Exploration of Emotion Modelling through Fuzzy Logic

William Frederick Blewitt

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Abstract

This work outlines a programme of research tasked with the exploration of representing psychologically grounded theories of emotion through fuzzy logic systems. It presents an introduction to the specific goals of the project, followed by an overview of the wider, multi-disciplinary field of emotion representation.

Two emotion theories are explored in detail. One, rooted in behaviourism, proposed by J. R. Millenson in 1967; the other, the Geneva Emotion Wheel proposed by K. R. Scherer in 2005. Each of these theories is independently abstracted mathematically, and represented in terms of both type-1 and type-2 fuzzy logic systems. Six potential implementations of these systems are presented. Of these, five are tested within this report. The results of these tests are analysed and discussed in the context of both computational behaviour and psychological analogue. There follows a critical review where the effectiveness of the different implementations and models is considered, informed by both testing results and the psychology upon which they are based.

A prototype of one implementation applied to govern the behaviour of an agent in a predator-prey scenario is included. Discussion of this prototype includes examples of how the implementation was practically applied to the environment, and an assessment of the behaviours of the agent in testing.

The work concludes with an overview of the thesis, including discussion of the results of the project and future avenues of research related to the completed work. The contributions of the thesis are explicitly outlined: the research of pre-existing, psychologically grounded models of emotional state suitable for computational representation; construction of mathematical representations of two models of emotion, using both type-1 and type-2 fuzzy logic; and, the presentation of five computational implementations of those representations, of which four are explicitly tested, compared and critically reviewed.

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Publications

The research towards this thesis has, to date, produced the following publications:

- William Blewitt, Shang-Ming Zhou, and Simon Coupland. A novel approach to type-2 fuzzy addition. In *Fuzzy Systems Conference, 2007. FUZZ-IEEE 2007. IEEE International*, pages 1 – 6, 23 – 26 July 2007.
- William Blewitt, Aladdin Ayesh, Robert I. John, and Simon Coupland. A millenson-based approach to emotion modeling. In *Conference on Human System Interactions, 2008*, pages 491 – 496, 2008.
- William F. Blewitt and Aladdin Ayesh. Modeling the emotional state of an agent through fuzzy logic with reference to the geneva emotion wheel. In *European Simulation and Modelling (ESMŠ2008) Conference, Le Havre, France*, 2008.
- William Blewitt and Aladdin Ayesh. Implementation of millensonŠs model of emotions in a game environment. In *AISB '09 Symposium: AI & Games, Edinburgh, UK*, 2009.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

The subject of accurately modelling the emotional state of an agent, in such a fashion as to be psychologically consistent while computationally efficient, is an area that has enjoyed consistent growth in interest in recent years [11, 50]. This work has varied in scope from the philosophical questions about why to make an emotional agent, to the sociological questions about what impact emotional agents have on human-computer interactions [20, 21, 105, 76, 100, 89, 38, 10, 40].

There have been some notable prior research efforts focussed upon conceptual issues regarding the quantification and categorisation of psychological concepts[61, 112]. Complementing these works are equally worthy explorations of the role emotion plays in human cognition and decision-making[54, 127, 119, 55, 34, 1, 5]. In the context of character representation, some recent work has centred around the establishment of hierarchical structures of behaviour that include emotional components as a key element [3, 96].

In general terms, however, the direction of such research has tended towards affective control systems [37, 120, 74, 52], and rarely specifically upon the determination of the emotional state of an agent outside that somewhat narrow context [33, 59]. While some efforts have been made to introduce fuzzy logic to the field of emotion modelling [31, 116] they have tended to discuss emotion in the context of deterministic behavioural architecture, rather than in the context of a psychological construct in its own right.

This work approaches the topic from the direction of fuzzy logic, with a view to establishing new results and providing meaningful discourse. Our goals are to show, within this document, the programme of research undertaken during the course of the research project.

1.1 Scope

Given the multidisciplinary nature of the topic of emotion modelling and representation, particularly when such research is approached from a primarily computational perspective, it is necessary that the limits of scope defined at the outset of the work are presented in the context of each discipline under consideration. Within this section, we consider scope as it applies to each separate discipline falling under the auspices of the project in question.

Firstly, the psychological aspect of the project is considered. From this perspective, it was determined that the scope of the project should extend to the exploration of previously published psychological models of emotion, and the theories upon which they were based. It was expressly determined that the scope should not extend to the establishment of wholly novel psychological models of emotion, as so doing would sacrifice veracity of the work and weaken the foundations upon which it would be built.

While multiple models of emotion would be explored, this exploration would be by no means wholly exhaustive of the field; that, in itself, would form a wholly separate research project. Instead, models with geometric structure that combined situational input with emotional output would be directly considered, with their psychological provenance a determining factor in their selection.

From a computational perspective, the scope of the work extended to the selection of models whose conceptual structure resonated strongly with the unique capacities for multi-value (fuzzy) logic systems to represent uncertainty and abstraction. It was determined that no orders of fuzzy logic higher than second-order would be considered, nor would adaptive training be used to weight desired results against those generated by psychological consistency with the geometry of any selected model.

The importance of this work lies in its goal of applying artificial intelligence methods to models of emotional state, while maintaining psychological analogue. As shall be discussed in greater depth in Chapter Two, the application of fuzzy logic to such situations is almost intuitive. Emotions are by their nature linguistic variables, bound by the strictures of the lexicon in which they are employed; Zadeh discusses the applicability of fuzzy logic to situations where linguistic variables are a consideration at some length [123, 124, 125].

In particular, the consideration of type-2 fuzzy logic is unique to the explorations of the field considered within this work. It has been asserted that type-2 systems grant a level of inherent uncertainty that is denied their type-1 equivalents [51]. We assert that this uncertainty is particularly worthy of exploration in the context of emotion representation, as a function of the uncertain nature of response to complex stimulus.

We concede that there are arguments made in favour of crisply defined emotions as determined by the lexicon [28], but assert that inconsistent human response to complex stimulus alone is enough justification for an exploration of uncertainty in a computational sense. To that end, representations using both type-1 and type-2 fuzzy logic are discussed and presented, where possible, as direct analogues to one another. Any testing is performed, and comparisons such as are made, within the scope of the project outlined in this section.

1.2 Thesis Outline

We shall first provide such background to this multidisciplinary topic as it appropriate for the level of the content, along with discussion regarding the more practical preliminary concerns of the development portion of this work.

We shall discuss two published, psychologically-grounded models of emotion. The first, published by J. R. Millenson in 1967 [53], is built upon conditioned emotional response theory and associates emotional response with stimulus input. The second, published by K. Scherer in 2005 [88], builds upon the previous work of Russell [75] to establish a system that draws connection between relative experiential magnitude of valence and control to emotional response.

Full mathematical representations, from the perspective of type-1 fuzzy logic, are defined and presented. Following this, we discuss the same two models in the context of type-2 fuzzy logic, similarly providing exhaustive mathematical representations.

Having clarified the mathematics upon which we base our implementations, we present a full account of the process of implementation undertaken during the course of this project, presenting five functional software implementations, four of Millenson's theory and one of Scherer's, and one hypothetical implementation of Scherer's theory.

The five functioning implementations are then exhaustively tested. The results are analysed in both mathematical and psychological terms, and testing data are used to provide contextual frames of reference. The behaviours of each implementation are then critically reviewed. Prototyping is then presented and discussed in the context of a single implementation, followed by our conclusions and discussions of future work.

In this section we also provide brief summaries of the contents of the chapters to follow, to facilitate ease of navigation within the document.

- Chapter Two: This chapter provides the first part of our literary overview of material relevant to the research discussed within this document. This chapter considers in particular detail the psychological modelling of emotional state; affective computing; relevant prior research; and, presents the two psychological models of emotion the remainder of our work shall focus upon.

- Chapter Three: This chapter concludes our literary overview. It provides an introdction to the type-1 and type-2 fuzzy logic computational methods applied in later chapters. It also provides an overview of the selected development platforms, both hardware and software, and the specifications of rejected potential development platforms.

- Chapter Four: In this chapter are presented three representations of psychologically grounded emotional state models, relying upon type-1 fuzzy logic. The first two representations are alternative interpretations of the Millenson theory as discussed at length in Chapter Two. The third representation is an interpretation of the Geneva Emotion Wheel, similarly discussed in Chapter Two.

- Chapter Five: This chapter presents three type-2 fuzzy logic representations of psychologically grounded models of emotional state. As with Chapter Four, two of the representations are built upon Millenson's theory, and the third draws from the Geneva Emotion Wheel.

- Chapter Six: The sixth chapter of this work presents implementations of the six representations discussed in Chapters Three and Four, three utilising type-1 fuzzy logic inferencing, and three utilising type-2 fuzzy logic inferencing.

- Chapter Seven: In this chapter we present the testing of five of the implementations outlined in Chapter Six. The schedule of testing, and rationale, is discussed at length. The results of these tests are then discussed in an isolated context.

- Chapter Eight: This chapter provides a critical analysis of the experimental results obtained in the previous chapter. It draws comparison between the implementations in addition to appropriate comparison between their associated psychologically grounded theories.

- Chapter Nine: This chapter provides discourse regarding a software application of one of the implementations presented in Chapter Six, using a Predator-Agent-Prey scenario. The testing environment is discussed, as is the fashion in which the model of emotional state influenced agent behaviour. Subsequently, two example tests are analysed in detail.

- Chapter Ten: This chapter concludes the work as presented in this document. Results and analysis from Chapters Seven and Eight are discussed, along with the consequences of those results. The original contributions outlined in Chapter One are revisited with a critical eye, with a view to assessing the meaning and impact of the work provided herein.

1.3 Aims and Objectives

This work seeks to further the field of affective computing through consideration of mathematical representations of psychologically grounded emotion models. Its particular aim is to present not only the models themselves, but to present them in such a way as to prompt further exploration into these and other psychological models of emotion from a computational perspective.

It is an objective of this work that it will demonstrate the process of extrapolation of the psychological emotion models and their conversion into fuzzy logic constructs. This shall be performed with all due deference to the abstract concepts represented in their makeup, so as to maintain psychological analogue, which shall be the key aspect of this research.

Further to this, it is intended that each representation presented herein shall be implemented in a fashion that is consistent with the mathematical abstractions of the model. These implementations, as with the representations they are built upon, shall concern themselves more with psychological consistency than computational efficiency. They shall be subject to a robust schedule of testing designed to demonstrate adherence, or otherwise, to those psychological principles.

It is the intent of this work to demonstrate, through exhaustive testing and analysis, the behaviours of these representations. In so doing, the work shall demonstrate consistency in its structure and goals.

1.4 Contributions of Thesis

In overview, the contributions of this work aim to be:

- Research of psychologically grounded models of emotional state suitable for computational representation.

- Construction of mathematical representations of one or more psychologically grounded models of emotional state, using type-1 fuzzy logic systems.

- Construction of mathematical representations of one or more psychologically grounded models of emotional state, using type-2 fuzzy logic systems.

- Computational implementations of these representations for the purposes of comparison and review.

The primary contribution of this work shall be the conversion, representation and implementation of psychologically grounded theories of emotion into computational constructs. In particular, we emphasise the psychologically consistent nature of the systems proposed, whereby the work is approached from the perspective of maintenance of psychological analogue over computational expediency. In this, the work presents novel methodolodies in the field of emotion modelling, and a foundation for future exploration of the place of emotion in agent behaviour.

Further to this, the work approaches representation of the two psychological theories discussed herein from the perspective of multi-value logic inferencing systems. It is the nature of these inferencing systems that provides an additional layer of novelty to the work, whereby conceptual inputs to a fuzzy system directly lead to a psychologically consistent emotional output.

The work presents the first known application of type-2 fuzzy logic in the field of computational emotion modelling. It seeks to provide new insight into the comparative behaviours of type-1 and type-2 fuzzy logic within this new and growing field, while establishing the foundations for further exploration of higher order multivalue logic within emotion modelling.

Subsequently, the work outlines original implementations of the incipient representations; their construction, testing, and analysis of their comparable behaviours. These implementations form the basis for our subsequent conclusions and the foundation of future related work.

Chapter 2

Literature Review: Psychology of Emotions and Affective Computing

2.1 Chapter Overview

The scope of this project was broad and cross-disciplinary requiring as it did intimate familiarity with both fuzzy logic systems and the pan-human psychology of emotion. Further to this, hardware and software development platforms had to be considered from both perspectives, as well as the more engineering-based concerns regarding versatility and capacity.

In order to fully appreciate the manner in which the subsequently discussed models were implemented, and the context in which they exist, it is necessary to include some significant preface regarding these areas of particular research interest. This preface forms our literature review, divided into two chapters. This chapter considers exclusively matters relating to psychology of emotion, and affective computing.

We first discuss the topics of research into and representation of emotions from a psychological context. This forms a foundation of the work that is to follow, providing an overview of the most relevant schools of thought from the nineteenth century onwards.

Following this psychological preamble, we approach the general subject of affective computing. We initially consider the topic from a wider scope, to provide context for the work this report presents. We subsequently highlight landmark developments within the overarching field of affective computing in the context of goal-oriented systems. Following that, we present and consider specific examples of work which bears some analogue with our own to provide insight into the state of the specific area our work regards.

We next outline the psychologically grounded emotion models that this research has primarily concerned. We discuss them from a psychological context, paying particular attention to their structures. Latterly, we define our usage of the term geometry in the context of each of the models the remainder of this work shall focus upon.

2.2 Emotion Research and Representation

2.2.1 Darwin

Within the various fields of psychological research, two schools of thought appear to dominate the debate regarding the nature of emotions and how they are best modelled [28, 60]. From a philosophical perspective, the nature of their divergence and their theoretical differences are of great importance; from a computing sciences perspective, however, their differences lie entirely in the nature of the models they propose.

The view of emotions as an evolutionary construct was initially proposed by Darwin in 1872 [17]. It was this work which postulated the idea of basic emotions, differing combined intensities of which might give rise to an overall emotional state.

Over the past century this has given rise to significant amounts of psychological research dedicated to determining both the number and nature of these basic emotions. The exact number of 'fundamental' emotions given varies widely from theory to theory. Plutchik first proposed his system of emotion classification in 1980 [69], containing eight fundamental emotions. In contrast, Ekman proposed a system consisting of six fundamental (or basic) emotions in 1982 [28]. Nevertheless, the maximum number of basic emotions is generally thought to be fourteen [88].

Following on from the definition of basic emotions comes the definition of more complex emotions. Occasionally, these categories are divided using nomenclature indicating primary and secondary emotions as in the structure proposed by Parrott [60]. Oftentimes, however, these more complex emotions are simply defined by the relative intensities of their parent emotions. In general terms, however, it is the view of this school of thought that the sum of human emotional experience can be defined as a function, or construct, of less than a dozen named emotions [29, 25].

2.2.2 Wundt

An alternative to the view that basic emotions could be named and categorised, proposed by Wundt in 1904, suggested that emotions could be better defined in the context of experience rather than crisp linguistics [114]. Research based on this principle has, as with the Darwinian view, given rise to many varied schools of thought following the same fundamental idea.

In Wundt's original model, emotional state was represented in terms of three facets of experience which he labeled Pleasantness, Approach and Arousal. He asserted that any individual emotion would be better modelled in the context of relative magnitudes of these facets of the emotional experience than through verbal labels.

Subsequent to Wundt's original work, significant research has been performed regarding this idea of a dimensional emotion model. In many cases it is common for the third axis to be ignored and, instead, for proponents of this view to model emotions in the context of Valence, which might be seen as a crisper definition of Pleasantness, and Arousal [88].

2.2.3 Plutchik

Robert Plutchik is generally credited with creating the psychoevolutionary theory of emotion [69]. Much of Plutchik's rationale is rooted in psychological behaviourism, citing as support for his eight basic emotions their link to the perceived "fight or flight" response when observed in nature. In addition to his eight basic emotions, Plutchik also supported the view of complex, or 'Advanced' emotions, these being defined by multiple emotions being experienced simultaneously.

This concept is useful to us when we consider the representation of emotional state by membership grade, which is a necessity when dealing with Fuzzy Logic. Indeed, all of our representations include the capacity for multiple emotions to be experienced to differing levels of intensity. While both of the selected models that are later discussed justify this within their own psychology, Plutchik's recognition of the concept is also worthy of note given the key role he played in the exploration of evolutionary emotions.

Plutchik's psychoevolutionary theory of basic emotions had ten postulates [69]:

1. The concept of emotion is applicable to all evolutionary levels and applies to animals as well as to humans.
2. Emotions have an evolutionary history and have evolved various forms of expression in different species.
3. Emotions served an adaptive role in helping organisms deal with key survival issues posed by the environment.
4. Despite different forms of expression of emotions in different species, there are certain common elements, or prototype patterns, that can be identified.
5. There is a small number of basic, primary, or prototype emotions.
6. All other emotions are mixed or derivative states; that is, they occur as combinations, mixtures, or compounds of the primary emotions.

7. Primary emotions are hypothethical constructs or idealized states whose properties and characteristics can only be inferred from various kinds of evidence.

8. Primary emotions can be conceptualized in terms of pairs of polar opposites.

9. All emotions vary in their degree of similarity to one another.

10. Each emotion can exist in varying degrees of intensity or levels of arousal.

Plutchik presents us with eight basic emotions and eight advanced emotions. Advanced emotions were considered compounds of basic emotions, expanding the breadth of human experience represented by his theory. Each emotion, basic and advanced, had a diametric opposite which described its emotional antithesis. Tables 2.1 and 2.2 present all sixteen of these emotions, identifying whether they are basic or advanced, providing a brief definition drawn from the Oxford Dictionary of English, and stating their diametric opposites. We note that the definition of *Aggressiveness* is drawn from the definition of *Aggression* within the Oxford Dictionary of English; this is due to the lack of an explicit definition of *Aggressiveness* in the context of an emotional experience [93].

We note that the Wheel of Emotions Plutchik provides, when one includes both the basic and advanced emotions, becomes analogous with our own geometric representations of complex emotional states, particularly in the context of Scherer, which is discussed later.

2.2.4 Ekman

Paul Ekman's work on emotions, their modelling, detection and classification has defined a career that spans over three decades. When considering his contributions to the field, it is necessary to discuss the multiple facets of his work individually.

The Autonomic Nervous System

Ekman provides an argument for specific basic emotions to elicit distinctive patterns of activity within the autonomic nervous system (hereafter ANS)

Table 2.1: Representation of Emotions Presented in Plutchik's Theory (i)

Name	Type	Definition, Including Component Basic Emotions Where Appropriate	Opposite
Anger	Basic	'A strong feeling of annoyance, displeasure, or hostility.'	Fear
Fear	Basic	'An unpleasant emotion caused by the threat of danger, pain, or harm.'	Anger
Sadness	Basic	'Feeling or showing sorrow; unhappy.'	Joy
Disgust	Basic	'A feeling of revulsion or strong disapproval aroused by something unpleasant or offensive.'	Trust
Surprise	Basic	'A feeling of mild astonishment or shock caused by something unexpected.'	Anticipation
Anticipation	Basic	'The action of anticipating something; expectation or prediction.'	Surprise
Trust	Basic	'Firm belief in the reliability, truth, or ability of someone or something.'	Disgust
Joy	Basic	'A feeling of great pleasure and happiness.'	Sadness
Optimism	Advanced	'Hopefulness and confidence about the future or the success of something.' Anticipation + Joy	Disappoint -ment
Love	Advanced	'A strong feeling of affection.' Joy + Trust	Remorse
Submission	Advanced	'The action of accepting or yielding to a superior force or to the will or authority of another person.' Trust + Fear	Contempt

[23]. This concept is of interest to us, particularly in the context of emotion-induced or emotion-attenuated behaviours of a virtual agent, connecting as it does reaction with emotional experience. Ekman also presented empirical analyses that indicated ANS reactions for given emotions were identical irrespective of the manner in which the emotion was generated [26, 48].

Examples he provides of ANS response to emotional stimuli include blood flowing to the hands in anger, as a predication of a fight response, and blood

Table 2.2: Representation of Emotions Presented in Plutchik's Theory (ii)

Name	Type	Definition, Including Component Basic Emotions Where Appropriate	Opposite
Awe	Advanced	'A feeling of reverential respect mixed with fear or wonder.' Fear + Surprise	Aggressive -ness
Disappoint -ment	Advanced	'Sadness or displeasure caused by the non-fulfilment of one's hopes or expectations.' Surprise + Sadness	Optimism
Remorse	Advanced	'Deep regret or guilt for a wrong committed.' Sadness + Disgust	Love
Contempt	Advanced	'The feeling that a person or thing is worthless or deserving scorn.' Disgust + Anger	Submission
Aggressive -ness	Advanced	'Feelings of anger or antipathy resulting in hostile or violent behaviour' Anger + Anticipation	Awe

flowing to the large skeletal muscles in fear, as a predication of a flight response [48]. From the perspective of our work, this assertion explicitly stipulates that emotional experience leads to physiological reaction, as such reinforcing our position that emotional experience can be argued to have a role in agent response to environment.

It should be noted that his work only draws connection between anger, fear, disgust and sadness and specific patterns of ANS reaction, his basic emotions of surprise and enjoyment lacking such connections. His counter argument revolves around the evolutionary basis of ANS responses, and the purpose which they have evolved to serve. We have chosen to interpret this in our implementation of Millenson in a game environment as a reaction to emotions we connect to enjoyment (Pleasure, Elation, Ecstasy - see Chapter Nine) being akin to contentment. This is discussed later.

Facial Expressions and Universality of Emotion

Much of Ekman's work in the field of emotions has revolved around the manifestation of emotions through facial expression, and the idea that one can determine emotional experience from certain key, physiological cues to facial muscles [25]. In this, Ekman takes initial cues from Darwin [17].

While expression itself is an issue conceptually distant from the purposes of the research within, some slight commentary should be provided in the context of potential future associations with the work. Indeed, some justification for the work can be considered in terms of emotion simulation and determination on the part of interactive agents.

Briefly, we consider Duchenne's preposition that while there are many different forms of smile, only one is associated with truly positive emotions [22]. Let us consider, then, the possibility that a computational model of emotional state might not be used simply as a behavioural governer for a given agent, but also hypothetically a measure for a system designed to determine the emotional state of the user.

The concept of universality in emotions is also a consideration in the context of justification of our work. Ekman's research into emotions and basic emotions is both built upon, and informs, the concept of universality of emotion expression whereby happiness has ubiquitously shared physiological markers [25].

Thus, the generation of a non-context-specific computational representation of emotional state which utilises emotion models grounded in psychological theory applies universally to all emotional agents and, hypothetically speaking, all affective computing environments. Of course, experimentation of that kind lies beyond the scope of this work in which the focus lies plainly upon the research, justification and modelling of emotion models, and their comparative consideration.

In either case, the concept of universality also permits us to draw direct comparison in otherwise disparate models of emotion, as shall be shown in subsequent sections of this work.

Basic Emotions

As we have observed previously, much work has been performed in the context of emotional experience in opposition to named, basic emotions. A great deal

Table 2.3: Representation of Basic Emotions Proposed by Ekman's Theory

Name	Definition
Anger	'A strong feeling of annoyance, displeasure, or hostility.'
Disgust	'A feeling of revulsion or strong disapproval aroused by something unpleasant or offensive.'
Fear	'An unpleasant emotion caused by the threat of danger, pain, or harm.'
Happiness	'Feeling or showing pleasure or contentment.'
Sadness	'Feeling or showing sorrow; unhappy.'
Surprise	'A feeling of mild astonishment or shock caused by something unexpected.'

of this work has been performed by Paul Ekman, and a brief overview of that work is included here.

Ekman is a strong proponent of the view that there are a limited number of basic emotions. He defines his usage of the word basic in three forms. First, that there are a number of separate emotions that are distinguished from one another in important ways. Second, that evolution was instrumental in defining both the unique and shared features that experience of these emotions displays. Finally, that there is a postulation that other, non-basic emotions exist, and that these are combinations of these basic emotions, which may be called 'blends', or 'mixed emotional states' [30, 68, 103].

This third concept is key to all aspects of the work we present here. Subsequently, multivalue logic systems are used to generate these 'mixed emotional states' on the basis of agent experience and, in test scenarios, inform the behaviour of said agent. Understandably, therefore, much is predicated upon this interpretation of the nature of 'Basic' emotions.

The six basic emotions Ekman defined in 1972 are shown in table 2.3, along with definitions drawn from the Revised Second Edition of the Oxford Dictionary of English, printed in 2005 [24, 93].

However, additions to this list were made in 1999 [25], adding new basic emotions, some of which were not encoded in facial expression (unlike his previous work). This enhanced list of basic emotions is included in table 2.4, along with definitions drawn from the same reference [93].

He concedes the possibility that 'guilt' is an arguable point, describing it as a 'likely candidate' [25], but makes no assertion that it not be included in his definitive list. He discounts 'interest' as a distinct emotion, as suggested by Tomkins and Izard, considering it rather a cognitive state. He also notes

Table 2.4: Revised Basic Emotions Proposed by Ekman in Later Work

Name	Definition
Amusement	'The state or experience of finding something funny.'
Anger	'A strong feeling of annoyance, displeasure, or hostility.'
Contempt	'The feeling that a person or thing is worthless or deserving scorn.'
Contentment	'A state of happiness and satisfaction.'
Disgust	'A feeling of revulsion or strong disapproval aroused by something unpleasant or offensive.'
Embarrassment	'A feeling or self-consciousness, shame, or awkwardness.'
Excitement	'A feeling of great enthusiasm and eagerness.'
Fear	'An unpleasant emotion caused by the threat of danger, pain, or harm.'
Guilt	'A feeling of having committed wrong or failed in an obligation.'
Pride (in Achievement)	'A feeling of deep pleasure or satisfaction derived from one's own achievements, the achievements of one's close associates'
Relief	'A feeling of reassurance and relaxation following release from anxiety or distress.'
Sadness / Distress	'Feeling or showing sorrow; unhappy.' / 'Extreme anxiety, sorrow, or pain.'
Satisfaction	'Fulfilment of one's wishes, expectations, or needs, or the pleasure derived from this.'
Sensory Pleasure	'A feeling of happy satisfaction and enjoyment' in the context of 'sensation or the physical senses'.
Shame	'A painful feeling of humiliation or distress caused by the consciousness of wrong or foolish behaviour.'

his own omission of romantic and parental love, grief, jealousy and hatred. He has argued that these are emotional *plots*, and endure longer than 'basic emotions' [27, 29, 28].

Ultimately, from Ekman's work on basic emotions, we draw support for their inclusion, support for the idea that there could be as few as six, or as many as fifteen or more, basic emotions, and concessions to the concept of 'mixed emotional states' being comprised of multiple 'basic' emotions.

Emotion Families

In the context of Ekman's work, when he describes basic emotions he does so in terms of each basic emotion actually representing a family of emotions that share the characteristics of these basic emotions [25]. In this, his work bears analogue with the model presented by Millenson which we later discuss, whereby it is possible to interpret Millenson's approach in the context of three 'families' of emotions (see Chapter Five).

He expands upon this point to state that basic emotions constitute a "theme", with associated "variations" [25]. The theme consists of characteristics unique to the associated family. He defines variations on a given theme to be the "product of various influences: individual differences in biological constitution; different learning experiences; and differences specific to and reflecting the nature of the particular occasion in which an emotion occurs" [29].

One benefit of Ekman's reasoning on the concept of emotion families is the freedom it grants him from lexicographal considerations. He observes that many of the issues and confusions that reside in the field of emotion research are due, in part, to a "failure to recognise that many of the emotion terms refer to variations within a family" [29]. By declaring families, therefore, Ekman avoids the pitfalls associated with exhaustive reliance upon the lexicon, and neatly avoids debates on the question of 'how angry is angry?'.

It is worth noting that Ekman has previously stipulated that he does not consider the boundaries between basic emotion families to be "fuzzy" [29], although how the word "fuzzy" is applied in this context is open to interpretation. Given that it follows on from discussion explicit to the manifestation of emotions through shared facial expression traits [30], the statement can be interpreted as a stipulation that he does not believe that in situations where a single, basic emotion is experienced, that this basic emotion could be confused with any other. Given his concessions to the idea of multiple emotions being experienced simultaneously, this does not directly counter the logic upon which our work is based.

2.3 Affective Computing

Affective Computing is a term generally applied to the study and development of systems and devices that analyse or simulate human emotions, or some combination of the two [63]. As the broad nature of this chapter highlights, it is a strongly multidisciplinary field including elements of cognitive science, psychology, computing sciences and philosophy.

While significant work has been done within this field in the context of recognising the emotional state of a human user [4, 43, 11, 104, 14, 16, 117, 118, 115, 2, 44], or specifically on designing agents to simulate emotions [41, 70, 108, 98, 99, 97, 102, 45], our interest focuses exclusively on the virtual representation of psychologically grounded emotional states. As such, the work herein is non-partisan in the context of emotion simulation versus emotion detection, as the product of our work should ultimately have uses in both.

Rosalind Picard is often credited with defining the field of Affective Computing in its accepted form, in her paper entitled Affective Computing [63], and has remained one of the defining influences in the field [66, 67, 65]. The context in which it was initially presented was primarily analytical, centered almost exclusively around designing "empathic" systems designed to adapt their behaviour on the basis of the emotional state of the user.

It is, perhaps, easy to dismiss this area as an esoteric approach to complex user interfaces and, perhaps, as an answer to questions that the computing industry at large has no interest in asking. The practical benefits of research into this area, however, cannot be overstated when viewed from the perspective of some of the most vulnerable members of society.

Much research centered around emotion analysis (the aforementioned empathic agents) has been undertaken in a medical context, to aid those suffering from ailments such as Autism and Down Syndrome [64, 35, 46]. In addition, much of this research has focussed on the physiological identifiers discussed elsewhere in this publication in the context of Ekman's emotion research. Again, this emphasises the multidisciplinary nature of the Affective Computing field [12, 18, 106, 62, 57, 58, 113, 101].

Our particular interest lies in the application of the principles of Fuzzy Logic to an affective computing environment. We discuss in an historical context three such contributions here, following a consideration of the contributions to the field of affective computing made in the area of cognitive, goal-oriented systems.

2.3.1 Cognitive, Goal-Oriented Approaches to Affect

Our work centres upon psychological representations of emotional state and, as such, our focus largely shies away from exploration of systems where emotion is embedded within a control system. Further to this the natural bias of our work, relating as it does to emotional state as a concept in and of itself generated by perception of external factors, leans towards the appraisal approach which is generally perceived as at odds with the goal-oriented approach. We would be remiss, however, if we did not address the wealth of research relating emotion to cognition in a goal-oriented, computational context.

Of particular interest is the fashion in which emotion can be linked to autonomy [19] which provides both context and value to our own work, even though that work is undertaken outside the scope of goal-oriented models of emotion. That stipulation made, one purpose of the work we undertake is to generate computational representations of psychologically grounded models of emotion such that those representations can be utilised in an agent that is aware of and affected by its environment. This reinforces the justification of our considering the fashion in which recent psychological theories have drawn links between emotions and goal-oriented cognition.

A goal-oriented view of emotions takes the position that emotions are the side-effect of environmental analysis, affected by the achievement, or otherwise, of goals defining agent desires or similar concepts. If we consider Frijda's definition of emotion [32], connecting stimuli to emotional response as a function of relevance to the agent's goals, we see immediate analogue with the Millenson Theory as discussed later in this Chapter. Indeed, the argument could be made that any strongly stimulus-based representation of emotional state is, on some level, goal-dependant.

Ortony, *et al*, associate emotional output with other agents, events and other items which exist within the agent's universe [56]. This assertion largely supports the models explored and implemented within this work, although the most obvious connections are found in the complex, subjective inputs we discuss later in the context of the Geneva Emotion Wheel. That model, connecting emotional output with perceived environmental valence and control, abstracts inputs away from the purely valenced perspective of Millenson's theory.

Considering more complex representations of emotion theory, the SPAARS model derived by Power and Dalgleish [71] adopts a multi-level approach connecting verbal associations, non-verbalised abstract concepts, and recalled situational analogues with eventual emotional output. Its multi-level nature presents a complex, interconnected web of the fashion in which these concepts both inform each other and the ultimate emotional state, but that same structure places a great deal of emphasis upon the perceptions and past experiences of the individual agent.

While we can draw little in terms of direct inspiration from goal-oriented models in the course of our own research, the topic does introduce layers and levels upon which the eventual manifestation of our work can be superimposed, to inform or be informed by goal-oriented analysis of an agent's particular environment.

2.3.2 OCEAN

Ören and Ghasem-Aghaee [72] considered 'state-of-the-art' psychological principles in their attempt to simulate human behaviour through fuzzy logic. Their model was based upon thirty facets of human personality, clustered into five groups, and they presented three concise representations of the primary characteristics of human personality.

The model they adopt is often referred to as the OCEAN model [36], and summarises human personality Traits into the aforementioned five Clusters under the following headings:

- O: Openness, culture, originality, or intellect
- C: Conscientiousness, consolidation, or will to achieve
- E: Extraversion
- A: Agreeableness or accommodation
- N: Need for stability, negative emotionality, or neuroticism

This model, while supported by a contemporary psychological theory referred to as the Five-Factor Model of Personality [13], seems to have its roots in socio-political consideration as much as in that psychology - the fact that the score of a personality's intellect and originality is dependent upon their emotional awareness and liberality [72] for example.

The proposed model for computational purposes gives each facet three possible values (low, medium, high), with each having a weighting factor affecting its overall effect upon the score of the Cluster (or Trait) it relates to. We instantly see here a potential opening for further iterations of fuzzy logic to be applied, as the membership of each facet is crisp, rather than fuzzy. A given facet (an example facet of Openness is Fantasy, the tendency to daydream) can be either low, medium or high - not 0.9 low, 0.3 medium, 0.1 high.

The fuzzification is introduced only in the context of Traits, where each Trait has two possible membership groups (in the case of Openness, Explorer or Preserver), and these provide membership levels (e.g. 0.3 Explorer, 0.7 Preserver).

Lastly, Ören and Ghasem-Aghaee borrow a personality template from Howard and Howard [36] as a method of formalising the weighting of each facet to the importance in its related trait, its symbolic, qualitative values and its numerical values. The model output is a vector-based surface area producing what they refer to as the compound personality type, presumably the surface area of the personality in each facet being proportional to some output relating to the highest scoring membership group for that facet (the lowest scoring group does not appear to feature in the final measurement).

2.3.3 Gershenson

Gershenson's 1999 [33] publication on emotion modelling through multivalued logic provides us with a less rigorously justified model of the personality, but one which makes noticeably better use of fuzzy logic (in terms of breadth of application). Gershenson's paper considers impetus-based emotion modelling rather than personality modelling - arguably a more interesting area, since it deals directly with the idea of human-agent interaction and applied emotion shift.

He justifies the use of multidimensional logic through consideration of the possibility it is possible to feel contradictory emotion - the example he gives is infidelity, which can generate feelings of seething resentment and instantaneous hatred, while not erasing feelings of love. While subjective, the argument does bear consideration and scrutiny.

Ultimately, Gershenson generates several membership functions, each representing two or more related emotional states, and proposes that through consideration of these aligned membership functions it should be feasible to model the instantaneous emotional state of a system.

This is probably the most important difference between his work and that of Ören and Ghasem-Aghaee - while the latter concerned itself with a whole personality model which could be used to derive emotional tendancy, the former considers exclusively the modelling of the emotional state at any given instant. As such, it is Gershenson's work which bears closest analogue to our own.

2.3.4 Fuzzy Logic Adaptive Model of Emotions

Lastly we discuss possibly the most publicised model considered in this review of prior research, that of the Fuzzy Logic Adaptive Model of Emotions (FLAME). El-Nasr, Yen and Ioerger [31] published an extensive paper outlining the basis of the system. Of all the models we have considered, only FLAME provides a multi-stage system, built upon three components - the emotional component, the learning component and the decision-making component. That said, from our perspective FLAME has significant shortcomings in terms of its emotion model.

A system using the FLAME architecture would observe an external event. What it perceives is then passed to both the learning component and the emotional component, which would also receive some limited input from the post-processed learning component, in order to generate an emotion-based behavioural response. This behaviour is then passed on to the decision-making component in order to determine the agent reaction.

Since FLAME concerns itself with a reactionary model, its implementation of fuzzy logic is related to a heuristic analysis of a given action's 'impact' from the perspective of the agent, a scale running from highly positive to highly negative. The importance of a given goal (linked to the affect a given event has upon the possibility of reaching that goal) is also considered in similar fashion, and used to derive the most subjective consideration, the 'desirability' of the event from the perspective of the agent.

The system is based entirely in type-1 fuzzy logic, with rules of the type:

IF Impact(prevent starvation, food dish taken away) is HighlyNegative

AND Importance(prevent starvation) is ExtremelyImportant

THEN Desirability(food dish taken away) is HighlyUndesired

Price, et al, [15] derived the equations that FLAME bases its emotional intensity upon in 1985. These quantitative equations were built upon a study in which participants described in the first person perspective individual emotional experiences. The paper concluded that there were multiplicative interactions between the anticipation of a positive event, the anticipation of a negative event, and overall emotional intensity.

FLAME does provide some interesting work in the concept of emotion filtering. This is handled through motivational states, which are used to determine which single emotion best enhances the agents probability of reaching a given goal - for example, if a given action provokes a response of both anger and depression, and anger is more likely to prompt an action to resolve the situation, the system will select anger as the primary emotional state.

While this might be useful in a purely control sense, it is in many ways contrary to a psychological view of the scenario, where a human-like agent might well experience emotions that are not conducive to resolving a situation.

Indeed, the idea of filtering out the less desirable emotions completely does seem somewhat at odds with the idea of creating a true representation of human emotional behaviour.

The learning component of FLAME is based upon the Q-learning algorithm within reinforcement learning. The decision-making component as described in the paper is an exhaustive series of if-then statements, linked to the situation of the specific agent and based upon the assumption that the agent has been programmed with a complete list of possible actions and their desirability or at the very least has the capacity to assume any event it is not programmed to react to is considered a neutral event.

Actual testing with FLAME was performed through user assessment, based upon a questionnaire filled out by 21 volunteers who interacted with the system. Little numerical information is provided beyond this, although there is some notable discussion of the perceptions of the test subjects.

As has been noted, our work bears closest analogue with that of Gershenson, as a function of parallels in our approach to representing emotional state. The OCEAN model, being a personality model, lacks direct comparability, and FLAME is, on closer inspection, a control system rather than a psychological 'model' of emotion. We acknowledge that authors such as Simon [90] have described the mind in the context of an emotion-motivated control system; our own focus, however, is to abstract emotion away from direct control and, instead, consider solely fashions in which emotional state can be internally represented. As such, while FLAME is of interest to us historically, it does not relate directly with our intended goals.

2.4 Selected Models

Having discussed both the Darwinian and Wundtian schools, we have also considered that the two are not mutually exclusive. Russell produced a circular model of emotions outlining the position of what he believed to be fundamental emotions in terms of relative values of what were effectively arousal and valence [75].

