvantages with respect to video and sound information in terms of the difficulty to guaranteeing "good" sensor readings. Factors affecting the acquisition of physiological data range from the characteristics of the equipment (A/D converters involving different pre-processing techniques, buffering, sampling rates, etc.) to power fluctuations and also the location of sensors on the body as well as their condition and calibration. Although the detrimental effects of some of these elements are difficult if not impossible to gauge or control, there are various measures that could be taken to prevent them from having a great impact on physiological emotion detection methods. First, equipment should be regularly serviced and maintained. Second, noise filters should be implemented at pre and post-processing stages (normalization is a simple way of eliminating noise in sensor readings while the use of AANN has also been shown to be effective in filtering undesirable data). Third, in regard to sensor location, SR sensors are said to be not sensitive to location whereas BVP appears to be more affected by movement than by location although it is generally accepted that BVP is highly dependant to correct placement [Picard97]. Still, I recognize the difficulties involved in the use bodily signals to detect emotions and appreciate the many challenges that physiological emotion detection pose.

Another important aspect of physiological emotion detection is the number and characteristics of the signals employed to identify emotional states. For the purpose of my investigation the number and type of physiological signals I utilized correspond to those used in other similar setups and satisfy the type of applications presented here. However, other environments might require different signal types and configurations. For example, it has been mentioned that BVP is a signal that could be affected by how the sensor is attached and therefore might require additional pre- or post-processing in order to be reliably used in applications involving extreme mobility, e.g. running. On the other hand, although SR is a very stable measure, it is normally regarded to be a slow signal (it has been mentioned that noticeable changes occur after 0.2 to 0.5 seconds). This type of response is useful for agents operating common household devices inside intelligent environments but might not be adequate for use in applications which involve life-threatening situation that need immediate attention. In this case the electromyogram might be the best option.

Although it is true that each different emotion detection application might need different physiological signals, I argue that the best option is to utilize as wide range of signals as possible so that all the different aspects, independent and correlated, of the human physiology are taken into account.

8.3 Further Work

Real-life studies involving pervasive environments and emotional states are very complex endeavours that demand system reliability, adaptability, portability and the meticulous monitoring of numerous parameters. To grasp the sophistication in the symbiotic relationship that develops between IIE agents and the user interacting with them, one would need to consider things like network traffic, hardware deterioration, operating systems, cross-platform issues, software performance including agent inference capacity, availability, quality and reliability of wireless communications, sensor wearing, and also all the different variables associated with the physical, mental, social and geographic/environmental circumstances of the user including family, educational, intellectual, physiological, financial, and medical aspects. Although the work presented here only addresses a few of the factors mentioned above, I suggest in the next paragraphs some specific areas that could be investigated as further work.

In addition to photographs, there are several other elicitation methods based on emotional imagery the most popular ones being the use of movie clips and various thespian techniques of affective self-regulation. The effects these different elicitation methods have on individuals differ from one another. Such effects might be investigated to determine whether they cause discrepancies in the tripartite emotional classification (neutral, positive and negative) used in my experiments. That is, even though emotional stimuli with a negative charge are likely to elicit similar negative response on experimental subjects, the intensity of such response might vary depending on whether a photograph, a movie or self-regulation is utilized. This in turn might require adjustments in the parameters delimiting emotional classes.

There are numerous psychological tests that have been developed to measure different factors affecting emotional expressiveness. In the experiments described in this thesis I only used one of them, the Affect Intensity Measure (AIM). Personality, emotional resilience, emotional intelligence, clinical depression, self-esteem, anxiety, vulnerability to stress, creativity, and hostility can all exert a crucial influence not only in the way we feel our emotions but also in the way we interact with and perceive the environment. It would be desirable that the consequences of these different parameters on emotional expressions should be analyzed together and separately to determine how they influence the reliability of emotion detection systems.

Physical exertion and fitness levels are only two of the many personal aspects affecting physiological signals. Normal bodily homeostatic state can be altered by such factors as weather changes, chronic diseases, menstrual cycle, medication, smoking and drinking habits, personal hygiene, individual problems, sleeping habits, and eating disorders among others. In the face of the mammoth challenge involved in quantifying detailed consequences of these parameters on the physiological concomitants of my participant's emotions, how these parameters might alter the recognition results of physiological emotion detection systems remains to be examined.

Intensive small-sample longitudinal studies are effective for my purposes because 1) they are practical, 2) they provide facts, and 3) as pointed out, they usually provide enough information to support a hypothesis and permit method replication. Long-term studies on the other hand increase the possibility to extend initial results to other desirable environments, situations, and/or experimental setups. Long-term studies could also cater for information about important technical variables not considered in this thesis and normally not contemplated in the literature of pervasive environments such as software and hardware failure recovery inside IIE, potential effects of long-term continuous adaptation on software agents due to constant or erratic behavioural changes, and sensor validation specially in those cases where friction between user and equipment exists. Some human aspects that could investigated based on long-term studies might include the psychological effects that result from delegating the control of our home to software agents for long periods of time, mental changes due to natural aging, chronic mental afflictions and habits alterations, and seasonal affective disorder and its effects on behaviour and consequently on agent operation.

Another aspect of my work that I have not been able to develop relates to how other agents might incorporate emotional information. In terms of coupling the emotional data into other agent architectures, that doesn't seem to represent a complex problem since the X-Vest can be considered as an independent sensing device. However, I have only described how the emotional information provided by the X-Vest is processed using a fuzzy logic controller (FLC). Agents using other supervised or unsupervised training techniques will have different ways of treating the emotional information. We know for example, that agents featuring adaptive neural models use temporal components to adapt themselves to what they regard as normal user behaviour. What would the effects on such a model be when dealing with highly variable emotional states? Reinforcement models on the other hand, operate by punishing "wrong" actions and adjusting the behavioural model accordingly. Some of them use prediction techniques to adjust to future actions using time windows. How might an agent accurately predict users emotional states over a period of time especially when such prediction is based on averaged values? These questions remain open issues for future research.

The number and type of emotional states I am using is another element that could be revised and improved. I am convinced that using valence-based emotional classes is sufficient for my initial purposes and, paraphrasing Joseph Ledoux, I'd rather direct my efforts into well-accepted emotional categories and how they might be advantageous to us rather than debating whether a specific subjective feeling could be regarded as an emotion or not. I recognize however that a more detailed classification of emotions might be useful and this is an area that also needs further investigation. This is particularly true if I intend to provide IIE with devices that display emotions or respond to people at an affective level. Emotion synthesis is an area of affective computing that could also be implemented inside Ambient Intelligence but has not been investigated as part of this research project. In this regard my system falls in the Third category of Affective pervasive systems described by Rosalind Picard, systems than can perceive but cannot express affect.

One of my immediate future plans includes the development of technical solutions that allow friendlier, more transparent, and accurate operation of the X-Vest. Such solutions include on-line AANN training substituting the use of data acquired off-line. This could be done by incorporating hardware-based neural networks into the X-Vest. During system set-up, the subject(s) being monitored would be asked to remain in semi-recumbent position for a pre-determined period of time while data associated with the neutral emotional state is used to train the AANN. The statistical measures utilized to configure the SPRT modules which require not only neutral but also non-neutral emotional states can be dynamically calculated through emotional elicitation. I could even use unsupervised methods such as self-organizing networks to automatically obtain the physiological parameters associated with emotional classes from natural living conditions. In fact, pre-operational training could be completely eliminated though the utilization of methods featuring on-line adaptation, i.e., training and operation at the same time. Such methods may include fuzzy neural networks and/or genetic algorithms. Finally, methods of sequential analysis similar to the SPRT could also be realized using mechanisms derived from Artificial Intelligence. There is at least one example in which Artificial Neural Networks (ANNs) have been offered as an alternative to SPRT [Guo96]. The advantage of using ANNs to perform sequential analysis is that they can be trained using techniques that do not require the calculation of statistical features thus being a more flexible way of detecting emotional changes. Such novel approaches however require further verification if they are to be compared with a well-established technique such as the SPRT.

I anticipate that future applications of physiological emotion detection will require enhanced portability. Therefore I am in the process of designing a "simplified" version of the X-Vest suitable for on-chip implementation. It would be advantageous that such "mini" X-Vest would operate on just a few physiological signals using on-line training and adaptation. Because of its reduced size and minimal requirements, this device could be easily embedded into clothing, appliances, or automobiles and still provide reliable emotion detection.

8.4 Beyond the Digital Home

We live in a time of constant innovation where technology is continuously evolving as a result of revolutionary ideas that nurture science and inspire people. Affective Computing is one of those ideas that are likely to survive and inspire not so much because of its technical or practical appeal as because of its human appeal. Emotions are universal, they are part of every human being and they accompany us from the day we are born. Unlike other circumstances surrounding our existence such as the country we come from, the access we have to technology, science, and education, the family we are part of, the religion we practice or the language we speak, emotions are not an option or a product of chance or fortune, they are an inescapable constituent of our lives.

One of the biggest differences between technology or society and emotions is that, in essence, the latter have remained more or less unaltered for thousands of years and will probably stay like that for yet a few thousand years more. Hence, when we consider that technology is amendable and customizable while emotions are not, the principle of pervasive computing in which technology must integrate with and adapt to human life becomes even more pressing. In this regard, Affective Computing is playing a vital role in the search for friendlier, more transparent, and widely-available computer applications. Since it would be a colossal task to enumerate all the various areas in which the various kinds of emotion detection could be of help, I will concentrate on the potential applications of the X-Vest and its underlying methodologies.

One of the immediate and most important practical uses of the X-Vest is that of medical care and therapy. Tele-care systems providing remote medical attention have received a great deal of publicity in recent years thanks to the advances in telecommunications, electronics and computing processing techniques. Since the majority of tele-care systems focus on the identification of pathological patterns on bodily signals, it is argued that these systems could be complemented with physiological real-time emotion detection to undertake appropriate anticipatory measures in response to negative emotions, a widely known detriment to health. Moreover, because the X-Vest is designed to operate in conjunction with IIE agents, it is possible to recognize and subsequently associate positive emotions with local ambience settings. Thus, an IIE could in theory promote a healthier lifestyle by adjusting the environment to match those settings linked to positive emotional states in attempt to overcome the harm of negative emotions. The same principle could be used to provide safety to elderly or handicapped people by informing medical staff of negative changes in the subject's emotional state.