It is upon this idea of hybridised conceptual models that our work pitches its focus. Such models permit us to consider the emotional state as an output, or resultant, of disparate and seemingly unrelated contextual inputs. As shall be discussed later, they permit a blend of geometry and discrete states that plays particularly to the strength of fuzzy representation.

The focus of our attention has been directed towards two such hybridised concepts. The first was proposed by Millenson in 1967 [53], hereafter referred to as the Millenson Model. The second is a more recent model called the Geneva Emotion Wheel, first presented by Scherer in 2005 [88], hereafter referred to interchangeably as the G.E.W. and the Scherer Model.

2.4.1 Millenson

Millenson's model of emotion, defined as a stand-alone model of emotion and not presented with its own psychological theory, was built upon Watson's three-factor theory [109, 110]. Often considered the father of behaviourism [111], Watson proposed the connection between applied and withdrawn stimulus, and resultant emotional response.

Millenson's model took this idea and derived a three-axis system that associated certain applied and removed stimulus with different facets of emotional experience. Figure 2.1 shows an interpretation of his modular structure, where S+ represents an applied positive stimulus, $+ represents a removed positive stimulus, S- represents an applied negative stimulus, and $- represents a removed negative stimulus.

Along each axis, Millenson places an emotional archetype. He associates the x-axis with anger, the y-axis with anxiety, and the z-axis with pleasure. He acknowledges that three emotions do not account for the sum total of emotional experience, and compensates for this in two ways.

First, he posits that some emotions vary from each other only in terms of their intensity. Given the structure of his model, this is a linguistically ambiguous statement with one of two meanings. The first possible meaning is that along a given axis, all named emotions are essentially the same emotion at varying levels of intensity. The second possible meaning is semantic inasmuch as it may be interpreted that his statement meant that emotions

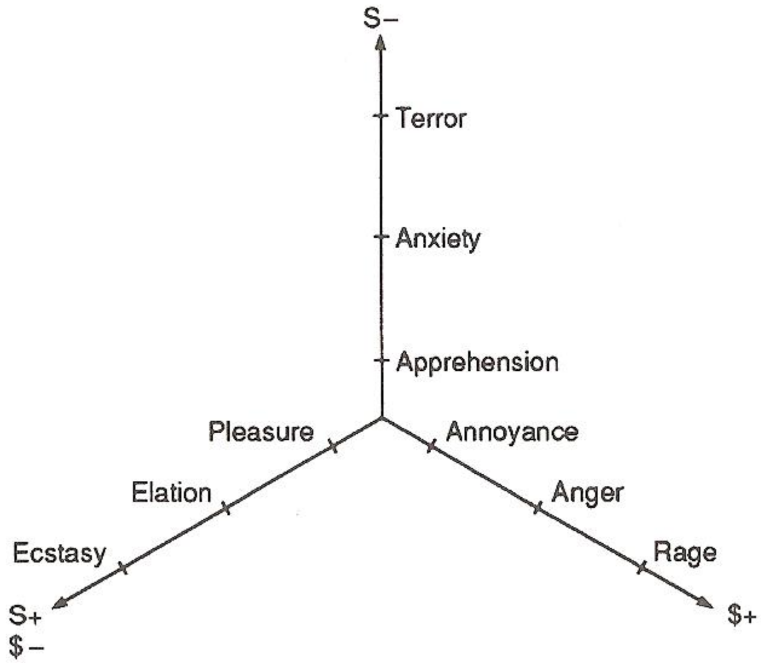

Figure 2.1: Millenson's 3-Dimensional Model of Emotional Intensity [94]

along a particular axis are only triggered by a more intensely felt application or removal of their associated stimulus. Both of these interpretations are explored in later discussions regarding mathematical transliteration of the model and subsequent implementation.

Second, he suggests that some emotions are simply complex compounds of the basic emotions his model acknowledges. In this, his theory is consistent with many subseqent works suggesting the existence of basic emotions; that complex emotions, which might be linguistically recognised in popular language, are complex compounds of two or more basic emotions [25].

In terms of an applied example of Millenson's theory in the context of compound emotional responses to stimulus, his own example was that of a child taking a cookie from a jar [94]. In this example, there is an associated applied positive stimulus with the action, that being to eat the cookie, and an associated applied negative stimulus, that being the fear of being caught. We can define this compound as guilt. We can also consider other combinations of more dramatically conflicting stimulus, such as behaviours that arise from neuroses.

As Figure 2.1 outlines, his nine basic emotions are divided into three groups: those associated with the removal of positive stimulus; those associated with the application of negative stimulus; and, those associated with the conceptual combination of applied positive stimulus and removed negative

Table 2.5: Representation of Basic Emotions Proposed by Millenson's Theory

Name	Definition
Annoyance	'The feeling or state of being annoyed; irritation.'
Anger	'A strong feeling of annoyance, displeasure, or hostility.'
Rage	'Violent uncontrollable anger.'
Apprehension	'Anxiety or fear that something bad or unpleasant will happen.'
Anxiety	'Feeling or showing pleasure or contentment.'
Terror	'Feeling or showing sorrow; unhappy.'
Pleasure	'A feeling of happy satisfaction and enjoyment.'
Elation	'Great happiness and exhilaration.'
Ecstasy	'An overwhelming feeling of great happiness or joyful excitement.'

stimulus. Presenting these respectively, and subsequently in order of implied intensity, including brief definitions drawn from the Oxford Dictionary of English [93], these emotions are shown in table 2.5.

Looking at Millenson's model in a process sense, fundamentally it associates a given event with a composite of application or removal of two stimuli. From this, it defines an emotional response associated with the event, represented by nine basic emotions. Over time, these emotional responses to stimuli can be used to define an adaptive emotional state.

Geometry of the Millenson Model

Throughout this work we shall refer to the 'geometry' of Millenson's representation of emotional state, specifically in a Cartesian fashion. In this context, we refer to the cuboid geometry of figure 2.1, which can be considered a three-dimensional region of Cartesian space, with an origin at the zero-value intercepts of the three experiential axes. In particular, we use the term in the context of emotional state representing a point in the three-dimensional space shown in the figure. We are mindful that Millenson's theory precludes any one of his axes directly affecting the other two, but the visualisation is helpful when considering his model in an hollistic sense.

2.4.2 Scherer

Early Work

Much of Scherer's early work bears analogue with the pan-cultural considerations of Ekman; where Ekman directed his attentions on physical (particularly facial) expression, Scherer discussed the pan-culturality of vocal expression of emotion [107, 78]. Performing his own studies in the context of surveying multiple different explorations of this area of emotion research, he proposed and pursued more complex studies of the topic where expression and impression were jointly analysed, rather than independently. Later work established correlation between emotional inferences and vocal cues across both cultures and languages [86].

His considerations of emotions as a concept were rooted firmly in the idea of situational appraisal and cognitive analysis [79, 81]. He asserted that an organism constantly and subjectively assessed its environment, in the context of its own well-being; emotions would then be generated as a response, based on the importance of the environmental stimulus to an individual, and other assessing factors, including needs and values [83, 87]. This links with discussions regarding emotions as a facet of goal-oriented behaviour patterns earlier in this document, although computational exploration of Scherer's work has been undertaken previously in the context of neural networks[77].

Scherer does not explicitly draw mutual exclusivity between 'appraisal' systems and cognitivistic approaches. Rather, he considers that on some level, appraisal is a cognitive process, but not necessarily one associated with higher level processing of environment. Indeed, he has discussed in depth the components of emotion that can be considered explicitly cognitive [85]. This is the view we adopt in consideration of our selected models of emotion; that appraisal of environment is a cognitive process, not necessarily driven by higher level assessment, informing the emotional state of an agent.

Dicussing the nature of emotions [82, 84], Scherer subscribes to an expansion of the triad view that emotions have three functional components: physiological arousal, motor expression, and subjective feeling. In particular, Scherer includes two additional components of emotion: behaviour preparation, and cognitive processes. From our perspective, these factors inform the 'output' of a system governed by the emotion models this work discusses. We acknowledge the theoretical implications of situational reinforcement of stimulus, that an agent whose behavioural or cognitive response to a given emotional state may be to generate a stimulus which reinforces that emotional state.

An additional aspect of prior work undertaken by Scherer which is of interest to our own work revolves around the issue of emotion blends. The utilisation of fuzzy logic systems in the representation of emotional state must, on some level, consider the debates surrounding the question of whether or not it is possible for an organism to 'feel' multiple emotions simultaneously. More importantly, from our perspective, we consider whether it is possible for a given stimulus event to trigger multiple 'basic' emotions in response. Like Plutchik, Scherer takes the position that emotion blends are observed regularly within nature [80]. This supports our own view that a fuzzy logic-based representation of emotional state can generate complex stimulus-based responses, where multiple basic emotions are triggered by a single event, without sacrificing psychological analogue.

The Geneva Emotion Wheel

Where Millenson's model associates the stimulus of a given event with an emotional component the Geneva Emotion Wheel adopts a more classical approach. Following on the principles outlined by Wundt over a century earlier, Scherer's work associates the agent's perceptions of its situation with a discrete emotional component.

In his paper presenting the Geneva Emotion Wheel, Scherer discusses a perceived relationship between specific emotions, and relative experiences of valence and control. Through empirical analysis, informed by extensive experimentation, Scherer postulates that a structure featuring sixteen basic emotions might be generated, with each emotions position and intensity being determined by a vector relationship defined by these two input factors.

Commenting on Russell's original circumplex work [75], Scherer takes some of the conclusions drawn and uses them to tune his model. He also makes note of the comparable results obtained through separate empirical experimentation. At length, the Geneva Emotion Wheel is presented in the form shown in Figure 2.2.

While Scherer admits that previous scholars suggested that, if basic emotions are the root of emotional experience, the maximum number of basic emotions would be fourteen, his circular model includes sixteen distinct emotions, each of which we may consider a basic emotion. These sixteen basic emotions, with associated definitions taken from the Oxford Dictionary of English [93] are presented in table 2.6.

In the interests of clarity, the Oxford Dictionary of English defines *bored* as 'Feeling weary and impatient because one is unoccupied or lacks interest

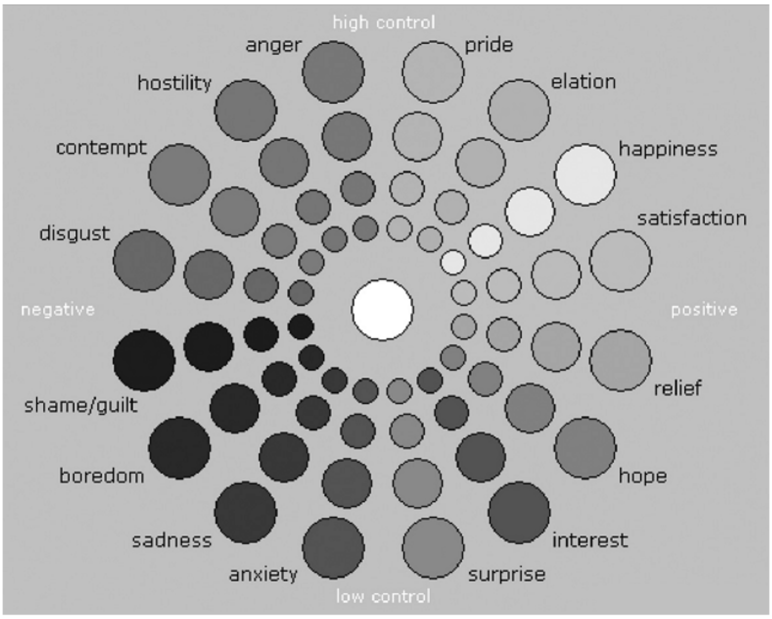

Figure 2.2: A Graphical Depiction of the Geneva Emotion Wheel [88]

in one's current activity'. Similarly, it defines *hostile* as 'Showing or feeling opposition or dislike; unfriendly' [93].

We note that three of these basic emotions are directly comparable to the list proposed by Millenson: anger, anxiety and elation. Indeed, these three emotions actually form the core of Millenson's model, as they represent the conceptual midpoint on each axis of his system. We also note in particular that the example of a complex emotion provided by Millenson, that of guilt, features as a basic emotion in the Geneva Emotion Wheel.

Considering further the graphical representation we note that it also indicates varying degrees of intensity, showing that as the relative magnitudes of valence and control become greater, the emotions they engender are experienced in a more dramatic fashion. As these relative magnitudes of the two determining factors tend towards zero, so too does the emotional impact they generate. At the centre of the model lies an emotional white space to reflect this.

Looking at the Geneva Emotion Wheel in a process sense, it connects an input based upon agent perception, specifically the agent's perception of the valence and control it feels in a given situation. From this, it defines an emotional response associated with the event, represented by sixteen basic emotions. As with Millenson, we would seek to use these event-associated emotions, over time, to present an adaptive emotional state, work initially discussed in 2008 [9].

Table 2.6: List of Basic Emotions Presented in the Geneva Emotion Wheel

Name	Definition
Pride	'A feeling of deep pleasure or satisfaction derived from one's own achievements, the achievements of one's close associates, or from qualities or possessions that are widely admired.'
Elation	'Great happiness and exhilaration.'
Happiness	'Feeling or showing pleasure or contentment.'
Satisfaction	'Fulfilment of one's wishes, expectations, or needs, or the pleasure derived from this.'
Relief	'A feeling of reassurance and relaxation following release from anxiety or distress.'
Hope	'A feeling of expectation and desire for a particular thing to happen.'
Interest	'The feeling of wanting to know or learn about something or someone.'
Surprise	'A feeling of mild astonishment or shock caused by something unexpected.'
Anxiety	'Feeling or showing pleasure or contentment.'
Sadness	'Feeling or showing sorrow; unhappy.'
Boredom	'The state of feeling bored.'
Shame / Guilt	'A feeling of having committed wrong or failed in an obligation.' / 'A painful feeling of humiliation or distress caused by the conscious -ness of wrong or foolish behaviour.'
Disgust	'A feeling of revulsion or strong disapproval aroused by something unpleasant or offensive.'
Contempt	'The feeling that a person or thing is worthless or deserving scorn.'
Hostility	'Hostile behaviour; unfriendliness or opposition.'
Anger	'A strong feeling of annoyance, displeasure, or hostility.'

Geometry of the Geneva Emotion Wheel

Throughout this work we use the term 'geometry' when discussing the Geneva Emotion Wheel, applying the term in a Cartesian context. Analogous to our application of the term in the context of Millenson's model, when 'geometry' is used in relation to the Geneva Emotion Wheel it specifically refers to the geometric shape shown in figure 2.2. In particular, it is used when discussing the relationship between given relative magnitudes of control, valence and emotional output, as informed by the circumplex. This geometry is also referred to in discussion of our implementations of the Geneva Emotion Wheel, where it is applied more literally.

Chapter 3

Literature Review: Fuzzy Logic and Development Platforms

3.1 Chapter Overview

This chapter presents the portions of our literature review regarding computational and technical aspects of the research undertaken. Initially, we provide a brief overview of fuzzy logic, upon which our mathematical representations and eventual implementations hinge. We firstly approach type-1 fuzzy logic, before providing some dicourse and notation with respect to type-2 fuzzy logic.

We next discuss the topic of developmental platforms for our work, both in terms of hardware and software. We outline the various software platforms that were selected for development, highlighting benefits and issues with all concerned. Finally, we discuss considered but discounted hardware platforms.

3.2 Introduction to Fuzzy Logic

3.2.1 Type-1 Fuzzy Logic

In traditional set theory, an object k has a binary relation, defined by a bivalent condition, with a set A. If k is a member of the set A, we denote this

$$k \in A \tag{3.1}$$

In fuzzy set theory, set A is actually represented as a pair, (A, μ) where A is a set, and

$$\mu\colon A \to [0, 1] \tag{3.2}$$

Membership of k in the set (A, μ) is now defined as $\mu(k)$; we call this the membership grade of k.

k is considered excluded from the set (A, μ) if $\mu(k) = 0$; k is considered fully included in the set (A, μ) if $\mu(k) = 1$; and, k is considered a fuzzy member of (A, μ) if $0 < \mu(k) < 1$. For a finite set $A = k_1, k_2, \ldots, k_n$, we denote the fuzzy set (A, μ) as $\mu(k_1)/k_1, \mu(k_2)/k_2, \ldots, \mu(k_n)/k_n$.

Fuzzy logic, the extension of fuzzy set theory, utilises degrees of truth to determine the nature of a system. In particular, while mathematical variables often take crisp, numerical values, fuzzy logic permits the use of linguistic

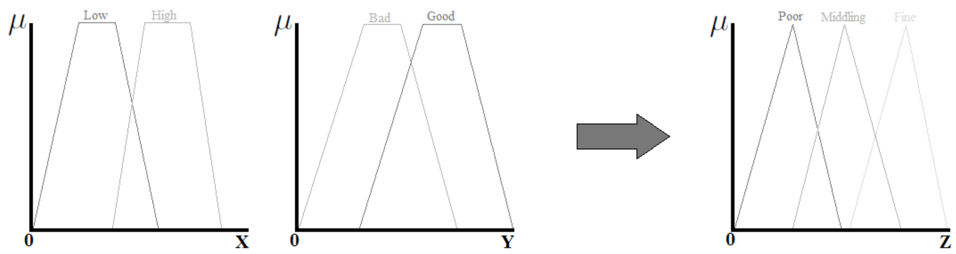

Figure 3.1: Two Fuzzy Inputs leading to One Fuzzy Output

variables [126, 122, 123, 124, 125]. These variables may be associated with qualifying terms such as short, warm or poor.

3.2.2 Type-1 Fuzzy Inferencing

In his original work regarding the application of fuzzy set theory to control systems [49], Mamdani described in detail an experiment regarding "linguistic" synthesis of a controller for a steam engine. He applied fuzzy logic to convert heuristic control rules as stated by a human operator into an automatic control strategy. His work was based on a paper published by Zadeh in 1973 discussing complex systems and decision making [121].

The structure of a Mamdani fuzzy inferencing system, or FIS, is comparatively simple, and built upon rules of the form

If X is 'x', then Y is 'y'

Or, in mathematical form,

$\{IF(Premise_i)THEN(Consequent_i)\}_i^N$
where x and y are linguistic values determined by fuzzy sets along the ranges X and Y. The 'if' statement we define as the premise, or antecedent, while the 'then' statement is defined as the conclusion or consequent [91].

Applying fuzzy logic to these statements, we introduce the idea of gradiated truth, or membership grades, of individual statements. For example, let us consider two input ranges: X possessed of two linguistic variables, $High$ and Low, and Y, possessed of two linguistic variables, $Good$ and Bad. These two input ranges are used in the determination of an output variable Z, with linguistic variables $Poor$, $Middling$ and $Fine$. These are shown in Figure 3.1.

Let us generate three rules for our example system.

Rule 1: If X is $High$, and Y is *Good*, then Z is $Fine$
Rule 2: If X is *Low*, and Y is *Good*, then Z is $Middling$
Rule 3: If X is *Low*, and Y is *Bad*, then Z is *Poor*

Our rules are using the And (min) operator. There are two operators we commonly use in Mamdani fuzzy inferencing systems: And (min), and Or (max). The axioms these functions represent are defined as follows:

Truth(A *OR* B) = *MAX*(Truth(A), Truth(B))
Truth(A *AND* B) = *MIN*(Truth(A), Truth(B))
Truth(*NOT* A) = 1 − Truth(A)

Where Truth in this sense is a value defining accuracy of an assertion, and the *MAX* and *MIN* operators have their usual meanings. In a binary logic system, Truth of a given assertion is either 1 or 0. In a fuzzy logic system, Truth is a value between 1 and 0, informed by the membership functions that define the inferencing system.

Our systems focus particularly upon the And case. Numerically, these are represented through simple equations relating to the membership function of a linguistic variable associated with an input. Let us consider the specifics of these relations here.

Let us consider input range X, with linguistic variables $High$ and *Low*. Following on from fuzzy set theory, we formalise this as

$$(X, \mu) = \{\mu(Low)/Low, \mu(High)/High\}$$

Likewise, in considering our input range Y and output Z, we formalise them as

$$(Y, \mu) = \{\mu(Bad)/Bad, \mu(Good)/Good\}$$

$$(Z, \mu) = \begin{array}{c}(\{\mu(Poor)/Poor, \mu(Middling)\\ /Middling, \mu(Fine)/Fine\})\end{array}$$

For any given values applied to the ranges X and Y, let us call these discrete values X' and Y', values of m associated with specific linguistic variables are produced and applied to the rules as follows. Let us consider Rule 1 in our hypothetical system. Rule 1 is an And rule, meaning that the membership of the linguistic output variable is determined by the minimum membership of the associated linguist input variables. Thus, for any values of X and Y, Rule 1 can be represented as

$$(\{\mu_Z(Fine)/Fine\} = \min\{\mu_X(High)/High, \mu_Y(Good)/Good\})$$

In a standard Mamdani fuzzy inferencing system, each of these rules is considered for a given input to the system. That is to say that for any value X and Y received by the system, all three rules shall be evaluated to determine the resultant membership grades of the linguistic variables within Z. These membership grades determine the contribution from each linguistic variable to the pre-defuzzified output of Z. Figure 3.2 illustrates this process by assigning the value 0.4 to X, and the value 0.8 to Y.

Note that, as previously stated, the output shown in Figure 3.2 has not yet been defuzzified. Indeed, it is important to realise that the fuzzy inferencing system does not return memberships for the three linguistic variables that define Z. Rather, the inferencing system should return to us a value within the limits of Z by which we can define our output.

As shall be discussed in the context of the first Millenson implementation featured within this paper, this crisp output can then be used to define other variables, dependent upon the needs and design of the system. For the purpose of this illustration, however, it is simply a desired, crisp value of Z.

In order to obtain this crisp output, it is required that the output shown in Figure 3.2 be defuzzified. The most common form of defuzzification associated with the Mamdani fuzzy inferencing system is known as centroid defuzzification.

Centroid defuzzification calculates the total area defined by the membership grades of the linguistic variables, with respect to their membership functions. In Figure 3.2 this area is represented by the dark grey region of the defuzzified output. Having determined the total area under the curve, the defuzzifier then calculates the value of Z representing the centre of the area. Explicitly, the point along the Z-axis where the area under the curve to the left of the output value is equal to the area under the curve to the right.

The description, in fuzzy terms, of the emotion models outlined in this paper, and how they may be used to generate a conceptual emotion model, is the dominant feature of Section 3 of this paper. The specifics of the

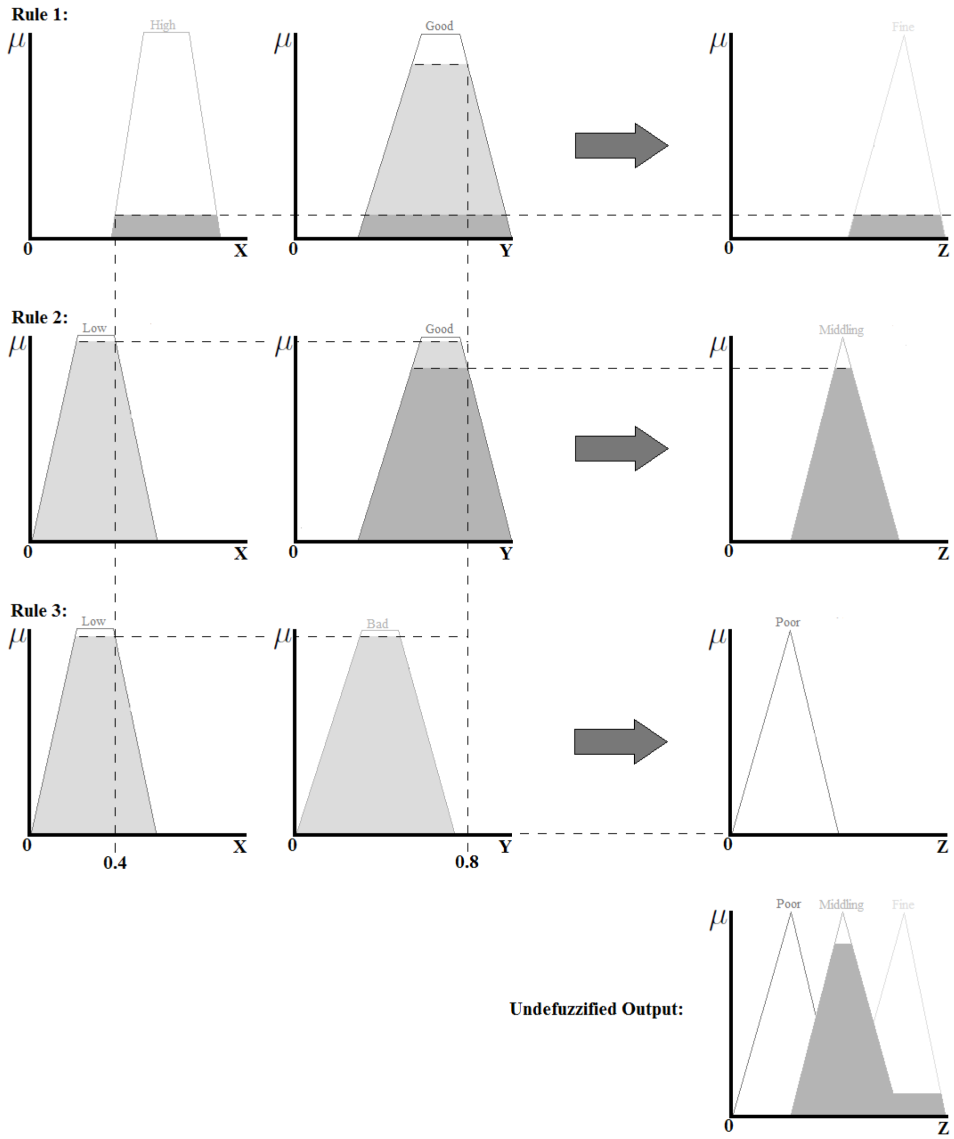

Figure 3.2: Fuzzy Rules Triggered by a Value X'

construction of the models' respective inferencing systems is covered in our Chapter devoted to *Implementation*.

3.2.3 Type-2 Fuzzy Logic Overview

Type 2 fuzzy set theory is a further extension of the Type-1 Fuzzy Logic outlined in the previous section, the mathematical nomenclature and clarity of which were significantly aided by Mendel and John in 2002 [51]. We denote a type 2 fuzzy set $\tilde{\mathbf{A}}$

$$\tilde{\mathbf{A}}\{((k,u),\mu_{\tilde{\mathbf{A}}}(k,u))|\forall k \in K, \forall u \in J_k \subseteq [0,1]\} \tag{3.3}$$

where $\tilde{\mathbf{A}}$ is characterised by the type-2 membership function $\mu_{\tilde{\mathbf{A}}}(k,u)$, $k \in K$, and $u \in J_k \subseteq [0,1]$; and where $0 \leq \mu_{\tilde{\mathbf{A}}}(k,u) \leq 1$.

Conceptually, a type 2 fuzzy set has, for any given value of k, several numerical membership grades which, themselves, have associated membership grades [8]. Let us consider the case of $k = k`$. $k`$ is best envisioned as a two-dimensional plane whose axes are u and $\mu_{\tilde{\mathbf{A}}}(k,u)$. In mathematical terms, we define this as

$$\mu_{\tilde{\mathbf{A}}}(k = k`, u) \equiv \mu_{\tilde{\mathbf{A}}}(k`) = \int_{u \in J_{k`}} f_{k`}(u)/u; J_{k`} \subseteq [0,1] \tag{3.4}$$

In the context of a discrete universe, where there were n unique values of u with associated membership grades μ, for $k = k`$, this could be denoted

$$\mu_{\tilde{\mathbf{A}}}(k`) = \mu(u_{1_{k`}})/u_{1_{k`}}, \mu(u_{2_{k'}})/u_{2_{k`}}, \ldots, \mu(u_{n_{k`}})/u_{n_{k`}} \tag{3.5}$$

for any discrete value of k, $k`$. Note that the above mathematics discusses a variable with only a single type 2 fuzzy set $\tilde{\mathbf{A}}$ attached to it. For a variable K with multiple related type 2 fuzzy sets $\tilde{\mathbf{A}}_1, \tilde{\mathbf{A}}_2, \ldots, \tilde{\mathbf{A}}_n$, parallel like equations are processed for each fuzzy set.

3.3 Development Tools

3.3.1 Selected Platforms

x86 Personal Computer

The term x86 refers explicitly to the instruction set initially associated with the Intel 8086 CPU first introduced in 1978. Though commonly used to describe IBM Compatible PCs, this application is erroneous. The PC itself has countless possible configurations as a function of the wide variet of available hardware. As such, it is impossible to list specifications in the manner of those provided for the consoles discussed above.

We can, however, discuss briefly the context in which the PC was considered as our development platform. At the time these discussions took place, the Intel Core 2 Duo P7450 was considered a consumer-end CPU, possessing two cores clocked at 2.13 GHz. 32-bit Operating Systems limited systems to utilising up to 4GB of RAM, to include both system RAM and video RAM.

In addition, software already existed on the PC to create and manage Fuzzy Inferencing Systems, in particular the MATLAB Fuzzy Logic Toolkit which shall be discussed later. Coupled with the fact that developing for the PC required less specialist equipment, and that the XBox demonstrated that development on the PC did not preclude compatibility with other platforms, it was determined that for the start of the project, and potentially throughout the project, the personal computer would be used for development.

In our specific case, the x86 personal computer used a Microsoft Windows operating system, to maintain compatibility with Microsoft's toolkits for Xbox 360 development, should that come to fruition. The system possessed 3GB of DDR2-800E system RAM, and 1GB of GDDR2 VRAM, a 250GB local hard drive and three USB 2.0 ports for connectivity.

MATLAB Fuzzy Logic Toolbox

The MATLAB Fuzzy Logic Toolbox is a graphic user interface within the MATLAB technical computing environment designed to permit the implementation and customisation of systems based upon fuzzy logic. The toolbox enables the user to establish multiple input and output variables, and multiple membership functions of different shapes and structures within each variable.

When examining the potential use of the MATLAB Fuzzy Logic Toolbox as a software platform for our research there were several factors to consider in depth. Parallel to these considerations were also investigations into development platform, and the one by necessity informed the other.

MATLAB providing support for both Linux and Windows systems, the possibility of utilising the Sony PlayStation 3, through its much vaunted support for Linux, was considered very seriously. In addition, it was also considered that we might within our own project develop a new C++ fuzzy inferencing toolkit through which to represent the emotion models that our work would focus upon.

It was determined that the development of an incipient C++ fuzzy logic interface lay outside the scope of our work, although it was felt that if the work proved fruitful some future development of such a system might be worthwhile. Similarly, without definitive clarification at the time these decisions were taken that MATLAB would function fully on the PlayStation 3, selection of a Windows or Linux PC implementation of MATLAB was deemed prudent.

As has been mentioned previously, Sony's firmware removal of Linux capability from the PlayStation 3 would have rendered the former point moot in any case. The latter point was settled in consideration of the fact we still desired the capacity to implement our system on a games console of some description, should there be time within the project. That being the case, it was determined that we would use the Windows implementation of Matlab, with a view to potentially exploring implementations within the Xbox 360's toolbox for homebrew game development.

The Matlab Fuzzy Logic Toolbox provided both desired ease of use, with customisable flexibility through its reliance on a structure that could be edited directly without reliance upon the Graphical User Interface (GUI). While the nature of the membership functions was inherently limited to triangular, trapezoidal and gaussian shapes, our implementations were proof of concept, rather than statistically analysed and determined structures, and thus the lack of truly customisable vertices was not of particular concern. In addition, the use of more complicated membership functions would not have been justifiable without significant psychological experimentation of our own, determining an incipient emotion model which would have lain outside the scope of this project - and, indeed, defied the nature of the project, which is to explore psychologically grounded emotion models and how they might best be represented in Fuzzy Logic.

In addition to its customisability, the fact that Fuzzy Inferencing Systems designed using the Matlab Fuzzy Logic Toolbox could be called and resolved via command line within the Matlab environment was a highly desirable feature in the context of testing and, ultimately, the Java experimentation which is discussed towards the end of this document. Ultimately, the selection of Matlab as a development environment, and in particular the Matlab Fuzzy Logic Toolbox as a platform, would simplify software development while maintaining the versatility required to explore the models presented.

De Montfort University Type-2 Fuzzy Logic Toolbox

While the Matlab Fuzzy Logic Toolbox is a highly versatile engine, it lacks any significant capacity to represent or explore higher order Fuzzy Logic systems. The rationale behind exploring Type 2 Fuzzy Logic in addition to Type 1 Fuzzy Logic is explained elsewhere, but having determined to explore Type 2 Fuzzy Logic in the context of emotion modelling, it behooved us to explore manners in which to computationally represent and resolve Type 2 interpretations of our chosen emotion models.

De Montfort University was already in possession of a system designed to operate under the Matlab technical computing environment which was capable of representing and resolving Type 2 Fuzzy Logic systems. Like the Matlab Fuzzy Logic Toolbox, the De Montfort University Type 2 Fuzzy Logic Toolbox provided a graphical user interface which permitted the declaration of multiple input and output variables. In addition, each input and output variable might be assigned multiple membership functions, which were themselves in possession of functionally symmetrical secondary membership functions.

When we say functionally symmetrical, in this context we mean that if the primary membership function was triangular in structure then so, too, would the associated secondary membership functions. This operational limitation was present in all forms of primary membership function, be they triangular, trapezoidal or Gaussian. It should be noted that it was possible to structure the secondary membership functions of a trapezoidal primary membership function such that they mimicked a triangle as a function of setting both maxima to the same value.

Again, as with the Matlab Fuzzy Logic Toolbox, the De Montfort University Type 2 Fuzzy Logic Toolbox was limited to three standard shapes when defining its membership functions (both primary and, symmetrically, secondary). Similarly to the rationale in Type 1 Fuzzy Logic, however, our concern was centred upon proof of concept and representation of geometry, rather than the exploration of statistics to define custom-shaped membership functions.

Another limitation with the De Montfort University Type 2 Fuzzy Logic Toolbox came in the form of its reliance upon the graphic user interface to relate resultant data. While this did not cause undue problems with the representations of Millenson, the sixteen solutions to Scherer required a special amendment to the system to obtain, which shall be discussed later.

In conclusion, however, the De Montfort University Type 2 Fuzzy Logic Toolbox provided a versatile and useful software platform upon which to develop representations of our chosen emotion models.

3.3.2 Discounted Hardware Platforms

During the inception of this project, discussions initially took place in the context of applications within the entertainment software industry. The rationale for this was rooted primarily in the fact that as an aspect of affective computing, the emotion model should be developed with a highly interactive hardware platform in mind. At the time these decisions were taken four potential development platforms were discussed, and while the IBM-compatible PC was eventually selected, a summary of the three alternative platform specifications and conclusions regarding suitability is included here for the sake of completeness.

Nintendo Wii

The Nintendo Wii is a Seventh Generation gaming platform produced by *Nintendo Kabushiki Gaisha*. While technical specifications from the manufacturer have never been released to the public, enthusiasts within the user base have deconstructed the console and obtained approximate numbers for clock speeds. As such, while the names of the processors in the subsequent specification list are accurate, the clock speeds are inherently speculative and have not been confirmed by Nintendo or their production partners.

- PowerPC-based "Broadway" CPU, @ 729 MHz and 2.9GFLOPS
- ATi "Hollywood" GPU, @ 243 MHz
- 24MB 1T-SRAM
- 64MB GDDR3 SDRAM
- 3MB embedded GPU frame buffer
- 512 MB NAND flash memory (Primary Storage)
- SD-Card support up to 32GB (Secondary Storage)

Designed specifically to showcase new, heightened levels of user interactivity in the gaming market, the Nintendo Wii was naturally considered as a possible development platform for our own work in affective computing. The Wii utilises motion sensitive remote controls for user-interface (dubbed "Wii-motes"), rather than the more traditional ergonomic double-handled controllers.

This has led to development of a great many titles which necessitate physical exertion to play, seeking to secure a greater level of personal investment in the game simulation. In addition, at the time these decisions were taken, the Nintendo Wii was outselling its competing platforms in a significant fashion. As such, development with the Wii in mind would increase the potential user base of the model when completed.

Negatively, the Nintendo Wii was designed expressly around efficient computing, and utilised a single-core processor capable of 2.9GFLOPS. As shall be subsequently discussed, this lack of 'wriggle room' in terms of processor cycles was of significant concern in the context of the Wii as a development platform for our model. In addition, the lack of manufacturer's published specifications, and having to rely solely on third parties for information regarding the system's capabilities, was problematic.

Sony PlayStation 3

The Sony PlayStation 3 is a Seventh Generation gaming platform produced by Sony Computer Entertainment. Unlike Nintendo, Sony unveiled complete technical specifications for their console at the 2006 Game Developer's Conference. A sample of the complete specifications is included below.

- Cell Microprocessor (CPU), one 3.2 GHz PPE and six SPEs, @ 204GFLOPS SP, 15GFLOPS DP
- RSX 'Reality Synthesiser' GPU, @ 550 MHz
- 256MB XDR DRAM
- 256MB GDDR3 @ 700 MHz
- 60GB 2.5" SATA HDD (Primary Storage)
- USB 2.0 Flash Drive Connectivity (Secondary Storage)

Housing one of the most advanced home user CPUs in existance at the time of these considerations, the Sony PlayStation 3 already enjoyed a plethora of titles boasting photorealistic graphics and high definition surround audio, adopting a more traditional, but refined, approach to user interactivity.

The multi-element Cell Processor granted significantly more freedom in terms of floating point operation overhead, making the console very attractive from a practical, development standpoint. In addition, the console's support for the Linux family of operating systems provided a ready platform for software development in terms of proof of concept.

At the time development platform was first mooted, Sony Computer Entertainment Europe (SCEE) proved difficult to contact, and initial information suggested utilising the PlayStation 3 as a testbed for our research would require significant financial outlay. Despite this, the PlayStation 3 was a favoured possibility and very strongly considered.

In hindsight, however, the decision not to use the PlayStation 3 has been vindicated. In April of 2010, Sony released a pushed firmware update which removed the option for PlayStation 3 owners to use the Linux family of operating systems. This would undoubtedly have had significant impact on our research project, had we been using the console as a development platform.

Microsoft Xbox 360

The Xbox 360 is a Seventh Generation gaming platform produced by the Microsoft Corporation. Similarly to SCE, Microsoft opted to put into the public domain the specifications of its second console offering to support its marketing campaign. A sample of the technical specifications is included below.

- "Xenon" PowerPC-based triple-core CPU @ 3.2 GHz, @ 96.0 GFLOPS SP, 57.6 GFLOPS DP
- 500 MHz ATi "Xenos" GPU
- 500 MHz GPU Daughterboard
- 512 MB Shared GDDR3 @ 700 MHz
- 60 GB HDD (Removable, Primary Storage)
- Memory Cards (Removable, Secondary Storage)

The Xbox 360 enjoyed both an exceptionally powerful CPU (theoretically half the operating speed of the PS3's Cell Processor at single precision, but almost four times the Cell Processor's operating speed at double precision) and accessibility for development from an early stage in its release (through the Xbox Live system's support for homebrew development). As such, it was considered a viable platform should our research culminate in implementation through a game engine.

The lack of secure Primary Storage was a concern at the time these discussions took place; it was uncertain whether the removable hard disk drive was suited for fast read-write operations, serving primarily as storage for downloaded media and save files. That said, consideration of methods of development for the Xbox 360 ultimately led to the selection of the PC as our development tool, given that many of the Xbox 360's development toolkits were designed for the PC.

Chapter 4

Type-1 Fuzzy Representation of Psychologically Grounded Emotion Models

4.1 Chapter Overview

In this chapter we discuss the Type-1 Fuzzy Logic representations of our emotion models, and provide an in-depth discussion of the models themselves. Each interpretation of each model is presented in exhaustive mathematical detail, considering both the abstract and specific numerical concepts represented therein.

We begin with discourse regarding the Millenson Model of emotions. Universally shared characteristics are presented and mathematically represented. Subsequently, two interpretations of Millenson's Model, built upon differing meanings of his linguistics, are provided and illustrated for clearer understanding.

Finally, this chapter goes on to present a mathematical representation of the Geneva Emotion Wheel in type-1 fuzzy logic terms. The psychology of the model is revisited from a computational standpoint, and points of interest are highlighted and discussed from the perspective of both fields.

4.2 Type-1 Fuzzy Logic Representations of the Millenson Model

As discussed previously, Millenson provides connective links between stimuli of differing valence and specific facets of emotional experience. As this link is contextual, we must first represent each axis as a conceptual relativistic sum of respective stimuli, with a crisp value between 0 and 1.

$$X = \sum\{\$+\}[0,1] \tag{4.1}$$

$$Y = \sum\{S-\}[0,1] \tag{4.2}$$

$$Z = \sum\{S+,\$-\}[0,1] \tag{4.3}$$

The nature of these variables, and the manner in which they are normalised into quantifiable values between 0 and 1, is naturally dependent upon the context in which they are applied and the setting in which they are being implemented. As an example, however, let us consider a mobile agent within a universe shared with two other objects: an item of food, and a predator.

Conceptually speaking, at a time t, the distance between the agent and the food we define as r_t, and the distance between the agent and the predator we define as s_t. The stimulus the agent receives between time t and time $t+1$ may be derived through changes to these two variables.

Thus we might consider the agent to have received application of positive stimulus ($S+$) if $r_{t+1} < r_t$, informing the variable Z. Conversely, if $r_{t+1} > r_t$, we might consider this a removal of positive stimulus ($+), informing the variable X.

Similarly, we might consider the application of negative stimulus ($S-$), associated with the variable Y, to be influenced should $s_{t+1} < s_t$. Likewise, if $s_{t+1} > s_t$ we could consider this the removal of negative stimulus ($−), and hence infer an impact on the variable Z.

Thus we define the concept of a Stimulus Event $\mathbf{J}$, that being an event which provides some form of experiential stimulus to the agent, impacting its emotional state. Mathematically, $\mathbf{J}$ is a column vector of the variables X, Y and Z such that

$$\mathbf{J} = \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} \tag{4.4}$$

At this point, the manner in which we associate the stimulus event with emotional output conceptually bifurcates, as was briefly discussed during the psychological outline of the model. First, it is possible to infer from Millenson's qualifications regarding multiple emotions that the differences between distinct emotions along a particular axis are solely defined in terms of experiential intensity. Alternatively, we might infer that the intensity he speaks of is explicitly the intensity of stimulus required to trigger individual emotions.

Conceptually, and psychologically, these two interpretations each require an alternative representation through fuzzy logic. Both shall be discussed in this chapter, beginning with the first interpretation, published initially in 2008 [7]. Prior to this exposition, however, we are obliged to clarify in specific terms how the emotional state shall be defined through either representation of the Millenson Model.

Millenson's model presents nine emotions that he describes as basic, irrespective of the interpretation of how they might be related to stimulus. It therefore stands to reason that in consideration of Millenson's emotion model, the emotional state include representation of all nine of these elements.

In explicit terms, this report defines the emotional state of an agent governed by the Millenson Model,

$$\mathbf{E_M} = \begin{bmatrix} \mu x_1[0,1] \\ \mu x_2[0,1] \\ \mu x_3[0,1] \\ \mu y_1[0,1] \\ \mu y_2[0,1] \\ \mu y_3[0,1] \\ \mu z_1[0,1] \\ \mu z_2[0,1] \\ \mu z_3[0,1] \end{bmatrix} \tag{4.5}$$

as an array of nine elements, and where μ in all cases represents the membership grade of the named emotion the variable is associated with, and where; x_1 represents *Annoyance*, x_2 represents *Anger*, and x_3 represents *Rage*; y_1 represents *Apprehension*, y_2 represents *Anxiety*, and y_3 represents *Terror*; z_1 represents *Pleasure*, z_2 represents *Elation*, and z_3 represents *Ecstasy*.

These relative magnitudes seek to indicate the level to which the agent is experiencing each individual emotion at a given instant, instigated by Stimulus Events and informed by the systems we now outline.

4.2.1 Millenson A

Let us assume a given interpretation of Millenson's model that connects the significance of applied and removed stimuli, of differing valence, with three emotional components. Let us explicitly define these connections of the form

$$\begin{aligned} X &\rightarrow Anger \\ Y &\rightarrow Anxiety \\ Z &\rightarrow Pleasure \end{aligned}$$

where X, Y and Z are defined in equations (4.1), (4.2) and (4.3), respectively, and their associated axes are clearly shown in Figure 2.1.

We assign variables to each of these emotional components, of the form

$$Anger \rightarrow x$$
$$Anxiety \rightarrow y$$
$$Pleasure \rightarrow z$$

Each of these emotional components possesses three associated emotions, differing from each other in terms of the degree with which the component is experienced. Mirroring our merging of the stimulus components into a single variable, we define the emotional experience index $\mathbf{e_J}$ associated with a discrete event $\mathbf{J}$, to be a vector of these three values, and normalise them to crisp numbers between 0 and 1.

$$\mathbf{e_J} = \begin{bmatrix} x[0,1] \\ y[0,1] \\ z[0,1] \end{bmatrix} \tag{4.6}$$

Obtaining e_J is a conceptual problem which we will approach from the perspective of fuzzy inferencing. Let us consider an individual component of $\mathbf{J}$, X.

As previously indicated, a given value assigned to X would be a number between 0 and 1, conceptually representing the significance of removed positive stimulus triggered by an event. Understanding that such a quantifier could not crisply represent the nature of stimuli affecting the system, taking into account our earlier discussions regarding the versatility fuzzy inferencing provides in systems using non-crisp concepts, we now look to consider the system from a fuzzy perspective.

Thus let us define X as an input to a Mamdani fuzzy inferencing system, with linguistic variables describing "Low Significance", "Medium Significance" and "High Significance". Thus we define X in fuzzy terms as

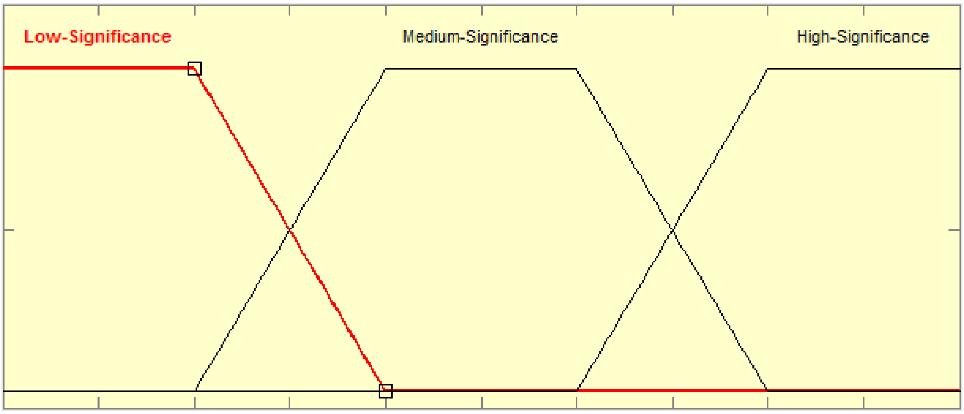

Figure 4.1: Potential Implementation of X as an Input Variable of a FIS

$$(X, \mu) = \begin{aligned} &\{\mu(\text{Low Significance})/\text{Low Significance}, \\ &\mu(\text{Medium Significance})/\text{Medium Significance}, \\ &\mu(\text{High Significance})/\text{High Significance}\} \end{aligned} \tag{4.7}$$

Figure 4.1 illustrates a hypothetical structure for X as the input to a fuzzy inferencing system, which we henceforth refer to by the acronym FIS.

Millenson stipulates the correlation between stimulus and implied emotional output is exclusive, meaning that only variables connected to specific stimuli application and removal can affect a given output. Thus we define x as an output of a Mamdani fuzzy inferencing system with linguistic variables describing "Low Response", "Moderate Response" and "Extreme Response" describing the agent's reaction to given behavioural stimuli in emotional terms. In mathematical terms, this clarifies x as

$$(x, \mu) = \begin{aligned} &\{\mu(\text{Low Response})/\text{Low Response}, \\ &\mu(\text{Moderate Response})/\text{Moderate Response}, \\ &\mu(\text{Extreme Response})/\text{Extreme Response}\} \end{aligned} \tag{4.8}$$

Figure 4.2 illustrates a potential interpretation of x as an output for a fuzzy inferencing system.

Further to this, let us ascribe three simple, fuzzy rules to this system:
Rule 1: If X is Low Significance, then x is Low Response
Rule 2: If X is Medium Significance, then x is Moderate Response

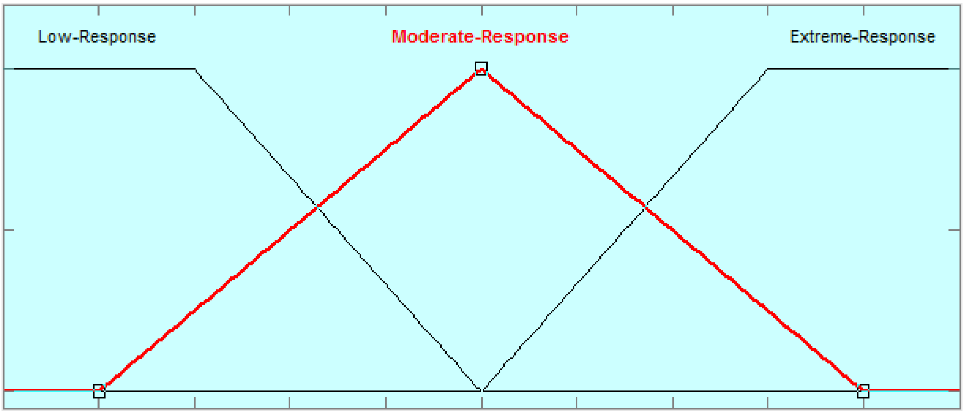

Figure 4.2: Potential Implementation of x as an Output Variable in a FIS

Rule 3: If X is High Significance, then x is Extreme Response

Following on from our earlier discussions regarding the Mamdani fuzzy inferencing system and centroid defuzzifier, it follows that this system can take a single, crisp variable defined as a component of $\mathbf{J}$, and provide a single, crisp variable which provides a component of $\mathbf{e_J}$. Conceptually, this principle extends to all three axes in a similar fashion, with identical rules, thus providing all three elements of the emotional experience index $\mathbf{e_J}$. The work, however, is only half done.

It is not the purpose of the model simply to quantify in vague terms the emotional response to stimulus. Rather, it is our intent to define an emotional state that may be informed and adapted through emotional response to environment. Having defined the emotional component of the stimulus $\mathbf{J}$, and clarified the means by which the two are connected, we determined to connect $\mathbf{e_J}$ in some direct fashion with an as yet undefined emotional state. Before this can be explored, however, we must first associate the emotional component $\mathbf{e_J}$ with the nine discrete emotions posited by Millenson.

The numerical values within $\mathbf{e_J}$ quantify the emotional component along the associated axis. Following Millenson's literature, that component can then be used to determine which emotions along that axis are triggered by the stimulus changes presented by event $\mathbf{J}$. Some have suggested that these emotions are linguistic terms and, as such, inherently fuzzy [88, 126], but whether or not this is the case, it is not at all assumed that a binary state of active or inactive is inferred by the grade of the emotional component along a given axis. Indeed, to assume such would deny the idea that emotions can be felt to varying degrees.

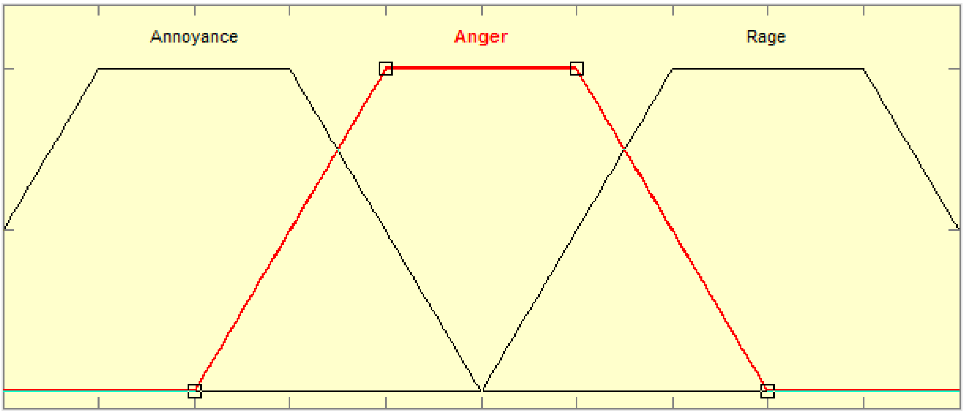

Figure 4.3: Illustrative Relationship of x with Named Emotions

Let us assume, then, that each named emotion might be represented by a fuzzy set along its parent axis. In fuzzy set terminology, referencing our previous example discussing the variable x in terms of a fuzzy set, this provides a new string of fuzzy relations. The axis with which x is associated houses three named emotions: Annoyance, Anger and Rage. If we consider these emotions as linguistic variables, we can define their relationship with x as

$$(x, \mu) = \begin{array}{r}\{\mu(\text{Annoyance})/\text{Annoyance},\\ \mu(\text{Anger})/\text{Anger},\\ \mu(\text{Rage})/\text{Rage}\}\end{array} \tag{4.9}$$

Figure 4.3 provides an illustration of what this construct might look like.

As with our interconnection of stimulus with emotional component, this relation between emotional component and named emotions can be extrapolated to all three variables. As such, y and z would take the form

$$(y, \mu) = \begin{array}{r}\{\mu(\text{Apprehension})/\text{Apprehension},\\ \mu(\text{Anxiety})/\text{Anxiety},\\ \mu(\text{Terror})/\text{Terror}\}\end{array} \tag{4.10}$$

$$(z,\mu) = \begin{aligned} \{&\mu(\text{Pleasure})/\text{Pleasure}, \\ &\mu(\text{Elation})/\text{Elation}, \\ &\mu(\text{Ecstasy})/\text{Ecstasy}\} \end{aligned} \tag{4.11}$$

It should be stressed that this is not a preamble to the application of a second fuzzy inferencing system. Rather, the functions connecting the various values of μ to the named, discrete emotions should be defined and employed in a more traditional, arithmetical manner.

Millenson's model gives us no reason to assume that the relations between a component and its associated discrete emotions are not uniform across individual components of equivalent scaling. Which is to say that within his derivation there is no reason to assume that the relationship associating x with Rage is in any way different to the relationship associating z with Ecstasy. That being the case, we define an array of equations associating the components of $\mathbf{e_J}$ with values for discrete emotions associated with their respective axes.

$$\mu_{\mathbf{J}}x_1 = f_1(x)[0,1] \tag{4.12}$$
$$\mu_{\mathbf{J}}x_2 = f_2(x)[0,1] \tag{4.13}$$
$$\mu_{\mathbf{J}}x_3 = f_3(x)[0,1] \tag{4.14}$$
$$\mu_{\mathbf{J}}y_1 = f_1(y)[0,1] \tag{4.15}$$
$$\mu_{\mathbf{J}}y_2 = f_2(y)[0,1] \tag{4.16}$$
$$\mu_{\mathbf{J}}y_3 = f_3(y)[0,1] \tag{4.17}$$
$$\mu_{\mathbf{J}}z_1 = f_1(z)[0,1] \tag{4.18}$$
$$\mu_{\mathbf{J}}z_2 = f_2(z)[0,1] \tag{4.19}$$
$$\mu_{\mathbf{J}}z_3 = f_3(z)[0,1] \tag{4.20}$$

where $\mu_{\mathbf{J}}$ represents explicitly the membership grade associated with the specified emotion for a given stimulus event $\mathbf{J}$, and where x_1, x_2 etceteras have the same meanings as outlined in equation 4.5. For the sake of succinctness, this relationship array condenses down to a single equation,

$$(4.21)$$

$$\mu_{\mathbf{J}} j_i = f_i(j)[0,1] \qquad for j = x, y, z \quad i = 1,2,3$$

Let us collect these nine membership grades into a single vector. We define this vector $\mathbf{E_J}$, the emotional state component of an event $\mathbf{J}$.

$$\mathbf{E_J} = \begin{bmatrix} \mu_{\mathbf{J}} x_1 \\ \mu_{\mathbf{J}} x_2 \\ \mu_{\mathbf{J}} x_3 \\ \mu_{\mathbf{J}} y_1 \\ \mu_{\mathbf{J}} y_2 \\ \mu_{\mathbf{J}} y_3 \\ \mu_{\mathbf{J}} z_1 \\ \mu_{\mathbf{J}} z_2 \\ \mu_{\mathbf{J}} z_3 \end{bmatrix} \tag{4.22}$$

The distinction between $\mathbf{E_J}$ and $\mathbf{E_M}$ is conceptually fundamental. $\mathbf{E_M}$ is the emotional state of the agent. $\mathbf{E_J}$ is the emotional impact of a given stimulus event $\mathbf{J}$; as such, $\mathbf{E_J}$ *informs* $\mathbf{E_M}$, but the two are not equivalent, as the distinctions in their notation emphasise. At this stage, the system can now inform the emotional state of the agent. How this emotional state is informed depends specifically upon the level of emotional memory it is desired that the agent experience; that meaning, how strongly the current emotional state mutes the impact of the stimulus event $\mathbf{J}$.

Let us return to the emotional state $\mathbf{E_M}$ as defined by equation 4.5. In merging $\mathbf{E_M}(t)$ with $\mathbf{E_J}$, to obtain $\mathbf{E_M}(t+1)$, the simplest operator would be to take the mean of the two vectors, such that

$$\mathbf{E_M}(t+1) = \frac{(\mathbf{E_M}(t) + \mathbf{E_J})}{2} \tag{4.23}$$

which is more exhaustively written as

$$\mathbf{E_M}(t+1) = \begin{bmatrix} (\mu x_1(t) + \mu_\mathbf{J} x_1)/2 \\ (\mu x_2(t) + \mu_\mathbf{J} x_2)/2 \\ (\mu x_3(t) + \mu_\mathbf{J} x_3)/2 \\ (\mu y_1(t) + \mu_\mathbf{J} y_1)/2 \\ (\mu y_2(t) + \mu_\mathbf{J} y_2)/2 \\ (\mu y_3(t) + \mu_\mathbf{J} y_3)/2 \\ (\mu z_1(t) + \mu_\mathbf{J} z_1)/2 \\ (\mu z_2(t) + \mu_\mathbf{J} z_2)/2 \\ (\mu z_3(t) + \mu_\mathbf{J} z_3)/2 \end{bmatrix} \tag{4.24}$$

However, this notation is inherently limiting and precludes study into the area of emotional memory and its impact on learning systems. As such, it is our preferred solution to use alternative notation of the form

$$\mathbf{E_M}(t+1) = \frac{(u\mathbf{E_M}(t) + v\mathbf{E_J})}{u+v} \tag{4.25}$$

where u and v are constants introduced at the point of implementation, permitting the application designer to adjust the weightings of import between a new event and an established emotional state. Those wishing to investigate systems where emotional memory makes up a large component have the freedom to do so with this notation, as do those who wish to study systems with a limited memory component where emotional state is based predominantly upon instantaneous stimulus.

4.2.2 Millenson B

Having outlined the first consideration of Millenson's theory in this work, it is appropriate to discuss another. From a psychological standpoint, let us consider the alternative interpretation of Millenson's intensity statement. If one chooses to interpret it in the context of a more intense stimulus leads to a different triggered emotion along an axis, then one already has the fundamental basis for a complete fuzzy inferencing system without the use of the two-stage process shown previously, as shall now be outlined.

Consider the stimulus event $\mathbf{J}$ in the context of its three components X, Y and Z. The previous section discussed these in terms of significance - the importance of the applied or withdrawn stimulus - and derived from this the

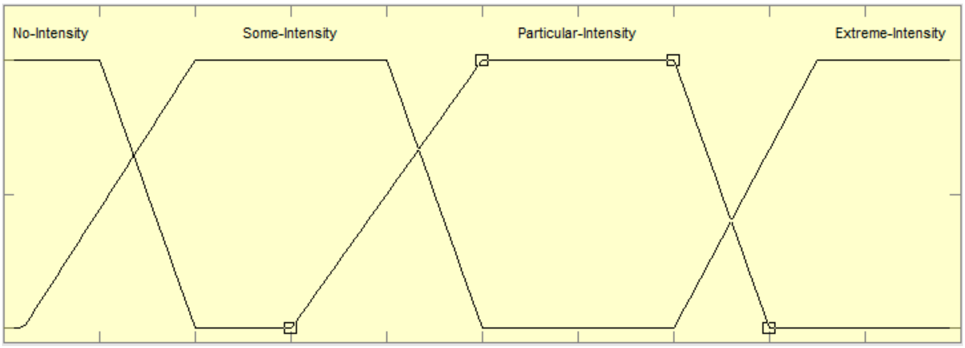

Figure 4.4: Potential Structure of X as a Gauge of Stimulus Intensity

intensity of the emotional response.

If we linguistically define stimulus in terms of intensity, however, rather than context, the shape of the problem shifts somewhat. The intensity Millenson discussed in an emotional context might not specifically interconnect his basic emotions with each other, but rather define their connections with the stimulus itself. Let us return to the removed positive (\$+) stimulus variable, X

$$X = \sum\{\$+\}[0,1] \tag{4.26}$$

As before, we consider this an input to a fuzzy system. Let us define its linguistic variables as "No Intensity", "Low Intensity", "Medium Intensity", and "High Intensity". Thus, linguistically, our model particularly considers the idea of stimulus intensity and its impact on emotional reaction. In fuzzy set terms,

$$(X,\mu) = \begin{aligned} &\{\mu(\text{No Intensity})/\text{No Intensity},\\ &\mu(\text{Low Intensity})/\text{Low Intensity},\\ &\mu(\text{Medium Intensity})/\text{Medium Intensity},\\ &\mu(\text{High Intensity})/\text{High Intensity}\} \end{aligned} \tag{4.27}$$

Figure 4.4 illustrates a potential structure of X in this context.

Further to that, if stimulus intensity is, as is implied by Millenson [94], the determining factor in which emotions are triggered along a particular axis, this system would require a redefinition of the previous interpretation's definition of x as a fuzzy set.

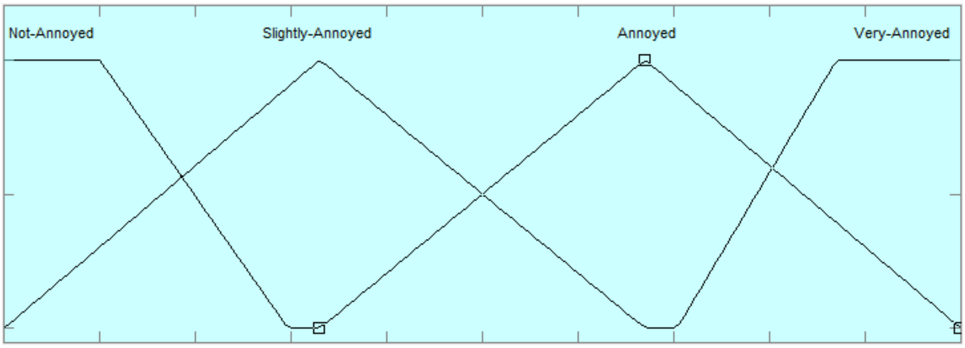

Figure 4.5: Potential Structure of x_1 as an Output for a FIS

Rather than discussing degrees of x, we shall instead consider x to simply be a geometric scalar indicating the relationship between three named emotions, Annoyance, Anger and Rage, and the removal of positive stimulus (represented through X).

Thus, instead of associating X with a single output variable, we associate X with three output variables, each with their own linguistic definitions outlining the level to which they are triggered. The first, representing Annoyance, we define as x_1, and describe in fuzzy set terms as

$$(x_1, \mu) = \begin{aligned} \{\mu(\text{Not Annoyed})/\text{Not Annoyed}, \\ \mu(\text{Slightly Annoyed})/\text{Slightly Annoyed}, \\ \mu(\text{Annoyed})/\text{Annoyed}, \\ \mu(\text{Very Annoyed})/\text{Very Annoyed}\} \end{aligned} \tag{4.28}$$

Figure 4.5 outlines this potential makeup for x_1, for illustrative purposes.

Using comparable linguistic variables, we can define the other two output variables associated with X, x_2 and x_3, with the following fuzzy terminology:

$$(x_2, \mu) = \begin{aligned} \{\mu(\text{Not Angry})/\text{Not Angry}, \\ \mu(\text{Slightly Angry})/\text{Slightly Angry}, \\ \mu(\text{Angry})/\text{Angry}, \\ \mu(\text{Very Angry})/\text{Very Angry}\} \end{aligned} \tag{4.29}$$

$$(x_3, \mu) = \begin{aligned} &\{\mu(\text{Not Enraged})/\text{Not Enraged}, \\ &\mu(\text{Slightly Enraged})/\text{Slightly Enraged}, \\ &\mu(\text{Enraged})/\text{Enraged}, \\ &\mu(\text{Very Enraged})/\text{Very Enraged}\} \end{aligned} \tag{4.30}$$

This alternative architecture, connecting multiple outputs to a single inputs, calls for rules which are significantly more complex, even as the system itself is markedly simplified. In the case of X, we propose a list of rules of the form:

Rule 1: If X is No Intensity, then x_1 is Slightly Annoyed, and x_2 is Not Angry, and x_3 is Not Enraged

Rule 2: If X is Low Intensity, then x_1 is Very Annoyed, and x_2 is Slightly Angry, and x_3 is Not Enraged

Rule 3: If X is Medium Intensity, then x_1 is Annoyed, and x_2 is Very Angry, and x_3 is Slightly Enraged

Rule 4: If X is High Intensity, then x_1 is Slightly Annoyed, and x_2 is Angry, and x_3 is Very Enraged

It should be clarified that these linguistic terms defining the level of the named emotions refer specifically to its level relative to the other emotions. One might say, for example, that to be Enraged one must be Very Angry by definition, but that would be considering the wrong context. Rather, when the agent is Very Enraged, but only Angry rather than Very Angry, this is because Anger and Rage are treated as two distinct basic emotions by Millenson, and the system is experiencing Rage to a greater degree than it is experiencing Anger.

As we have with all other numerical variables, we apply limits of [0,1] to x_1, x_2 and x_3. That is to say that upon the conclusion of centroid defuzzification, as discussed in a previous section, the crisp output associated with each of the three named emotions shall be a value between 0 and 1. We explicitly label these outputs as μx_1, μx_2, and μx_3 explicitly as, for our purposes, they define membership of their associated emotion within the emotional output associated with the stimulus vector $\mathbf{J}$, $\mathbf{E_J}$.

Expanding this system to include the other two input variables, and their associated six basic emotions, permits us to generate a Mamdani fuzzy inferencing system which will absorb the numerical contents of the stimulus vector $\mathbf{J}$ and produce a value, between 0 and 1, for each of the nine named emotions in Millenson's model.

As these nine values represent the experiential level of the individual emotions, they are considered analogous to the emotional state generated by the previous implementation of Millenson's model, and thus we define a vector formed with these nine elements, generated as a function of the stimulus vector $\mathbf{J}$, as $\mathbf{E_J}$.

$$\mathbf{E_J} = \begin{bmatrix} \mu_{\mathbf{J}} x_1 \\ \mu_{\mathbf{J}} x_2 \\ \mu_{\mathbf{J}} x_3 \\ \mu_{\mathbf{J}} y_1 \\ \mu_{\mathbf{J}} y_2 \\ \mu_{\mathbf{J}} y_3 \\ \mu_{\mathbf{J}} z_1 \\ \mu_{\mathbf{J}} z_2 \\ \mu_{\mathbf{J}} z_3 \end{bmatrix} \tag{4.31}$$

At this stage, the system can now inform the emotional state of the agent. We have kept our notation and vector structure consistent throughout both interpretations of the Millenson model. As such, the manner in which the emotional state is informed, with respect to the emotional state $\mathbf{E_M}$, is analogous with that discussed in the previous subsection.

4.3 Type-1 Fuzzy Logic Representation of the Geneva Emotion Wheel

Scherer himself described emotions, and their surrounding linguistic conventions, in terms of fuzziness [88]. Indeed, were our interest entirely fixed on the implementation of a singular, emotionally-informed cognitive engine, his work alone might provide a suitable basis for in-depth explanation. As the terms of this project reflect a broader topic, however, we are compelled to focus our interest upon specific aspects of his work.

A significant contrast between the Geneva Emotion Wheel and the Millenson model is Scherer's inherent geometricalisation. Within the Millenson model, geometry was, to an extent, immaterial. This was primarily due to the independent nature of the variables. Within the Geneva Emotion Wheel, however, specific geometry and positional relativity enjoy significantly more prominence. Put simply, Millenson considered three aspects of stimulus, each of which could only affect three associated emotions; Scherer considers two aspects of experience, with each of his sixteen associated emotions being impacted by both.

Description of the Geneva Emotion Wheel as a concept was largely covered in Chapter Two; here we consider the wheel as a geometric construct and circumplex.

Scherer provides us with two conceptual axes: the level of control experienced by the agent, ranging from 'High' to 'Low', and the valence (positivity or negativity) of the experience. Defined by these axes are two matters: the specific experienced emotion of the agent, and its intensity.

In Scherer's conceptual prototype, upon which our own prototyping is based, each named emotion had four represented degrees of intensity. In addition, each named emotion had a crisply defined occupational region in terms of relative magnitudes of control and valence. These are shown in Figure 2.2.

Each of the named emotions in Scherer's prototype might be described in terms of a ratio of the control and experience magnitudes, irrespective of specific emotional intensity (though that is obviously important to our considerations). That is to say that one might assume a 'prideful' emotional state for any situation where the values of control and valence were positive, and the ratio of control to valence was significantly weighted in favour of control. Conceptually, this raised interesting questions regarding how best to represent the Geneva Emotion Wheel in fuzzy terms.

In our preamble discussing the nature of fuzzy sets and systems, we acknowledged that one of fuzzy logic's strengths was the capacity to represent linguistic variables. As has been outlined previously, we consider the level to which a given, named emotion is experienced as fuzzy.

When considering a fuzzy system relating to the Geneva Emotion Wheel, therefore, Scherer has already provided us with two 'fuzzy' concepts. First, magnitudes of control and valence, and second, the intensity of resultant named emotions.

The question comes in the manner in which we conceptually fuzzify these factors, and in order to clarify that we must first define the inputs received by a system utilising the Scherer model of emotions, and the outputs our implementation of that system should provide. The inputs Scherer provides are the concepts of Control and Valence. We name these $x_{\mathbf{J}}$ and $y_{\mathbf{J}}$ for a given situation, and define them in the context of conceptual sums of experiential perceptions,

$$x_{\mathbf{J}} = \frac{1}{n_u} \sum_{i=1}^{n} f_{u_i}(u_{i_{\mathbf{J}}})[-1,1] \tag{4.32}$$

$$y_{\mathbf{J}} = \frac{1}{n_v} \sum_{i=1}^{n} f_{v_i}(v_{i_{\mathbf{J}}})[-1,1] \tag{4.33}$$

where $u_{i_{\mathbf{J}}}$ is an element of the agent's environment which impacts its sense of valence, of which there are n_u for any given $x_{\mathbf{J}}$, and whose individual impact is defined by an associated function f_{u_i}; and, $v_{i_{\mathbf{J}}}$ is an element of the agent's environment which impacts its sense of control, of which there are n_v for any given $y_{\mathbf{J}}$, and whose individual impact is defined by an associated function f_{v_i}; and, where the sums are normalised to a value between -1 and 1, to reflect the juxtapositions they represent.

Usage of $\mathbf{J}$ with respect to Scherer is analogous to usage of the variable with respect to Millenson, up to a point. Whereas Millenson permitted the explicit association of stimulus events with $\mathbf{J}$, Scherer's model requires a more esoteric interpretation. Rather than an event, in this context $\mathbf{J}$ represents the agent's perception of its situation at a given instant, in the context of valence and control. Thus the input $\mathbf{J}$ is defined,

$$\mathbf{J} = \begin{bmatrix} x \\ y \end{bmatrix} \tag{4.34}$$

As previously stated, the output of any system covered within this work should be that of a discrete emotional state, defining at any given instant the emotional state of the agent in the context of experienced magnitudes of a given number of named emotions. Scherer's model presents sixteen named emotions, thus the desired output of any implementation is defined as a vector which indicates the relative magnitudes of each of these sixteen emotions, between values of 0 and 1. Numerically, this emotional state $\mathbf{E_S}$ is written

$$\mathbf{E_S} = \begin{bmatrix} e_{\text{Pride}} \\ e_{\text{Elation}} \\ e_{\text{Happiness}} \\ e_{\text{Satisfaction}} \\ e_{\text{Relief}} \\ e_{\text{Hope}} \\ e_{\text{Interest}} \\ e_{\text{Surprise}} \\ e_{\text{Anxiety}} \\ e_{\text{Sadness}} \\ e_{\text{Boredom}} \\ e_{\text{Shame/Guilt}} \\ e_{\text{Disgust}} \\ e_{\text{Contempt}} \\ e_{\text{Hostility}} \\ e_{\text{Anger}} \end{bmatrix} \tag{4.35}$$

where e represents the relative level with which a given emotion is being experienced, with that given emotion identified in explicit terms by its subscript.

Having defined the generalist input and desired output of the system, one must now consider the best way to approach it from a fuzzy perspective. That is to say, whether to approach it from a fuzzified geometric perspective, or to approach it from a linguistic perspective.

It should be clarified that by 'linguistic perspective', we mean description of inputs linguistically, rather than geometrically. For example, one could connect the concept of a 'steep' relationship between Valence and Control, and an intense experience, with a 'high' relative magnitude of Pride. The issue with such a system, however, is the inherently geometrical nature of Scherer's model.

While it might be possible to devise a multitude of adjectives to describe experienced level of Valence or Control, and thus map them in fuzzy terms, ultimately such linguistic variables would simply be geometric place-holders, not having any particular linguistic meaning, and thus defeating the purpose of their inclusion.

We are mindful that the Geneva Emotion Wheel contains fuzzy, linguistic components within its structure. The emotions themselves, particularly in relation to their conceptual intensities, are one fuzzy aspect. Another is the fashion in which the emotions themselves relate to specific ratios of control to valence, although this is largely a reciprocal relationship. As these are fuzzified in the method now outlined, it is felt the application of fuzzy logic is still wholly justified in this context.

Shown in Figure 2.2, the Geneva Emotion Wheel can be viewed from a geometric perspective. This means that rather than interpret inputs in the context of linguistic variables such as "Low", "Medium" or "High", we instead consider the inputs geometric coordinates, and fuzzify the emotions they represent.

As with the Millenson model, it is possible to dissect this emotion representation in the context of its axes, and associate each axis with one of the variables defined in **J**. Let us consider first the axis associated with the variable x, that of Valence.

Considering the model geometrically in the context of the x-axis, it is evident that all discrete regions therein can be conceptually represented by thirty-three unique sets. We say thirty-three, rather than the sixty-five unique regions indicated on the model, because the model is a geometrical mirror of itself, with only the thirty-third unique set crossing the intersection. Thus is it possible to define the variable x, in fuzzy terms, as

$$(x,\mu) = \begin{array}{r} \{\mu(x_1)/x_1, \mu(x_2)/x_2, \mu(x_3)/x_3, \\ \ldots, \\ \mu(x_{31})/x_{31}, \mu(x_{32})/x_{32}, \mu(x_{33})/x_{33}\} \end{array} \tag{4.36}$$

These sets are described as unique, but it should be noted that many of the sets share elements; that is to say that many discrete values of x are found in more than one set. Figure 4.6 illustrates such a structure.

It is necessary that the values assigned to these sets be geometrically consistent with the model, or the psychology upon which it is ground ceases to have meaning. The explicit limits that were defined for our particular implementation of the Geneva Emotion Wheel are included in the *Implementation* section.

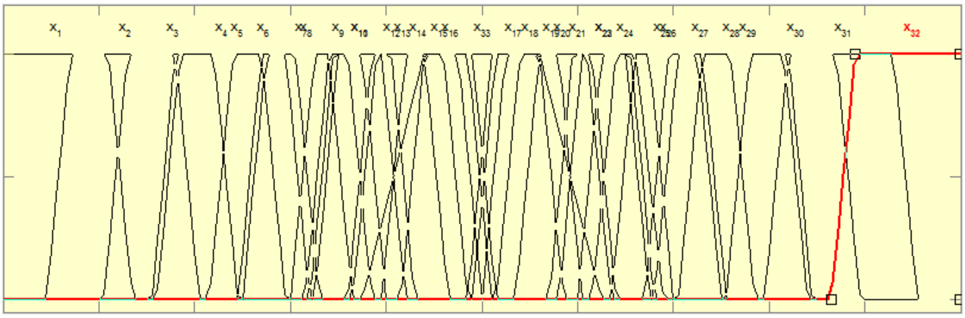

Figure 4.6: Possible Fuzzy Structure of Variable x

Consequently, it was reasoned that these sets should be defined such that their maxima coincide with the geometrically crisp regions defined by Scherer's prototype at their widest points. The ranges defining alternative non-trivial memberships vary, dependent upon how broadly the implementation seeks to fuzzify the emotions. In our own interpretation, however, the non-maximal, non-trivial bands remain proportionally consistent across different grades of the same emotion, thereby maintaining the ratio-based relationship that psychologically associates the conceptual inputs with the named emotions.

Let us now consider the variable y, which we previously paired with the concept of control. As one compares the structure of y to the structure of x the identical, if tangential, nature of their relationship coincides with the ideals of a circumplex representation. Again, each discrete grade of a named emotion can be represented by a single function, and thirty-three functions can be applied to represent the entire circumplex. As a fuzzy construct, we similarly define y in terms of

$$(y, \mu) = \begin{array}{r} \{\mu(y_1)/y_1, \mu(y_2)/y_2, \mu(y_3)/y_3, \\ \ldots, \\ \mu(y_{31})/y_{31}, \mu(y_{32})/y_{32}, \mu(y_{33})/y_{33}\} \end{array} \tag{4.37}$$

where the meanings are comparable with those espoused in the representation of x, and consistent with fuzzy principles as outlined in the preamble.