An obvious extension to the use of X-Vest in medical applications would be the development of systems to assist sportspersons in sports science and associate fields. Athletes, just like everyone else under stress, are subjected to emotional tension that could severely hinder their performance during competitions. Examples of how emotions such as anxiety, fear, or anger play against sportsmen are numerous. In 2001, researches at the University of Calgary designed a virtual reality space to simulate tournament conditions for ice speed skaters. The rationale supporting this endeavour was the fact that at high speeds skaters tend to become frightened of their own velocity and tend to slow down thus losing valuable acceleration. Although an obstacle to achieving their full potential, the fear skaters experience has an involuntary component rooted in the fact that at higher-speeds accidents often involve greater physical damage than those happening at low speeds. By exposing skaters to high-speed scenarios including track, noise and stadium conditions similar to the ones normally occurring in competitions, they are capable of gradually overcoming their fears and at the same increasing their physical performance. The X-Vest could be of enormous help to detect not only the moments during a race in which negative emotions occur but also to probe whether other types of emotions, e.g. positive ones, arise while speed skaters are competing and how they inflict changes in physical output. Many important studies could derive from an accurate mapping between emotional fluctuations and physical performance.

In general, the X-Vest could be used whenever physiological signals are available and in those situations in which emotions are relevant. Another one of those candidate environments is an automobile. We drivers know how our emotions are exposed to all kinds of contingent phenomena when we are at the steering wheel and we also know how negative (road rage in particular) and sometimes even positive emotions (musical "overexcitement" for example) could cloud or perturb our judgement and become a threat to our safety and that of others. Thus, the detection of on-the-road negative emotions for example, could be used to advise the driver, to enforce security measures (for example limit the car's maximum speed or even apply emergency breaking), or even to use therapeutic, relaxation mechanisms to overcome the negative emotion thus reducing the latent danger. In fact car prototypes featuring very basic emotion detection and simulation systems have been developed in recent years, e.g. Toyota´s POD, but have thus far not been made available to the car market. What the X-Vest and its underlying methods could provide for the car industry is an inexpensive, robust, reliable system that is capable of detecting valance-based emotions under real-life circumstances for either a single driver or a group of individuals. Furthermore, the agent-oriented design of the X-Vest means that my artefact could interact with other computing systems to provide an entire model of the driver's affective states and the existing road conditions.

Entertainment, leisure and household activities are three of the most promising application fields for the X-Vest. Without going into too much technical detail, physiological emotion detection could be used to automatically adjust entire domestic spaces in accordance with the user's most frequent preferences and taking into consideration his/her emotional state. Multimedia systems, room lights, air conditioning, appliances, telecommunication systems, windows, doors, computer hardware and software, and even food and drinking habits could be dynamically linked to levels of emotional arousal so that they could operate in tune with the user's moods, wishes, and immediate needs.

Although the role played by humans in the current trend of global warming is still a subject of debate with different theories pointing towards different causes and consequences, it is undeniable that pollution is and has been an ongoing problem affecting everyone's lives. Hence it is everyone's responsibility to try to reduce waste in all its forms. In this respect, one of the most important aspirations of the X-Vest and its underlying emotion detection methods is to become a tool for enhancing and improving the environmental friendliness of current ambient intelligence systems. Because of the empirical evidence demonstrating that emotional information could improve the opportune identification of user actions, the incorporation of emotion detection mechanisms into IIE agents could lead to faster, more appropriate and timely ambience adjustments therefore potentially reducing energy waste. A future project could involve the quantification of energy savings that result from the enhanced action modelling provided by affective systems.

One of the biggest concerns while designing and implementing emotion detection systems of the type employed in the X-Vest should be the right of the user to utter and unconditional privacy. Provisions should be taken to ensure that the local network to which the X-Vest connects is fully protected against viruses, ad-ware, spy-ware, mal-ware, worms, Trojan horses, browser highjackers, keyloggers, and other computer threats that might infiltrate the host computer and attempt to steal personal information or unlawfully monitor user's physiological and/or emotional states. In fact, I suggest that future improvements of the X-Vest should be realized in conjunction with encrypting technologies that will increase security against undesired accessibility to bodily and emotional information. It is more important than ever to ensure that, in the face of the current state of affairs in the world arena, individual liberties are preserved. We have seen on many occasions that the governments' response to social unease has been the creation of tools to control and monitor people's movements with ever more sophisticated means and without the subject being aware of it.

This has caused a sense of fear in many people and led them to become wary of technology especially when they feel that intimate aspects of their lives are being monitored. Instead of causing apprehension technology should provide individuals with a greater degree of autonomy so that they would not have worry about banal activities and have more time to foster those creative, emotional, and constructive factors that bring personal satisfaction, healthier life-styles and social well-being. That is a prerogative of the user and that's also why future versions of the X-Vest will offer increased security, reliability, support, and performance.

We at the dawn of the 21st Century are, perhaps like every other preceding generation, faced with formidable challenges and extremely complex problems like war, poverty, disease, and injustice. We live in a time of great uncertainty and apprehension. A wide-spread feeling of vulnerability, discrimination, and hopelessness has eroded the most valuable principles of humanity and left many succumbing at the hands of greed, irrationality, violence, intolerance, and deception. However, unlike our ancestors, we have the technological basis to bring hope of better living conditions at a great scale to even the most remote places thus fostering better communication and promoting prosperity. The research presented in this thesis hopes to contribute to an improvement in the way individuals and computerized spaces act upon one another by promoting a better understanding of human nature as revealed by emotional expressions.

As a final note, it is worth mentioning that the methods and technology described in this thesis concern the first steps of our research group into the vast field of Affective Computing. As such, we hope it will promote curiosity and interest for the reader and a deeper sense of awareness about the importance of emotions in our lives.

"Let's not forget that the little emotions are the great captains of our lives and we obey them without realizing it" Vincent Van Gohg

Chapter 9

Conclusions

The research presented in this thesis provides preliminary but compelling evidence on the importance of emotional information for inhabited intelligent environments. In doing this I have developed a strong theoretical foundation and undertaken detailed experimentation that shows that an affective agent, based on discrete emotional categories, can improve significantly levels of user comfort in comparison to an agent which does not include affective information. Furthermore, the research has shown that affective agents are capable of discovering behavioural clues that other non-emotional agents repeatedly ignore. In respect of inhabited intelligent environments, my work suggests that emotional information complements other types of information to provide an enhanced behavioural model.

These results are consistent with the arguments and findings of researchers in other fields in that they suggest that emotions and rationality operate harmoniously in human decision making, both being an indispensable element of our being.

References

[Abowd00] Abowd, Gregory D. and Mynatt, Elizabeth D., "Charting Past, Present, and Future Research in Ubiquitous Computing", ACM Transactions on Computer-Human Interaction, Vol. 7, No. 1, pp. 29–58, March 2000.

[Adelstein05] Adelstein, Frank, Gupta, Sandeep KS, Golden, Richard III, and Schwiebert, Loren, "Fundamentals of Mobile and Pervasive Computing", McGraw-Hill Professional Engineering, New York, NY, USA, 2005.

[AHRI04] "The Aware Home Research Initiative", Georgia Tech Broadband Institute's Residential Laboratory, Georgia Institute of Technology, http://www.awarehome.gatech.edu/projects/index.html.

[Ainsworth93] Ainsworth, Barbara E., Haskell, William L., Leon, Arthur S., Jacobs, David R. Jr., Montoye, Henry J., Sallis, James F., and Paffenbarger, Ralph S. Jr., "Compendium of physical activities: Classification of Energy costs of human physical activities", Medicine and Science in Sports and Exercise, Vol. 25, No. 1, pp. 71-80, 1993.

[Alcañiz05] Alcañiz, Mariano and Rey, Beatriz, "New technologies for Ambient Intelligence, Ambient intelligence: the evolution of technology, communication and cognition towards the future of human-computer interaction", G. Riva, F. Vatalaro, F. Davide, M. Alcañiz Editors, IOS Press, Amsterdam, The Netherlands, 2005.

[Amigoni05] Amigoni, Francesco, Gatti, Nicola, Pinciroli, Carlo, and Roveri, Manuel, "What Planner for Ambient Intelligence Applications?", IEEE Transactions on Systems, Man, and Cybernetics Part A: Systems and Humans, Vol. 35, No. 1, pp. 7-21, January 2005.

[Anderson06] Anderson, Keith and McOwan, Peter W., "A Real-time Automated System for the Recognition of Human Facial Expressions", IEEE Transactions on Systems, Man, and Cybernetics Part B: Cybernetics, Vol. 36, No. 1, pp. 96-105, February 2006.

[Andreassi67] Andreassi, John L. and Whalen, Pamela M., "Some physiological correlates of learning and overlearning", Psychophysiology, Vol. 3, No. 4, pp. 406-413, April 1967.

[Andreassi95] Andreassi, John L., "Psychophysiology: human behavior and physiological response", Lawrence Erlbaum Associates, Inc. Publishers, Hillsdale, NJ, USA, 1995.

[Ang04] Ang, Lou Benedict P., Belen, Erwin F., Bernardo, Ramon A. Jr., Boongaling, Eleazar R., Briones, Grace H., and Coronel, Jonathan B., "Facial Expression Recognition through Pattern Analysis of Facial Muscle". In: Proceedings of the 2004 IEEE Region 10 Conference, Chiang Mai, Thailand, November 2004

[Ark99] Ark, Wendy, Dryer, D. Christopher, and Lu, Davia J., "The Emotion Mouse". In: Proceedings of Human Computer Interaction, Edinburgh, Scotland, 1999.

[Avent94] Avent, R. Richard, Ng, Chong Teck, and Neal, John A., "Machine Vision Recognition of Facial Affect Using Backpropagation Neural Networks". In: Proceedings of the 16th Annual International Conference of the IEEE on Engineering in Medicine and Biology Society, 1994. Engineering Advances: New Opportunities for Biomedical Engineers, Vol. 2, pp. 1364-1365, 1994.

[Aylett04] Aylett, Ruth S., “Agents and affect: why embodied agents need affective systems Invited paper”. In: Proceedings of the 3rd Hellenic Conference on AI, Samos, Greece, Springer Verlag LNAI 3025, pp. 496-504, May 2004.

[Barger05] Barger, Tracy S., Brown, Donald E., and Alwan, Majd, “Health-Status Monitoring Through Analysis of Behavioral Patterns”, IEEE Transactions on Systems, Man, and Cybernetics, Part A: Systems and Humans, Vol. 35, No. 1, pp. 22-27, January 2005.