It should be noted that, while linguistic variables are not employed in this case, the very nature of what each fuzzy function within the variables represents is inherently fuzzy, as shall become evident as the links between the input and output variables are explicitly clarified.

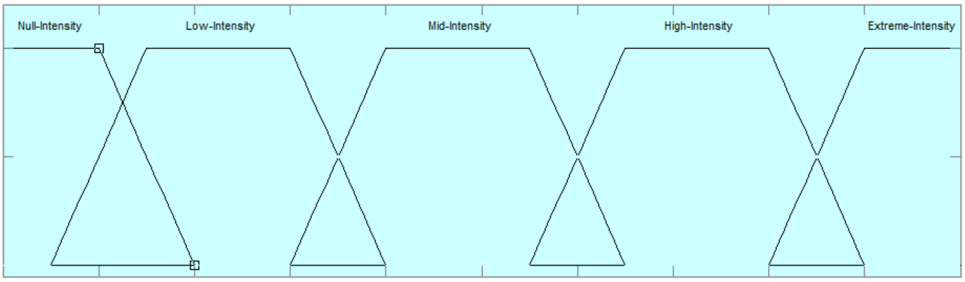

Figure 4.7: Possible Fuzzy Structure of Output $e_{\text{Satisfaction}}$

Let us consider the output structure of a system informed by these two fuzzy input variables. As stipulated in the psychological outline of the Geneva Emotion Wheel, this system represents the intensity of sixteen named emotions, as a function of the variables we have defined as x and y. The output of such a system, then, should be a relative intensity of each of these sixteen emotions, individually. It should be assumed that, geometrically, there shall often be trivial results from emotions that lie on the opposite end of the spectrum when the system experiences extreme inputs.

Let us consider a single emotion, Satisfaction, as a fuzzy construct, with its structure informed by the Geneva Emotion Wheel. We define Satisfaction, in this context, as $(e_{\text{Satisfaction}}, \mu)$, and in specific terms as

$$(e_{\text{Satisfaction}}, \mu) = \begin{aligned} &\{\mu(\text{Null Intensity})/\text{Null Intensity}, \\ &\mu(\text{Low Intensity})/\text{Low Intensity}, \\ &\mu(\text{Middle Intensity})/\text{Middle Intensity}, \\ &\mu(\text{High Intensity})/\text{High Intensity}, \\ &\mu(\text{Extreme Intensity})/\text{Extreme Intensity}\} \end{aligned} \tag{4.38}$$

Figure 4.7 illustrates such a structure visually.

Further to this, let us introduce such a structure to the remaining discrete emotions, and thus define our system output. The links between input and output, however, have not yet been clarified. Let us return to our fuzzy construct $(e_{\text{Satisfaction}}, \mu)$. The structure of $(e_{\text{Satisfaction}}, \mu)$ is drawn from the geometric model, with a null membership function ascribed to the central emotional whitespace, and gradiated emotional intensities based upon the four discrete intensities shown in figure 2.2. Hence we may consider the fuzzy system rules which connect membership functions of our inputs to all of $(e_{\text{Satisfaction}}, \mu)$'s membership functions.

Such rules would be of the form:

Rule 1: If x is x_{33}, and y is y_{33}, then $e_{\text{Satisfaction}}$ is Null Intensity
Rule 2: If x is x_{17}, and y is y_{24}, then $e_{\text{Satisfaction}}$ is Low Intensity
Rule 3: If x is x_{18}, and y is y_{27}, then $e_{\text{Satisfaction}}$ is Mid Intensity
Rule 4: If x is x_{19}, and y is y_{30}, then $e_{\text{Satisfaction}}$ is High Intensity
Rule 5: If x is x_{20}, and y is y_{32}, then $e_{\text{Satisfaction}}$ is Extreme Intensity

Following the principles outlined in our preamble discussing the processes of the Mamdani fuzzy inferencing system, the minimum membership grade of each doublet of input-related fuzzy sets is projected onto their associated emotional grade. The centroid of all of these grades, for a given named emotion, determined its numerical output, between 0 and 1. In the case of $e_{\text{Satisfaction}}$, we call this discrete value $e'_{\text{Satisfaction}}$

Thus the structure of a geometrically conceptualised, fuzzy representation of the Geneva Emotion Wheel becomes clear. Any given values for x and y obtain membership grades for the thirty-three fuzzy functions that constitute their makeup, and such memberships are compared to rules explicitly connecting combinations of these inputs with grades of specific output emotions. This will provide discrete values for the sixteen emotional outputs, between 0 and 1, thereby constructing an instantaneous emotional response $\mathbf{E}'_{\mathbf{S}}$, which is defined

$$\mathbf{E}'_{\mathbf{S}} = \begin{bmatrix} e'_{\text{Pride}} \\ e'_{\text{Elation}} \\ e'_{\text{Happiness}} \\ e'_{\text{Satisfaction}} \\ e'_{\text{Relief}} \\ e'_{\text{Hope}} \\ e'_{\text{Interest}} \\ e'_{\text{Surprise}} \\ e'_{\text{Anxiety}} \\ e'_{\text{Sadness}} \\ e'_{\text{Boredom}} \\ e'_{\text{Shame/Guilt}} \\ e'_{\text{Disgust}} \\ e'_{\text{Contempt}} \\ e'_{\text{Hostility}} \\ e'_{\text{Anger}} \end{bmatrix} \tag{4.39}$$

As discussed in the context of the Millenson representation, the instantaneous result of the fuzzy inferencing system informs the emotional state; that is to say, in this context, $\mathbf{E}'_{\mathbf{S}}$ informs $\mathbf{E}_{\mathbf{S}}$. Let us consider $\mathbf{E}_{\mathbf{S}}$ at time t and time $t+1$, where the interval represents the time taken for the system to obtain a value for $\mathbf{E}'_{\mathbf{S}}$.

As both $\mathbf{E}_{\mathbf{S}}$ and $\mathbf{E}'_{\mathbf{S}}$ are vectors of the same structure, the method of combining them is analogous to that used with respect to the Millenson model.

$$\mathbf{E}_{\mathbf{S}}(t+1) = \frac{(u\mathbf{E}_{\mathbf{S}}(t) + v\mathbf{E}'_{\mathbf{S}})}{u+v} \tag{4.40}$$

where u and v are constants introduced at the point of implementation, permitting the system to adjust the weightings of import between the newly-calculated emotional component $\mathbf{E}'_{\mathbf{S}}$ and the established emotional state $\mathbf{E}_{\mathbf{S}}$. Again, those wishing to investigate systems where emotional memory has significant influence on decision-making have the freedom to do so with this notation. Similarly, those who wish to study systems with a limited memory component where emotional state is based predominantly newly obtained environment-driven emotional components can make alternative weightings.

Chapter 5

Type-2 Fuzzy Representation of Psychologically Grounded Emotion Models

5.1 Chapter Overview

In this chapter we discuss the Type-2 Fuzzy Logic representations of our emotion models, and provide an in-depth discussion of the models themselves. Prior to discussing specific representations, however, we discuss the rationale for our exploration of Type-2 Fuzzy Emotion Modelling. It is not enough to simply declare this as a numerical extension of the previously covered work. Rather, we must discuss the key differences, from the perspective of psychological context, and their justifications.

Both of the psychological theories we have pursued share key aspects. They espouse a geometrical relationship between named, basic emotions, with axes declared in the context of abstracted, environmental concepts. The application of Type 1 Fuzzy Logic in this instance is intuitive. Ekman himself acknowledges that basic emotions are experienced with differing intensities [25], and while he does not believe the boundaries between those basic emotions are fuzzy, he makes no argument that perceptibly identical stimuli will trigger exactly the same emotion in one individual as they will in the next. Nor is there any justification for the view that a given, contextual event should have absolutely identical impact, on any of the abstracted input variables proposed, from one individual to the next.

Within our Type-1 representations, we attempt to represent this issue by virtue of fuzzifying the outputs to our system in such a fashion that a given event provides membership in several emotions simultaneously, of differing degree. This should not be taken to mean that our system is exclusively reliant upon the idea that basic emotions are compounded, although that is one possible application of our representations. Instead, it can equally be assumed that our models function as raw, fuzzy controllers, indicating that a given stimulus $\mathbf{J}$ can be associated with those named emotions that provide non-trivial resultants. Nevertheless, this representation is limited in terms of dimensionality of uncertainty.

Type-2 Fuzzy Logic provides an additional level of fuzzification which permits us to both represent the inherent uncertainty in triggered emotions, and the uncertainty in defining the nature of our abstracted inputs. It is in this light with which we pursue the subject, with a view to comparing the effectiveness of Type-1 with Type-2 from a numerical standpoint.

5.2 Type-2 Fuzzy Logic Representations of the Millenson Model

As in our previous Chapter, we divide this section into considerations of our dual interpretations of Millenson's linguistic definitions. The definitions of $\mathbf{J}$ and $\mathbf{E_M}$ remain consistent across the two differing orders of fuzzy logic. This permits us to draw direct comparisons between results, while maintaining psychological analogue with Millenson's theory.

5.2.1 Millenson A

As in the prior chapter, let us assume a given interpretation of Millenson's model that connects the significance of applied and removed stimuli, of differing valence, with three emotional components. Let us explicitly define these connections of the form

$$\begin{aligned} X &\rightarrow Anger \\ Y &\rightarrow Anxiety \\ Z &\rightarrow Pleasure \end{aligned}$$

where X, Y and Z are defined in equations (4.1), (4.2) and (4.3), respectively, and their associated axes are clearly shown in Figure 2.1.

We assign variables to each of these emotional components, of the form

$$\begin{aligned} Anger &\rightarrow x \\ Anxiety &\rightarrow y \\ Pleasure &\rightarrow z \end{aligned}$$

Each of these emotional components possesses three associated emotions, differing from each other in terms of the degree with which the component is experienced. Mirroring our merging of the stimulus components into a single variable, we define the emotional experience index $\mathbf{e_J}$ associated with a discrete event J, to be a vector of these three values, and normalise them to crisp numbers between 0 and 1.

$$\mathbf{e_J} = \begin{bmatrix} x[0,1] \\ y[0,1] \\ z[0,1] \end{bmatrix} \tag{5.1}$$

As before, e_J is approached from the perspective of fuzzy inferencing. Let us consider an individual component of $\mathbf{J}$, X.

A given value assigned to X is a number between 0 and 1, conceptually representing the significance of removed positive stimulus from the system. Understanding that such a quantifier cannot crisply represent the nature of stimuli affecting the system, the strengths of Type-2 Fuzzy Logic in management of linguistic variables are appropriate in their application [51].

We define X as an input to a Mamdani fuzzy inferencing system. The input X is associated with three type 2 fuzzy sets, assigned linguistic variables describing "Low Significance", "Medium Significance" and "High Significance". Let us consider the type 2 fuzzy set, "Low Significance", and designate it $\tilde{\mathbf{X}}_1$. Mathematically, we define this type 2 fuzzy set $\tilde{\mathbf{X}}_1$ as

$$\tilde{\mathbf{X}}_1\{((k,u),\mu_{\tilde{\mathbf{X}}_1}(k,u))|\forall k \in X, \forall u \in J_k \subseteq [0,1]\} \tag{5.2}$$

Let us similarly define "Medium Significance" in terms of $\tilde{\mathbf{X}}_2$, and "High Significance" in terms of $\tilde{\mathbf{X}}_3$

$$\tilde{\mathbf{X}}_2\{((k,u),\mu_{\tilde{\mathbf{X}}_2}(k,u))|\forall k \in X, \forall u \in J_k \subseteq [0,1]\} \tag{5.3}$$

$$\tilde{\mathbf{X}}_3\{((k,u),\mu_{\tilde{\mathbf{X}}_3}(k,u))|\forall k \in X, \forall u \in J_k \subseteq [0,1]\} \tag{5.4}$$

Thus we can define variable X, in type-2 fuzzy terms, as being represented by

$$\tilde{\mathbf{X}}_i\{((k,u),\mu_{\tilde{\mathbf{X}}_i}(k,u))|\forall k \in X, \forall u \in J_k \subseteq [0,1]\} \tag{5.5}$$

for $i = 1, 2, 3$. We define each of the variables X, Y and Z to be of the same form, represented by mirrored type-2 fuzzy sets. Thus Y and Z are written

$$\tilde{\mathbf{Y}}_i\{((l,u),\mu_{\tilde{\mathbf{Y}}_i}(l,u))|\forall l \in Y, \forall u \in J_l \subseteq [0,1]\} \tag{5.6}$$

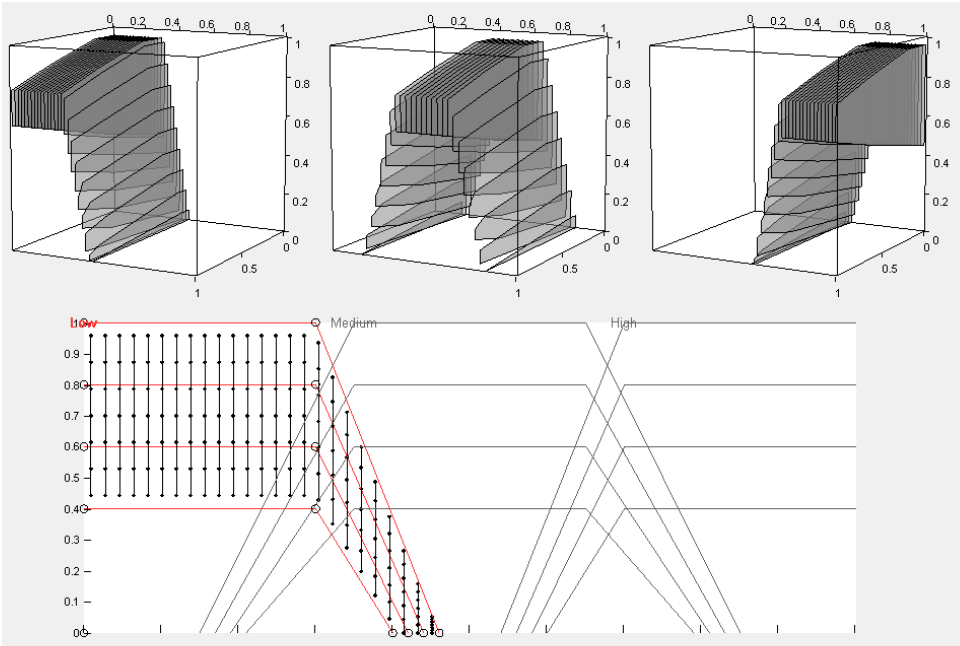

Figure 5.1: Potential Implementation of X as an Input Variable of a Type 2 FIS

$$\tilde{\mathbf{Z}}_i\{((m,u),\mu_{\tilde{\mathbf{Z}}_i}(m,u))|\forall m \in Z, \forall u \in J_m \subseteq [0,1]\} \tag{5.7}$$

for $i = 1, 2, 3$. Figure 5.1 illustrates a hypothetical structure for X as the input to a type 2 fuzzy inferencing system (FIS), utilising trapezoidal primary and secondary membership functions.

We define x as an output of a Mamdani fuzzy inferencing system. x is associated with three linguistic variables describing "Low Response", "Moderate Response" and "Extreme Response"; these variables are each represented by a type 2 fuzzy set describing the agent's reaction to given behavioural stimuli in emotional terms. Let us consider the linguistic variable "Low Response", which we assign to $\tilde{\mathbf{x}}_1$

$$\tilde{\mathbf{x}}_1\{((k,u),\mu_{\tilde{\mathbf{x}}_1}(k,u))|\forall k \in x, \forall u \in J_k \subseteq [0,1]\} \tag{5.8}$$

This is similarly expanded, associating $\tilde{\mathbf{x}}_2$ with "Moderate Response" and $\tilde{\mathbf{x}}_3$ with "Extreme Response"; and projected across the three output variables x, y and z, producing mathematical definitions of them in terms of

$$\tilde{\mathbf{x}}_i\{((k,u),\mu_{\tilde{\mathbf{x}}_i}(k,u))|\forall k \in x, \forall u \in J_k \subseteq [0,1]\} \tag{5.9}$$

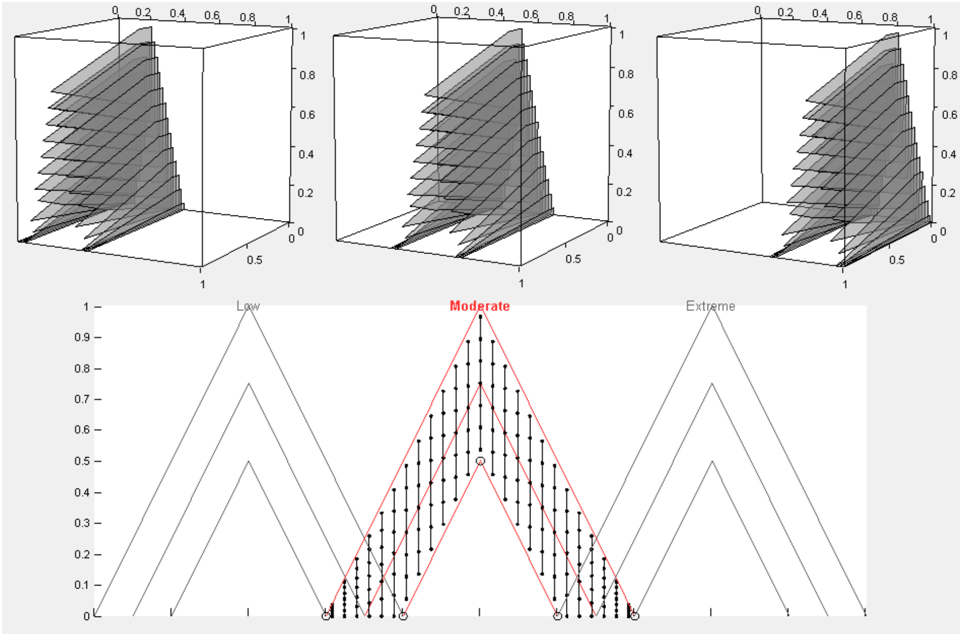

Figure 5.2: Potential Implementation of x as an Output Variable in a Type 2 FIS

$$\tilde{\mathbf{y}}_i\{((l,u),\mu_{\tilde{\mathbf{y}}_i}(l,u))|\forall l \in y, \forall u \in J_l \subseteq [0,1]\} \tag{5.10}$$

$$\tilde{\mathbf{z}}_i\{((m,u),\mu_{\tilde{\mathbf{z}}_i}(m,u))|\forall m \in z, \forall u \in J_m \subseteq [0,1]\} \tag{5.11}$$

for $i = 1,2,3$. Figure 5.2 illustrates a potential interpretation of x as an output for a fuzzy inferencing system, using triangular primary and secondary membership functions. The true nature of the type 2 fuzzy sets is illustrated comparatively well in terms of vertical slices in this figure, where the tips of each triangular slice represent a secondary membership grade of unity.

Let us ascribe three simple, fuzzy rules to this system:
Rule 1: If X is Low Significance, then x is Low Response
Rule 2: If X is Medium Significance, then x is Moderate Response
Rule 3: If X is High Significance, then x is Extreme Response

These rules maintain psychological analogue with the intent of Millenson's model, associating the variable X, which represents a quantification of removed positive stimulus \$+, with the variable x, which is connected to the emotions Annoyance, Anger and Rage. Through the application of a type 2 fuzzy inferencing system informed by these rules, a discrete value assigned to X provides a discrete value of x; and, expanding upon these rules across

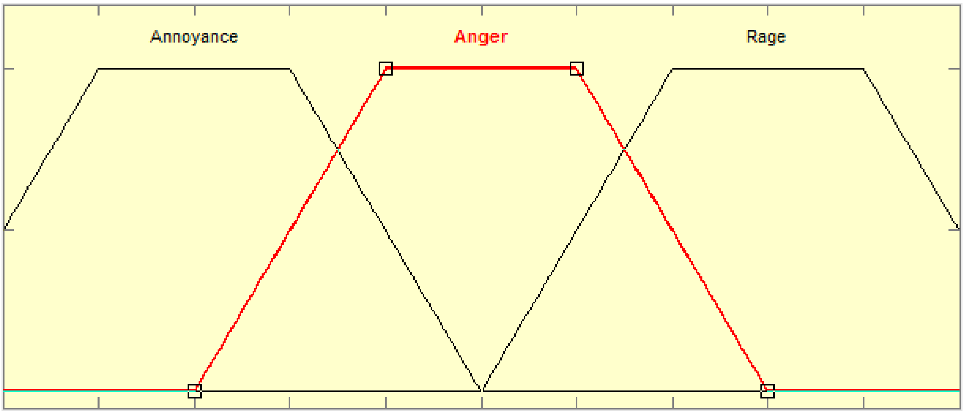

Figure 5.3: Illustrative Relationship of x with Named Emotions

the other two variables, we show how the vector $\mathbf{J}$ is be used to generate the vector $\mathbf{e_J}$.

Continuing with our analogue to the type-1 representation of our first interpretation of Millenson, we must now associate $\mathbf{e_J}$ with the nine basic emotions associated with Millenson's theory. Each named emotion shall be represented by a fuzzy set along its parent axis. As with type-1, the axis with which x is associated houses three named emotions: Annoyance, Anger and Rage. If we consider these emotions as linguistic variables, we define their relationship with x as

$$(x, \mu) = \begin{aligned} \{\mu(\text{Annoyance})/\text{Annoyance}, \\ \mu(\text{Anger})/\text{Anger}, \\ \mu(\text{Rage})/\text{Rage}\} \end{aligned} \tag{5.12}$$

Figure 5.3 provides an illustration of what this construct might look like.

This relation between named emotions and emotional component is projected to all three variables. As such, y and z would take the form

$$(y, \mu) = \begin{aligned} \{\mu(\text{Apprehension})/\text{Apprehension}, \\ \mu(\text{Anxiety})/\text{Anxiety}, \\ \mu(\text{Terror})/\text{Terror}\} \end{aligned} \tag{5.13}$$

$$(z, \mu) = \begin{aligned} &\{\mu(\text{Pleasure})/\text{Pleasure}, \\ &\mu(\text{Elation})/\text{Elation}, \\ &\mu(\text{Ecstasy})/\text{Ecstasy}\} \end{aligned} \tag{5.14}$$

It should be noted, as with the type-1 representation, that this relationship is that of a type 1 fuzzy set, rather than the creation of a second type-2 fuzzy inferencing system. The functions connecting the various values of μ to the named discrete emotions are defined and employed arithmetically.

Following the precedent set in the previous chapter, we define an array of equations associating the discrete, numeric components of $\mathbf{e_J}$ with values for discrete emotions associated with their respective axes.

$$\mu_{\mathbf{J}} x_1 = f_1(x)[0, 1] \tag{5.15}$$
$$\mu_{\mathbf{J}} x_2 = f_2(x)[0, 1] \tag{5.16}$$
$$\mu_{\mathbf{J}} x_3 = f_3(x)[0, 1] \tag{5.17}$$
$$\mu_{\mathbf{J}} y_1 = f_1(y)[0, 1] \tag{5.18}$$
$$\mu_{\mathbf{J}} y_2 = f_2(y)[0, 1] \tag{5.19}$$
$$\mu_{\mathbf{J}} y_3 = f_3(y)[0, 1] \tag{5.20}$$
$$\mu_{\mathbf{J}} z_1 = f_1(z)[0, 1] \tag{5.21}$$
$$\mu_{\mathbf{J}} z_2 = f_2(z)[0, 1] \tag{5.22}$$
$$\mu_{\mathbf{J}} z_3 = f_3(z)[0, 1] \tag{5.23}$$

where $\mu_{\mathbf{J}}$ represents explicitly the membership grade associated with the specified emotion for a given stimulus event $\mathbf{J}$, and where x_1, x_2 etceteras have meanings analogous with those in equation 4.5. Let us collect these nine membership grades into a single vector. We define this vector $\mathbf{E_J}$, the emotional state component of an event $\mathbf{J}$.

$$\mathbf{E_J} = \begin{bmatrix} \mu_{\mathbf{J}} x_1 \\ \mu_{\mathbf{J}} x_2 \\ \mu_{\mathbf{J}} x_3 \\ \mu_{\mathbf{J}} y_1 \\ \mu_{\mathbf{J}} y_2 \\ \mu_{\mathbf{J}} y_3 \\ \mu_{\mathbf{J}} z_1 \\ \mu_{\mathbf{J}} z_2 \\ \mu_{\mathbf{J}} z_3 \end{bmatrix} \tag{5.24}$$

At this stage, the system can now inform the emotional state of the agent. How this emotional state is informed depends specifically upon the level of emotional memory that is desired, or how strongly the current emotional state mutes the impact of the stimulus event $\mathbf{J}$.

Returning to the emotional state $\mathbf{E_M}$ as defined by equation 4.5, it is possible to merge $\mathbf{E_M}(t)$ with $\mathbf{E_J}$ to obtain $\mathbf{E_M}(t+1)$. Once again, we use the weighted average function

$$\mathbf{E_M}(t+1) = \frac{(u\mathbf{E_M}(t) + v\mathbf{E_J})}{u+v} \tag{5.25}$$

where u and v serve the same purposes outlined in the previous chapter in the context of favouring one over the other, depending upon the nature and intent of the implementation.

5.2.2 Millenson B

Having considered our initial interpretation of Millenson from both a type-1 and type-2 context, we now move on to discuss the representation of the alternative Millenson interpretation from the perspective of the latter.

Let us consider the removed positive ($+) stimulus variable, X

$$X = \sum \{\$+\}[0,1] \tag{5.26}$$

As before, we consider this an input to a fuzzy system. Let us define its linguistic variables as "No Intensity", "Low Intensity", "Medium Intensity", and "High Intensity". Linguistically, therefore, our model particularly considers the idea of stimulus intensity and its impact on emotional reaction. In terms of a type 2 fuzzy representation, let us consider the linguistic variable "No Intensity", to which we assign the variable $\tilde{\mathbf{X}}_0$. This we define as

$$\tilde{\mathbf{X}}_0\{((k,u),\mu_{\tilde{\mathbf{X}}_0}(k,u))|\forall k \in X, \forall u \in J_k \subseteq [0,1]\} \tag{5.27}$$

We expand this across the remaining three variables, associating "Low Intensity" with $\tilde{\mathbf{X}}_1$, "Medium Intensity" with $\tilde{\mathbf{X}}_2$ and "High Intensity" with $\tilde{\mathbf{X}}_3$. Thus we summarise the type 2 fuzzy sets associated with variable X as

$$\tilde{\mathbf{X}}_i\{((k,u),\mu_{\tilde{\mathbf{X}}_i}(k,u))|\forall k \in X, \forall u \in J_k \subseteq [0,1]\} \tag{5.28}$$

for $i = 0,1,2,3$. Figure 5.4 illustrates a potential structure of X in this context, formed from trapezoidal type 2 fuzzy sets.

Further to that, as before, we define x as a fuzzy construct. Rather than discussing degrees of x, we instead consider x to simply be a geometric construct indicating the relationship between three named emotions (Annoyance, Anger and Rage) and the contextual removal of positive stimulus (X).

Thus, instead of associating X with a single output variable, we associate X with three output variables, each with their own linguistic definitions outlining the level to which they are triggered. The first, representing Annoyance, is defined as x_1, with linguistic variables of "Not Annoyed", "Slightly Annoyed", "Annoyed" and "Very Annoyed". Let us assign the linguistic variable "Not Annoyed" the designation $\tilde{\mathbf{x}}_{\mathbf{1_0}}$ and describe it in type 2 fuzzy terms as

$$\tilde{\mathbf{x}}_{\mathbf{1_0}}\{((k,u),\mu_{\tilde{\mathbf{x}}_{\mathbf{1_0}}}(k,u))|\forall k \in x_1, \forall u \in J_k \subseteq [0,1]\} \tag{5.29}$$

Let us expand this relation to include all four type 2 fuzzy sets associated with the output variable x_1. In doing so, "Slightly Annoyed" is assigned identifier $\tilde{\mathbf{x}}_{\mathbf{1_1}}$, "Annoyed" $\tilde{\mathbf{x}}_{\mathbf{1_2}}$, and "Very Annoyed" $\tilde{\mathbf{x}}_{\mathbf{1_3}}$. Thus the type 2 fuzzy sets associated with the output variable x_1 can be consolidated thus,

$$\tilde{\mathbf{x}}_{\mathbf{1_i}}\{((k,u),\mu_{\tilde{\mathbf{x}}_{\mathbf{1_i}}}(k,u))|\forall k \in x_1, \forall u \in J_k \subseteq [0,1]\} \tag{5.30}$$

for $i = 0,1,2,3$. Figure 5.5 outlines this potential makeup for x_1, utilising triangular membership functions, for illustrative purposes only.

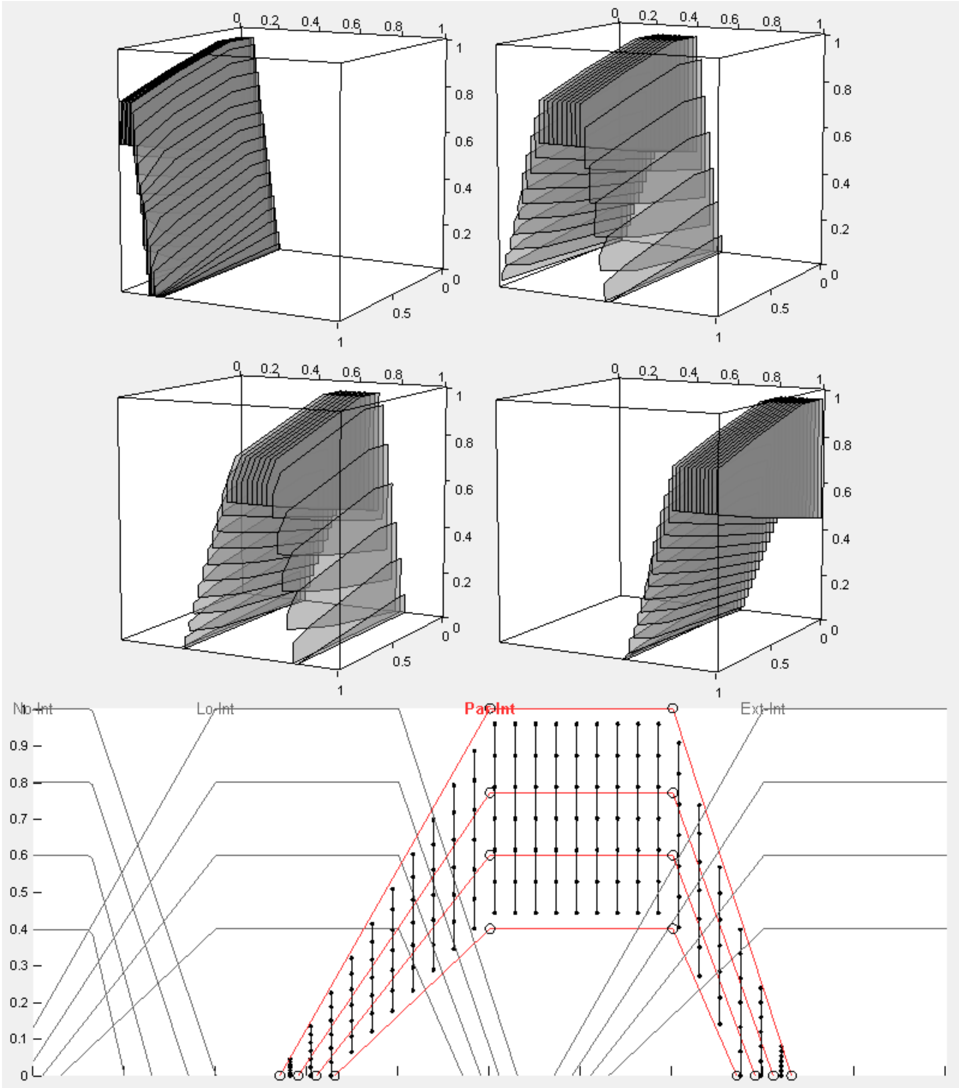

Figure 5.4: Potential Structure of X as a Gauge of Stimulus Intensity through Type 2 Fuzzy Sets

This structure is extended and applied to the other output variables associated with the X input, such that they can be written in the form

$$\tilde{\mathbf{x}}_{\mathbf{2_i}}\{((k,u),\mu_{\tilde{\mathbf{x}}_{\mathbf{2_i}}}(k,u))|\forall k \in x_2, \forall u \in J_k \subseteq [0,1]\} \tag{5.31}$$

$$\tilde{\mathbf{x}}_{\mathbf{3_i}}\{((k,u),\mu_{\tilde{\mathbf{x}}_{\mathbf{3_i}}}(k,u))|\forall k \in x_3, \forall u \in J_k \subseteq [0,1]\} \tag{5.32}$$

for $i = 0, 1, 2, 3$. This in turn can be consolidated to represent all discrete emotions associated with X, with the form

$$\tilde{\mathbf{x}}_{\mathbf{j_i}}\{((k,u),\mu_{\tilde{\mathbf{x}}_{\mathbf{j_i}}}(k,u))|\forall k \in x_j, \forall u \in J_k \subseteq [0,1]\} \tag{5.33}$$

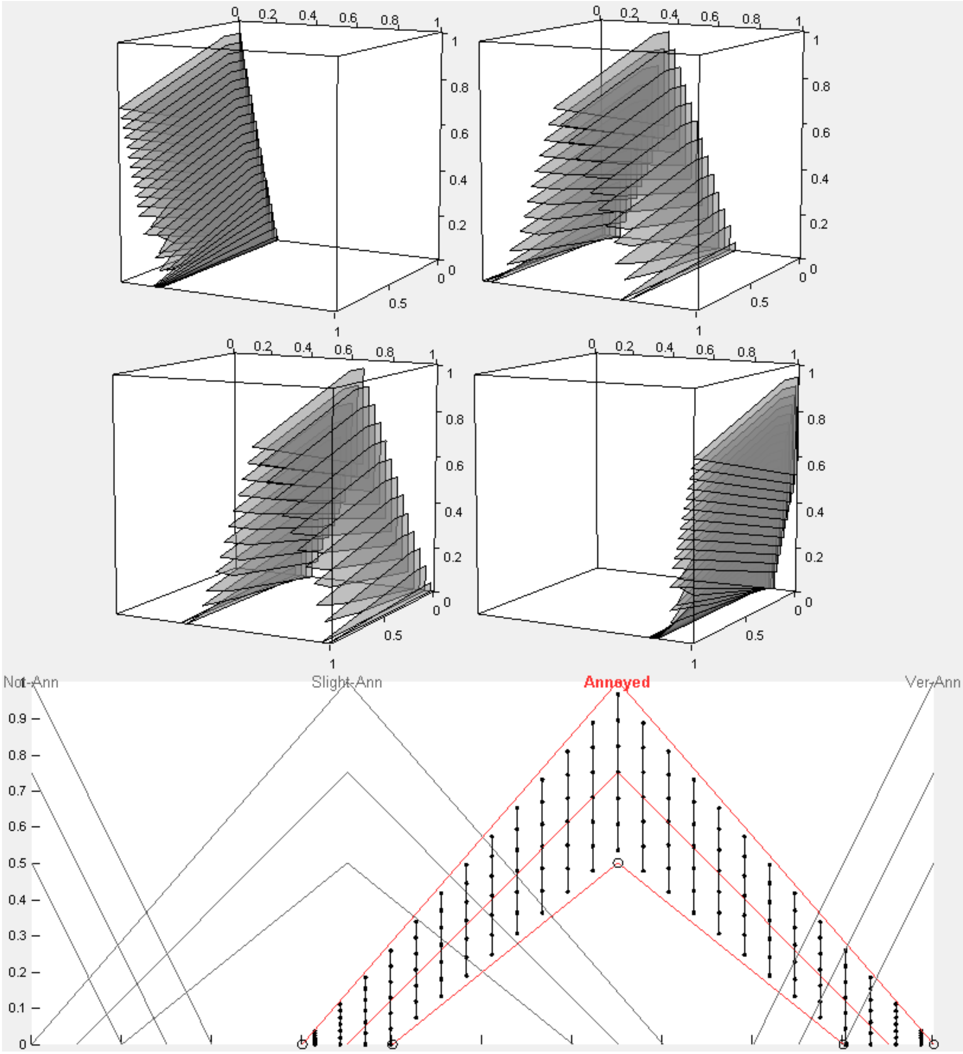

Figure 5.5: Potential Structure of x_1 as an Output for a Type 2 FIS

where $i = 0, 1, 2, 3$ and $j = 1, 2, 3$. This is naturally extended to the other two output axes, y and z, which are like represented

$$\tilde{\mathbf{y}}_{\mathbf{j_i}}\{((k,u), \mu_{\tilde{\mathbf{y}}_{\mathbf{j_i}}}(k,u))|\forall k \in y_j, \forall u \in J_k \subseteq [0,1]\} \tag{5.34}$$

$$\tilde{\mathbf{z}}_{\mathbf{j_i}}\{((k,u), \mu_{\tilde{\mathbf{z}}_{\mathbf{j_i}}}(k,u))|\forall k \in z_j, \forall u \in J_k \subseteq [0,1]\} \tag{5.35}$$

where, again, $i = 0, 1, 2, 3$ and $j = 1, 2, 3$.

This architecture demands rules equivalent to those discussed in our earlier type-1 deliberations. In the case of X, we create a list of rules of the form:

Rule 1: If X is "No Intensity", then x_1 is "Slightly Annoyed", and x_2 is "Not Angry", and x_3 is "Not Enraged"

Rule 2: If X is "Some Intensity", then x_1 is "Very Annoyed", and x_2 is "Slightly Angry", and x_3 is "Not Enraged"
Rule 3: If X is "Particular Intensity", then x_1 is "Annoyed", and x_2 is "Very Angry", and x_3 is "Slightly Enraged"
Rule 4: If X is "Extreme Intensity", then x_1 is "Slightly Annoyed", and x_2 is "Angry", and x_3 is "Very Enraged"

We apply limits of [0,1] to x_1, x_2 and x_3, as we have previously. We identify these outputs as μx_1, μx_2, and μx_3. As with type-1, these elements define membership of their associated emotion within the emotional output associated with the stimulus vector $\mathbf{J}$, $\mathbf{E_J}$.

Expanding this system to include the other two input variables, and their associated six basic emotions, permits us to generate a type 2 fuzzy inferencing system which will absorb the numerical contents of the stimulus vector $\mathbf{J}$ and produce a value, between 0 and 1, for each of the nine named emotions in Millenson's model.

As these nine values represent the experiential level of the individual emotions, they are considered analogous to the emotional state generated by all other representations of the Millenson model. Thus we define a vector formed with these nine elements, generated as a function of the stimulus vector $\mathbf{J}$, as $\mathbf{E_J}$.

$$\mathbf{E_J} = \begin{bmatrix} \mu_{\mathbf{J}} x_1 \\ \mu_{\mathbf{J}} x_2 \\ \mu_{\mathbf{J}} x_3 \\ \mu_{\mathbf{J}} y_1 \\ \mu_{\mathbf{J}} y_2 \\ \mu_{\mathbf{J}} y_3 \\ \mu_{\mathbf{J}} z_1 \\ \mu_{\mathbf{J}} z_2 \\ \mu_{\mathbf{J}} z_3 \end{bmatrix} \tag{5.36}$$

At this stage, the system can now inform the emotional state of the agent. As we have kept our notation and vector structure consistent throughout both interpretations of the Millenson model, the manner in which it does this, with respect to the emotional state $\mathbf{E_M}$ is identical to that discussed previously.

5.3 Type-2 Fuzzy Logic Representation of the Geneva Emotion Wheel

We have previously acknowledged that one of fuzzy logic's strengths was the capacity to represent linguistic variables, particularly within type 2 fuzzy logic. In subsequent discussion of the emotion models themselves, it becomes evident that the level to which an emotion is triggered by a specific impetus cannot be crisply defined.

As has been discussed, the inputs Scherer provides are the concepts of Control and Valence. We name these $x_{\mathbf{J}}$ and $y_{\mathbf{J}}$ for a given situation, and define them in the context of conceptual sums of experiential perceptions,

$$x_{\mathbf{J}} = \frac{1}{n_u} \sum_{i=1}^{n} f_{u_i}(u_{i_{\mathbf{J}}})[-1, 1] \tag{5.37}$$

$$y_{\mathbf{J}} = \frac{1}{n_v} \sum_{i=1}^{n} f_{v_i}(v_{i_{\mathbf{J}}})[-1, 1] \tag{5.38}$$

where $u_{i_{\mathbf{J}}}$ is an element of the agent's environment which impacts its perception of situational valence, of which there are n_u for any given $x_{\mathbf{J}}$, and whose individual impact is defined by an associated function f_{u_i}; and, $v_{i_{\mathbf{J}}}$ is an element of the agent's environment which affects its sense of control, of which there are n_v for any given $y_{\mathbf{J}}$, and whose individual impact is defined by an associated function f_{v_i}; and, where the sums are normalised to a value between -1 and 1.

In this context $\mathbf{J}$ represents the agent's perception of its situation at a given instant, in the context of valence and control. Thus the input $\mathbf{J}$ is defined,

$$\mathbf{J} = \begin{bmatrix} x \\ y \end{bmatrix} \tag{5.39}$$

It should be noted that the event/situational association is purely subjective. It is entirely feasible to associate events with valence and control, and environment with the application and removal of stimuli, making both models mutually versatile. It is conceded, however, that there is a greater level of abstraction required in the representation of Scherer's associated inputs being as they are inherently abstract concepts, and making them highly suited to a type-2 approach.

Irrespective of the type of logic employed, the emotional state $\mathbf{E_S}$ which forms the output of the Geneva Emotion Wheel is written

$$\mathbf{E_S} = \begin{bmatrix} e_{\text{Pride}} \\ e_{\text{Elation}} \\ e_{\text{Happiness}} \\ e_{\text{Satisfaction}} \\ e_{\text{Relief}} \\ e_{\text{Hope}} \\ e_{\text{Interest}} \\ e_{\text{Surprise}} \\ e_{\text{Anxiety}} \\ e_{\text{Sadness}} \\ e_{\text{Boredom}} \\ e_{\text{Shame/Guilt}} \\ e_{\text{Disgust}} \\ e_{\text{Contempt}} \\ e_{\text{Hostility}} \\ e_{\text{Anger}} \end{bmatrix} \tag{5.40}$$

where e represents the relative level with which a given emotion is being experienced, with that given emotion identified in explicit terms by its subscript.

In terms of the general geometry of the model, the format as outlined for type-1 provides a suitable framework, that being a model represented by thirty-three unique type-2 fuzzy sets. Let us consider the first of these type 2 fuzzy sets, $\tilde{\mathbf{x}}_\mathbf{1}$, which is defined

$$\tilde{\mathbf{x}}_\mathbf{1}\{((k,u),\mu_{\tilde{\mathbf{x}}_\mathbf{1}}(k,u))|\forall k \in x, \forall u \in J_k \subseteq [0,1]\} \tag{5.41}$$

In order to represent the variable x in the context of all thirty-three of its unique type 2 fuzzy sets, we adopt this consolidation

$$\tilde{\mathbf{x}}_\mathbf{i}\{((k,u),\mu_{\tilde{\mathbf{x}}_\mathbf{i}}(k,u))|\forall k \in x, \forall u \in J_k \subseteq [0,1]\} \tag{5.42}$$

for $i = 1, 2, \ldots, 33$. These sets are described as unique, but it should be

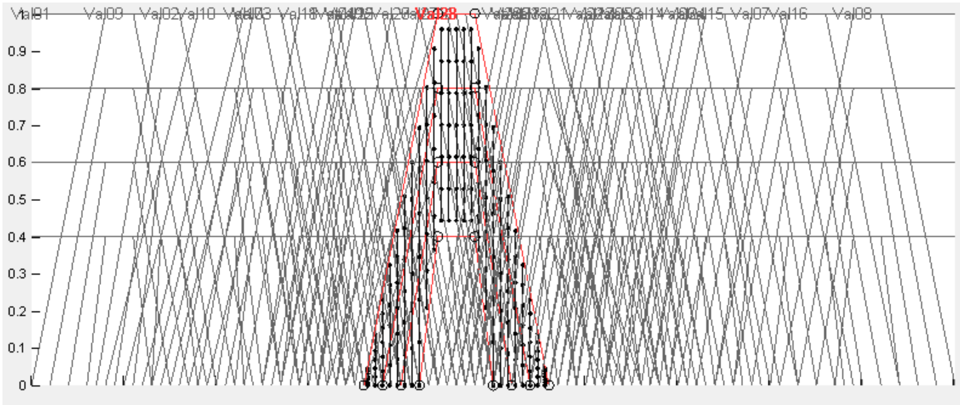

Figure 5.6: Possible Type 2 Fuzzy Structure of Variable x

noted that many of the sets share elements; that is to say that many discrete values of x have non-trivial membership in more than one set. Figure 5.6 illustrates such a structure and its inherent complexity.

Again, the explicit limits that were defined for our theoretical type-2 implementation of the Geneva Emotion Wheel are included in subsequent chapters.

Again, it was reasoned that these sets should be defined such that their maxima coincide with the geometrically crisp regions defined by Scherer's prototype at their widest points. The borders defining the secondary membership function should also be determined in a fashion suitable to this overarching geometry.

Let consider the variable y, which we pair with the concept of control. As with type-1, the numerical structure of the sets defining x and y is identical, merely tangential. As a fuzzy construct, we summarily define the type 2 sets within y in terms of

$$\tilde{\mathbf{y}}_{\mathbf{i}}\{((l,u),\mu_{\tilde{\mathbf{y}}_{\mathbf{i}}}(l,u))|\forall l \in y, \forall u \in J_l \subseteq [0,1]\} \tag{5.43}$$

for $i = 1, 2, \ldots, 33$, where the meanings are comparable with those espoused in the representation of x, and consistent with fuzzy principles as outlined in the preamble.

We shall discuss the specific links between emotional intensities and membership of sets relating to x and y within our discussions on particular implementation, but the general relationship is geometrical in nature. Let us instead give overview to the output structure of a system informed by these two fuzzy input variables. The input variables we have outlined as x and

y, while the output of the system should be an associated fuzzy emotional state, based upon the Geneva Emotion Wheel's psychology. The output of such a system, then, should be a relative intensity of each of these sixteen emotions, individually.

As we did in type-1, let us consider Satisfaction as a fuzzy construct with its structure informed by the Geneva Emotion Wheel. We define Satisfaction, in this context, as $e_{\text{Satisfaction}}$, and declare it to contain five type 2 fuzzy sets, associated with the linguistic variables "Null Intensity", "Low Intensity", "Middle Intensity", "High Intensity" and "Extreme Intensity". Psychologically, the first of these is associated with the central emotional white space, and the other four are associated with the four gradiated levels of intensity shown in Figure 2.2.

Considering explicitly the "Null Intensity" type 2 fuzzy set, which is designated $\tilde{\mathbf{e}}_{\text{Satisfaction}_\mathbf{0}}$, let us define it in the form

$$\tilde{\mathbf{e}}_{\text{Satisfaction}_\mathbf{0}}\{((m,u),\mu_{\tilde{\mathbf{e}}_{\text{Satisfaction}_\mathbf{0}}}(m,u))\} \tag{5.44}$$

$\forall m \in z$, and $\forall u \in J_m \subseteq [0,1]$. Expanding this to all five type 2 fuzzy sets associated with variable $e_{\text{Satisfaction}}$, associating "Low Intensity" with $\tilde{\mathbf{e}}_{\text{Satisfaction}_\mathbf{1}}$, "Middle Intensity" with $\tilde{\mathbf{e}}_{\text{Satisfaction}_\mathbf{2}}$, "High Intensity" with $\tilde{\mathbf{e}}_{\text{Satisfaction}_\mathbf{3}}$, and "Extreme Intensity" with $\tilde{\mathbf{e}}_{\text{Satisfaction}_\mathbf{4}}$, the following consolidation of the type 2 fuzzy constituents of $e_{\text{Satisfaction}}$ is defined

$$\tilde{\mathbf{e}}_{\text{Satisfaction}_\mathbf{i}}\{((m,u),\mu_{\tilde{\mathbf{e}}_{\text{Satisfaction}_\mathbf{i}}}(m,u))\} \tag{5.45}$$

$\forall m \in z$, and $\forall u \in J_m \subseteq [0,1]$, and for $i = 0,1,2,3,4$. Figure 5.7 abstractly illustrates the vertices and footprint of uncertainty of such a structure.

Let us introduce such a structure to the remaining discrete emotions, defining the elements of our system output, and discuss the conceptual links between input and output. Returning to our fuzzy construct $(e_{\text{Satisfaction}}, \mu)$, the structure of $(e_{\text{Satisfaction}}, \mu)$ is drawn from the geometric model, with a null membership function ascribed to the central emotional whitespace and gradiated emotional intensities based upon the four discrete intensities shown in figure 2.2. Thus let us consider the fuzzy system rules which connect membership functions of our inputs to all of $(e_{\text{Satisfaction}}, \mu)$'s membership functions.

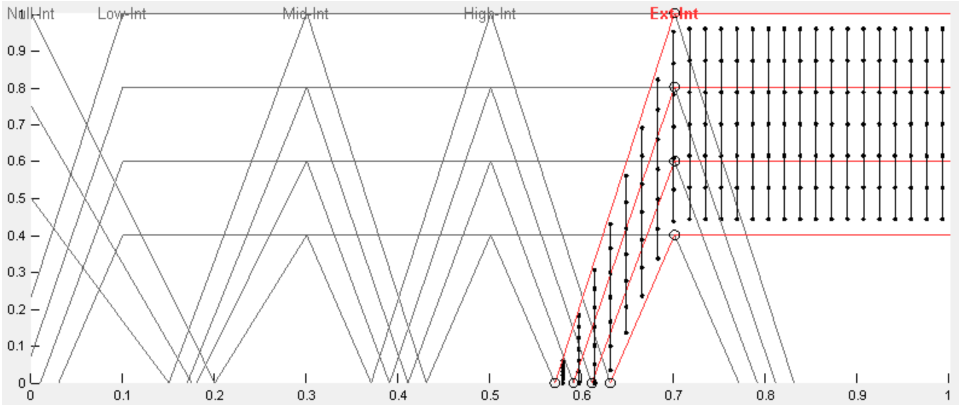

Figure 5.7: Possible Fuzzy Structure of Output $e_{\text{Satisfaction}}$

Such rules would be of the form,

Rule 1: If x is $\tilde{\mathbf{x}}_{\mathbf{33}}$, and y is $\tilde{\mathbf{y}}_{\mathbf{33}}$, then $e_{\text{Satisfaction}}$ is $\tilde{\mathbf{e}}_{\text{Satisfaction}_\mathbf{0}}$
Rule 2: If x is $\tilde{\mathbf{x}}_{\mathbf{17}}$, and y is $\tilde{\mathbf{y}}_{\mathbf{24}}$, then $e_{\text{Satisfaction}}$ is $\tilde{\mathbf{e}}_{\text{Satisfaction}_\mathbf{1}}$
Rule 3: If x is $\tilde{\mathbf{x}}_{\mathbf{18}}$, and y is $\tilde{\mathbf{y}}_{\mathbf{27}}$, then $e_{\text{Satisfaction}}$ is $\tilde{\mathbf{e}}_{\text{Satisfaction}_\mathbf{2}}$
Rule 4: If x is $\tilde{\mathbf{x}}_{\mathbf{19}}$, and y is $\tilde{\mathbf{y}}_{\mathbf{30}}$, then $e_{\text{Satisfaction}}$ is $\tilde{\mathbf{e}}_{\text{Satisfaction}_\mathbf{3}}$
Rule 5: If x is $\tilde{\mathbf{x}}_{\mathbf{20}}$, and y is $\tilde{\mathbf{y}}_{\mathbf{32}}$, then $e_{\text{Satisfaction}}$ is $\tilde{\mathbf{e}}_{\text{Satisfaction}_\mathbf{4}}$

The defuzzified crisp output of all associated rules, for a given named emotion, determines its final membership between 0 and 1. In the case of $e_{\text{Satisfaction}}$, we call this discrete value $e'_{\text{Satisfaction}}$.

The structure defined, the process becomes one of obtaining secondary membership grades of the sixteen discrete emotions, based upon the values of the inputs, which are further defuzzified to provide crisp membership grades. This provides discrete values for the sixteen emotional outputs, between 0 and 1, determining an instantaneous emotional response $\mathbf{E'_S}$, which is defined

$$
\mathbf{E}'_{\mathbf{S}} = \begin{bmatrix} e'_{\text{Pride}} \\ e'_{\text{Elation}} \\ e'_{\text{Happiness}} \\ e'_{\text{Satisfaction}} \\ e'_{\text{Relief}} \\ e'_{\text{Hope}} \\ e'_{\text{Interest}} \\ e'_{\text{Surprise}} \\ e'_{\text{Anxiety}} \\ e'_{\text{Sadness}} \\ e'_{\text{Boredom}} \\ e'_{\text{Shame/Guilt}} \\ e'_{\text{Disgust}} \\ e'_{\text{Contempt}} \\ e'_{\text{Hostility}} \\ e'_{\text{Anger}} \end{bmatrix} \tag{5.46}
$$

The process by which this instantaneous emotional state can be used to determine an ongoing and evolving emotional state is discussed in-depth in the context of the type-1 fuzzy representation of the Geneva Emotion Wheel - both models finding that method suitable due to the identical nature of their resultant outputs.

Chapter 6

Implementation

6.1 Chapter Overview

In this chapter we discuss the technical implementations of each model that were constructed over the course of this project. In all, there were five successful implementations, these being: Type-1 Millenson A; Type-1 Millenson B; Type-1 Geneva Emotion Wheel; Type-2 Millenson A; and, Type-2 Millenson B.

The implementation of the Geneva Emotion Wheel in type-2 fuzzy logic encountered practical problems in terms of the selected development platform. These will be discussed in detail in the specific section relating to its implementation. The section discussing the manner in which it was implemented remains a part of this document as the geometry and rule base formed part of the wider research topic.

This chapter begins with an outline of the type-1 implementations of the selected models. All three of these implementations, as mentioned in the discussions regarding development platform, utilised the Fuzzy Logic Toolbox within the MATLAB Technical Computing Environment. The raw code defining the fuzzy inferencing systems for the type-1 implementations is included as an appendix to this work.

Following presentation of the type-1 implementations, the chapter continues into the type-2 systems. The type-2 implementations discussed were similarly implemented in the MATLAB Technical Computing Environment, using the De Montfort University Fuzzy Logic Toolkit.

6.2 Type-1 Fuzzy Logic Implementations of the Millenson Model

6.2.1 Millenson A in MATLAB

Within MATLAB's Fuzzy Logic Toolbox, a Mamdani fuzzy inferencing system was generated, three inputs to three outputs. This fuzzy inferencing system utilised the minimum 'And' operator as discussed in Chapter Three, and the centroid method of defuzzification. This structure is illustrated by Figure 6.1.

As indicated in Chapter Four, these inputs were declared so as to represent the elements of a stimulus event, **J**, which was previously declared

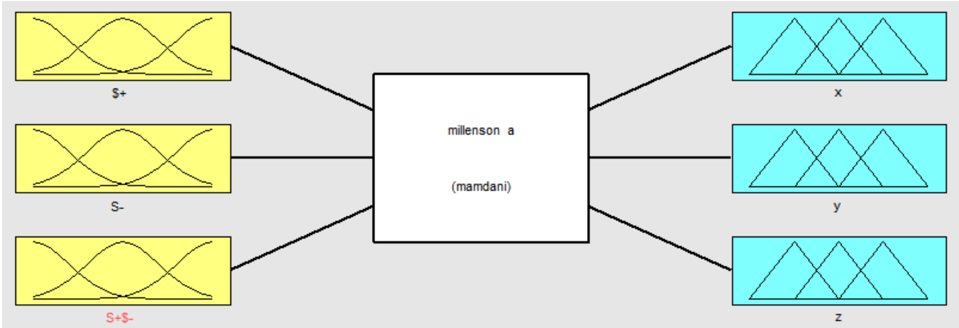

Figure 6.1: Millenson A: FIS Structure

Table 6.1: Millenson A: Input MFs

Low-Sig	–	0.0	0.5
Med-Sig	0.2	0.5	0.8
Hi-Sig	0.5	1	–

$$\mathbf{J} = \begin{bmatrix} X \\ Y \\ Z \end{bmatrix}$$

where

$$X = \sum\{\$+\}[0, 1]$$
$$Y = \sum\{S-\}[0, 1]$$
$$Z = \sum\{S+, \$-\}[0, 1]$$

The symbols have previously declared contextual meanings. Each of the input elements X, Y and Z were, as a fuzzy construct, defined as having three associate fuzzy membership functions representing quantified levels of associated stimulus in the context of significance to the agent. Within this implementation, those fuzzy membership functions were represented as triangular functions, with their geometric vertices given by table 6.1.

The reason triangular membership functions were selected to represent the Millenson theory came from Millenson's geometry as presented in Figure 2.1. In that figure, we see named emotions declared as points along a sliding scale; maintaining analogue with this, we determined the most readily justifiable shape was a triangular membership function which, by its very nature, possesses but a single point of maximum membership. Figure 6.2 illustrates the membership functions described by Table 6.1, as applied to

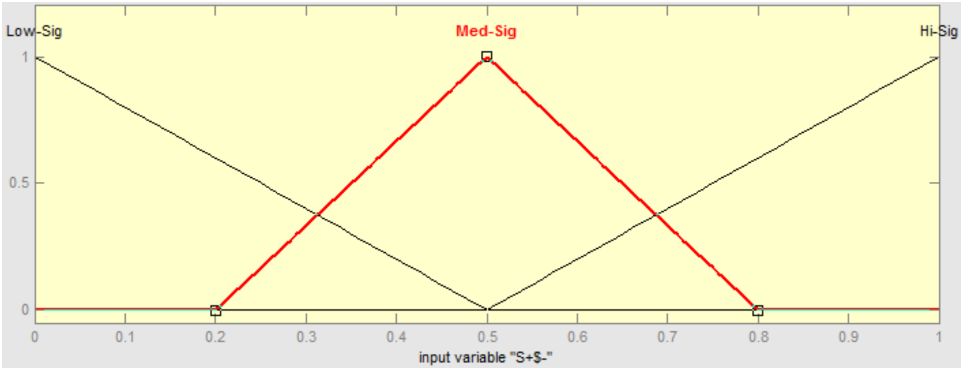

Figure 6.2: Millenson A: MFs of Input Variable Z

Table 6.2: Millenson A: Output MFs

Low-Resp	–	0.0	0.5
Mod-Resp	0.2	0.5	0.8
Ext-Resp	0.5	1	–

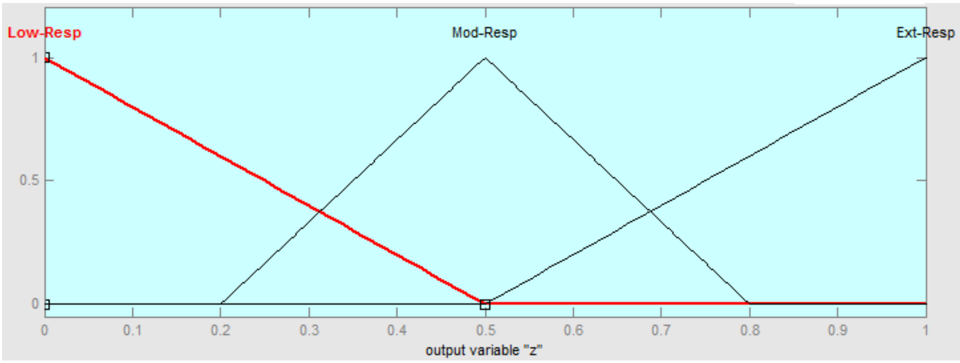

Figure 6.3: Millenson A: MFs of Output Variable z

input variable Z. These structures were deemed to be conceptually uniform across all three axes and were applied thus.

The output variables of the fuzzy inferencing system, x, y and z, were described and outlined in Chapter Four as having three intrinsic membership functions. These were, explicitly, *Low Response*, *Moderate Response* and *High Response*. Millenson's model gives rise to direct equivalency across the input and output variables; thus it was determined there should be equivalency in their description as triangular fuzzy membership functions. The geometric vertices of these three membership functions were applied uniformly across all three output variables. These are given in 6.2 and their application to the output variable z is illustrated by Figure 6.3.

Fuzzy Inferencing Rules as outlined in Chapter Four in the context of input variable X and output variable x were defined and implemented across all three variable pairings. The internal structure of the fuzzy inferencing

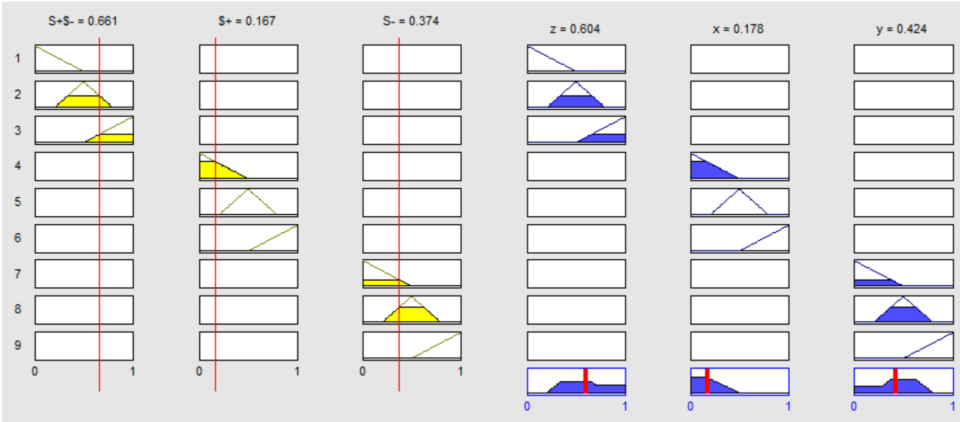

Figure 6.4: Millenson A: MATLAB Fuzzy Logic Toolbox Rules Screen

system was constructed such that any vector $\mathbf{J}$, within the limits of the system's boundaries, produced a suitable output $\mathbf{e_J}$ where

$$\mathbf{e_J} = \begin{bmatrix} x[0,1] \\ y[0,1] \\ z[0,1] \end{bmatrix}$$

Figure 6.4 illustrates MATLAB's internal results calculation mechanism included within the Fuzzy Inferencing System Environment (hence FISE). It should be noted, however, that the actual testing environment utilised MATLAB's command line functions, and the figure is included for the sake of completion only.

The process by which the vector $\mathbf{e_J}$ was used to generate the desired output $\mathbf{E_J}$ associated with a given stimulus $\mathbf{J}$ required additional analysis to implement.

As a function of the usage of centroid defuzzification applied in this representation, coupled with the specific representation of the triangular membership functions, ensured that the minimum value for any output was 0.163. Conversely, the maximum output value for any output was 0.837.

Returning to Millenson's geometry, it was required that we suitably scale the named emotions along a given axis in accordance with his structure. That is to say that, along the axis, the maximum for the lowest grade would appear at 20%, the next highest grade at 60%, and the highest grade at 100%. Thus it was determined to scale these grades to fit the value range granted by the fuzzy inferencing system, when defining the fuzzy functions linking the output variables to the specific emotions they influenced.

Table 6.3: Millenson A: Discrete Emotions Associated with z

Pleasure	0.1630	0.2978	0.5674
Elation	0.4326	0.5674	0.8370
Ecstasy	0.7022	0.8370	–

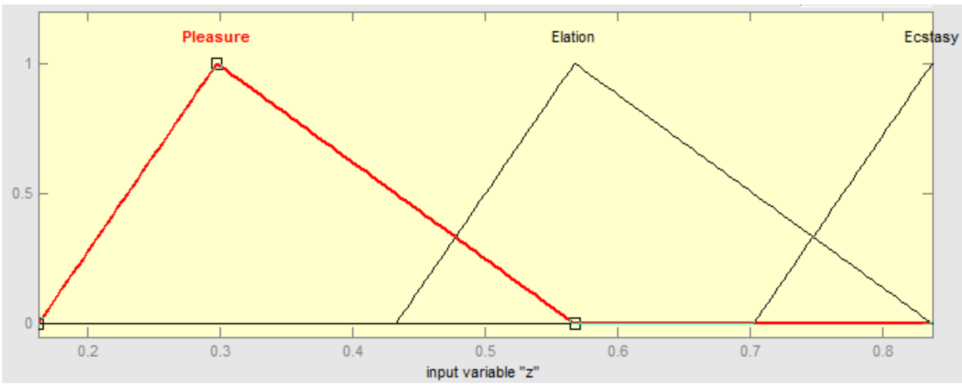

Figure 6.5: Millenson A: Discrete Emotions Associated with z

While the calculations that processed the individual outputs x, y and z into discrete grades of the nine named emotions were explicitly not a second fuzzy inferencing system, the nature of the associative functions was inherently fuzzy in nature. These functions were likewise triangular in structure, so as to maintain internal consistency within representations, though not symmetrical. Their vertices are presented in the context of output variable z in Table 6.3, which is illustrated in Figure 6.5.

These relations between a variable and its associated discrete emotions were applied uniformly. For each vector $\mathbf{e_J}$, a simple MATLAB M-file used these fuzzy relations to determine membership grades for each discrete emotion, producing the desired output for a given iteration, $\mathbf{E_J}$.

6.2.2 Millenson B in MATLAB

A Mamdani fuzzy inferencing system was generated using the MATLAB Fuzzy Logic Toolbox, three inputs to nine outputs. This fuzzy inferencing system utilised the minimum 'And' operator as discussed in Chapter Three, and the centroid method of defuzzification. This structure is illustrated by Figure 6.6.

Implementation of this alternative representation of Millenson's model through MATLAB was a simpler process than that of Millenson A, primarily due to the removal of the intermediary layer of calculation associated with $\mathbf{e_J}$. The structure of the input vector remained consistent, that being the

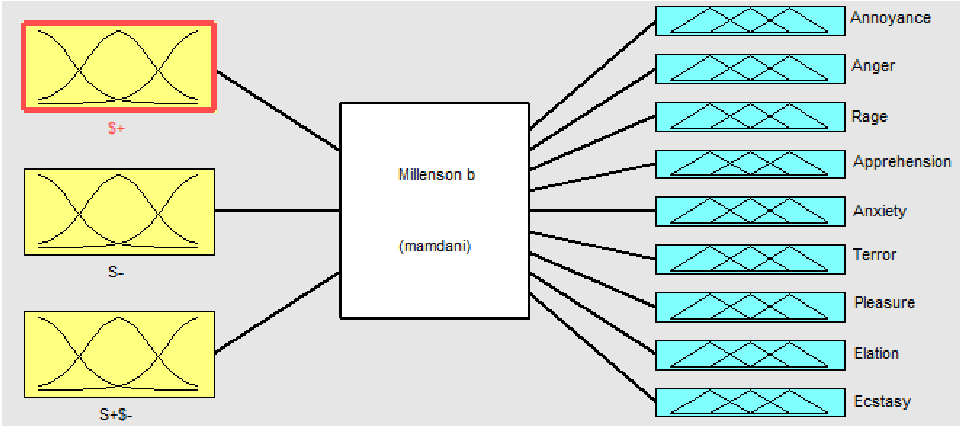

Figure 6.6: Millenson B: FIS Structure

Table 6.4: Millenson B: Input MFs

No Intensity	–	0.0	0.3
Low Intensity	0.0	0.3	0.6
Medium Intensity	0.4	0.7	1.0
High Intensity	0.7	1.0	–

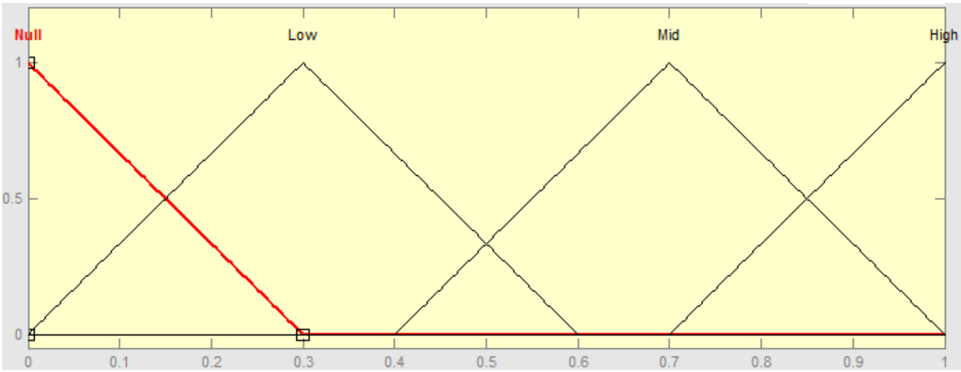

Figure 6.7: Millenson B: MFs of Input Variable X

stimulus event **J**, although its context differs, as described earlier.

Each of the input elements X, Y and Z were, as a fuzzy construct, defined as having four associate fuzzy membership functions, representing quantified levels of associated stimulus in the context of intensity with which the agent felt the stimulus. Within this implementation, those fuzzy membership functions were represented as triangular functions, with their geometric vertices given by Table 6.4. These are illustrated in the context of variable X in Figure 6.7.

These membership functions were applied uniformly to the three input variables X, Y and Z. The nine output variables, mathematically denoted as x_{1-3}, y_{1-3}, and z_{1-3}, were each associated with four membership functions as outlined in Chapter Four. In implementing them, these membership

Table 6.5: Millenson B: Output MFs

Not Annoyed	–	0.0	0.33
Slightly Annoyed	0.0	0.33	0.67
Annoyed	0.33	0.67	1.0
Very Annoyed	0.67	1.0	–

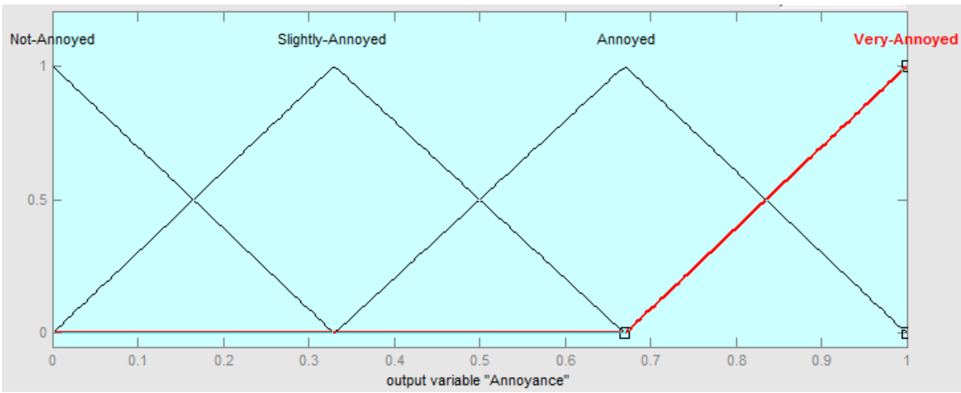

Figure 6.8: Millenson B: MFs of Output Variable x_1 - Annoyance

functions were represented as triangular functions; their vertices are given in Table 6.5, in the context of the output x_1, or the 'Annoyed' emotion. They are illustrated, again in the context of output x_1, in Figure 6.8.

These membership functions were applied uniformly across all nine output emotions to maintain consistency across the target resultant, vector $\mathbf{E_J}$, elements.

Rules were input into the system as outlined in Chapter Four, where the mathematics of this model were discussed in depth. The rules were applied uniformly across input variables, connecting them each with their three associated output variables. An M-File obtained the nine discrete values, one for each output, and combined them into the desired iterative output vector $\mathbf{E_J}$, representing the instantaneous emotional state.

6.3 Type-1 Fuzzy Logic Implementation of the Geneva Emotion Wheel

Implementation of the Geneva Emotion Wheel through Matlab proved to be a complex endeavour, both in terms of the geometric analysis required in order to maintain psychological analogue, and in terms of limitations of the MATLAB Fuzzy Logic Toolbox.

Within MATLAB, a Mamdani fuzzy inferencing system was generated,

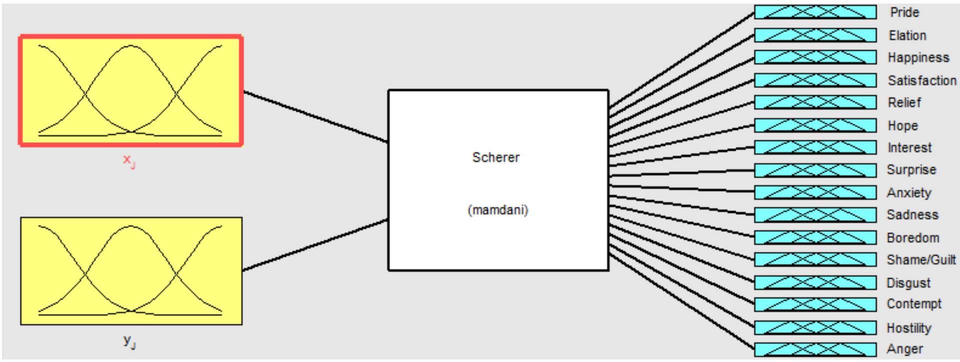

Figure 6.9: Scherer: FIS Structure

two inputs leading to sixteen outputs. This fuzzy inferencing system utilised the minimum 'And' operator as discussed in Chapter Three, and the centroid method of defuzzification. This structure is illustrated by Figure 6.9.

As outlined in Chapter Four, the input vector to this system, **J**, is defined in this context as

$$\mathbf{J} = \begin{bmatrix} x \\ y \end{bmatrix}$$

where x and y represent a quantified determination of valence and control, respectively, within the value ranges of -1 to 1. As fuzzy constructs, it has already been determined that each of these input variables has thirty-three fuzzy functions associated with it; the matter of the implementation is to calculate in discrete terms and so encode the thirty-three functions and their associated rules.

In this implementation, the nature of the fuzzy functions faced applied constraints. Firstly, that the fuzzy functions would be trapezoidal. Secondly, that the maxima of these trapezia would, along either axis, coincide with the diameter of each discrete geometrical region determined by Scherer's prototype. Thirdly, that each shoulder of a trapezium would be equal in width along its axis to the width of its maximum. Finally, that the absolute values of -1 and 1 along each axis would be determined by the edge of the maximum of the first and thirty-second membership functions for that axis (mindful that the thirty-third occurs out of sequence, and functionally occupies the origin of the circumplex).

Following these constraints, and applying geometrical analysis to four significant figures of accuracy, Table 6.6 was constructed to indicate the vertices of each trapezoidal membership function. As the x and y axes on Scherer's

Table 6.6: Type-1 Scherer: Input MFs

1	-1.240	-1.000	-0.760	-0.520
2	-1.111	-0.871	-0.631	-0.391
3	-0.933	-0.742	-0.551	-0.360
4	-0.867	-0.627	-0.387	-0.147
5	-0.835	-0.644	-0.453	-0.262
6	-0.649	-0.458	-0.267	-0.076
7	-0.645	-0.516	-0.387	-0.258
8	-0.578	-0.449	-0.320	-0.191
9	-0.547	-0.307	-0.067	0.173
10	-0.449	-0.320	-0.191	-0.062
11	-0.444	-0.351	-0.258	-0.165
12	-0.418	-0.227	-0.036	0.155
13	-0.400	-0.307	-0.214	-0.121
14	-0.315	-0.222	-0.129	-0.036
15	-0.285	-0.156	-0.027	0.102
16	-0.200	-0.107	-0.014	0.079
17	-0.173	0.067	0.307	0.547
18	-0.155	0.036	0.227	0.418
19	-0.102	0.027	0.156	0.285
20	-0.079	0.014	0.107	0.200
21	0.036	0.129	0.222	0.315
22	0.062	0.191	0.320	0.449
23	0.076	0.267	0.458	0.649
24	0.121	0.214	0.307	0.400
25	0.147	0.387	0.627	0.867
26	0.165	0.258	0.351	0.444
27	0.191	0.320	0.449	0.578
28	0.258	0.387	0.516	0.645
29	0.262	0.453	0.644	0.835
30	0.360	0.551	0.742	0.933
31	0.391	0.631	0.871	1.111
32	0.520	0.760	1.000	1.240
33	-0.360	-0.120	0.120	0.360

prototype mirrored each other, this table presents the membership functions of both the x and y variables, numericised according to the value of their first coordinate. It should be noted that coordinates that fall outside of the input value range are included for the sake of completeness; likewise it should be noted that membership function 33 occurs out of sequence, as it is a special case.

These functions are naturally applied uniformly across both x and y. A graphic representation of these membership functions as applied to the x input variable is included as Figure 6.10. It should be clarified that trapezoidal

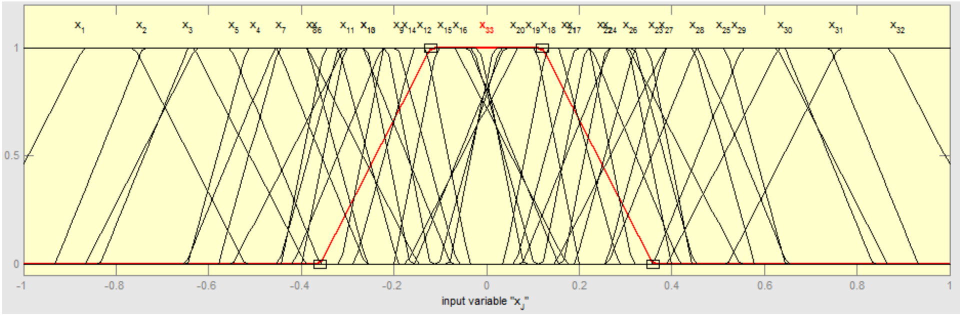

Figure 6.10: Type-1 Scherer: MFs of Input Variable x

membership functions were selected to represent the regions of the Geneva Emotion Wheel for reasons analogous to the selection of triangular membership functions representing the Millenson Theory. By selecting membership functions that possessed regions of maximal membership, rather than points, it was felt the geometry of the Geneva Emotion Wheel as shown in Figure 2.2 would be more accurately represented.