[BBC05] British Broadcasting Corporation (BBC), http://news.bbc.co.uk/1/hi/education/4477834.stm, 2005.

[Berkowitz93] Berkowitz, Leonard, “Aggression: its causes, consequences, and control”, McGraw-Hill, New York, NY, USA, 1993.

[Bezdek81] Bezdek, James C., “Pattern recognition with fuzzy objective function algorithms”, Plenum Press, New York, NY, USA, 1981.

[Bezerianos03] Bezerianos, Anastasios, Tong, Shanbao, and Thakor, Nitish V., “Time-Dependent Entropy Estimation of EEG Rhythm Changes Following Brain Ischemia”, Annals of Biomedical Engineering, Vol. 31, No. 2, pp. 221-232, February 2003.

[Birch05] Birch, Karen, MacLaren, Don, and George, Keith, “Sport and Exercise Physiology”, Garland Science/BIOS Scientific Publishers, New York, NY, USA, 2005.

[Böhme99] Böhme, Thomas J., Cox, Chris S., Valentin, Nicolas, and Denoeux, Therry, “Comparison of Autoassociative Neural Networks and Kohonen Maps for Signal Failure Detection and Reconstruction”, Intelligent Engineering Systems through Artificial Neural Networks 9, Proceedings of Artificial Neural Networks in Engineering 1999, pp. 637-644., C. H. Dagli et al. Editors, ASME Press, New York, NY, USA, 1999.

[Bowlby82]Bowlby, John, “Attachment”, Basic Books Inc., New York, NY, USA, 1982.

[Brdiczka05] Brdiczka, Oliver, Reignier, Patrick, and Crowley, James L., “Supervised Learning of an Abstract Context Model for an Intelligent Environment”. In: Proceedings of Smart Object and Ambient Intelligence Conference (sOc-EUSAI), Grenoble, France, October 2005.

[Brown77] Brown, Byron Wm. Jr. and Hollander, Myles, “Statistics, A Biomedical Introduction”, John Weiley & Sons, New York, NY, USA, 1977.

[Callaghan04] Callaghan, Victor, Clarke, Graham, Colley, Martin, Hagras, Hani, Chin, J. Jeannette, and Doctor, Faiyaz, “Intelligent Inhabited Environments”, BT Technology Journal, Vol.22, No.3, Klywer Academic Publishers, Dordrecht, Netherlands, July 2004.

[Callaghan07] Callaghan, Victor, Clarke, Graham, and Chin, Jeannette, “The Digital Home, Workplace and Ethics”. To appear in: Journal of Ubiquitous Computing and Communications, June 2007.

[Cañamero00] Cañamero, Lola D. and Fredslund, Jakob, “How Does It Feel? Emotional Interaction with a Humanoid LEGO Robot”, Socially Intelligent Agents: The Human in the Loop. Papers from the AAAI 2000 Fall Symposium, K. Dautenhahn Editor, AAAI Press, Menlo Park, CA, USA, 2000.

[Capera03] Capera, Davy, Gleizes, Marie-Pierre, and Glize, Pierre, "Self-organizing agents for Mechanical Design". In: Proceedings of the First International Workshop on Engineering Self-Organising Applications (ESOA 2003), Melbourne, Australia, 2003.

[Careagents03] "CareAgents", Intelligent Inhabited Environments Group, Department of Computer Science, University of Essex, http://iieg.essex.ac.uk/careagents.htm.

[Carlson92] Carlson, Neil R., "Foundations of Physiological Psychology", Allyn and Bacon Publishers, Needham Heights, MA, USA, 1992.

[Carlson98] Carlson, Neil R., "Physiology of Behaviour", Allyn and Bacon Publishers, Needham Heights, MA, USA, 1998.

[Chanel05] Chanel, Guillaume, Kronegg, Julien, Grandjean, Didier and Pun, Thierry, "Emotion Assessment: Arousal Evaluation Using EEG's and Peripheral Physiological Signals", Technical Report No. 05.02, Computer Vision Group, Computer Science Center, University of Geneva, December 2005.

[Chen98] Chen, Lawrence S. and Huang, Thomas S., "Multimodal Human Emotion/Expression Recognition". In: Proceedings of the Third IEEE International Conference on Automatic Face and Gesture Recognition, Nara, Japan, 1998.

[Cheng02] Cheng, Qi, Varshney, Pramod K., Mehrotra, Kishan G., Mohan, Chilukuri, K., "Optimal bandwidth assignment for distributed sequential detection". In: Proceedings of the Fifth International Conference on Information Fusion, Vol. 2, pp. 1550- 1556, Annapolis, MD, 2002.

[Claus98] Claus, Caroline and Boutilier, Carig, "The dynamics of reinforcement learning in cooperative multiagent systems". In: Proceedings of the fifteenth national/tenth conference on Artificial Intelligence/Innovative Applications of Artificial Intelligence, Madison, WI, USA, 1998.

[Codispoti01] Codispoti, Maurizio, Bradley, Margaret M., and Lang, Peter J., "Affective reactions to briefly presented pictures", Psychophysiology, Vol. 38, pp. 474–478, 2001.

[Cook05] Cook, Diane J. and Das Sajal K., "Smart Environments. Technology, Protocols, and Applications", Wiley-InterScience, John Wiley & Sons, Hoboken, NJ, USA, 2005.

[Cowie01] Cowie, Roddy, Douglas-Cowie, Ellen, Tsapatsoulis, Nicolas, Votsis, George, Kollias, Stefanos, Fellenz, Winfried, and Taylor, John G., "Emotion Recognition in Human-Computer Interaction", IEEE Signal Processing Magazine, January 2001, pp. 32-80, 2001.

[Cunningham04] Cunningham, William A., Raye, Carol L., and Johnson, Marcia K., "Implicit and Explicit Evaluation: fMRI Correlates of Valence, Emotional Intensity, and Control in the Processing of Attitudes", Journal of Cognitive Neuroscience, Vol. 16, No. 10, pp. 1717-1729, December 2004.

[Damasio95] Damasio, Antonio, "Descartes' Error: Emotion, Reason, and the Human Brain", Avon Books, New York, NY, USA, 1995.

[Darwin1859] Darwin, Charles, "The origin of species by means of natural selection or The preservation of favoured races in the struggle for life", The Modern Library, New York, NY, USA, 1998.

[Davies79] Davies, David L. and Bouldin, Donald W., "A Cluster Separation Measure", IEEE Transactions on Pattern Recognition and Machine Intelligence, Vol. PAMI-1, No.2, April 1979.

[DeSilva99] De Silva, Liyanage C. and Ng, Pei Chi, “Bimodal Emotion Recognition”. In: Proceedings of the IEEE International Conference on Information Communications and Signal Processing (ICICS1999), Singapore, Singapore, 1999.
[DeSousa87] De Sousa, Ronald, “The Rationality of Emotion”, MIT Press, Cambridge, MA, USA, 1987.

[Dittmar91] Dittmar, André, Delhomme, Georges, Caterini, R., and Vernet-Maury, E., “Analysis of Skin Potential Response using a Novel Feature Code for the Study of the Emotional Response”. In: Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Vol. 13, No. 1, pp. 427-428, 1991.

[Doctor04] Doctor, Faiyaz, Hagras, Hani, Callaghan, Victor, and Lopez, Antonio, “An Adaptive Fuzzy Learning Mechanism for Intelligent Agents in Ubiquitous Computing Environments”. In: Proceedings of the 2004 World Automation Conference, Seville, Spain, July 2004.

[Doctor05] Doctor, Faiyaz, Hagras, Hani, and Callaghan, Victor, “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, Vol. 35, No.1, pp.55-65, 2005.

[Dodier94] Dodier, Robert H., Lukianow, Diane, Ries, James, and Mozer, Michael C., “A comparison of neural net and conventional techniques for lighting control”, Applied Mathematics and Computer Science, Vol. 4, 447-462, 1994.

[Duman06] Duman, Hakan, Hagras, Hani, and Callaghan, Victor, “Intelligent Association Selection of Embedded Agents in Intelligent Inhabited Environments”. To appear in: Pervasive and Mobile Computing, Special Issue on Design and Use of Smart Environments, November 2006.

[Egadgets03] “eGadgets”, Intelligent Inhabited Environments Group, Department of Computer Science, University of Essex, Colchester, UK, http://iieg.essex.ac.uk/egadgets.htm.

[Ekman73] Ekman, Paul, “Cross-cultural studies of facial expression”. In P. Ekman (Ed.), Darwin and facial expression. A century of research, Edited by Paul Ekman, Academic Press, New York, NY, USA, 1973.

[Ekman83] Ekman Paul, Levenson Robert W., and Friesen Wallace V., “Autonomic nervous system activity distinguishes among emotions”, Science, Vol. 221, pp. 1208–1210, 1983.

[Ekman94] Ekman, Paul, “Strong evidence for universals in facial expressions: A reply to Russell's mistaken critique”, Psychological Bulletin, Vol. 115, No. 2, pp. 268-287, 1994.

[Elster89] Elster, Jon, “Solomonic Judgments. Studies in the limitations of rationality”, Cambridge University Press, Cambridge, UK, 1989.

[Eng04] Eng, Kynan, Douglas, Rodney J., and Verschure, Paul F. M. J., “An interactive space that learns to influence human behaviour”, IEEE Transactions on Systems, Man, and Cybernetics, Vol. 35, No. 1, pp. 66-77, 2005.

[Fernandez97] Fernandez, Raul, “Stochastic Modelling of Physiological Signals with Hidden Markov Models: A Step Toward Frustration Detection in Human-Computer Interfaces”, M.Sc. Thesis, Department of Computer Science, Massachusetts Institute of Technology, 1997.

[Fiedler00] Fiedler, Edna R., Rocco, Pam Della, Schroeder, David J, and Nguyen, Kiet T., “The Relationship between Aviators’ Home-based Stress to Work Stress and Self-Perceived Performance”, Technical Report

DOT/FAA/AM-00/32, Civil Aeromedical Institute, Federal Aviation Administration, Oklahoma City, OK, USA, October 2000.

[Foresee97] Foresee, F. Dan and Hagan, Martin T., "Gauss-Newton approximation to Bayesian learning". In: Proceedings of the International Joint Conference on Neural Networks, Houston, Texas, USA, pp. 1930-1935, June, 1997.