Each of the sixteen outputs as described in Chapter Four is required to have five membership functions describing its relative magnitude. These were described as *Null Intensity*, *Low Intensity*, *Middle Intensity*, *High Intensity* and *Extreme Intensity*. The idea, as explained, was to map individual couplets of input membership functions to a specific grade of an individual output variable. Experimentation, however, revealed a weakness in the application of the centroid defuzzification mechanism.

In this system, there were naturally instances where individual outputs would have membership of 0; in situations where Extreme Pride was triggered, for example, Anxiety would have no membership output. In such situations, Matlab's implementation of centroid defuzzification returns the median value of the output range. As such, in the above example e_{Anxiety} would return membership of 0.5.

The solution to this problem was to introduce a sixth output membership function. This function had a discernible membership area of 5×10^{-5} units^2, and would be the default state for all outputs unless one of their other rules was triggered. Regrettably, this introduced a potential error margin within obtained outputs. This error margin is factored in to results obtained from this implementation of the Geneva Emotion Wheel, as discussed in Chapters Seven and Eight.

As a result of this, the mathematical construct describing the emotion of satisfaction with respect to μ, $e_{\text{Satisfaction}}$, given in Chapter Four was amended

Table 6.7: Type-1 Scherer: Output MFs

No Intensity	–	–	–	0.0001
Null Intensity	–	0.00	0.10	0.20
Low Intensity	0.05	0.15	0.30	0.40
Middle Intensity	0.30	0.40	0.55	0.65
High Intensity	0.55	0.65	0.80	0.90
Extreme Intensity	0.80	0.90	–	–

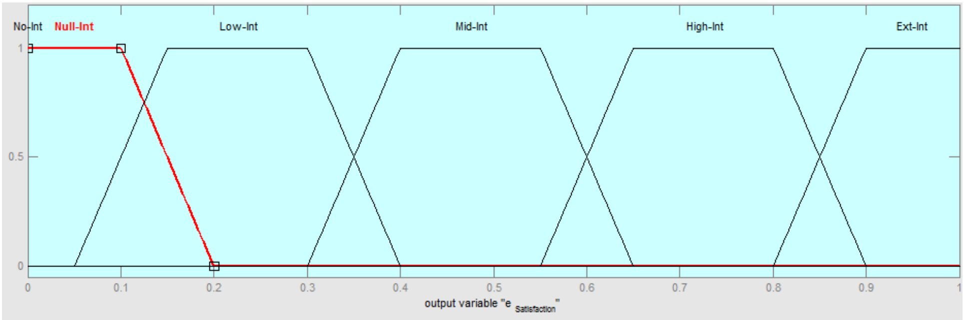

Figure 6.11: Type-1 Scherer: MFs of Output Variable $e_{\text{Satisfaction}}$

to

$$
(e_{\text{Satisfaction}}, \mu) = \begin{array}{r}
\{\mu(\text{No Intensity})/\text{No Intensity}, \\
\mu(\text{Null Intensity})/\text{Null Intensity}, \\
\mu(\text{Low Intensity})/\text{Low Intensity}, \\
\mu(\text{Middle Intensity})/\text{Middle Intensity}, \\
\mu(\text{High Intensity})/\text{High Intensity}, \\
\mu(\text{Extreme Intensity})/\text{Extreme Intensity}\}
\end{array}
$$

Where *Null Intensity* represented an emotional state occupying the central zone of the circumplex, *No Intensity* represented instead situations where an emotion was definitively not triggered by a given input pairing. Each of these fuzzy terms is represented by a trapezoidal membership function, the coordinates of which are given in Table 6.7. This table is illustrated by Figure 6.11 in the context of the output $e_{\text{Satisfacton}}$.

Whereas the rules required to represent both interpretations of the Millenson Model were self-explanatory in the context in which they were presented, the geometric representation of the Geneva Emotion Wheel is not so. Each rule in the implementation associated one membership function from each input variable with a specific membership function of one of sixteen output variables. Tables 6.8 and 6.9 explicitly outline in terms of x_i, y_j and grade

Table 6.8: Scherer: Rules

e_{Pride} , Low	x_{20}	y_{26}
e_{Pride} , Middle	x_{19}	y_{28}
e_{Pride} , High	x_{18}	y_{30}
e_{Pride} , Extreme	x_{17}	y_{32}
e_{Elation} , Low	x_{21}	y_{24}
e_{Elation} , Middle	x_{22}	y_{27}
e_{Elation} , High	x_{23}	y_{29}
e_{Elation} , Extreme	x_{25}	y_{31}
$e_{\text{Happiness}}$, Low	x_{24}	y_{21}
$e_{\text{Happiness}}$, Middle	x_{27}	y_{22}
$e_{\text{Happiness}}$, High	x_{29}	y_{23}
$e_{\text{Happiness}}$, Extreme	x_{31}	y_{25}
$e_{\text{Satisfaction}}$, Low	x_{26}	y_{20}
$e_{\text{Satisfaction}}$, Middle	x_{28}	y_{19}
$e_{\text{Satisfaction}}$, High	x_{30}	y_{18}
$e_{\text{Satisfaction}}$, Extreme	x_{32}	y_{17}
e_{Relief} , Low	x_{26}	y_{16}
e_{Relief} , Middle	x_{28}	y_{15}
e_{Relief} , High	x_{30}	y_{12}
e_{Relief} , Extreme	x_{32}	y_{9}
e_{Hope} , Low	x_{24}	y_{14}
e_{Hope} , Middle	x_{27}	y_{10}
e_{Hope} , High	x_{29}	y_{6}
e_{Hope} , Extreme	x_{31}	y_{4}
e_{Interest} , Low	x_{21}	y_{13}
e_{Interest} , Middle	x_{22}	y_{8}
e_{Interest} , High	x_{23}	y_{5}
e_{Interest} , Extreme	x_{25}	y_{2}
e_{Surprise} , Low	x_{20}	y_{11}
e_{Surprise} , Middle	x_{19}	y_{7}
e_{Surprise} , High	x_{18}	y_{3}
e_{Surprise} , Extreme	x_{17}	y_{1}

of e_k, what these rules were.

Note that the rules outlined in tables 6.8 and 6.9 indicate the explicit connections. An additional rule exists associating all outputs' "Null" membership functions to x_{33} and y_{33}, as has been suggested previously. Also, by necessity, all of the above couplets are also associated with the "No Intensity" error-correction membership function for all output emotions to which they are not explicitly connected.

Figure 6.12 illustrates an excerpt of Matlab's internal results calculation mechanism included within the FISE. It should be noted, however, that the

Table 6.9: Scherer: Rules, Continued

e_{Anxiety} , Low	x_{16}	y_{11}
e_{Anxiety} , Middle	x_{15}	y_{7}
e_{Anxiety} , High	x_{12}	y_{3}
e_{Anxiety} , Extreme	x_{9}	y_{1}
e_{Sadness} , Low	x_{14}	y_{13}
e_{Sadness} , Middle	x_{10}	y_{8}
e_{Sadness} , High	x_{6}	y_{5}
e_{Sadness} , Extreme	x_{4}	y_{2}
e_{Boredom} , Low	x_{13}	y_{14}
e_{Boredom} , Middle	x_{8}	y_{10}
e_{Boredom} , High	x_{5}	y_{6}
e_{Boredom} , Extreme	x_{2}	y_{4}
$e_{\text{Shame/Guilt}}$, Low	x_{11}	y_{16}
$e_{\text{Shame/Guilt}}$, Middle	x_{7}	y_{15}
$e_{\text{Shame/Guilt}}$, High	x_{3}	y_{12}
$e_{\text{Shame/Guilt}}$, Extreme	x_{1}	y_{9}
e_{Disgust} , Low	x_{11}	y_{20}
e_{Disgust} , Middle	x_{7}	y_{19}
e_{Disgust} , High	x_{3}	y_{18}
e_{Disgust} , Extreme	x_{1}	y_{17}
e_{Contempt} , Low	x_{13}	y_{21}
e_{Contempt} , Middle	x_{8}	y_{22}
e_{Contempt} , High	x_{5}	y_{23}
e_{Contempt} , Extreme	x_{2}	y_{25}
$e_{\text{Hostility}}$, Low	x_{14}	y_{24}
$e_{\text{Hostility}}$, Middle	x_{10}	y_{27}
$e_{\text{Hostility}}$, High	x_{6}	y_{29}
$e_{\text{Hostility}}$, Extreme	x_{4}	y_{31}
e_{Anger} , Low	x_{16}	y_{26}
e_{Anger} , Middle	x_{15}	y_{28}
e_{Anger} , High	x_{12}	y_{30}
e_{Anger} , Extreme	x_{9}	y_{32}

actual testing environment utilised Matlab's command line functions, and the diagram is included for the sake of completion only. It should also be noted that this is only a portion of the triggered ruleset.

A simple M-File was used to generate the desired output vector $\mathbf{E'_S}$ from the sixteen discrete numerical values generated by the fuzzy inferencing system outputs.

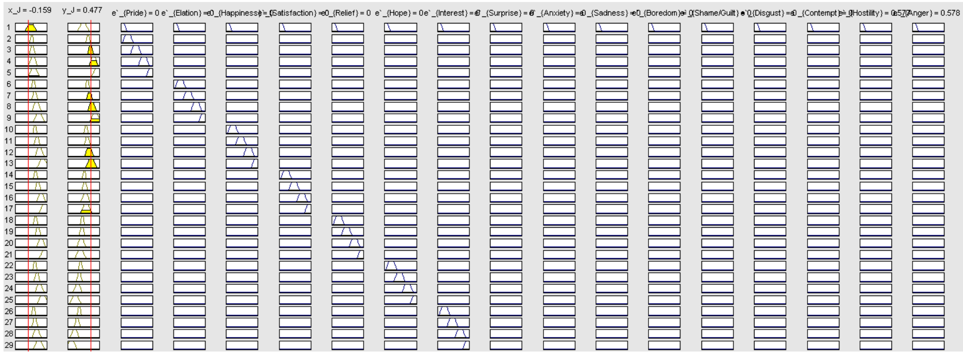

Figure 6.12: Type-1 Scherer: Matlab Rules Screen Example

6.4 Type-2 Fuzzy Logic Implementations of the Millenson Model

6.4.1 Millenson A in the Type 2 Fuzzy Controller

Using the Type 2 Fuzzy Controller software developed by De Montfort University, a type 2 Mamdani fuzzy inferencing system was generated, connecting three inputs to three outputs. This inferencing system utilised centroid defuzzification in both the obtaining of the resultant 'slice' of a type 2 set, and then subsequently in the solution of that slice. Contextually speaking, figure 6.1 also illustrates the connections of this type 2 implementation.

As with the type 1 implementations, the inputs corresponded to the three facets of a given stimulus event **J** in the context Millenson provides. Similarly, the type 2 fuzzy sets are informed by the sets defined in type 1, but with a given level of applied uncertainty.

The sets themselves were triangular, as in the type 1 case and for the justifications outlined in the context of the type 1 implementations, with the secondary membership functions for any given slice similarly triangular. Figure 6.15 illustrates the structure of variable Z. Table 6.10 illustrates the geometric vertices of the type 2 membership function, with the meaning of each vertex explained below.

The first vertex defines the lower bound of the secondary membership function, meaning the lower value at which zero secondary membership was guaranteed. The second vertex identifies the lower point of maximal secondary membership grade, or the lower point along zero primary membership where secondary membership would be 1. The third vertex is the upper minimum for secondary membership value, with respect to the lower point

Table 6.10: Type-2 Millenson A: Vertices of Membership Functions Associated with Input Variables

Low-Sig	0.00	0.00	0.00	0.00	0.45	0.50	0.55
Med-Sig	0.15	0.20	0.25	0.50	0.75	0.80	0.85
Hi-Sig	0.45	0.50	0.55	1.00	1.00	1.00	1.00

of the triangle. The fourth vertex represents the maximum point of primary membership for a given triangle. The fifth point represents the lower bound of zero secondary membership for the upper point of the triangle. The sixth represents the maximal secondary membership grade for the upper point of the triangle. Lastly, the seventh represents the uppermost bound of zero secondary membership for the upper point of the triangle.

These definitions remain uniform for all triangular type 2 membership functions implemented through the De Montfort University Type 2 Fuzzy Logic Toolbox, for the type 2 implementations of both Millenson A and Millenson B. These structures were deemed to be conceptually uniform across all three axes and were applied in that fashion.

To illustrate this structure further, figure 6.13 shows a membership function generated using the vertices 0.00, 0.10, 0.20, 0.40, 0.60, 0.70, 0.80. These are labelled A, B, C, D, E, F and G, respectively. A three dimensional representation of the membership function the toolbox generates related to figure 6.13 is included as figure 6.14. From a software perspective, the Toolbox will only utilise the vertices A, C, D, E and G, however.

This is due to the fact that the Toolbox automatically assigns the vertex B to be equidistant between A and C, and assigns F to be equidistant between E and G. An additional value can be input into the Toolbox to inform the lower boundary of the maximum membership at vertex D; unlike vertices A, C, E and G, this defines a triangle in the vertical plane rather than the horizontal, as shown in figure 6.14. The triangular membership function structure described here is relevant to the vertices shown in tables 6.10, 6.11, 6.13 and 6.14.

The three output variables of the fuzzy inferencing system have been extensively clarified and further reiteration here serves no purpose. As with the type-1 system, these variables were linked to their associate input variable. The output variable z is shown in figure 6.16, while the vertices of the secondary membership maxima can be found in table 6.11, their meanings being the same as those outlined explicitly with respect to table 6.10.

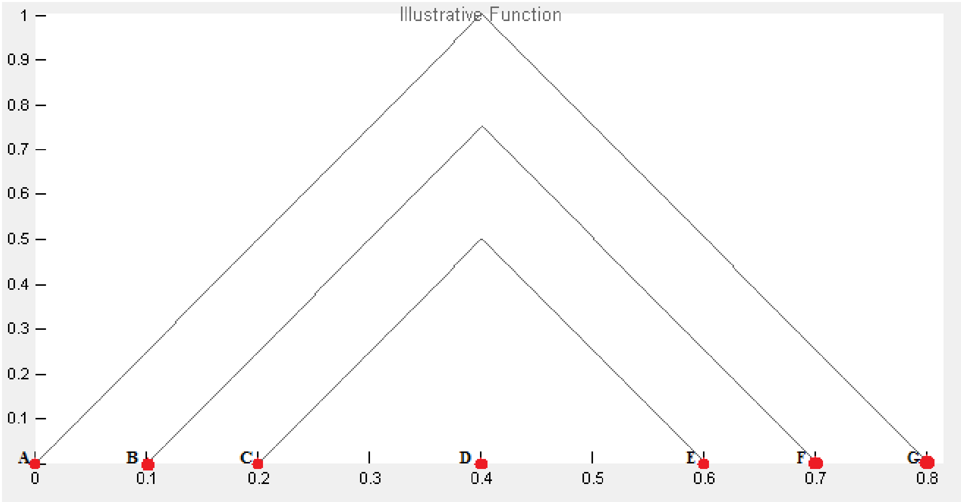

Figure 6.13: Illustrative Type-2 Triangular Membership Function

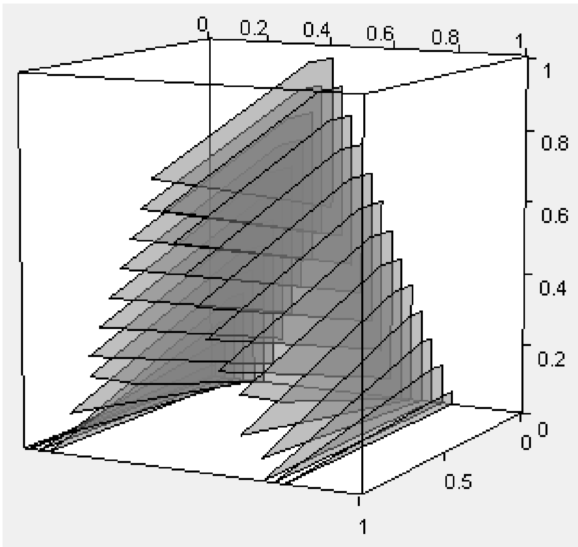

Figure 6.14: Illustrative Type-2 Triangular Membership Function in 3D

Table 6.11: Type-2 Millenson A: Vertices of Membership Functions Associated with Output Variables

Low-Sig	0.00	0.00	0.00	0.00	0.45	0.50	0.55
Med-Sig	0.15	0.20	0.25	0.50	0.75	0.80	0.85
Hi-Sig	0.45	0.50	0.55	1.00	1.00	1.00	1.00

Rules identical to those used in the type 1 implementation, as outlined previously, were implemented in the system. Figure 6.17 illustrates the rules declaration system within the Type 2 Fuzzy Controller, while Figure 6.18 gives an overview of the toolkit structure.

It should be noted that, as opposed to the Type 1 implementation, it is impossible to call the De Montfort University Type-2 Fuzzy Toolbox from the command line. As such, the graphic user interface was relied upon exclusively

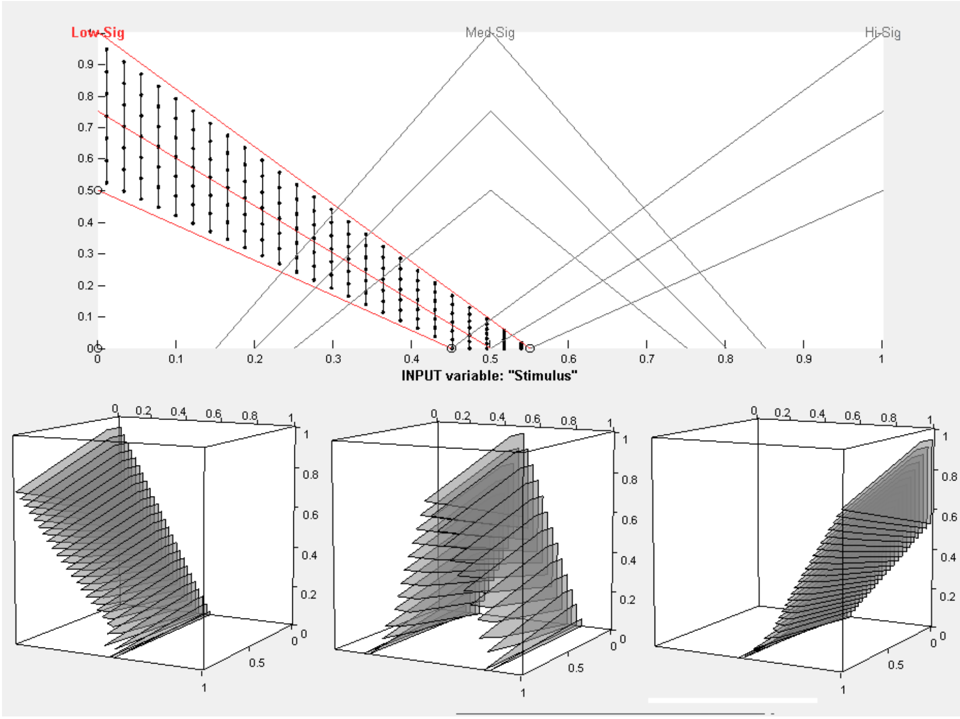

Figure 6.15: Type-2 Millenson A: Membership Functions of Input Variable Z

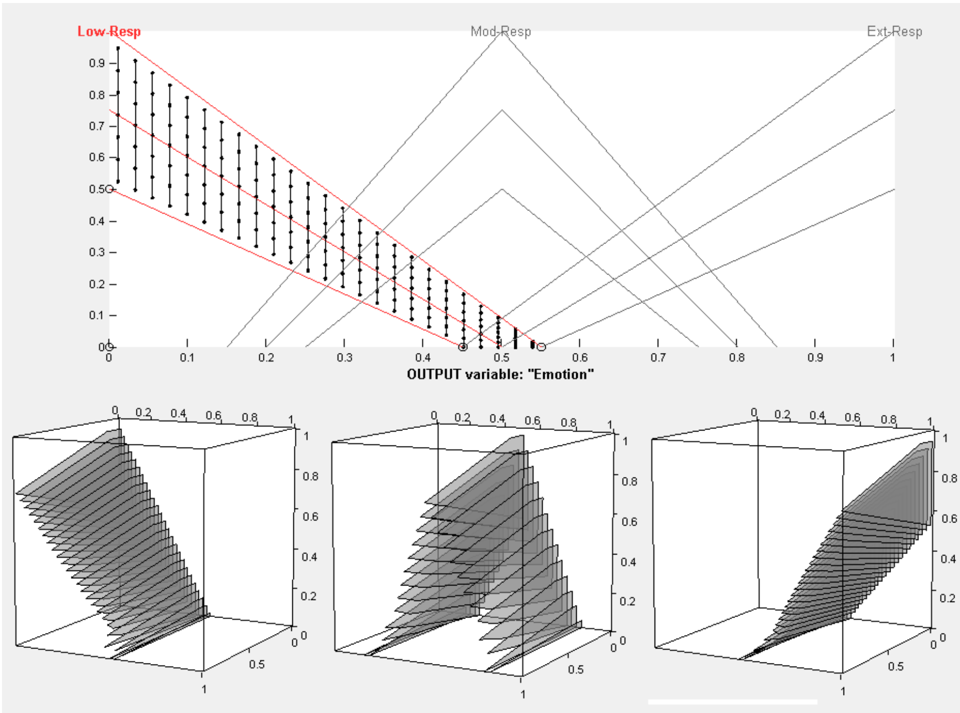

Figure 6.16: Type-2 Millenson A: Membership Functions of Output Variable z

in testing.

The usage of centroid defuzzification applied in this representation, cou-

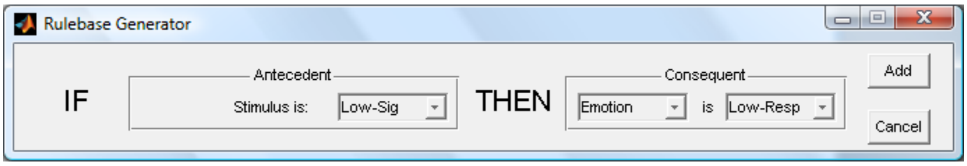

Figure 6.17: Declaring Rules in the Type 2 Fuzzy Controller

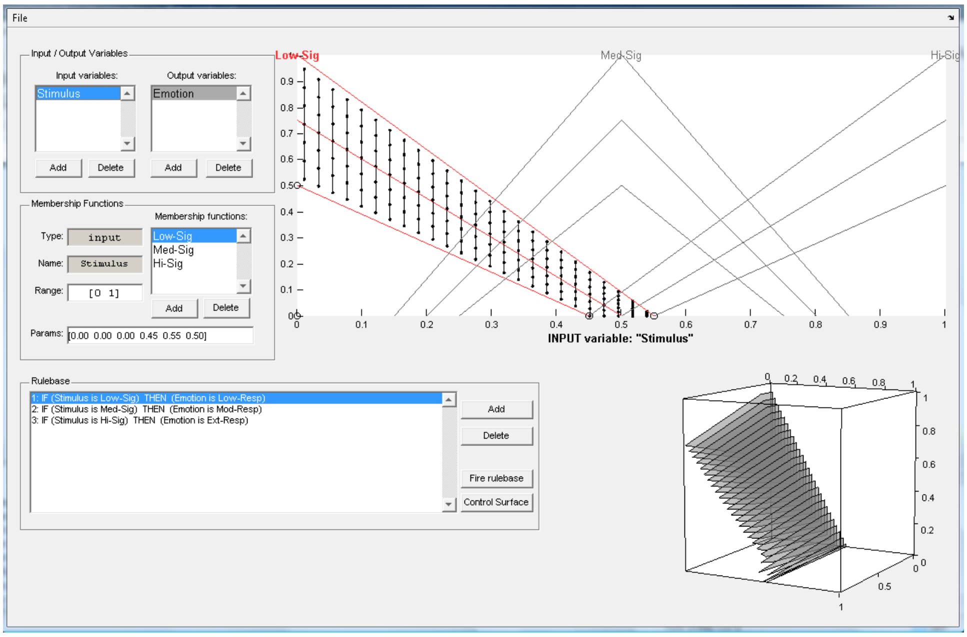

Figure 6.18: Overview of the Type 2 Fuzzy Controller Interface

pled with the specific representation of the triangular membership functions, ensured that the minimum value for any output was 0.258. Conversely, the maximum output value for any output was 0.742.

Returning to Millenson's geometry, it was required that we suitably scale the named emotions along a given axis in accordance with his structure. Once again, the maximum for the lowest grade would appear at 20%, the next highest grade at 60%, and the highest grade at 100%. .

As with type-1, while the calculations that processed the individual outputs into discrete grades of the nine named emotions were explicitly not a second fuzzy inferencing system, the nature of the associative functions was inherently fuzzy. These functions were likewise triangular in structure so as to maintain internal consistency within representations, though not symmetrical, in line with Millenson's own weightings of proportionality (although these are inferred from the scaling of his diagram, rather than explicitly stated numerically). Their vertices are presented in the context of output variable z in Table 6.12, which is illustrated in Figure 6.19.

These relations between variable and its associated discrete emotions were

Table 6.12: Type 2 Millenson A: Discrete Emotions Associated with z

Pleasure	0.2580	0.3548	0.5484
Elation	0.4516	0.5484	0.7420
Ecstasy	0.6452	0.7420	–

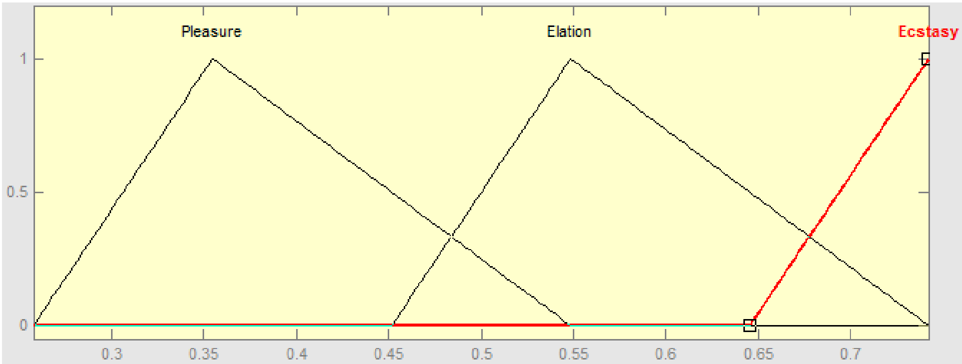

Figure 6.19: Type 2 Millenson A: Discrete Emotions Associated with z

applied uniformly. For each vector $\mathbf{e_J}$, these fuzzy relations were manually triggered to determine membership grades for each discrete emotion, producing the desired output for a given iteration, $\mathbf{E_J}$.

6.4.2 Millenson B in the Type-2 Fuzzy Controller

Turning once again to the Type-2 Fuzzy Controller software developed by De Montfort University, a type-2 Mamdani fuzzy inferencing system was generated, connecting three inputs to nine outputs. This inferencing system utilised centroid defuzzification in both the obtaining of the resultant 'slice' of a type-2 set and the solution of that slice.

Contextually speaking, figure 6.6 also illustrates the connections of this type-2 implementation. As with type-1, the implementation of this variation on Millenson was simpler due to the removal of the intermediary step connecting the defuzzified outputs with named emotions. As with Millenson A, the structure of Millenson B in type-2 is analogous to its type-1 counterpart

Each of the input elements X, Y and Z was, as a type-2 fuzzy construct, defined as having four associate fuzzy membership functions, representing quantified levels of associated stimulus in the context of intensity with which the agent felt said stimulus.

The sets were triangular, as in the type-1 case, with the secondary membership functions for any given slice also triangular. Figure 6.20 illustrates the structure of variable Z. Table 6.13 illustrates the geometric vertices of

Table 6.13: Type-2 Millenson B: Vertices of Input Membership Functions

No Intensity	0.00	0.00	0.00	0.00	0.25	0.30	0.35
Low Intensity	-0.05	0.00	0.05	0.30	0.55	0.60	0.65
Medium Intensity	0.35	0.40	0.45	0.70	0.95	1.00	1.05
High Intensity	0.65	0.70	0.75	1.00	1.00	1.00	1.00

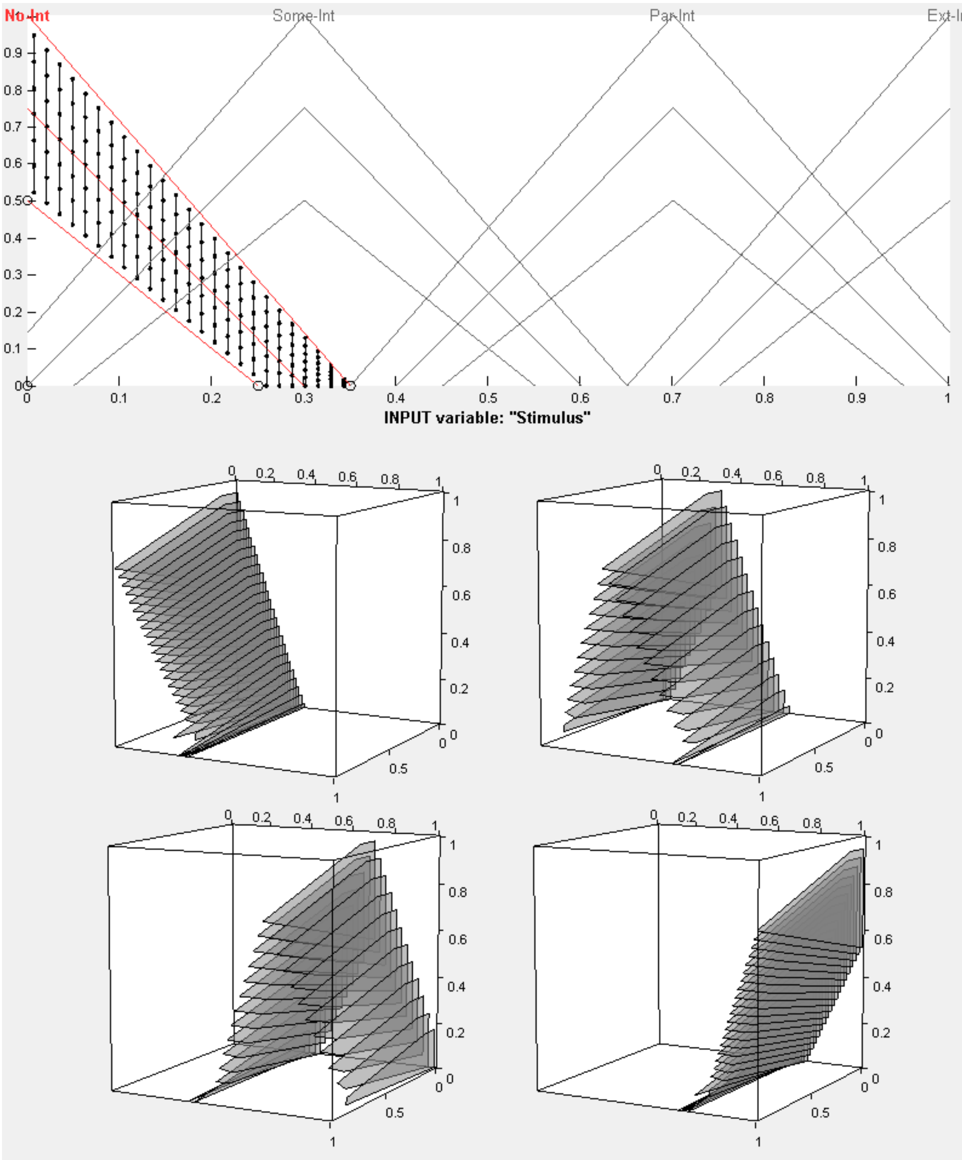

Figure 6.20: Type 2 Millenson B: MFs of Input Variable X

the maximal secondary membership functions, the elements serving the same purpose as those discussed with respect to table 6.10. These structures were deemed to be conceptually uniform across all three axes.

These membership functions were applied uniformly to the three input variables X, Y and Z. The nine output variables, x_{1-3}, y_{1-3}, and z_{1-3}, were each associated with four membership functions as outlined previously.

Table 6.14: Type-2 Millenson B: Vertices of Output Membership Functions

Not Pleased	0.00	0.00	0.00	0.00	0.28	0.33	0.38
Slightly Pleased.	-0.05	0.00	0.05	0.33	0.62	0.67	0.72
Pleased	0.28	0.33	0.38	0.67	0.95	1.00	1.05
Very Pleased.	0.62	0.67	0.72	1.00	1.00	1.00	1.00

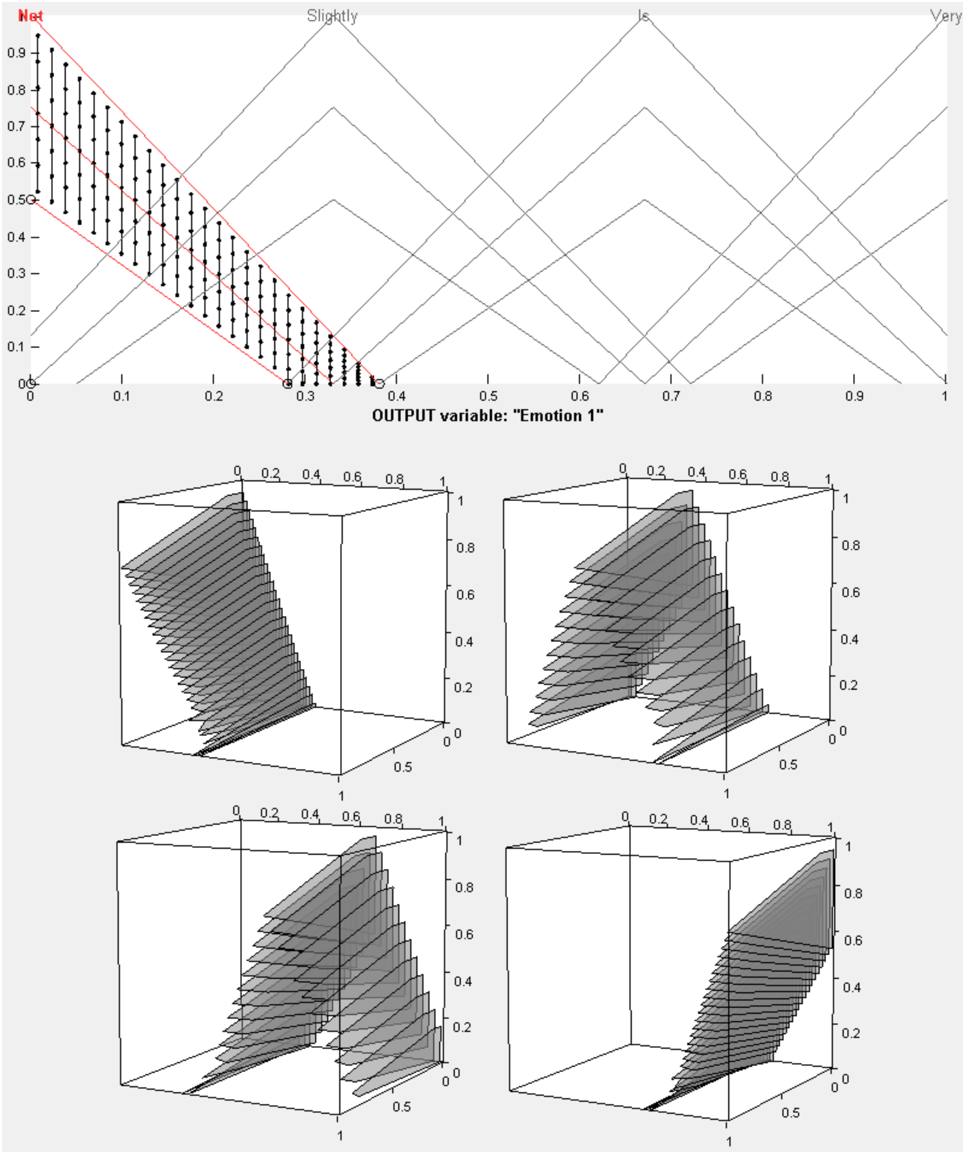

Figure 6.21: Type-2 Millenson B: Output Variable z_1 - Pleasure

These output variables, as with the type-1 system, are represented by triangular membership functions, with the secondary membership functions also being triangular in nature. The output variable z_1 is shown in figure 6.21, while the vertices of the type-2 membership functions are found in table 6.14.

These membership functions were applied uniformly across all nine output emotions to maintain consistency across the target resultant, vector $\mathbf{E_J}$, elements.

Rules were input into the system reflecting those outlined previously, where the mathematics of this model were discussed in depth. The rules were applied uniformly across input variables, connecting them each with their three associated output variables. Nine discrete values, one for each output, were obtained manually and combined to generate the desired iterative output vector $\mathbf{E_J}$.

6.5 Type-2 Fuzzy Logic Implementation of the Geneva Emotion Wheel

Implementation of the Geneva Emotion Wheel in type-2 fuzzy logic was a more taxing exercise than the implementation of either interpretation of Millenson. Through the Type-2 Fuzzy Controller software, a type-2 Mamdani fuzzy inferencing system was generated, connecting two inputs to sixteen outputs. This inferencing system utilised centroid defuzzification in both the obtaining of the resultant 'slice' of a type-2 set, and then subsequently in the solution of that slice.

Figure 6.9 illustrates the conceptual structure of this fuzzy inferencing system. As with our previous expansions from Type-1 into Type-2, we chose to maintain the causal connections between input and output variables in order to retain consistency of comparison.

The membership functions within the Type-2 Geneva Emotion Wheel were far more complicated than those in Type-1. In addition, there was a limitation within the De Montfort University Type-2 Fuzzy Logic Toolbox (hence DMU T-2 FLT) which prevented the vertices of the membership functions being as accurately represented as they were in Type-1. Specifically, the De Montfort Univerity Type 2 Fuzzy Logic Toolbox limited the accuracy of vertices to three significant figures, wheras the vertices utilised in the Type 1 representation were accurate to five significant figures.

In addition to this, while the MATLAB Fuzzy Logic Toolbox accepted raw numerical inputs, the DMU T-2 FLT only accepted inputs as proportionalities between 1 and 0, with numbers above 1 and below zero, while capable of being inputted, could play no role in the system's calculations. While this made no difference in our implementations of Millenson, it made significant difference when implementing the Geneva Emotion Wheel due to its -1 to 1 range.

These two factors combined to require a moderate re-geometricalisation of the Geneva Emotion Wheel, which we undertook with the following design paradigms. Firstly, that maintaining symmetry across both axes was of paramount importance, as it was that symmetry which defined the proportional connections between the two inputs and any given basic emotion. Secondly, that proportionality between the magnitude of the trapezoidal maxima and the trailing edges should be maintained; and, associatedly, that the difference between the lowermost and uppermost boundaries of the secondary membership functions should equal the length of the maximum of the primary membership function. And, lastly, that the coordinates should as closely match those used in type-1 Scherer as possible, within the constraints of the above.

To that end, we determined the vertices of our type-2 fuzzy sets, included in table 6.15. In this table, the first four coordinates indicate the lowermost secondary membership boundary of a given type-2 fuzzy set's lower bound, the lower maximum of that lower bound, the upper maximum of that lower bound, and the uppermost secondary membership boundary of that lower bound, respectively. The fifth and sixth coordinates indicate the lower and upper maxima, respectively, of the primary membership trapezoid. The seventh through tenth coordinates mirror the first through fourth, but define the upper bound of the type-2 fuzzy set.

In addition to this, the user interface of the DMU T-2 FLT required the inclusion of values to represent the division of the trapezoidal, vertical slices of the secondary membership region. The system automatically determined the upper bounds of the secondary membership region to be 1 for the duration of the primary membership function's upper boundary. We opted to set the other boundaries at 0.8, 0.7, and 0.5, these being the upper maximum, lower maximum, and lower boundary, respectively.

Having defined the actual input data, we converted that input data back into de-facto coordinates from the perspective of the type-1 Scherer implementation, in order to facilitate more straightfoward comparison. These conversions are included in table 6.16.

Considering input variable x, the boundaries of the type-2 membership functions associated with Valence are shown in figure 6.22. This is included to provide the reader with a better understanding of the significantly increased complexity necessary in the representation of the Geneva Emotion

Table 6.15: Type 2 Scherer: Actual Vertices of Input MFs

1	-0.18	-0.14	-0.10	-0.06	0.00	0.12	0.18	0.22	0.26	0.30
2	-0.12	-0.08	-0.04	0.00	0.06	0.18	0.24	0.28	0.32	0.36
3	-0.02	0.01	0.05	0.08	0.13	0.22	0.27	0.30	0.34	0.37
4	0.01	0.05	0.09	0.13	0.19	0.31	0.37	0.41	0.45	0.49
5	0.03	0.06	0.10	0.13	0.18	0.27	0.32	0.35	0.39	0.42
6	0.12	0.15	0.19	0.22	0.27	0.37	0.42	0.45	0.49	0.52
7	0.15	0.17	0.19	0.21	0.24	0.31	0.34	0.36	0.38	0.40
8	0.18	0.20	0.22	0.24	0.27	0.34	0.37	0.39	0.41	0.43
9	0.17	0.21	0.25	0.29	0.35	0.47	0.53	0.57	0.61	0.65
10	0.25	0.27	0.29	0.31	0.34	0.41	0.44	0.46	0.48	0.50
11	0.26	0.27	0.29	0.30	0.33	0.37	0.40	0.41	0.43	0.44
12	0.24	0.27	0.31	0.34	0.39	0.48	0.53	0.56	0.60	0.63
13	0.28	0.29	0.31	0.32	0.35	0.39	0.42	0.43	0.45	0.46
14	0.32	0.33	0.35	0.36	0.39	0.43	0.46	0.47	0.49	0.50
15	0.33	0.35	0.37	0.39	0.42	0.49	0.52	0.54	0.56	0.58
16	0.38	0.39	0.41	0.42	0.45	0.49	0.52	0.53	0.55	0.56
17	0.35	0.39	0.43	0.47	0.53	0.65	0.71	0.75	0.79	0.83
18	0.37	0.40	0.44	0.47	0.52	0.61	0.66	0.69	0.73	0.76
19	0.42	0.44	0.46	0.48	0.51	0.58	0.61	0.63	0.65	0.67
20	0.44	0.45	0.47	0.48	0.51	0.55	0.58	0.59	0.61	0.62
21	0.50	0.51	0.53	0.54	0.57	0.61	0.64	0.65	0.67	0.68
22	0.50	0.52	0.54	0.56	0.59	0.66	0.69	0.71	0.73	0.75
23	0.48	0.51	0.55	0.58	0.63	0.73	0.78	0.81	0.85	0.88
24	0.54	0.55	0.57	0.58	0.61	0.65	0.68	0.69	0.71	0.72
25	0.51	0.55	0.59	0.63	0.69	0.81	0.87	0.91	0.95	0.99
26	0.56	0.57	0.59	0.60	0.63	0.67	0.70	0.71	0.73	0.74
27	0.57	0.59	0.61	0.63	0.66	0.73	0.76	0.78	0.80	0.82
28	0.60	0.62	0.64	0.66	0.69	0.76	0.79	0.81	0.83	0.85
29	0.58	0.61	0.65	0.68	0.73	0.82	0.87	0.90	0.94	0.97
30	0.63	0.66	0.70	0.73	0.78	0.87	0.92	0.95	0.99	1.02
31	0.64	0.68	0.72	0.76	0.82	0.94	1.00	1.04	1.08	1.12
32	0.70	0.74	0.78	0.82	0.88	1.00	1.06	1.10	1.14	1.18
33	0.26	0.30	0.34	0.38	0.44	0.56	0.62	0.66	0.70	0.74

Wheel in type-2 fuzzy logic. A more readily comprehensible example of a single input type-2 membership function, defining x_{33}, included as figure 6.23. It is a reasonable representation of what a given function would look like, scaling notwithstanding, and should hopefully allow the reader a clearer mental image of the overall structure of the input membership functions as a whole.

Having implemented the inputs, we move on to discussion of how we implemented the outputs. Each of the sixteen outputs was geometrically identical to its fellows. One benefit the DMU T-2 FLT had over the MATLAB

Table 6.16: Type 2 Scherer: Effective Vertices of Input MFs

1	-1.36	-1.28	-1.2	-1.12	-1.00	-0.76	-0.64	-0.56	-0.48	-0.40
2	-1.24	-1.16	-1.08	-1.00	-0.88	-0.64	-0.52	-0.44	-0.36	-0.28
3	-1.04	-0.98	-0.90	-0.84	-0.74	-0.56	-0.46	-0.40	-0.32	-0.26
4	-0.98	-0.90	-0.82	-0.74	-0.62	-0.38	-0.26	-0.18	-0.10	-0.02
5	-0.94	-0.88	-0.80	-0.74	-0.64	-0.46	-0.36	-0.30	-0.22	-0.16
6	-0.76	-0.70	-0.62	-0.56	-0.46	-0.26	-0.16	-0.10	-0.02	0.04
7	-0.70	-0.66	-0.62	-0.58	-0.52	-0.38	-0.32	-0.28	-0.24	-0.20
8	-0.64	-0.60	-0.56	-0.52	-0.46	-0.32	-0.26	-0.22	-0.18	-0.14
9	-0.66	-0.58	-0.50	-0.42	-0.30	-0.06	0.06	0.14	0.22	0.30
10	-0.50	-0.46	-0.42	-0.38	-0.32	-0.18	-0.12	-0.08	-0.04	0.00
11	-0.48	-0.46	-0.42	-0.40	-0.34	-0.26	-0.20	-0.18	-0.14	-0.12
12	-0.52	-0.46	-0.38	-0.32	-0.22	-0.04	0.06	0.12	0.20	0.26
13	-0.44	-0.42	-0.38	-0.36	-0.30	-0.22	-0.16	-0.14	-0.10	-0.08
14	-0.36	-0.34	-0.30	-0.28	-0.22	-0.14	-0.08	-0.06	-0.02	0.00
15	-0.34	-0.30	-0.26	-0.22	-0.16	-0.02	0.04	0.08	0.12	0.16
16	-0.24	-0.22	-0.18	-0.16	-0.10	-0.02	0.04	0.06	0.10	0.12
17	-0.30	-0.22	-0.14	-0.06	0.06	0.30	0.42	0.50	0.58	0.66
18	-0.26	-0.20	-0.12	-0.06	0.04	0.22	0.32	0.38	0.46	0.52
19	-0.16	-0.12	-0.08	-0.04	0.02	0.16	0.22	0.26	0.30	0.34
20	-0.12	-0.10	-0.06	-0.04	0.02	0.10	0.16	0.18	0.22	0.24
21	0.00	0.02	0.06	0.08	0.14	0.22	0.28	0.30	0.34	0.36
22	0.00	0.04	0.08	0.12	0.18	0.32	0.38	0.42	0.46	0.50
23	-0.04	0.02	0.10	0.16	0.26	0.46	0.56	0.62	0.70	0.76
24	0.08	0.10	0.14	0.16	0.22	0.30	0.36	0.38	0.42	0.44
25	0.02	0.10	0.18	0.26	0.38	0.62	0.74	0.82	0.90	0.98
26	0.12	0.14	0.18	0.20	0.26	0.34	0.40	0.42	0.46	0.48
27	0.14	0.18	0.22	0.26	0.32	0.46	0.52	0.56	0.60	0.64
28	0.20	0.24	0.28	0.32	0.38	0.52	0.58	0.62	0.66	0.70
29	0.16	0.22	0.30	0.36	0.46	0.64	0.74	0.80	0.88	0.94
30	0.26	0.32	0.40	0.46	0.56	0.74	0.84	0.90	0.98	1.04
31	0.28	0.36	0.44	0.52	0.64	0.88	1.00	1.08	1.16	1.24
32	0.40	0.48	0.56	0.64	0.76	1.00	1.12	1.2	1.28	1.36
33	-0.48	-0.40	-0.32	-0.24	-0.12	0.12	0.24	0.32	0.40	0.48

Fuzzy Logic Toolbox was its ability to return zero memberships for rules providing null surface area. As such, there was no requirement to include the 'corrective' level of intensity that we discussed earlier in this chapter as regards the type-1 implementation of the Geneva Emotion Wheel.

Let us consider the output variable $e_{\text{Happiness}}$. Geometric analogue in the context of output variables with respect to the type-1 implementation was easier to maintain, due to their boundaries matching the intrinsic boundaries of the DMU T-2 FLT user interface. The vertices of $e_{\text{Happiness}}$, and by extension those of all sixteen output variables, are given in table 6.17. Figures

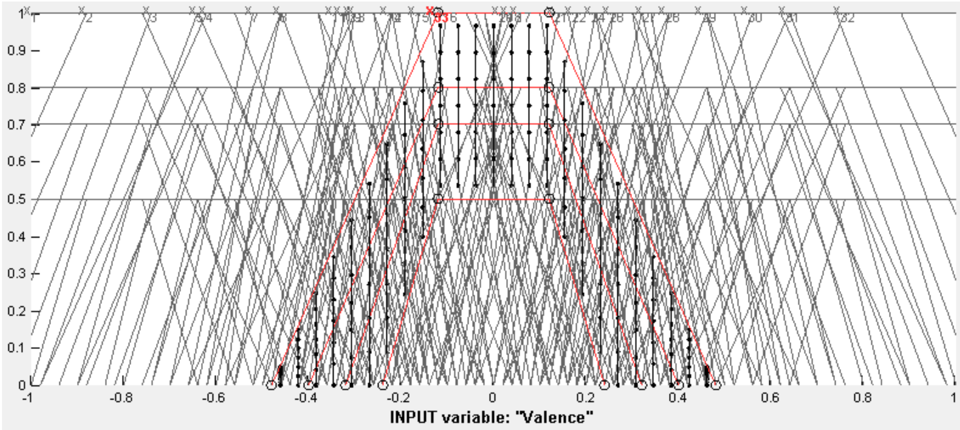

Figure 6.22: Type 2 Scherer: Membership Functions Associated with Valence

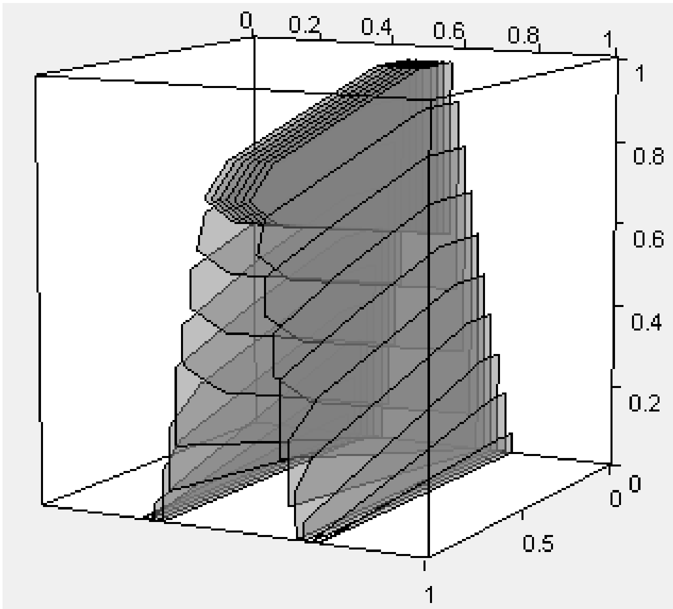

Figure 6.23: Type 2 Scherer: Membership Function Associated with x_{33}, the Central Region

Table 6.17: Type-2 Scherer: Output MFs

Null Int	0.00	0.00	0.00	0.00	0.00	0.10	0.17	0.19	0.21	0.23
Low Int	0.02	0.04	0.06	0.08	0.15	0.30	0.37	0.39	0.41	0.43
Mid Int	0.27	0.29	0.31	0.33	0.40	0.55	0.62	0.64	0.66	0.68
High Int	0.52	0.54	0.56	0.58	0.65	0.80	0.87	0.89	0.91	0.93
Ext Int	0.77	0.79	0.81	0.83	0.90	1.00	1.00	1.00	1.00	1.00

6.24 and 6.25 give a clearer view as to the graphical format generated from table 6.17.

The rules base for this implementation remained consistant with that listed in tables 6.8 and 6.9, in order to maintain consistency with the psychological model and, again, to facilitate more direct comparison between

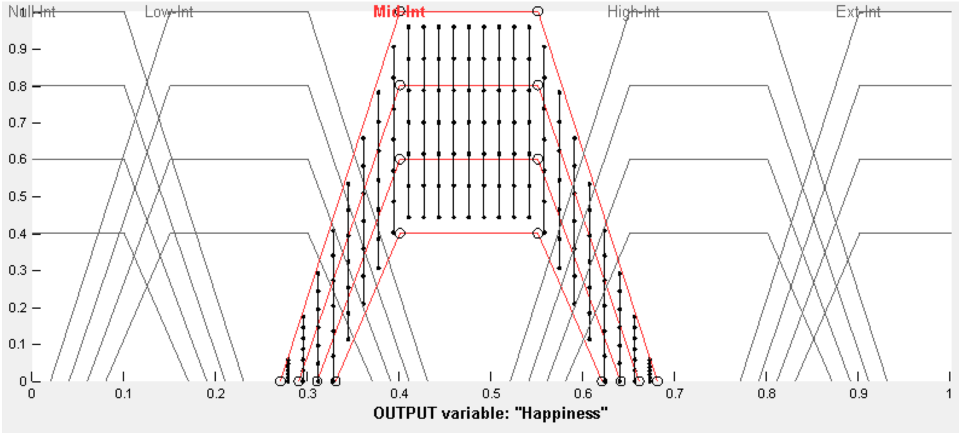

Figure 6.24: Type 2 Scherer: Membership Functions Associated with Happiness

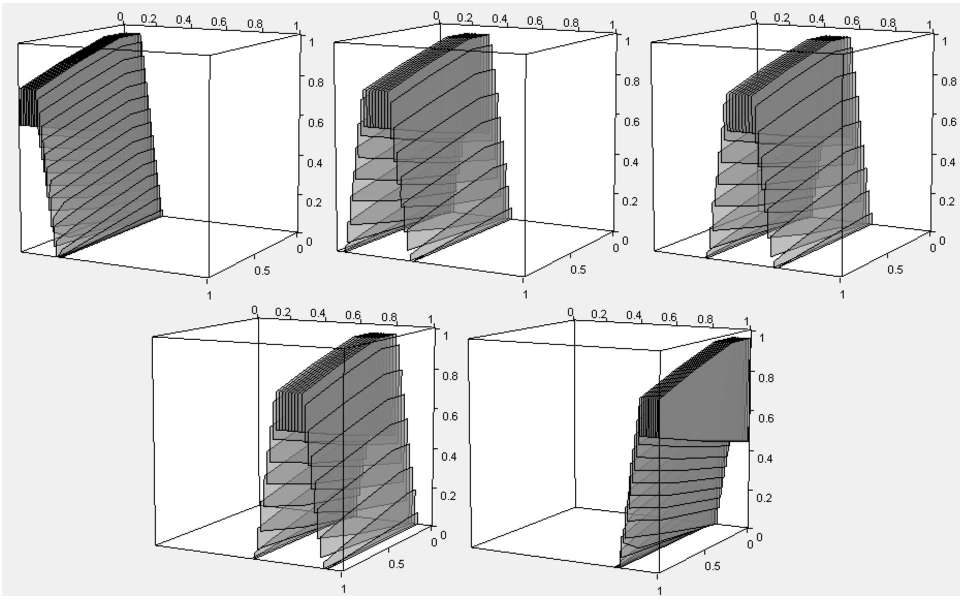

Figure 6.25: Type 2 Scherer: Detailed Membership Functions Associated with Happiness

type-1 and type-2 implementations of the Geneva Emotion Wheel.

As was mentioned at the start of this chapter, the implementation described here was never successfully tested. This was due to an issue with a GUI-based limitation of the DMU T-2 FLT, and the fact that the system was not initially designed to serve the sixteen outputs required by the Geneva Emotion Wheel. When testing of the implementation began, it became clear that it would be impossible to obtain the necessary data from the system, as only three or four of the output memberships would be displayed, often those returning 0 membership. We shall discuss the impact this had upon the project later in this report, particularly in the context of future work.

Chapter 7

Experiments

7.1 Chapter Overview

The chapter first presents, in the context of each psychological theory, the specific testing its implementations underwent. This begins with Millenson, discussing the comparable testing applied to all implementations, both type-1 and type-2, then progresses into discussion of the Geneva Emotion Wheel.

Subsequent to this, each individual implementation is analysed in the context of the testing results. Type-1 Millenson implementations are discussed first, followed by both type-2 Millenson systems. The type-1 Geneva Emotion Wheel implementation is then discussed in light of its testing results. While notable results are highlighted in the sections that follow, exhaustive compilations of experimental results are included in the appendices.

7.2 Testing Overview

All testing discussed in this Chapter, relating to both type-1 and type-2 fuzzy logic implementations, took place within the MATLAB Technical Computing Environment.

For the testing of type-1 Millenson A, type-1 Millenson B and type-1 Scherer, M-files were written to automate the process of data acquisition. These M-files are included in Appendix A. All of these tests were repeated three times in order to ensure consistency and veracity of numerical outputs. These results were then verified manually, using the MATLAB Fuzzy Logic Toolbox user interface.

For the testing of type-2 Millenson A and type-2 Millenson B, automation was impossible and, as such, all experiments had to be performed manually. Each set of experiments was repeated three times for the same reasons as those indicated above, with a fourth iteration of manual testing being used for verification purposes. All manual tests used the De Montfort University Type-2 Fuzzy Logic Toolbox's graphical user interface within the MATLAB Technical Computing Environment.

We divided our testing into several forms. While the specifics of each are outlined in their respective sections, we present a brief overview here by way of introduction. The first form of testing was initial defect testing, as defined by Sommerville [92], designed to determine at the most basic level whether the implementations accepted data within their specified ranges. This could be considered analogous to an aspect of Black Box Testing called Boundary

Value Analysis [39].

The second form of testing was a White Box defect test, whereby a very wide range of potential inputs within the accepted ranges of each implementation were utilised to obtain a database of emotional states. The purpose of this testing was to ensure that the data provided by each implementation was meaningful in a broader, psychological context, undertaken in consideration of the functional workings of the system [39].

The final set of tests selected specific, test case inputs analysed in the second set of experiments and used them to examine the behaviour of each implementation in terms of chained events, in the Black Box context of pure functionality [39]. Further to this, these tests would form the basis of cross-implementation comparison and, as such, were required to focus upon conceptually uniform features shared by both psychological theories. These tests were the most complex to design and require the greatest level of preface here.

Millenson's nine basic emotions were clearly defined for implementations using his theory; but there was not significant overlap between his list of basic emotions and those of Scherer. Indeed, the two theories only share three common 'basic' emotions: Elation, Anxiety and Anger. Importantly, however, each of these three represented a different axis with respect to Millenson. By extension, in the context of Millenson A, they represented to a degree all nine of Millenson's basic emotions (following on from our discussions regarding the linguistic use of 'intensity' in prior Chapters).

Thus it was determined that our contextual testing would revolve around these three basic emotions, and combinations thereof, in a manner explicitly defined in the following sections.

7.3 Testing Methodologies

In this section we outline in explicit terms the testing methodologies applied to the five implementations that were analysed over the course of this work, divided by the psychological theories that spawned them.

7.3.1 Millenson Testing

Due to the uniformity of the nature of our four implementations of Millenson's emotion theory, divided as they are into two interpretations of his linguistics, their modes of testing are theoretically consistent. As such, these can be addressed simultaneously, limiting the need for repetition.

Where necessary, differences are highlighted. Numerical data is used sparingly in this section, as it is more rightfully featured later in this Chapter and in Chapter Eight as each implementation's testing results are individually analysed. Where numerical data is included, it applies to all four implementations of Millenson's theory.

Boundary Value Analysis Testing

This testing was designed to examine the reliability of each software implementation from a technical, rather than psychological, standpoint.

It was determined that testing both within and without the accepted range of data should be performed on type-1 systems, and testing only within the accepted range with type-2 systems, the DMU T-2 FLT being unable to input values outside of the specified limits. Sommerville tells us that wherever possible, where user input is required, a system should be tested with both correct and incorrect input [92].

For all implementations of Millenson, acceptable input and output values ranged from 0 to 1. It was determined that increments of 10 percent of the system's range should be utilised, this being 0.1 in all cases. It was further asserted that each axis of each implementation should be tested independently, in order to confirm correlation between associated input and output variables, and to establish independence of unassociated input and output variables.

For each input variable of each implementation, thirteen incremental values were tested using an automated M-File. Given the implementation input lower boundary was stipulated to be 0, and the upper boundary was stipulated to be 1, the following list of input values was applied to each of the three input variables, for each implementation: -0.1, 0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1.

Each input value was tested for each axis three times, for a total of 117 autonomous experiments per type-1 implementation, and 117 manual experiments per type-2 implementation. A further 39 manual experiments per implementation were performed to ensure consistency of the data, for a total of 624 tests across the four Millenson implementations. Each test obtained a resultant value of $\mathbf{E_J}$, the analyses of which are discussed in Chapter Eight.

Analysis of White Box Defect Testing

This testing was designed to obtain a list of emotional states generated by the four implementations of Millenson's psychological theory, for discussion in a meaningful, psychological context. Sommerville reminds us that a truly "exhaustive" test is impossible [92], thus this test sought to provide a broad view of the capacities of the system, and not an exhaustive view.

This should not be taken to mean that the analysis of each result shall be discussed in this work, but rather that results that were inconsistent with the intent of the model shall be highlighted and discussed individually during our analysis section. Lack of such shall also be discussed in a similar fashion.

The view was maintained that increments of 10 percent would provide an acceptable overview of trends within all four systems. The testing here being psychological in nature, testing beyond the boundaries of the system would not yield useful results. It was determined to run every combination and permutation of possible increments for the three input variables within that 10 percent limitation, for all four implementations.

The crisp input values were defined as: 0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0.

This experimentation generated 1331 potential inputs for the systems, leading to 1331 discrete outputs of $\mathbf{E_J}$ for each. The experimentation was repeated three times, autonomously, for each type-1 implementation, and manually for each type-2 implementation. A final manual test was performed across all implementations to ensure veracity of the results, for a total of 21,296 experiments in all.

Exhaustive results of the experimental results are included as an appendix, though we omit duplicated experiments in this document except where it highlights some error in the system, whereby it would be discussed in the Analysis sections of this Chapter and in Chapter Eight.

Black Box Test Cases

As discussed previously, the conceptual testing within this work was designed to provide a platform of comparison between the five implementations discussed in this Chapter, as well as facilitate a better understanding of the 'real-world' behaviours of those implementations.

To that end, three values of $\mathbf{J}$ were selected that represented the membership maxima of Elation, Anger and Anxiety, respectively. The limitations upon their selection were:

- That they represented values of **J** that possessed the lowest numerical values of the associated axis at which obtaining maximum membership of the named emotion was possible.
- That they represented values of **J** that minimised membership of all other emotions as far as possible.

These three articles of testing data were obtained for each implementation of the Millenson theory, and represented half of the testing data required for our considerations.

Further to this, three additional values of **J** were selected to represent hybrid-pairs of named emotions, these being Elation-Anger, Anger-Anxiety, and Anxiety-Elation. The limitations upon their selection were:

- That they represented values of **J** that generated the highest membership of both emotions within the hybrid-pair that it was possible to obtain within the system.
- That, aside from restrictions placed by the above condition, they represented values of **J** that minimised the membership of any emotions not named in their pairing.

In total, this provided six testing data for each implementation of Millenson. In determining our testing data we referred to the results obtained over the course of the exhaustive testing for each implementation.

Having obtained testing data for each implementation, the testing process itself was uniform. Each testing datum was determined to represent a stimulus that defined its associated emotion, or hybrid-pair of emotions, from the perspective of the agent. Each was applied to its associated implementation of the Millenson model and used to generate, respectively, six values of $\mathbf{E_J}$. These values of $\mathbf{E_J}$ were mapped to $\mathbf{E_M}$ to define six starting states.

Each starting state was exposed to one of the values of $\mathbf{E_J}$ ten times, using the unweighted mean method to determine resultant $\mathbf{E_M}$ at $t + 1$. These results were recorded over time. That starting state would then be exposed to another of the $\mathbf{E_J}$ values ten times; and so on, until it had been exposed to all five other testing data.

Where these experiments related to type-1 implementations of Millenson's theory, they were largely automated for three runs each, with one subsequent manual run for sake of veracity. Where they related to type-2 implementations, all three runs of experiments were performed manually, as well as a fourth control run. This provided a total of 480 experiments.

7.3.2 Geneva Emotion Wheel Testing

Where the previous section outlines the testing for four of the fuzzy-logic based emotion models presented in this work, this section covers only the testing specific to our type-1 implementation of the Geneva Emotion Wheel. In the interests of meaningful comparison, these tests were designed to mirror those performed upon our implementations of Millenson's theory, but the structure of the models is different enough to warrant seperate discussion with respect to the specifics of the testing.

Boundary Value Analysis Testing

As before, this testing was designed purely around the basis of determining reliability of the software from a computational perspective. Maintaining analogue with the tests upon the Millenson implementations, it was determined that testing both within and without the accepted range of data should be performed. It was decided that each axis of the implementation should be tested independently, with the tangential axis being set at its lowermost boundary of -1. It was determined that increments of 5 percent of the system's range should be utilised.

This differed from the 10 percent used in Millenson for two reasons. Firstly, with significantly greater number of membership functions, and a higher number of total emotions, divided between fewer inputs, it was hypothesised that the type-1 Scherer implementation would be more susceptible to smaller incremental changes than either Millenson model. Secondly, the Scherer model's circumplexial nature spread its range of data in both positive and negative directions, allowing numerical consistency to be maintained if relative magnitude were amended.

Twenty-three input values were applied to each axis, twenty-one within the boundaries, and two without. These were: -1.1, -1.0, -0.9, -0.8, -0.7, -0.6, -0.5, -0.4, -0.3, -0.2, -0.1, 0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1

Both axes were tested, and the tests were performed three times using an autonomous M-file, for a total of 138 experiments. The results of these experiments are included in Appendix B, and are discussed in the Analysis section of this Chapter and in the subsequent Chapter.

Analysis of White Box Defect Testing

For the White Box defect testing segment with respect to the Geneva Emotion Wheel, we maintained the view that increments of 5 percent would provide an acceptable overview of trends within the comapratively delicate and sensitive system. In addition, it was determined to run every combination and permutation of possible increments for the input variables x and y within that 5 percent limitation, for a total of 441 values of input vector $\mathbf{J}$, producing 441 distinct resultants for $\mathbf{E}'_{\mathbf{S}}$.

The purpose of this testing was to assess the implementation for consistency with the Geneva Emotion Wheel's psychology. The analysis performed upon the results is discussed in Chapter Eight. Again, not all resultant $\mathbf{E}'_{\mathbf{S}}$ vectors are explicitly analysed within this work, but all are included within Appendix B and were reviewed as a matter of course.

These experiments were performed autonomously three times to ensure veracity and numerical consistency of the results. A final run was performed manually to confirm that consistency, for a total of 1,764 experiments.

Black Box Test Cases

As with Millenson, the case testing of our Geneva Emotion Wheel implementation was designed to analyse the behaviour of an emotional state informed by the model over the course of time. Some consideration was given while devising these tests as to what they ought to seek to generate, meaning, should the tests be designed to give an overview of the Scherer implementation's performance in its own right, or should they instead be designed to facilitate ease of comparison between this implementation and the four Millenson implementations.

After considering attempts to define equivalence between additional discrete emotions within the two models, it was determined instead that contextual testing would revolve entirely around the three shared emotions, and the appropriate hybrid-pairs of those emotions. Explicitly: Elation, Anger, Anxiety, Elation-Anger, Anger-Anxiety, and Anxiety-Elation.

That being decided, three values of **J** were selected that represented the membership maxima of Elation, Anger and Anxiety, respectively. The limitations upon their selection were:

- That they represented values of **J** that possessed the lowest numerical values of the associated axis at which obtaining maximum membership of the named emotion was possible.
- That they represented values of **J** that minimised membership of all other emotions as far as possible.

Analogous with Millenson, a further two values of **J** were selected for the hybrid pairs Anger-Anxiety and Anger-Elation. The limitations upon their selection were:

- That they represented values of **J** that generated the highest summed membership of both emotions within the hybrid-pair that it was possible to obtain within the system, with neither having membership of zero. In such situations as two **J** vectors provide equal summed memberships, arbitrarily we give priority to the named emotions alphabetically.
- That, aside from restrictions placed by the above condition, they represented values of **J** that minimised the membership of any emotions not named in their pairing.

These limitations had greater meaning for the Geneva Emotion Wheel implementation than they did for any interpretation of Millenson, primarily due to the codependant nature of Scherer's axes. As such, it was a very real possibility that the highest point of both emotions within a pair would occur at a value of **J** that provided an even higher membership of an emotion not included within the pairing. Such situations are described in detail in the subsequent analysis section of this Chapter and in Chapter Eight.

The sixth testing datum provided by our implementation of the Scherer model is truly contextual. We recall that Millenson equated the concept of an Anxiety-Elation axial pairing with Guilt [94], as discussed in Chapter 2, while not including it as one of his nine basic emotions. The Geneva Emotion Wheel, by contrast, includes Shame/Guilt as a discrete emotion referenced both in our mathematical representation and subsequent implementation. As such, rather than choosing a value of **J** which nominally includes non-zero membership grades of Anxiety and Elation, we instead opt to select the value of **J** which yields the highest resultant value of $e_{\text{Shame/Guilt}}$, within the limits listed above in the context of the individual emotions Anger, Anxiety and Elation.

All of the experimental data was drawn from the results of the previous exhaustive testing.

Having obtained six testing data values of **J**, each was applied to the Geneva Emotion Wheel implementation, obtaining six values for $\mathbf{E'_S}$. From here, the experimentation was analogous to that performed using the Millenson contextual testing data, with each value of $\mathbf{E'_S}$ being exposed to the other five ten times in order to observe behaviour of the emotional state under reinforcement of a new environmental input.

The experiments were largely automated for the initial three runs, with a fourth run being performed manually for the sake of veracity of information. This led to a total of 120 experiments. These experiments are included within the appendices and notable results are discussed in-depth in the Analysis section, and in the context of comparisons between models.

7.4 Analysis

In this section we present key results of the tests outlined earlier in the Chapter. Excerpts from the testing results are included, where appropriate, to illustrate this analysis but in order to conserve space the bulk of the test results form Appendix B, accompanying this report.

In order, we first assess the performance of the type-1 implementation of Millenson A, followed by the type-1 implementation of Millenson B. Subsequent to this, we analyse the testing results of the type-2 implementation of Millenson A and the type-2 implementation of Millenson B. Lastly, we analyse the results of the type-1 implementation of the Geneva Emotion Wheel.

Comparisons of the performance of these implementations, along with analysis specifically of the contextual testing, is featured in Chapter Eight, rather than being explicitly discussed in this section.

Table 7.1: Type-1 Millenson A: Boundary Value Analysis Test Results

Input	$+	S-	S+$-
-0.1	Error	Error	Error
0.0	Success	Success	Success
0.1	Success	Success	Success
0.2	Success	Success	Success
0.3	Success	Success	Success
0.4	Success	Success	Success
0.5	Success	Success	Success
0.6	Success	Success	Success
0.7	Success	Success	Success
0.8	Success	Success	Success
0.9	Success	Success	Success
1.0	Success	Success	Success
1.1	Error	Error	Error

7.4.1 Type-1 Millenson A

We shall first discuss the results of the software engineering testing with respect to this implementation. Following that shall be discourse on the exhaustive tests and, subsequently, the contextual tests.

Boundary Value Analysis Testing Results

When performing these tests, our criteria for success were simple and direct; numerical results that did not include an error, whatever their meaning psychologically, constituted success; the exception being that any numerical result prompted in an axis not associated with the input axis being tested would also be considered an error. It was anticipated that intentionally applied inputs that fell outside the acceptable range of the system would return errors. The experiments were performed as outlined in the previous testing and, as anticipated, all repetitions yielded identical results.

Table 7.1 presents the results of this testing, across all three axes of the implementation. It should be noted that while inputs outside the accepted range of the system did produce numerical results, those results were prefaced by error warnings. As is evident from the table, these tests yielded successful results. The specific numerical results are discussed in context as a function of subsequent exhaustive testing.

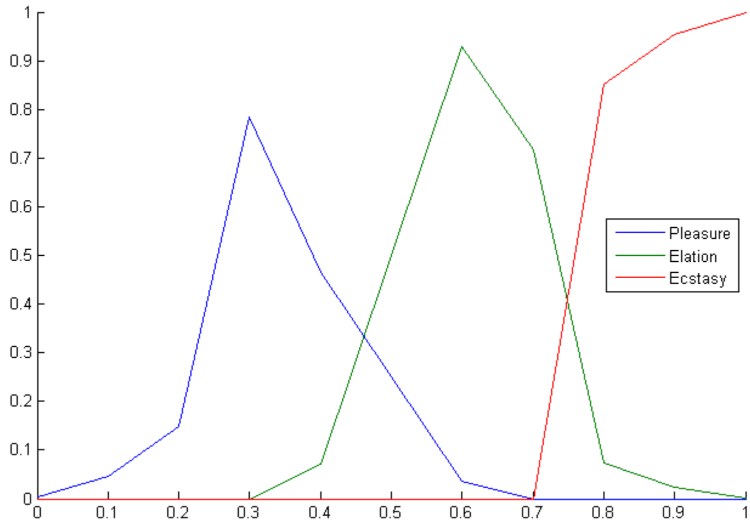

Figure 7.1: Type-1 Millenson A: Emotion Membership over S+\$- Value

Analysis of White Box Defect Testing

The White Box testing of this implementation of Millenson A confirmed several anticipated properties of the system that simplified analysis of the results considerably. The most important of these was identical and independant behaviour of the system across axes.

Let us consider a given numeric value n, input as the variable Z in $\mathbf{J}$ yielding specific membership values of z_1, z_2, and z_3. Were that value n applied to the variable Y, experimentation confirmed that the same specific membership values would be yielded as results for y_1, y_2, and y_3; and that the same pattern repeated for X.

As such, when analysing the behaviour of the system as a whole, we can consider solely a single input-output relationship, and extrapolate it across all three input-output relationships. That aside, this extrapolation was confirmed through careful analysis of the resultant data.

Let us consider the variable Z, associated as it is with the concepts $S{+}\$-$. Figure 7.1 shows the relationship between named emotional outputs and the input value of Z between 0 and 1. Table 7.2 provides this information in numerical terms.

For this axis of the model to function such that its behaviour matched our perceptions of the psychological theory upon which it is built, several features were required to be observed. Firstly, that at low, non-zero values of Z, μz_1 should be higher than μz_2 or μz_3. Secondly, that at around 60%, or 0.6, in accordance with the extrapolated geometry from Millenson's diagram,

Table 7.2: Type-1 Millenson A: White Box Test Results, S+\$- Variable

S+\$-	μz_1	μz_2	μz_3
0.0	0.0024481	0.0000000	0.0000000
0.1	0.0470330	0.0000000	0.0000000
0.2	0.1487400	0.0000000	0.0000000
0.3	0.7841200	0.0000000	0.0000000
0.4	0.4650200	0.0699550	0.0000000
0.5	0.2500000	0.5000000	0.0000000
0.6	0.0349780	0.9300400	0.0000000
0.7	0.0000000	0.7158800	0.0000000
0.8	0.0000000	0.0743690	0.8512600
0.9	0.0000000	0.0235160	0.9529700
1.0	0.0000000	0.0012240	0.9975500

μz_2 should be greater than μz_1 or μz_3. Thirdly, that as Z tends towards 1, μz_3 should be greater than μz_1 or μz_2.

These experiments demonstrated that for all values within the accepted system boundaries, the above three conditions were met. Furthermore, they were intrinsically assumed to be true for the other two axes, and explicitly verified to be so.

Psychologically, figure 7.1 demonstrates that for an agent whose emotional state is governed by this implementation, the addition of positive stimulus and removal of negative stimulus shall lead to greater levels of pleasure, and/or elation, and/or ecstasy. By extension, and through the manifold data provided in the appendices, this testing also demonstrates that for this implementation of Millenson A: the application of negative stimulus will lead to the agent's emotional state presenting higher levels of apprehension, anxiety, and/or terror; and, the removal of positive stimulus will lead to the agent's emotional state presenting higher levels of annoyance, anger and/or rage. In this, it demonstrates adherence to the psychology behind Millenson's theory.

Analysis of Test Cases

From our exhaustive tests, we determined appropriate values of $\mathbf{J}$ to meet the criteria presented earlier in the Chapter. These are presented in table 7.3, where the table includes: the associated emotion or hybrid-pairing, the $\mathbf{J}$ vector, and the associative emotional output, $\mathbf{E_J}$. We are reminded, from equation 4.22, that $\mathbf{E_J}$ is a column vector of nine elements, each between 0 and 1 in magnitude. The third column in table 7.3 presents these raw values as a horizontal vector of nine elements, for formatting reasons. The first

Table 7.3: Type-1 Millenson A: Test Case Data

Emotion	$\mathbf{J}$	$\mathbf{E_J}$
Anger	[0.6,0.0,0.0]	[0.035,0.930,0.000,0.000,0.000,0.000,0.000,0.000,0.000]
Anxiety	[0.0,0.6,0.0]	[0.000,0.000,0.000,0.035,0.930,0.000,0.000,0.000,0.000]
Elation	[0.0,0.0,0.6]	[0.000,0.000,0.000,0.000,0.000,0.000,0.035,0.930,0.000]
Ang-Anx	[0.6,0.6,0.0]	[0.035,0.930,0.000,0.035,0.930,0.000,0.000,0.000,0.000]
Ang-Ela	[0.6,0.0,0.6]	[0.035,0.930,0.000,0.000,0.000,0.000,0.035,0.930,0.000]
Anx-Ela	[0.0,0.6,0.6]	[0.000,0.000,0.000,0.035,0.930,0.000,0.035,0.930,0.000]

three selected emotional input vectors, $\mathbf{J}$, represent the points which generated maximum achievable values of Anger, Anxiety and Elation, respectively. The last three represent the points at which maximum achievable values of the pairings of Anger with Anxiety, Anger with Elation, and Anxiety with Elation, respectively, were obtained.