[Fortenbaugh75] Fortenbaugh, William W, "Aristotle on emotion: a contribution to philosophical psychology, rhetoric, poetics, politics, and ethics", Duckworth Publishers, London, UK, 1975.

[Fredrickson98] Fredrickson, Barbara L. and Levenson, Robert W., "Positive Emotions Speed Recovery from the Cardiovascular Sequelae of Negative Emotions", Cognition and Emotion, Vol. 12, No. 2, pp. 191-220, 1998.

[Fu68] Fu, King Sun, "Sequential methods in pattern recognition and machine learning", Academic Press, New York, NY, USA, 1968.

[Garzon02] Garzon, Max H., Ankaraju, Prashant, Drumwright, Evan, and Kozma, Robert, "Neurofuzzy Recognition and Generation of Facial Features in Talking Heads". In: Proceedings of the IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), Hawaii, HI, USA, pp. 926-931, 2002.

[Goff05] Goff, Max, "Network Distributed Computing: Fitscapes and Fallacies", Prentice Hall Professional Technical Reference, Indianapolis, IN, USA, 2004.

[Goldie00] Goldie, Peter, "The emotions: A philosophical exploration", Clarendon Press, Oxford, UK, 2000.

[Goleman97] Goleman, Daniel, "Emotional Intelligence. Why it can matter more than IQ", Bantam Books, New York, NY, USA, 1997.

[Gopalratnam04] Gopalratnam Karthik and Cook, Diane J., "Active LeZi: An Incremental Parsing Algorithm for Sequential Prediction", International Journal of Artificial Intelligence Tools, Vol. 14, No. 1-2, pp. 917-930, 2004.

[Green87] Green, Simon, "Physiological Psychology. An Introduction", Routledge & Kegan Paul Editors Ltd., London, UK, 1987.

[Gribok00] Gribok, Andrei, Hines, J. Wesley, and Uhrig, Robert E., "Use of Kernel based Techniques for Sensor validation in Nuclear Power plants". In: Proceedings of the International Topical Meeting on Nuclear Plant Instrumentation, Controls, and Human-Machine Interface Technologies, Washington, DC, USA, November 2000.

[Gross01] Gross, James J., "Emotion Regulation in Adulthood: Timing Is Everything", Current Directions in Psychological Science, Vol. 10, No. 6, pp. 214-219, December 2001.

[Gross98] Gross, James J., "Sharpening the focus: Emotion regulation, arousal, and social competence", Psychological Inquiry, Vol. 9, No. 4, pp. 287-290, 1998.

[Guo96] Guo, Chengan and Kuh, Anthony, "A learning sequential detection method based on neural networks". In: Proceedings of the 3rd International Conference on Signal Processing, Beijing, China, Vol. 2, pp. 1409-1412, October 1996.

[Hagan94] Hagan, Martin T. and Menhaj, Mohammad. B., “Training Feedforward Networks with the Marquardt Algorithm”, IEEE Transactions on Neural Networks, Vol. 5, No. 6, pp.989-939, 1994.

[Hagras02] Hagras, Hani, Callaghan, Victor, Clarke, Graham, Colley, Martin, Pounds-Cornish, Anthony, Holmes, Arran, and Duman, Hakan, “Incremental Synchronous Learning for Embedded-Agents Operating in Ubiquitous Computing Environments”, Soft Computing Agents: A New Perspective for Dynamic Information Systems, Frontiers in Artificial Intelligence and Application, IOS Press, Amsterdam, Netherlands, 2002

[Handbook05] “Mobile Computing Handbook”, Mohammad Ilyas and Imad Mahgoud Editors, CRC Press, London, UK, 2005.

[Haykin99] Haykin, Simon, “Neural Networks. A Comprehensive Foundation”, Prentice Hall, Upper Saddle River, NJ, USA, 1999.

[Healey00] Healey, Jennifer, “Wearable and Automotive Systems for Affect Recognition from Physiology”. Ph.D. Thesis, Department of Computer Science, Massachusetts Institute of Technology, Cambridge, MA, USA 2000.

[Healey02] Healey, Jennifer and Picard, Rosalind W., “Eight-emotion Sentics Data”, MIT Affective Computing Group, http://affect.media.mit.edu, 2002.

[Healey98] Healey, Jennifer, Picard, Rosalind, and Dabek, Frank, “A new Affect-Perceiving Interface and its Application to Personalized Music Selection”. In: Proceedings of the Workshop on Perceptual User Interfaces, San Francisco, CA, USA, 1998.

[Heider58] Heider, Fritz, “The psychology of interpersonal relations”, John Wiley & Sons, New York, NY, USA, 1958.

[Heierman04] Heierman, Edwin O., Youngblood, Michael, and Cook, Diane J., “Mining Temporal Sequences to Discover Interesting Patterns”. In: Proceedings of the Workshop on Mining Temporal and Sequential Data, Tenth ACM International Conference on Knowledge Discovery and Data Mining, Seattle, WA, USA, August 2004.

[Heyward98] Heyward, Vivian H., “Advanced Fitness Assessment and Exercise Prescription”, 3rd Edition, Human Kinetics, Champaign, IL, USA, 1998.

[Himmelblau95] Himmelblau, David M. and Bhalodia, Mohan, “On-line Sensor Validation of Single Sensors using Artificial Neural Networks”. In: Proceedings of the 1995 American Control Conference, pp. 766-770, Seattle, WA, USA, 1995.

[Hines97] Hines, J. Wesley, Wrest, Darryl J., and Uhrig, Robert E., “Use of Auto-Associative Neural Networks for Signal Validation”. In: Proceedings of NEURAP 97 Neural Network Applications, Marseille, France, March 1997.

[Homelab03] “365 days’Ambient Intelligence research in HomeLab”, Phillips Research, Boris de Ruyter Editor, April 2003.

[Housen05] “The PlaceLab”, Department of Architecture, Massachusetts Institute of Technology, Cambridge, MA, USA, http://architecture.mit.edu/house_n/projects.html.

[Ibargüengoitia96] Ibargüengoitia, Pablo H., Sucar, Luis E., and Vadera, Sunil, "A Probabilistic Model for Sensor Validation". In: Proceedings of the 12th Conference on Uncertainty in Artificial Intelligence, Portland, OR, USA, pp. 332-339, August 1996.

[Inoue96] Inoue, Kakyu, Kawabata, Kuniaki, and Kobayashi, Hisato, "On a decision making system with emotion". In: Proceedings of the 5th IEEE International Workshop on Robot and Human Communication, Tsukuba, Japan, pp. 461–465, November 1996.

[Intille04] Intille, Stephen S., Larson, Kent, Beaudin, Jennifer S., Nawyn, Jason, Munguia Tapia, Emannuel, and Kaushik, Pallavi, "A living laboratory for the design and evaluation of ubiquitous computing technologies". In: Extended Abstracts of the 2005 Conference on Human Factors in Computing Systems, Portland, OR, USA, 2004.

[ISTAG01] IST Advisory Group, Scenarios for ambient intelligence in 2010, Final Report, February 2001.

[Ito98] Ito, Tiffany A., Cacioppo, John T., and Lang, Peter J., "Eliciting affect using the International Affective Picture System: Trajectories through evaluative space", Personality and Social Psychology Bulletin, Vol. 24, No. 4, pp. 855–879, August 1998.

[Itoh04] Itoh, Kazuko, Miwa, Hiroyasu, Matsumoto, Munemichi, Zecca, Massimiliano, Takanobu, Hideaki, Roccella, Stefano, Carrozza, Maria Chiara, Dario, Paolo, and Takanishi, Atsuo, "Various emotional expressions with emotion expression humanoid robot WE-4RII". In: proceedings of the 1st IEEE Technical Exhibition Based Conference on Robotics and Automation, pp. 35-36, Tokyo, Japan, November 2004.

[Jackson90] Jackson, Andrew S., Blair, Steven N., Mahar, Matthew T., Wier, Larry T., Ross, Robert M., and Stuteville, Joseph E., "Prediction of functional aerobic capacity without exercise testing", Medicine and Science in Sports Exercise, Vol. 22, No. 6, pp. 863-70, December 1990.

[Johnston98] Johnston, P.D., "Should sequential designs be used for comparative experiments on animals", New Zealand Journal of Agricultural Research, Vol. 41, pp. 561-566, 1998.

[Kaelbling96] Kaelbling, Leslie P., Littman, Michael L., and Moore, Andrew W., "Reinforcement Learning: A Survey", Journal of Artificial Intelligence research, Vol. 4, pp. 236-285, 1996.

[Keeler96] Keeler, James David, Havener, John Paul, Godbole, Devendra, and Ferguson, Ralph Bruce II, "Virtual Continuous Emission Monitoring System", U.S. Patent 5548528, 1996.

[Keil02] Keil, Andreas, Bradley, Margaret M., Hauk, Olaf, Rockstroh, Brigitte, Elbert, Thomas, and Lang, Peter J., "Large-scale neural correlates of affective picture processing", Psychophysiology, Vol. 39, pp. 641-649, 2002.

[Kidd99] Kidd, Cory D., Orr , Robert J., Abowd, Gregory D., Atkeson, Christopher G., Essa, Irfan A., MacIntyre, Blair, Mynatt, Elizabeth, Starner, Thad E. and Newstetter, Wendy, "The Aware Home: A Living Laboratory for Ubiquitous Computing Research". In: the Proceedings of the Second International Workshop on Cooperative Buildings - CoBuild'99, Pittsburgh, PA, USA, 1999.

[Kim02] Kim, Kyung Hwan, Bang, Seok Won, and Kim, Sang Ryong, "Development of person-independent emotion recognition systems based on multiple physiological signals". In: Proceedings of the Second Joint EMBS/BMES Conference, Houston, TX, USA, pp. 50-51, October 2002.

[Kim04] Kim, Kyung Hwan, Bang, Seok Won, and Kim, Sang Ryong, "Emotion recognition system using short-term monitoring of physiological signals", Medical and Biological Engineering and Computing, Vol. 42, No. 3, pp. 419-427, May 2004.

[KimJ05] Kim, Jonghwa, André, Elisabeth, Rehm, Matthias, Vogt, Thurid, and Wagner, Johannes, "Integrating information from speech and physiological signals to achieve emotional sensitivity". In: Proceedings of the 9th European Conference on Speech Communication and Technology, Lisboa, Portugal, September 2005.

[Kobayashi91] Kobayashi, Hiroshi and Hara, Fumio, "The Recognition of Basic Facial Expressions by Neural Networks". In: Proceedings of the IEEE International Joint Conference on Neural Networks, Seattle, WA, USA, Vol. 1, pp. 460-466, 1991.

[Kobayashi93] Kobayashi, Hiroshi and Hara, Fumio, "Dynamic recognition of Basic facial Expressions by Discrete-time Recurrent Neural Networks". In: Proceedings of the International Joint Conference on Neural Networks, Nagoya, Japan, pp. 155-158, October 1993.

[Kramer98] Kramer, Mark A., "Autoassociative Neural Networks", Computers and Chemical Engineering, Vol. 16, No. 4, pp. 313-328, 1998.

[Lang79] Lang, Peter J., "A Bio-Informational Theory of Emotional Imagery", Psycophysiology, Vol. 16, No. 6, pp. 495-512, 1979.

[Lang01] Lang, Peter J., Bradley, Margaret M., and Cuthbert, Bruce N., "International affective picture system (IAPS): Instruction manual and affective ratings", Technical Report A-5, The Center for Research in Psychophysiology, University of Florida, 2001.

[Larsen86] Larsen, Randy J., Diener, Ed, and Emmons, Robert A., "Affect Intensity and Reactions to Daily Life Events", Personality and Social Psychology, Vol. 51, No. 4, pp. 803-814, 1986.

[Ledoux98] Ledoux, Joseph, "The emotional brain", Weidenfeld & Nicholson, The Orion Publishing Group Ltd, London, UK, 1998.

[Lee94] Lee, S. C., "Sensor Value Validation Based on Systematic Exploration of the Sensor Redundancy for Fault Diagnosis KBS", IEEE Transactions on Systems, Man and Cybernetics, Vol. 24, No. 4, pp. 594-605, 1994.

[Leon04] Leon, Enrique, Clarke, Graham, Callaghan, Victor, and Sepulveda, Francisco, "Real-time Detection of Emotional Changes for Inhabited Environments", Computer and Graphics, Vol. 28, No. 5, pp. 635-642, 2004.

[Leon05a] Leon, Enrique, Clarke, Graham, Sepulveda, Francisco, Callaghan, Victor, "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, 2004.

[Leon05b] Leon, Enrique, Clarke, Graham, Callaghan, Victor, "Towards a robust real-time emotion detection system for intelligent buildings". In: Proceedings of the First IEE International Workshop on Intelligent Environments, Colchester, UK, 2005.

[Levenson91] Levenson, Robert W., Carstensen, Laura L., Friesen, Wallace V., and Ekman, Paul, "Emotion, physiology and expression in old age", Psychology and Aging, Vol. 6, No. 1, pp. 28-35, 1991.

[Levenson92] Levenson, Robert W., "Autonomic Nervous System Differences among Emotions", Psychological Science, Vol.3, No. 1, pp. 23-27, 1992.

[Li99] Li, X. Rong and Wang, Lu, "Fault Detection Using Sequential Probability Ratio Test". In: Proceedings of the IEEE Power Engineering Society Winter Meeting, New York, NY, USA, Vol. 2, pp. 938-943, February 1999.

[Lu01] Lu, Pong-Jeu, Zhang, Ming-Chuan, Hsu, Tzu-Cheng, and Zhang, Jin, "An Evaluation of Engine Faults Diagnostics Using Artificial Neural Networks", Journal of Engineering for Gas Turbines and Power, Vol. 123, No. 2, pp. 340-346, April 2001.

[Luo98] Luo, Rongfu, Misra, Manish, Qin, S. Joe, Barton, Randall, and Himmelblau, David M., "Sensor Fault Detection via Multiscale Analysis and Nonparametric Statistical Inference", Industrial and Engineering Chemistry Research, Vol. 37, pp. 1024-1032, 1998.

[Matsuno94] Matsuno, Katsuhiro, Tsuji, Saburo, and Lee, Chil-Woo, "Recognition of Human Facial Expressions using a 2-Dimensional Physical Model". In: Proceedings of IEEE Workshop on Visualization and Machine Vision, Seattle, WA, USA, pp. 74 -83, June 1994.

[Messie04] Derek Messie and Jae C. Oh, "Self-Organizing Lightweight Agents for Large-Scale Real-Time Systems Scheduling". In: Proceedings of Workshop on Games and Emergent Behaviors in Distributed Computing Environments, the 8th International Conference on Parallel Problem Solving from Nature, Birmingham, UK, 2004.

[Mischel86] Mischel, Walter, "Introduction to Personality". Fourth Edition: A New Look, CBS College Publishing, Holt, Rinehart and Winston Editors, New York, NY, USA, 1986.

[Mobahi03] Mobahi, Hossein and Ansari, Shahin, "Fuzzy Perception, Emotion and Expression for Interactive Robots". In: Proceedings of the IEEE International Conference on Systems, Man and Cybernetic, Vol. 4, pp. 3918-3923, Washington, D.C., USA, October 2003.

[Modler98] Modler, Paul, Hofmann, Frank, and Zannos, Ioannis, "Gesture Recognition by Neural Networks and the Expression of Emotions". In: Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics, Sand Diego, CA, USA, Vol. 2, pp. 1072 -1075, October1998.

[Moran01] Moran, Thomas P. and Dourish Paul, "Context-Aware Computing", Human-Computer Interaction, Volume 16, No 2-4, 2001.

[Morishima00] Morishima, Shigeo, "Real-time face Analysis and Synthesis using Neural Networks". In: Proceedings of 2000 IEEE Workshop on Neural Networks for Signal Processing, Sidney, Australia, pp. 13-21, 2000.

[Moriyama99] Moriyama, Tsuyoshi and Ozawa, Shinji, "Emotion Recognition and Synthesis System on Speech". In: Proceedings of the IEEE International Conference on Multimedia Computing and Systems, Florence, Italy, pp. 840-844, 1999.

[Mozer95] Mozer, Michael C., Dodier, Robert H., Anderson, Marc, Vidmar, Lucky, Cruickshank III, Robert F., and Miller, Debra, "The neural network house: An overview", Current trends in connectionism, Lars Niklasson & Mikael Boden Editors, Lawrence Erlbaum Associates Hillsdale, NJ, USA, 1995.

[Mozer98] Mozer, Michael C., "The Neural Network House: An Environment that Adapts to its Inhabitants". In: Proceedings of the American Association for Artificial Intelligence Spring Symposium on Intelligent Environments, Menlo, Park, CA, USA, 1998.

[Music01] Music, Graham, "Affect and Emotion", Ideas in Psychoanalysis, Icon Books Ltd., Cambridge, UK, 2001.

[Nakatsu99] Nakatsu, Ryohei, Nicholson, Joy, and Tosa Naoko, "Emotion Recognition and its Application to Computer Agents with Spontaneous Interactive Capabilities". In: Proceedings of the IEEE International Conference on Multimedia Computing and Systems, Florence, Italy, pp. 439-444, 1999.

[Napolitano98] Napolitano, Marcelo, Windon, Dale A., Casanova, Jose L., Innocenti, Mario, and Silvestri, Giovanni, "Kalman Filters and Neural-Network Schemes for Sensor Validation in Flight Control Systems", IEEE Transactions on Control Systems Technology, Vol. 6, No. 5, pp. 596-611, 1998.

[Nasoz03a] Nasoz, Fatma., Alvarez, Kaye, Lisetti, Christine L., and Finkelstein, Neal, "Emotion recognition from Physiological Signals for Presence Technology", International Journal of Cognition, Technology, and Work - Special Issue on Presence, Vol. 1, No. 1, 2003.

[Nasoz03b] Nasoz, Fatma, Lisetti, Christine L., Alvarez, Kaye, and Finkelstein, Neal, "Emotion recognition from Physiological Signals for User Modelling of Affect". In: Proceedings of the 3rd Workshop on Affective and Attitude user Modelling, Pittsburgh, PA, USA, 2003.

[Nicholson00] Nicholson, Joy, Takahashi, Kazuhiko, and Nakatsu, Ryohei, "Emotion recognition in speech using Neural Networks", Neural Computing and Applications, Vol. 9, No. 4, pp. 290-296, 2000.

[Oatley04] Oatley, Keith, "Emotions: A Brief History", Blackwell Publishing Inc., Malden, MA, USA, 2004.

[Ordoñez97] Ordoñez, Raúl, Zumberge, Jon, Spooner, Jeffrey T. and Passino, Kevin M., "Adaptive Fuzzy Control: Experiments and Comparative Analyses", IEEE Transactions on Fuzzy Systems, Vol. 5, No. 2, pp. 167-188, May 1997.

[Ortony88] Ortony, Andrew, Clore, Gerald L., Collins, Allan, "The cognitive structure of emotions", Cambridge University Press, Cambridge, UK, 1988.

[Osgood57] Osgood, Charles E., Suci, George J., and Tannenbaum, Percy H., "The Measurement of Meaning", University of Illinois Press, Champaign, IL, USA, 1957.

[Park02] Park, Chang-Hyun, Lee, Dong-Wook, and Sim, Kwee-Bo, "Emotion Recognition of Speech based on RNN". In: Proceedings of the First International Conference on Machine Learning and Cybernetics, Beijing, China, pp. 2010-2013, 2002.

[Pecchinenda96] Pecchinenda, Anna and Smith, Craig A., "The motivational significance of skin conductance activity during a difficult problem-solving task", Cognition and Emotion, Vol. 10, pp. 481-503, 1996.

[Peters99] Peters, Richard Alan II, Wilkes, D. Mitch, Gaines, Daniel M., and Kawamura, Kaz, “A Software Agent Based Control System for Human-Robot Interaction”. In: Proceedings of the Second International Symposium on Humanoid Robots, Tokyo, Japan, October 1999.

[Phillips06] “Phenom Project”, Phillips Research, Eindhoven, Netherlands, http://www.research.philips.com/technologies/syst_softw/phenom/index.html.

[Picard01] Picard, Rosalind, Vyzaz, Elias, and Healey, Jennifer, “Toward Machine Emotional Intelligence: Analysis of Affective Physiological State”, IEEE Transactions on Pattern Analysis and Machine Intelligence, No. 23, Vol. 10, October, 2001.

[Picard95] Picard, Rosalid, “Affective Computing”, Technical Report No. 321, Media Laboratory, Perceptual Computing Section, MIT, Cambridge, MA, USA, 1995.

[Picard97] Picard, Rosalind and Healey, Jennifer, “Affective Wearables”, Personal Technologies, Vol. 1, No. 4, pp. 231-240, 1997.

[Plutchik94] Plutchik, Robert, “The Psychology and Biology of Emotion”, HarperCollins College Publishers, New York, NY, USA, 1994.

[Poloniecki04] Poloniecki, Jan, Sismanidis, Charalambos, Bland, Martin, Jones, Pau, “Retrospective cohort study of false alarm rates associated with a series of heart operations: the case for hospital mortality monitoring groups”, BMJ Journal, pp. 328:375, doi:10.1136/bmj.37956.520567.44, January 2004.

[Pounds-Cornish02] Pounds-Cornish, Anthony and Holmes, Arran, “The iDorm - a Practical Deployment of Grid Technology”. In: Proceedings of the 2nd IEEE International Symposium on Cluster Computing and the Grid, Berlin, Germany, May 2002.

[Prendinger06] Prendinger, Helmut, Becker, Christian, and Ishizuka, Mitsuru, “A study in users' physiological response to an empathic interface agent”, International Journal of Humanoid Robotics, Vol. 3, No. 3, pp. 371-391, September 2006.

[Prkachin99] Prkachin, Kenneth M., Williams-Avery, Rhonda, Zwaal, Caroline, and Mills, David E., “Cardiovascular Changes during Induced Emotion: An Application of Lang's Theory of Emotional Imagery”, Journal of Psychosomatic Research, Vol. 47, No. 3, pp. 255-267, 1999.

[Rivera05] Rivera-Illingworth, Fernando, Callaghan, Victor, and Hagras, Hani, “A Neural Network Agent Based Approach to Activity Detection in AmI Environments”. In: Proceedings of IEE International Workshop on Intelligent Environments 2005 (IE05), Colchester, UK, June 2005.

[Rosenblum96] Rosenblum, Mark, Yacoob, Yaser, and Davis, Larry S., “Human Expression Recognition from Motion using Radial Basis Function Network Architecture”, IEEE Transactions on Neural Networks, Vol. 7, No. 5, pp. 1121-1138, September 1996.

[Rutishauser05] Rutishauser, Ueli, Joller, Josef, and Douglas, Rodney, “Control and learning of ambience by an intelligent building”, IEEE Transactions on Systems, Man, and Cybernetics Part A: Systems and Humans, Vol. 35, No. 1, pp. 121-132, January 2005.

[Salovey90] Salovey, Peter and Mayer, John D., “Emotional intelligence”, Imagination, Cognition, and Personality, Vol. 9, pp. 185-211, 1990.

[Sandhu04] Sandhu Jaspal S., Agogino Alice M., and Agogino, Adrian K., "Wireless Sensor Networks for Commercial Lighting Control: Decision Making with Multi-agent Systems". In: Working Notes of the American Association for Artificial Intelligence, AAAI, Sensor Networks Workshop, pp. 88-92, 2004.

[Satyanarayanan01] Satyanarayanan, Mahadev, "Pervasive Computing: Visions and Challenges", IEEE Personal Communications, Vol. 8, No. 4, pp. 10-17, 2001.

[Sepulveda04] Sepulveda, Francisco, Meckes, Matthew, and Conway, Bernie A., "Cluster Separation Index Suggests Usefulness of Non-Motor EEG Channels in Detecting Wrist Movement Direction Intention". In: Proceedings of the IEEE Conference on Cybernetic and Intelligent Systems, Singapore, Singapore, December 2004.

[Sinha92] Sinha, Rajita, Lovallo, William R., and Parsons, Oscar A., "Cardiovascular differentiation of emotions", Psychosomatic Medicine, Vol. 54, No. 4, pp. 422-435, 1992.

[Sloan86] Sloan, Stephen J. and Cooper, Cary L., "Pilots under stress", Routledge and Kegan Paul Books Ltd., London. UK, 1986.

[Smith02] Smith, J. Carson, O'Connor, Patrick J., Crabbe, James B., and Dishman, Rod K., "Emotional Responsiveness after low-and moderate-intensity Exercise and Seated Rest", Medicine and Science in Sports Exercise, Vol. 34, No. 7 , pp. 1158-1167, 2002.

[Smith03] Smith, J. Carson and O'Connor, Patrick J., "Physical activity does not disturb the measurement of startle and corrugator responses during affective picture viewing", Biological Psychology, Vol. 63, No. 3, pp. 293-310, 2003.

[Spiegelhalter03] Spiegelhalter, David, Grigg, Olivia, Kinsman, Robin and Treasure, Tom, "Risk-adjusted sequential probability ratio tests: applications to Bristol, Shipman and adult cardiac surgery", International Journal for Quality in Health Care, Vol. 15, pp. 7-13, 2003.

[Suzuki98] Suzuki, Kenji, Camurri, Antonio, Ferrentino, Pasqualino, and Hashimoto, Shuji, "Intelligent Agent System for Human-Robot Interaction through Artificial Emotion". In: Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics, San Diego, CA, USA, October 1998.

[SWAMI05] "The Safeguards in a World of Ambient Intelligence (SWAMI) Project", The brave new world of ambient intelligence: A state-of-the-art review, Deliverable D1, July 2005.

[Sycara98] Sycara, Katia P., "Multiagent Systems", AI magazine Volume 19, No.2, 1998.

[Tartakovsky01] Tartakovsky, Alexander, "Quickest Detection of Targets in Multiple-Resolution-Element Systems: Sequential Detection Versus Non-Sequential Detection", In: Proceedings of the Workshop on Estimation, Tracking, and Fusion: A Tribute to Yaakov Bar-Shalom, pp. 326-350, Monterey, CA, May 2001.

[Tugade04] Tugade, Michele M. and Fredrickson, Barbara L., "Resilient individuals use positive emotions to bounce back from negative emotional experiences", Journal of Personality and Social Psychology, Vol. 86, No. 2, pp. 320-333, 2004.

[Wall70] Wall, William Douglas and Williams H. L., "Longitudinal studies and the social sciences", Heinemann Educational Books Ltd, London, UK, 1970.

[Wehrle94] Wehrle, Thomas, “New fungus eater experiments”, From Perception to Action, P. Gaussier and J. D. Nicoud Editors, IEEE Computer Society Press, Los Alamitos, CA, USA, pp. 400-403, 1994.

[Weiser91] Weiser, Mark, “The Computer for the 21st Century”, Scientific American, Vol. 265, No. 3, pp.94-104, September 1991.

[Weiss99] “Multiagent Systems: A Modern Approach to Distributed Artificial Intelligence”, Gerhard Weiss Editor, MIT Press, Cambridge, MA, USA, 1999.

[Winston92] Winston, Patrick H., “Artificial Intelligence”, Third Edition, Addison Wesley Pub. Co., Reading, MA, USA, 1992.

[Witten00] Witten, Ian, H. and Eibe, Frank, “Data mining: practical machine learning tools and techniques with Java implementations”, Morgan Kaufmann, San Francisco, CA, USA, 2000.

[Yoo05] Yoo, Sun K., Lee, Chung K., Park, Youn J., Kim, Nam H., Lee, Byung C. and Jeong, Kee S., “Neural Network Based Emotion Estimation Using Heart Rate Variability and Skin Resistance”. In: Advances in Natural Computation, Lecture Notes in Computer Science, Springer, Berlin, Germany, pp. 818-824, 2005.

[Yoshitomi00] Yoshitomi, Yasunari, Kim, Sung-III., Kawano, Takako, and Kitazoe, Tetsuro, “Effect of sensor Fusion for Recognition of Emotional States using Voice, Face Image and Thermal Image of Face”. In: Proceedings of the 2000 IEEE International Workshop on Robot and Human Interactive Communication, Osaka, Japan, pp. 178-183, 2000.

[Young91] Young, Copeland H., Savola, Kristen L., and Phelps, Erin, “Inventory of longitudinal studies in the social sciences”, Sage Publications, Newbury Park, CA, USA,1991.

[Zheng06] Zheng, Wenming, Zhou, Xiaoyan, Zou, Cairong, and Zhao, Li, “Facial Expression Recognition Using Kernel Canonical Correlation Analysis”, IEEE Transactions on Neural Networks, Vol. 17, No. 1, pp. 233-238, January 2006.

Appendix 1 Compendium of Relevant Work in Affective Computing

Appendix 1 presents a small compendium of some of the most relevant work in the area of affective computing (in chronological order). The first column refers to the name of the paper describing the detection or simulation system. If the approach includes a description of the measures employed to detect and/or simulate emotions and the methods employed to classify or represent emotional classes these are indicated in the columns "Detection/Simulation Mechanism" and "Inference Mechanism" respectively. Real-time operability refers to whether the method provides sufficient indication of its suitability for real-time processing regardless of whether that particular issue is explicitly addressed in the paper. Wearability is the capability or potential of the detection approach of being implemented as a wearable artefact providing physical contact with the user in a "long-term intimate way" [Picard97]. User-independence indicates whether that particular mechanism is able to perform emotion detection on different groups of people either by pre-training or dynamic adaptation regardless of whether a particular individual was included during system setup or not. Robustness-Ambient/Activity mobility refers to the provisions taken by the author or designer to endow their emotion detection system with the capacity of operating reliably regardless of the user's activity and location inside a pervasive environment.

Approach	Detection	Simulation	Detection/Simulation Mechanism						Inference Mechanism			Real-time Operability	Wearability	User independence	Robustness- Ambient /Activity Mobility	Comment
			Physiological	Speech	Facial	Gestural	Event-based	Other	AI-based	Statistical	Other					
A Real-time Automated System for the Recognition of Human Facial Expressions [Anderson06]	☑				☑				☑			☑		☑		A recent novel approach to facial emotion detection based on face tracking, optical flow and Support Vector Machines (SVMs). This model improves on previous approaches by providing computationally-inexpensive, fully-automated, real-time recognition of facial expressions associated with 6 emotions. The system is however limited in terms of user mobility (the subject has to be in front of the camera at all times) and picture resolution.
Facial Expression Recognition Using Kernel Canonical Correlation Analysis [Zheng06]	☑				☑					☑						This paper presents a method for detecting 6 emotional expressions using Kernel Canonical Correlation Analysis (KCCA) which is a method to perform non-linear correlation of two multidimensional variables. Zheng et al. employed KCCA to find the correlation between facial emotional expressions and their corresponding semantic ratings. The best results were achieved in cross-validation tests using discrete emotional

																classes (as opposed to semantic ratings) with 98.36% recognition rates.
A study in users' physiological response to an empathic interface agent [Prendinger06]	☑		☑							☑		☑				Predinger employs Electromyogram and skin conductance signals to measure the levels of emotional arousal and valence associated with affective reactions in an interactive game.
Integrating information from speech and physiological signals to achieve emotional sensitivity [KimJ05]	☑		☑	☑						☑		☑				Jonghwa Kim et al. present an analysis on the advantages of following a multimodal rather unimodal approach for the problem of emotion detection. They combined features extracted from speech and 4 physiological signals (Electromyogram, electrocardiogram, skin conductivity and respiration change) to perform recognition of combinations of arousal and valence values.
Emotion Assessment: Arousal Evaluation Using EEG's and Peripheral Physiological Signals [Chanel05]	☑		☑							☑						A method for classifying emotional arousal (low, neutral or high) using statistical features calculated from physiological signals stemming from the central (Electroencephalograms, EEGs) and autonomous nervous system. Two classifiers were compared: Naïve Bayes and Fisher Discriminat Analysis. The best results were achieved using Bayes classification and EEG signals with 72% recognition rate.
Neural Network Based Emotion Estimation Using Heart Rate Variability and Skin Resistance [Yoo05]	☑		☑						☑							Used an Artificial Neural Network to estimate 4 different emotions based on the valence/arousal classes. Yoo et al. achieved a recognition rate of 80.2% for 4 individuals using time and frequency features extracted from electrocardiogram and the skin resistance.

Emotion recognition system using short-term monitoring of physiological signals [Kim04]	☑		☑						☑				☑	☑		Kim et al. present another set of experiments carried out using the SVMs mechanism introduced in [Kim02]. This time recognition rates were in the ranged of 78.4 and 61.8% for 50 children. According to Kim, this approach provides user-independent recognition and could potentially be implemented as a wearable artefact.
Emotion Recognition from Physiological Signals for Presence Technologies [Nasoz03a]	☑		☑						☑	☑		☑	☑	☑		This effort from Christine Lisetti's team emphasises on social "presence". The main goal of this approach is to enhance training systems by incorporating emotional information into the learning environment.
Emotion recognition from Physiological Signals for User Modelling of Affect [Nasoz03b]	☑		☑						☑	☑			☑	☑		Nasoz's approach to the problem of physiological emotion detection is based on the utilization of GSR, temperature, and heart rate. Nasoz compared two classification methods using averaged values of three physiological signals (GSR, temperature, and HR) linked to 6 emotional states. K-nearest neighbour and Discriminant Function Analysis (DFA) were employed to recognized emotional states in cross-validation tests for 31 individuals. The best results were those from DFA with 90% of recognition rate for the "fear" emotional state.
Emotion Recognition of Speech based on RNN [Park02]	☑			☑					☑			☑				It employs Recurrent Neural Networks for detecting speech parameters associated with neutral emotion, angry, laugh (happy) and surprise.
Development of person-independent emotion recognition systems based on multiple physiological signals [Kim02]	☑		☑							☑			☑	☑		Extracted information from 50 children aged 5-8 years old. It requires shorter signal monitoring than other approaches using statistical analysis, e.g, [Picard01]. The accuracy is 77.8% in cross-validation trials. Classification involved 3-4 emotional states and was based on Support Vector Machines (SVMs).

Toward Machine Emotional Intelligence: Analysis of Affective Physiological State [Picard01]	☑		☑							☑		☑	☑			Picard et al. present a survey of the latest approaches in physiological emotion detection as well as a very good introduction on emotion recognition. The paper provides a list of the factors that affect the collection of physiological data and offers some advice on a manner to collect good emotional data. The accuracy of Picard's physiological emotion detection method is 81%.
Emotion Recognition in Human-Computer Interaction [Cowie01]	☑			☑	☑				☑					☑		This paper offers a good survey of techniques for detecting emotions using facial and vocal expressions. It also presents some results from experiments using Artificial Neural Networks (ANNs).
Wearable and Automotive Systems for Affect Recognition from Physiology [Healey00]	☑		☑							☑	☑	☑	☑			This work describes the utilization of physiological data for detecting emotions in various situations including a very controlled lab environment, an ambulatory environment, and while driving a car. Healey describes the sensors utilized, the characteristics of some physiological signals (skin conductance, heart activity (heart rate), respiration, and muscle activity) as well as some problems related to the acquisition of physiological data.
Effect of sensor Fusion for Recognition of Emotional States using Voice, Face Image and Thermal Image of Face [Yoshitomi00]	☑			☑	☑			☑	☑	☑		☑		☑		This work introduces a method for integrating information from facial and vocal expressions as well as from thermal imaging into a single emotion recognition system. Hidden Markov Models and ANNs are used to estimate emotions with an 85% recognition rate for 5 emotions.
Bimodal Emotion Recognition [DeSilva99]	☑			☑	☑					☑		☑				This paper outlines a new approach for performing emotion detection using a combination of both facial and speech emotional information.
Real-time face Analysis and Synthesis using Neural Networks [Morishima00]	☑	☑			☑				☑			☑				Morishima describes a way for providing animated faces the ability to mimic a given emotional expression using real-time facial recognition.

Emotion Recognition in Speech Using Neural Networks [Nicholson00]	☑			☑					☑			☑		☑		Approach to detect joy, teasing, fear, sadness, disgust, anger, surprise and the neutral emotion using an array of back-propagated neural networks and 300 features extracted from vocal utterances. Recognition rates of 50%.
Emotion Recognition and its application to computer agents with spontaneous interactive capabilities [Nakatsu99]	☑	☑		☑					☑			☑		☑		Naktsu et al. introduce a model for detecting emotions based on speech and a federation of ANNs. This model is employed for providing artificial movie characters the capability to respond to speech emotional content.
Emotion Recognition and Synthesis System on Speech [Moriyama99]	☑	☑		☑						☑		☑				Good results on speech synthesis are provided with 87.5% recognition rates.
The emotion mouse [Ark99]	☑		☑							☑	☑	☑				A model is proposed for improving computers response to user actions. Ark et al. employed heart rate, skin conductance, temperature, and somatic movement collected from various sensors and that are related to computer mouse activity.
A new Affect-Perceiving Interface and its Application to personalized Music Selection [Healey98]	☑		☑								☑	☑	☑		☑	Healey et al. developed a device capable of detecting user's musical preferences using emotional information embedded in skin conductance variations.
Gesture Recognition by Neural networks and the Expression of Emotions [Modler98]	☑					☑			☑			☑	☑			This approach utilizes ANNs to recognize hand gestures associated with emotions although little attention is paid to emotion classification.
Multimodal Human Emotion/Expression Recognition [Chen98]	☑			☑	☑				☑	☑		☑				Chen's offers a combination of rule-based systems and statistical methods to provide bimodal emotion detection.
Stochastic Modeling of Physiological Signals with Hidden Markov Models: A Step Toward Frustration Detection in Human-Computer Interfaces [Fernandez97]	☑		☑							☑		☑		☑		Fernandez proposed a mechanism for detecting frustration based on galvanic skin response and blood volume pressure.
Affective Wearables [Picard97]	☑		☑								☑		☑		☑	This paper provides a list of references on different alternatives to implement an interface for physiological data collection. It also offers a good description of possible applications of affective computer.

Human Expression Recognition from Motion using Radial Basis Function Network Architecture [Rosenblum96]	☑				☑				☑			☑		☑		Rosemblum employs facial expression and radial basis ANNs for detecting emotions. It enhances regular radial basis ANNs in order to accommodate temporal processing.
Machine Vision Recognition of facial affect using backpropagation neural networks [Avent94]	☑				☑				☑					☑		Avent et al. proposed a facial emotion detection system featuring image capture, face detection, edge detection, face feature detection, and face feature analysis. The face detection and face feature analysis modules are ANN-based.
Recognition of Human Facial Expressions using a 2-Dimensional Physical Model [Matsuno94]	☑				☑					☑	☑			☑		This paper introduces a system to detect emotions based on the whole facial expression and not only on some given facial features as most facial-based approaches do.
Dynamic recognition of Basic facial Expressions by Discrete-time Recurrent Neural Networks [Kobayashi93]	☑				☑				☑			☑				It is basically the same approach proposed in 1991 [Kobayashi91] with recurrent neural networks replacing back-propagated neural networks.
Analysis of skin potential response using a Novel feature Code for the study of the emotional response [Dittmar91]	☑		☑								☑	☑		☑		This paper provides detailed information on the importance of skin potential for detecting emotions. Dittmar also described a method used for extracting features from skin electrodermal signals.
The Recognition of Basic Facial Expressions by Neural Networks [Kobayashi91]	☑				☑				☑			☑				It employs a single ANN for detecting six emotions: surprise, fear, disgust, anger, happiness, and sadness.

Appendix 2 Emotion Detection Experiments: Procedure, Consent and Personal Information forms, Physical Rating, Affect Intensity Measure

Emotion Detection Experiments

IIEG GROUP. Investigator: Enrique Leon

Thank you for taking part in this experiment. We are very grateful for you participation. The present 3-day study has been designed to evaluate your emotional response to visual stimuli. During the three-day period you will be shown a set of pictures from the International Affective Pictures System (IAPS) while your physiological signals are recorded. The IAPS has been widely used in psychology to elicit and evaluate 3 different types of emotional states: neutral, positive, and negative. Pleasant pictures include babies, families, food, and erotic couples; unpleasant pictures consist of mutilated bodies and scenes of attack and threat. IAPS images should not cause an excessive amount of distress on you. However, if you feel discomfort, aversiveness to the pictures or have been previously diagnosed with an emotional disorder please inform the investigator.

In order to analyse the effect physical exertion has on the bodily signals associated with your emotional state, you will be required to perform a light exercise routine (at 40% of your hypothetical cardiovascular capacity) on day 3. Such exercise routine has been planned to adequately stress your cardiovascular systems without overexertion even if your do not exercise regularly and as along as you have not any physical problem.

Next is the overall schedule of the entire study.

Day 1

On arrival, you will be required to complete one consent forms and two questionnaires (including the Physical Activity Rating-PA-R). You will be then shown a 21-picture presentation and will be asked to rate each picture's emotional content. The total testing time should not involve more than 30 minutes. Your answer to the PA-R will be employed to estimate your physical fitness (Cardiorespiratory endurance).

Day 2

You will be shown a second 21-picture power point presentation (Total time: 14.4 min) while your physiological response is recorded. You will then rest for 25-45 minutes and, immediately after, be shown a third set of 21 pictures (Total slide-show time: 14.4 min) also involving acquisition of physiological signals.

Day 3

You will be shown a fourth 21 picture power point presentation (Total time: 14.4 min) while your physiological response is recorded. You will be then required to exercise on a stationary bicycle for 25 minutes (after a 5-minute war-up) and given a 20 minute semirecumbant recovery afterwards. Finally, you will view the last 21-picture slide presentation (Total slide-show time: 14.4 min) while your physiological signals are measured.

Emotion Detection Experiments

Please complete the following questionnaire (remember that your information will remain confidential).

Section 1 - Personal Information

Full Name:____

Age:____ Gender:____ Height (in meters):_____ Weight (in kilograms):_____

Section 2 – Medication. Please read the following questions carefully and answer each one honestly: check YES or NO.

YES	NO	
☐	☐	Are you taking any kind of medication (including oral contraceptive or antidepressants)? If yes, please explain.
☐	☐	Are you on your menstrual phase?

Section 3 - Physical Activity Readiness.

YES	NO	
☐	☐	Has your doctor ever said that you have a heart condition <u>and</u> that you should only do physical activity recommended by a doctor?
☐	☐	Do you feel pain in your chest when you do physical activity?
☐	☐	In the past month, have you had chest pain when you were not doing physical activity?
☐	☐	Do you lose your balance because of dizziness or do you ever lose consciousness?
☐	☐	Do you have a bone or joint problem that could be made worse by a change in your physical activity?
☐	☐	Is your doctor currently prescribing drugs (for example, water pills) for your blood pressure or heart condition?
☐	☐	Do you know of <u>any other reason</u> why you should not do physical activity?

NASA/JSC Physical Activity Rating (PA-R)

The NASA/Johnson Space Center Physical Activity Rating (PA-R) scale was developed to provide an assessment score of 0-7 on a person's level of regular physical activity. There are a series of eight statements about routine physical activity. Participants are to select only one response that best describes their physical activity level. Each response is given a numerical value which you can see in parentheses next to the selection button.

CURRENT PHYSICAL CONDITION: Please check only one to rate your current physical fitness level.
I. I don't participate regularly in programmed recreation sport or physical activity:

(0) Avoid walking or exertion (e.g. always use elevator, drive whenever possible instead of walking)

(1) Walk for pleasure, routinely use stairs, occasionally exercise sufficiently to cause heavy breathing or perspiration.

II. I participate regularly in recreation or work requiring modest physical activity, such as golf, horseback riding, calisthenics, gymnastics, table tennis, bowling weight lifting, or yard work:

(2) 10 to 60 minutes per week

(3) Over one hour per week

III. I Participate regularly in heavy physical exercise (such as running or jogging, swimming, cycling, rowing, skipping rope, running in place) or engage in vigorous aerobic type activity (such as tennis, basketball, or handball).

(4) Run less than one mile per week or spends less than 30 min per week in comparable physical activity.

(5) Run 1 to 5 miles per week or spends 30 to 60 min per week in comparable physical activity.

(6) Run 5 to 10 miles per peek or spends 1 to 3 hours per week in comparable physical activity.

(7) Run over 10 miles per week or spends over 3 hours per week in comparable physical activity.

UNIVERSITY OF ESSEX

FORM OF CONSENT TO TAKE PART AS A SUBJECT IN A RESEARCH PROJECT

CONFIDENTIAL

Title of project / investigation: Emotion Detection

Brief outline of project, including an outline of the procedures to be used:

The purpose of this project is to collect and analyse physiological data associated with emotional states. Experiments will be carried out over a 3 day period. On day one subjects will view a set of pictures and will rate their emotional content. On day two participants will be shown two separate sets of pictures while their physiological data is collected. A first set of pictures will be viewed on arrival and the second one after a 30-minutes resting period. On day three, subjects will also be shown two sets of pictures while their physiological response is recorded. However, the resting period between slideshows will be replaced by 25 minutes of low-intensity exercise (at 40% of the participants' hypothetical cardiovascular capacity). All pictures involved in this experiment have been taken from the International Affective Picture System (IAPS).

I, ... *(**subject's** full name) agree to take part in the above named project / investigation. The experimental procedures and potential risks have been fully explained to me and described in writing. I understand that I have the right to withdraw at any time without explanation.

Signed .... Date ....
(Subject)

I, Enrique Edgar Leon Villeda.. *(**Investigator's** full name) certify that the experimental procedures and potential risks of this project / investigation have been fully explained and described in writing to the subject named above and have been understood by him / her.

Signed .... Date ....
(Investigator)

*Please type or print in block capitals

Appendix 3 List of IAPS Pictures Used for Emotion Elicitation

List of pictures utilized to elicit emotions in subjects during physiological data collection sessions.

Presentation 1

Positive			Neutral			Negative		
Picture No.	Valence	Arousal	Picture No.	Valence	Arousal	Picture No.	Valence	Arousal
4533/4180	6.22/6.21	5.01/5.54	2720	5.43	3.43	3030	1.91	6.76
4680	7.25	6.02	5533	5.31	3.12	3120	1.56	6.84
5629	7.03	6.55	7006	4.88	2.33	6200	2.71	6.21
5830	8.00	4.92	7050	4.93	2.75	6350	1.90	7.29
8040	6.64	5.61	7170	5.14	3.21	9250	2.57	6.60
8190	8.10	6.28	7560	4.47	5.24	9300	2.26	6.00
8490	7.20	6.68	9210	4.53	3.08	9420	2.31	5.69

Presentation 2

Positive			Neutral			Negative		
Picture No.	Valence	Arousal	Picture No.	Valence	Arousal	Picture No.	Valence	Arousal
1710	8.34	5.41	2690	4.78	4.02	1120	3.79	6.93
4532/4150	6.40/6.35	4.15/4.86	5532	5.19	3.79	3080	1.48	7.22
4660	7.40	6.58	7002	4.97	3.16	3170	1.46	7.21
5626	6.71	6.10	7040	4.69	2.69	6260	2.44	6.93
8034	7.06	6.30	7150	4.72	2.61	6540	2.19	6.83
8180	7.12	6.59	7550	5.27	3.95	9530	2.93	5.20
8470	7.74	6.14	9070	5.01	3.63	9810	2.09	6.62

Presentation 3

Positive			Neutral			Negative		
Picture No.	Valence	Arousal	Picture No.	Valence	Arousal	Picture No.	Valence	Arousal
2080	8.09	4.70	2410	4.62	4.13	2710	2.52	5.46
4531/4002	5.81/5.78	4.28/5.32	5531	5.15	3.69	3071	1.88	6.86
4650	6.96	5.67	7000	5.00	2.42	3150	2.26	6.55
5623	7.19	5.67	7035	4.98	2.66	6230	2.37	7.35
8033	6.66	5.01	7140	5.50	2.92	6510	2.46	6.96
8170	7.63	6.12	7500	5.33	3.26	9500	2.42	5.82
8460	6.40	4.55	8260	6.18	5.85	9600	2.48	6.46

Presentation 4

Positive			Neutral			Negative		
Picture No.	Valence	Arousal	Picture No.	Valence	Arousal	Picture No.	Valence	Arousal
2070	8.17	4.51	2220	5.03	4.93	3010	1.71	7.16
4520/4255	7.04/6.06	5.48/5.11	5530	5.38	2.87	3110	1.79	6.70
4640	7.18	5.52	6910	5.31	5.62	3530	1.80	6.82
5621	7.57	6.99	7034	4.95	3.06	6313	1.98	6.94
8031	6.76	5.58	7130	4.77	3.35	9040	1.67	5.82
8161	6.71	6.09	7235	4.96	2.83	9050	2.43	6.36
8400	7.09	6.61	8060	5.36	5.31	9800	2.04	6.05

Presentation 5

Positive			Neutral			Negative		
Picture No.	Valence	Arousal	Picture No.	Valence	Arousal	Picture No.	Valence	Arousal
2050	8.20	4.57	2210	4.38	3.56	3060	1.79	7.12
4510/4279	6.91/5.47	4.0/4.38	5520	5.33	2.95	3140	1.83	6.36
4609	6.71	5.54	6150	5.08	3.22	6212	2.19	6.01
5470	7.35	6.02	7030	4.69	2.99	6370	2.70	6.44
8030	7.33	7.35	7100	5.24	2.89	9410	1.51	7.07
8130	6.58	5.49	7233	5.09	2.77	9430	2.63	5.26
8370	7.77	6.73	7830	5.26	4.08	9910	2.06	6.20

Presentation 6

Positive			Neutral			Negative		
Picture No.	Valence	Arousal	Picture No.	Valence	Arousal	Picture No.	Valence	Arousal
1720	6.79	5.32	2215	4.63	3.38	3000	1.45	7.26
2040	8.17	4.64	2381	5.25	3.04	3015	1.52	5.90
2222	7.11	4.08	5740	5.21	2.59	3069	1.70	7.03
4652	6.79	6.62	5120	4.39	3.07	6315	2.31	6.38
5450	7.01	5.84	7285	5.67	3.83	6360	2.23	6.33
8080	7.73	6.65	7179	5.06	2.88	6570	2.19	6.24
8200	7.54	6.35	7182	5.16	4.02	6821	2.38	6.29

Presentation 7

Positive			Neutral			Negative		
Picture No.	Valence	Arousal	Picture No.	Valence	Arousal	Picture No.	Valence	Arousal
1650	6.65	6.23	2235	5.64	3.36	3053	1.31	6.91
1722	7.04	5.22	7080	5.27	2.32	3068	1.80	6.77
4651	6.32	6.34	7224	4.45	2.81	3102	1.40	6.58
4664	6.61	6.72	7237	5.43	3.88	3168	1.56	6.00
8179	6.48	6.99	7490	5.52	2.42	3400	2.35	6.91
8496	7.58	5.79	7595	4.55	3.77	8230	2.95	5.91
8501	7.91	6.44	7700	4.25	2.95	9570	1.68	6.14