While tables are included within the appendices that record all of the contextual experimentation outlined in the previous section, for the purposes of this report we discuss solely the case of an agent beginning a scenario in a state of Anger. This agent then experiences stimuli that reinforce the Anxiety-Elation pairing which Millenson defines as representing Guilt [94].

In calculating $\mathbf{E_M}$ from $\mathbf{E_J}$, we take a mean value of the summed emotion memberships. We justify this in consideration of Ekman's assertion that, except in cases of complex emotional plots, emotions are brief and do not linger [25]. By giving a new emotional stimulus the same importance as the previous emotional state, we ensure that the system evolves with each iteration. Further to this, while we discuss iterations in terms of t, t itself has no discrete unit beyond cycles of the system. The nature of t, and any conclusions drawn regarding it, shall be discussed during the Critical Review.

Figure 7.2 presents the values of $\mathbf{E_M}$ generated by the type-1 implementation of Millenson's theory when an agent in an angered state is serially exposed to stimulus events prompting an Anxiety-Elation pairing response. Importantly, this illustrates the compound nature of emotional outputs we expect to be generated by representations of Millenson's psychological theory. We recall in particular that Millenson described 'Guilt' as a complex emotion including both elation and anxiety components; the emotional state of the system is similarly complex in its output. The experiment covered ten iterations, and only emotions possessing non-zero memberships are shown. Table 7.4 presents the numerical values creating figure 7.2, considering only non-trivial memberships; the exhaustive list upon which this figure is based is included within the appendices.

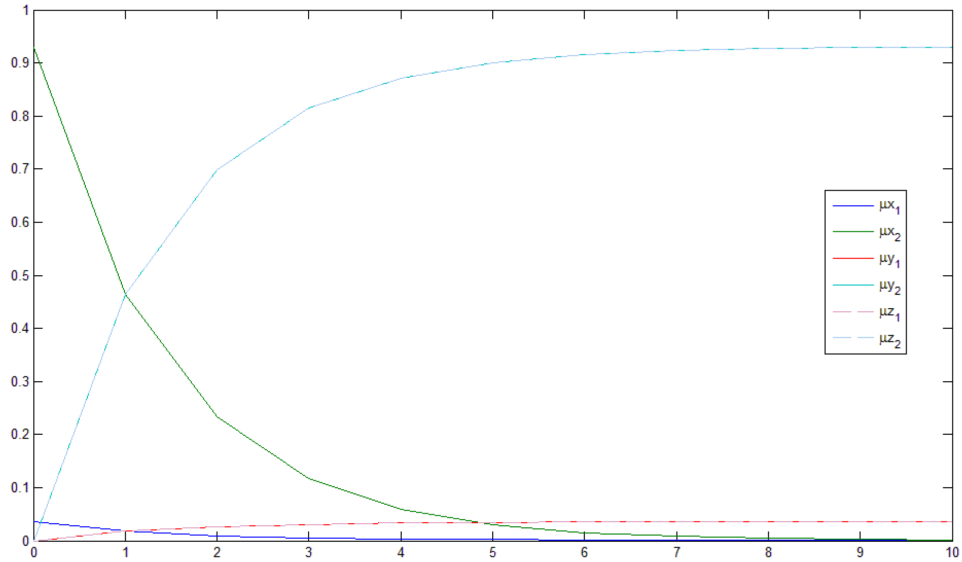

Figure 7.2: Type-1 Millenson A: Emotion Membership over t Iterations

Table 7.4: Type-1 Millenson A: Emotion Membership over t Iterations

t	μx_1	μx_2	μy_1	μy_2	μz_1	μz_2
0	0.035	0.930	0.000	0.000	0.000	0.000
1	0.018	0.465	0.018	0.465	0.018	0.465
2	0.009	0.233	0.027	0.698	0.027	0.698
3	0.005	0.117	0.031	0.814	0.031	0.814
4	0.003	0.059	0.033	0.872	0.033	0.872
5	0.002	0.030	0.034	0.901	0.034	0.901
6	0.001	0.015	0.035	0.916	0.035	0.916
7	0.001	0.008	0.035	0.923	0.035	0.923
8	0.001	0.004	0.035	0.927	0.035	0.927
9	0.001	0.002	0.035	0.929	0.035	0.929
10	0.001	0.001	0.035	0.930	0.035	0.930

Examining figure 7.2, we see that by the second iteration, as is expected, the reinforced stimulus event **J** has caused Anger and Annoyance to decrease below the intensity of Apprehension, Anxiety, Pleasure and Elation. The exponential relationships shown in figure 7.2 are to be expected, given the arithmetic upon which they are based (explained more fully in Chapter Four). That said, the purpose of these tests is to place the outputs generated by this implementation into context as an evolving model of emotions, which these results demonstrate is thoroughly feasible.

Table 7.5: Type-1 Millenson B: Boundary Value Analysis Test Results

Input	$+	S-	S+$-
-0.1	Error	Error	Error
0.0	Success	Success	Success
0.1	Success	Success	Success
0.2	Success	Success	Success
0.3	Success	Success	Success
0.4	Success	Success	Success
0.5	Success	Success	Success
0.6	Success	Success	Success
0.7	Success	Success	Success
0.8	Success	Success	Success
0.9	Success	Success	Success
1.0	Success	Success	Success
1.1	Error	Error	Error

7.4.2 Type-1 Millenson B

We shall initially address the results of the software engineering testing applied to this implementation. After that shall be consideration of the exhaustive testing results and, subsequently, the contextual tests.

Boundary Value Analysis Testing Results

The same success criteria as were applied to the previous implementation's Black Box defect testing also applied here. For all inputs within the specified operational range of the system, a numerical return was considered a success. An error was defined as an input that prompted an error message in the MATLAB Technical Computing Environment, or an input that prompted numerical changes in outputs to which it was not causally associated. Error results were anticipated for all inputs outside the specified operational range of the system.

The experiments were performed on all three axes as outlined previously within this Chapter, and as anticipated all repetitions yielded identical results. The results themselves are included in table 7.5.

Again, it should be noted that while inputs outside the specified range of the system produced numerical outputs, these were prefaced by error warnings. The implementation performed as anticipated, successfully functioning within the limits of its range. The specific numerical results are included as part of the exhaustive testing section of the appendices, and where appro-

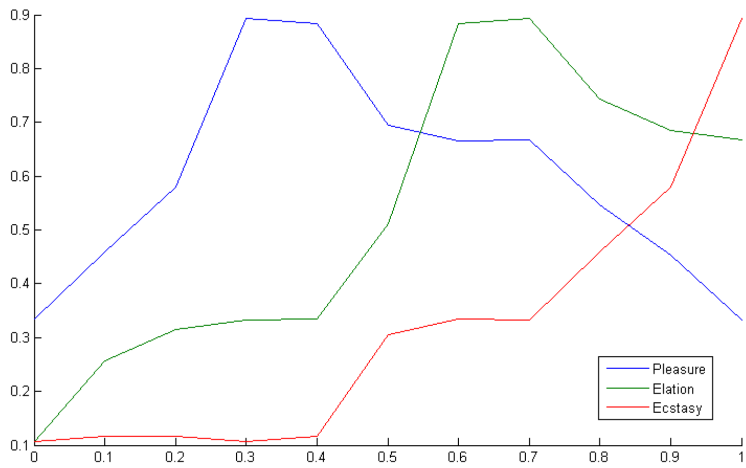

Figure 7.3: Type-1 Millenson B: Emotion Membership over S+$- Value

Table 7.6: Type-1 Millenson B: White Box Test Results, S+$- Variable

S+$-	Pleasure	Elation	Ecstasy
0.0	0.33333	0.10667	0.10667
0.1	0.45999	0.2571	0.11644
0.2	0.57938	0.3147	0.11644
0.3	0.89333	0.33333	0.10667
0.4	0.88356	0.3336	0.11644
0.5	0.69501	0.5109	0.30499
0.6	0.6664	0.88356	0.3336
0.7	0.66667	0.89333	0.33333
0.8	0.54577	0.7429	0.45999
0.9	0.45423	0.6853	0.57938
1.0	0.33333	0.66667	0.89333

priate are discussed in the subsequent analysis.

Analysis of White Box Defect Testing

As should be inferred from our discussion of the Type-1 implementation of Millenson A, the independence of the three axes permits us to discuss the performance of the system in the context of a single axis and project that onto the other three. Of course, all analysis we include is borne out by discrete examination of the results obtained for all three variables. This independence has been explicitly clarified in Section 2.1.2.

Let us consider the variable Z. Figure 7.3 shows the relationship between membership of named emotional outputs and the input value of Z between 0 and 1. Table 7.6 provides this information in numerical terms.

It is clear from the initial data that, importantly, there are no points within operational range of the system where all three named emotions do not provide non-zero results. This is a marked change with respect to the Millenson A interpretation, which assumed that there were no input stimuli in which both Pleasure and Ecstasy might be provoked simultaneously (although, as is discussed in the Critical Review section, this does not preclude the agent's emotional state at any given instant from containing non-zero memberships of both).

For this axis of the model to function such that its behaviour matched our perceptions of the psychological theory upon which it is built, as was the case with Millenson A, several criteria had to be met by the test results. Firstly, that at low, non-zero values of Z, μz_1 should be higher than μz_2 or μz_3. Secondly, that at around 60%, or 0.6, in accordance with the extrapolated geometry from Millenson's diagram, μz_2 should be greater than μz_1 or μz_3. Thirdly, that as Z tends towards 1, μz_3 should be greater than μz_1 or μz_2.

This testing demonstrated that for all tested input values between the stipulated operational limits of the system, the above criteria were met. As such, we infer that for any given acceptable input, the implementation functioned in accordance with Millenson's theory of emotions. Explicit comparison of this implementation and our other implementations is included later, and discusses in-depth different perspectives regarding the manner in which the psychology is obeyed.

Analysis of Test Cases

Our exhaustive testing permitted us to determine appropriate values of $\mathbf{J}$ in accordance with the criteria stipulated earlier in the Chapter. We present these in table 7.7. The table includes the associated emotion or hybrid-pairing, the $\mathbf{J}$ vector, and the respective emotional output vector of each, $\mathbf{E_J}$. Again, we are reminded that the structure of $\mathbf{E_J}$, as defined in equation 4.22, is that of a nine element vector with values between 0 and 1. As was the case with Millenson A, the selected vectors $\mathbf{J}$ were those which generated the values of $\mathbf{E_J}$ representing maximum membership of the emotions or emotion pairings they were intended to trigger.

As with the type-1 implementation of Millenson A, we consider for the purposes of this report the scenario of an agent beginning the simulation in a state defined by our testing data as Angry. It is then subject to reinforced stimulus prompting a reaction defined by our testing data as a hybrid of Anxiety and Elation, which we have previously described as analogous to

Table 7.7: Type-1 Millenson B: Test Case Data

Emotion	**J**	$\mathbf{E_J}$
Anger	[0.7,0.0,0.0]	[0.667,0.893,0.334,0.333,0.107,0.107,0.333,0.107,0.107]
Anxiety	[0.0,0.7,0.0]	[0.333,0.107,0.107,0.667,0.893,0.334,0.333,0.107,0.107]
Elation	[0.0,0.0,0.7]	[0.333,0.107,0.107,0.333,0.107,0.107,0.667,0.893,0.334]
Ang-Anx	[0.7,0.7,0.0]	[0.667,0.893,0.334,0.667,0.893,0.334,0.333,0.107,0.107]
Ang-Ela	[0.7,0.0,0.7]	[0.667,0.893,0.334,0.333,0.107,0.107,0.667,0.893,0.334]
Anx-Ela	[0.0,0.7,0.7]	[0.333,0.107,0.107,0.667,0.893,0.334,0.667,0.893,0.334]

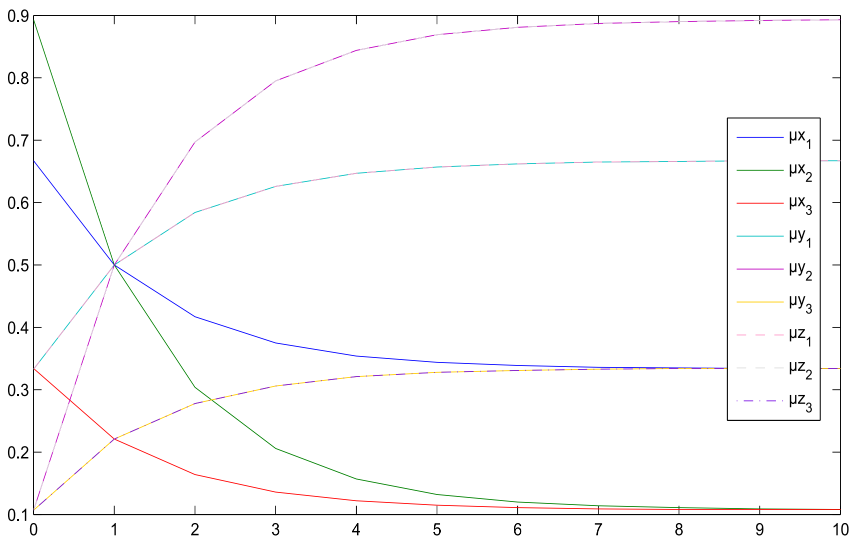

Figure 7.4: Type-1 Millenson B: Emotion Membership over t Iterations

Guilt. This stimulus is applied for 10 iterations, using the unweighted mean approach as described in Chapter Four. Figure 7.4 provides a graphical representation of the change in basic emotion membership over the course of the simulation, while table 7.8 provides, for clarity, the numerical values upon which the figure is based. Again, we are mindful of the complex nature of the emotional output shown in figure 7.4, conveying as it does the application of a complex emotion to stimulate changes to a model defined by nine basic emotions.

The figure demonstrates, as expected, an exponential decrease in the three emotions associated with \$+. By the second iteration, the initially dominant emotion of Anger has only marginally greater membership than the lowermost Anxiety- and Elation-related basic emotions. Interestingly, the loss in membership of Anger occurs at a far steeper angle than the loss in membership of Annoyance. While this is naturally a function of the lower bounds of the membership grades, as seen in the previous exhaustive testing,

Table 7.8: Type-1 Millenson B: Emotion Membership over t Iterations

t	μx_1	μx_2	μx_3	μy_1	μy_2	μy_3	μz_1	μz_2	μz_3
0	0.667	0.893	0.334	0.333	0.107	0.107	0.333	0.107	0.107
1	0.500	0.500	0.221	0.500	0.500	0.221	0.500	0.500	0.221
2	0.417	0.304	0.164	0.584	0.697	0.278	0.584	0.697	0.278
3	0.375	0.206	0.136	0.626	0.795	0.306	0.626	0.795	0.306
4	0.354	0.157	0.122	0.647	0.844	0.321	0.647	0.844	0.321
5	0.344	0.132	0.115	0.657	0.869	0.328	0.657	0.869	0.328
6	0.339	0.120	0.111	0.662	0.881	0.331	0.662	0.881	0.331
7	0.336	0.114	0.109	0.665	0.887	0.333	0.665	0.887	0.333
8	0.335	0.111	0.108	0.666	0.890	0.334	0.666	0.890	0.334
9	0.334	0.109	0.108	0.667	0.892	0.334	0.667	0.892	0.334
10	0.334	0.108	0.108	0.667	0.893	0.334	0.667	0.893	0.334

this has the interesting psychological consequence that higher order emotions trail off quicker than those of a lower order.

In the context of our simulation, while the agent's anger subsides as it begins to feel 'Guilt', it still feels a given level of Annoyance at its situation ultimately equal to its experience of Terror and Ecstasy. In addition, by the end of the simulation the emotions with the lowest membership are Rage, which began as the third highest, and Anger, which began as the highest.

The above clarified, this contextual testing demonstrates adherence to the psychology of the model it is built upon. In addition, this implementation makes solid use of the features of fuzzy logic, providing non-zero membership grades for all emotions at all times, without dampening the psychological grounding of the model. As in all cases, while we have directed our attentions to a single facet of the contextual experimentation, exhaustive results are included within the appendices.

7.4.3 Type-2 Millenson A

Firstly we shall address the results of the software engineering testing applied to this implementation. After that shall be consideration of the exhaustive testing results and, subsequently, the contextual tests.

Boundary Value Analysis Testing Results

Given that it was impossible to input a value to this implementation that lay outside of its accepted limits, Black Box defect testing was limited to ensuring that inputs within the limits provided a numerical return. The criteria given

Table 7.9: Type-2 Millenson A: Boundary Value Analysis Test Results

Input	\$+	S-	S+\$-
0.0	Success	Success	Success
0.1	Success	Success	Success
0.2	Success	Success	Success
0.3	Success	Success	Success
0.4	Success	Success	Success
0.5	Success	Success	Success
0.6	Success	Success	Success
0.7	Success	Success	Success
0.8	Success	Success	Success
0.9	Success	Success	Success
1.0	Success	Success	Success

for success were that a numerical result would constitute a success, unless it were prefaced by an error.

Within this type-2 implementation, each axis was processed completely independently. As such, it was impossible, for any reason, for the results of one axis to impinge upon the other two. This simplified the testing criteria significantly. Table 7.9 presents the results of this testing. As evidenced therein, the tests yielded successful results. Discourse of the numerical values of these results forms part of the analysis of Exhaustive Testing.

Analysis of White Box Defect Testing

As per previous discussions of Millenson testing, we explicitly present results for only one variable in this section, though the exhaustive results are included within the appendices and bear out the analysis we now outline. Figure 7.5 provides a graphical representation of the memberships of the named emotions Pleasure, Elation and Ecstasy, with respect to increasing value of the variable Z, defining the $S + \$-$ stimulus. Table 7.10 outlines figure 7.5 in numerical terms.

Our success criteria for the type-2 implementation of Millenson A were consistent with those of the type-1 implementation. In the context of the Z variable, the model would maintain psychological consistency if at 20% of range, z_1, or Pleasure, was the dominant emotion; if at 60% of range, z_2, or Elation, was the dominant emotion; and if, at 100% of range, Ecstasy was the dominant emotion.

All of these criteria are demonstrably met in the above results, and those results were mirrored across all three input variables. Psychologically speak-

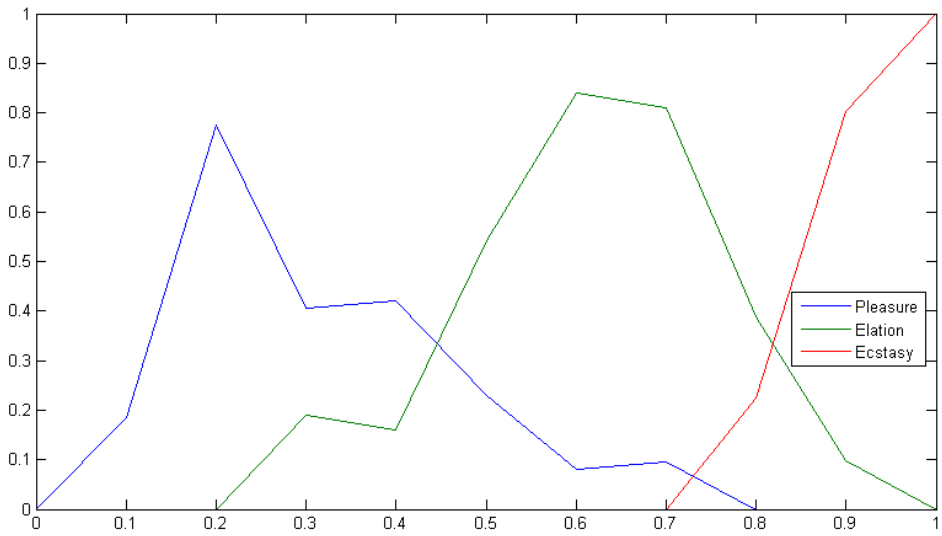

Figure 7.5: Type-2 Millenson A: Emotion Membership over S+$- Value

Table 7.10: Type-2 Millenson A: White Box Defect Test Results, S+$- Variable

S+$-	Pleasure	Elation	Ecstasy
0.0	0.0000	0.0000	0.0000
0.1	0.1860	0.0000	0.0000
0.2	0.7748	0.0000	0.0000
0.3	0.4050	0.1901	0.0000
0.4	0.4205	0.1591	0.0000
0.5	0.2293	0.5413	0.0000
0.6	0.0795	0.8409	0.0000
0.7	0.0950	0.8099	0.0000
0.8	0.0000	0.3874	0.2252
0.9	0.0000	0.0981	0.8037
1.0	0.0000	0.0000	1.0000

ing, however, there are more features to consider in our analysis of these results.

Importantly, the trends of increasing and decreasing membership of emotion are not ubiquitous across the model. If we consider the membership of z_1, Pleasure, at Z values of 0.3 and 0.4, respectively, we see a reversal of the downward trend following the main peak at 0.2, with μz_1 being slightly increased. This trend-reversal is repeated for Pleasure between Z values of 0.6 and 0.7. It is also present for Elation, in an inverted form, between the Z values of 0.3 and 0.4, whereby the initial increase in Elation as Z increases is stymied, temporarily, before resuming.

While this might run contrary to an obvious, causal approach to the interpretation of Z, it should be recognised that the inclusion of type-2 systems

Table 7.11: Type-2 Millenson A: Test Case Data

Emotion	$\mathbf{J}$	$\mathbf{E_J}$
Anger	[0.6,0.0,0.0]	[0.080,0.841,0.000,0.000,0.000,0.000,0.000,0.000,0.000]
Anxiety	[0.0,0.6,0.0]	[0.000,0.000,0.000,0.080,0.841,0.000,0.000,0.000,0.000]
Elation	[0.0,0.0,0.6]	[0.000,0.000,0.000,0.000,0.000,0.000,0.080,0.841,0.000]
Ang-Anx	[0.6,0.6,0.0]	[0.080,0.841,0.000,0.080,0.841,0.000,0.000,0.000,0.000]
Ang-Ela	[0.6,0.0,0.6]	[0.080,0.841,0.000,0.000,0.000,0.000,0.080,0.841,0.000]
Anx-Ela	[0.0,0.6,0.6]	[0.000,0.000,0.000,0.080,0.841,0.000,0.080,0.841,0.000]

was explicitly to increase uncertainty with respect to how an agent would react, emotionally, to given stimuli. The fact that our hypothetical agent might react with lower Elation to higher levels of positive stimulus, for example, could be considered a function of stimulus context and, albeit unexceptionally, agent reaction thereof. As should be expected, these interesting features of the implementation's behaviour were mirrored across all three axes.

Analysis of Test Cases

From the results obtained in our exhaustive testing, table 7.11 was obtained, listing the six testing data which best matched the criteria of selection. Table 7.11 presents the associated emotion or hybrid-pairing, the input vector $\mathbf{J}$, and the emotional output vector $\mathbf{E_J}$. We recall the structure of $\mathbf{E_J}$ from equation 4.22 as being a nine element vector of values ranging from 0 to 1, this structure remaining true in both the type 1 and type 2 fuzzy logic cases. As with the type 1 cases, the selected values of $\mathbf{J}$ presented in table 7.11 are those which demonstrated the highest membership of their associated named emotion or pairing of named emotions.

Uniform with previous explorations of this contextual testing, this report directs its attention to a single scenario. Within this scenario, an agent governed by the type-2 implementation of Millenson A begins its existance in a state of Anger. It is exposed to a stimulus event $\mathbf{J}$ defined in table 7.11 as 'Anx-Ela', or the Anxiety-Elation hybrid pairing, previously defined as 'Guilt'. This event is serially applied to the agent for ten system cycles or iterations.

Figure 7.6 shows in graphical terms the effect upon basic emotion membership caused by each iteration of this experiment, while table 7.12 provides the raw numerical data. Once again, this demonstrates the interactions of a complex emotion, comprised by definition of multiple basic emotions, upon a model defined by nine basic emotions. The impact on overall emotional state

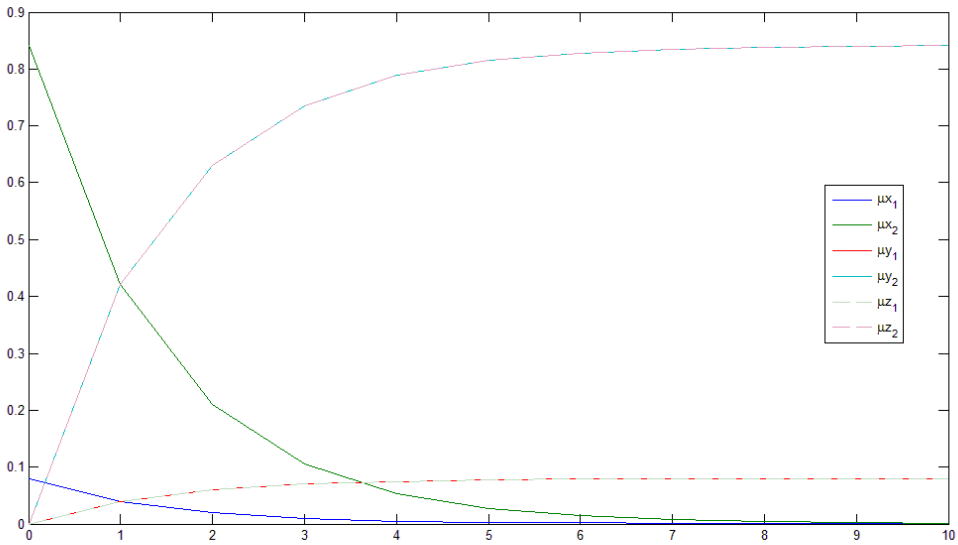

Figure 7.6: Type-2 Millenson A: Emotion Membership over t Iterations

Table 7.12: Type-2 Millenson A: Emotion Membership over t Iterations

t	μx_1	μx_2	μy_1	μy_2	μz_1	μz_2
0	0.080	0.841	0.000	0.000	0.000	0.000
1	0.040	0.421	0.040	0.421	0.040	0.421
2	0.020	0.211	0.060	0.631	0.060	0.631
3	0.010	0.106	0.070	0.736	0.070	0.736
4	0.005	0.053	0.075	0.789	0.075	0.789
5	0.003	0.027	0.078	0.815	0.078	0.815
6	0.002	0.014	0.079	0.828	0.079	0.828
7	0.001	0.007	0.080	0.835	0.080	0.835
8	0.001	0.004	0.080	0.838	0.080	0.838
9	0.001	0.002	0.080	0.840	0.080	0.840
10	0.001	0.001	0.080	0.841	0.080	0.841

is more pronounced when stimulated in complex fashion, as it affects multiple axes simultaneously. Note that neither include basic emotions unaffected by this experiment (those whose membership grades do not exceed 0 at any point during the test) for the sake of clarity. The exhaustive data, including trivial results, is included within the appendices.

As anticipated as a function of our averaging method, using unweighted means as outlined in Chapter Four, Anger has ceased to be the dominant emotion by the second iteration of the system. The membership values of Anxiety and Elation rise in tandem as a pair of exponents whose maxima naturally lie at 0.841, the membership that the stimulus event **J** being applied associates with them.

The lower order emotions Apprehension and Pleasure rise in like fashion,

Table 7.13: Type-2 Millenson B: Boundary Value Analysis Test Results

Input	\$+	S-	S+\$-
0.0	Success	Success	Success
0.1	Success	Success	Success
0.2	Success	Success	Success
0.3	Success	Success	Success
0.4	Success	Success	Success
0.5	Success	Success	Success
0.6	Success	Success	Success
0.7	Success	Success	Success
0.8	Success	Success	Success
0.9	Success	Success	Success
1.0	Success	Success	Success

while their gradient is mirrored by the descent of Annoyance. Annoyance and Anger possess the lowest non-zero memberships within the system by the fourth iteration, both tending towards zero as the simulation ends. Psychologically, this represents a pure application of Millenson's theory of emotion, whereby specific stimulus events lead to their associated emotions, and reinforcement of those events reinforces the emotional state.

7.4.4 Type-2 Millenson B

Here we present analysis of the testing performed upon the type-2 fuzzy logic implementation of the Millenson Model's second interpretation, which we dub Millenson B. We begin with analysis of the software engineering testing applied to the system, followed by discussion of results obtained in exhaustive testing and, subsequently, contextual testing of the system.

Boundary Value Analysis Testing

As with the type-2 implementation of Millenson A, it proved impossible to apply inputs to this implementation which fell outside its acceptable ranges. That being the case, in these tests success was defined as the return of a numerical result for a given input that was not preceded by an error. Table 7.13 provides the results of this testing.

By the success criteria, the system demonstrated absolute mechanical functionality. The numerical results themselves, and their psychological context, are discussed subsequently.

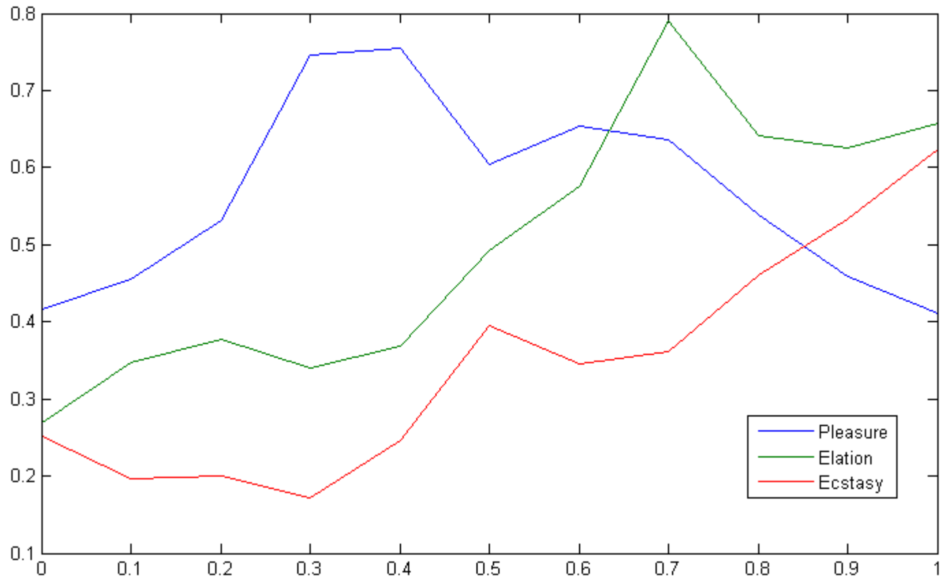

Figure 7.7: Type-2 Millenson B: Emotion Membership over S+$- Value

Table 7.14: Type-2 Millenson B: White Box Defect Test Results, S+$- Variable

S+$-	Pleasure	Elation	Ecstasy
0.0	0.416	0.269	0.252
0.1	0.455	0.347	0.196
0.2	0.531	0.377	0.200
0.3	0.746	0.340	0.171
0.4	0.754	0.369	0.246
0.5	0.605	0.492	0.395
0.6	0.653	0.576	0.346
0.7	0.636	0.791	0.361
0.8	0.539	0.641	0.460
0.9	0.459	0.625	0.533
1.0	0.411	0.658	0.623

Analysis of White Box Defect Testing

As previously in the context of Millenson, we explicitly present results for only one variable in this section, though the results bear out the analysis we now outline and are included within the appendices. Figure 7.7 provides a graphical representation of the memberships of the named emotions Pleasure, Elation and Ecstasy, with respect to increasing value of the variable Z, defining the $S + \$-$ stimulus, while table 7.14 outlines these results numerically.

Our success criteria for the type-2 implementation of Millenson B were consistent with those of the type-1 implementation. As regards the Z variable

Table 7.15: Type-2 Millenson B: Test Case Data

Emotion	$\mathbf{J}$	$\mathbf{E_J}$
Anger	[0.7,0.0,0.0]	[0.636,0.791,0.361,0.416,0.269,0.252,0.416,0.269,0.252]
Anxiety	[0.0,0.7,0.0]	[0.416,0.269,0.252,0.636,0.791,0.361,0.416,0.269,0.252]
Elation	[0.0,0.0,0.7]	[0.416,0.269,0.252,0.416,0.269,0.252,0.636,0.791,0.361]
Ang-Anx	[0.7,0.7,0.0]	[0.636,0.791,0.361,0.636,0.791,0.361,0.416,0.269,0.252]
Ang-Ela	[0.7,0.0,0.7]	[0.636,0.791,0.361,0.416,0.269,0.252,0.636,0.791,0.361]
Anx-Ela	[0.0,0.7,0.7]	[0.416,0.269,0.252,0.636,0.791,0.361,0.636,0.791,0.361]

considered here, the model would maintain psychological consistency if at 20% of range, z_1, or Pleasure, was the dominant emotion; if at 60% of range, z_2, or Elation, was the dominant emotion; and if, at 100% of range, Ecstasy was the dominant emotion.

This implementation failed to meet two of the above criteria. At 60%, Pleasure, and not Elation, was the dominant experienced emotion. At 100%, Elation, and not Ecstasy, was the dominant emotion. This pattern was repeated across all three axes, with the model always favouring lower order emotions, and the highest order emotion on any given axis never achieving dominance. In this sense, the implementation lost psychological analogue with Millenson's theory as presented. Potential solutions to this issue are discussed later. It was not felt that this failure should preclude this implementation from being subject to contextual testing and critical review.

Analysis of Test Cases

Six data were identified that satisfied our selection criteria for testing data. These are included in table 7.15. The table identifies the associated emotion or hybrid-pair, the input vector $\mathbf{J}$ and the emotional output $\mathbf{E_J}$. Again, we are mindful of the definition of $\mathbf{E_J}$ from equation 4.22 , which is suitably represented by the elements provided in the third column of table 7.15. Again, these values of $\mathbf{J}$ were selected in accordance with the stipulated criteria, representing the maximum obtained memberships of their associated emotions or pairs of emotions.

As with other implementations, while all proposed contextual experiments were performed and their results are included within the appendices, we direct our attentions in this report to a specific scenario. An agent governed by the type-2 implementation of Millenson B exists in a state defined by the stimulus event $\mathbf{J}$ identified as 'Anger' in table 7.15. It is subject to reinforcement of a 'Guilt' stimulus, represented by the Anxiety-Elation pair-

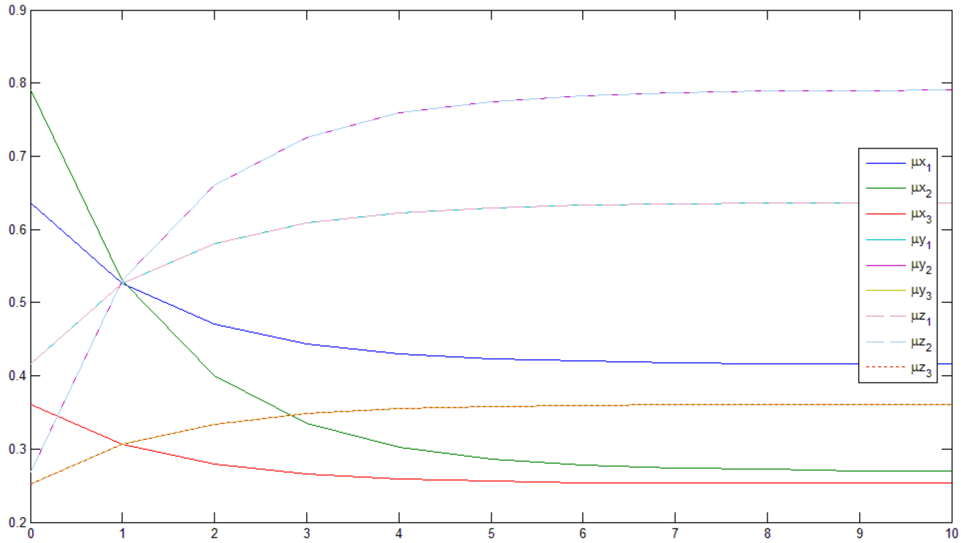

Figure 7.8: Type-2 Millenson B: Emotion Membership over t Iterations

Table 7.16: Type-2 Millenson B: Emotion Membership over t Iterations

t	μx_1	μx_2	μx_3	μy_1	μy_2	μy_3	μz_1	μz_2	μz_3
0	0.636	0.791	0.361	0.416	0.269	0.252	0.416	0.269	0.252
1	0.526	0.530	0.307	0.526	0.530	0.307	0.526	0.530	0.307
2	0.471	0.400	0.280	0.581	0.661	0.334	0.581	0.661	0.334
3	0.444	0.335	0.266	0.609	0.726	0.348	0.609	0.726	0.348
4	0.430	0.302	0.259	0.623	0.759	0.355	0.623	0.759	0.355
5	0.423	0.286	0.256	0.630	0.775	0.358	0.630	0.775	0.358
6	0.420	0.278	0.254	0.633	0.783	0.360	0.633	0.783	0.360
7	0.418	0.274	0.253	0.635	0.787	0.361	0.635	0.787	0.361
8	0.417	0.272	0.253	0.636	0.789	0.361	0.636	0.789	0.361
9	0.417	0.270	0.253	0.636	0.790	0.361	0.636	0.790	0.361
10	0.417	0.270	0.253	0.636	0.791	0.361	0.636	0.791	0.361

ing defined in the same table. For the purposes of our test, exposure lasts for ten system cycles or iterations.

Figure 7.8 graphically indicates the changes to basic emotion membership for each iteration of the experiment. Table 7.16 provides this data numerically for clarity.

The simulation begins with Anger as the dominant emotion, with Annoyance the next highest, and Pleasure and Apprehension sharing the third highest membership. Anger trails off with the steepest negative gradient, while Anxiety and Elation both increase with a mirrored positive gradient. Annoyance trails off with a shallower gradient, mirroring the rise in Apprehension and Pleasure.

By the second iteration, the membership of Anger only exceeds the memberships of Rage, Terror and Ecstasy, while Annoyance begins to plateau as the fifth highest membership. By the third iteration, Anger's membership has descended to the point where it only exceeds that of Rage. At the end of the simulation, both Elation and Anxiety have reached a plateau tending towards the maximum membership associated with the Anxiety-Elation **J** stimulus event.

By the final iteration, Annoyance possesses the highest membership of the emotions associated with the $+ axis. This indicates that under these constraints, higher order emotions trail off quicker than lower order emotions. While this is obviously a side-effect of the model's geometry combined with our method of obtaining $\mathbf{E_M}$, it is interesting, psychologically. It suggests a situation where, while our agent is primarily experiencing Anxiety and Elation, and their lower-order associated emotions Apprehension and Pleasure, the Anger it felt previously has been replaced by simple annoyance at its situation.

7.4.5 Type-1 Geneva Emotion Wheel

In this subsection we present analysis of results obtained in our testing of the type-1 fuzzy logic implementation of the Geneva Emotion Wheel. We begin with analysis of the software engineering testing results. Subsequently, we address the exhaustive testing applied to the implementation, followed by discourse regarding the contextual testing.

Boundary Value Analysis Testing

By necessity, the success criteria for the implementation of the Geneva Emotion Wheel were different to those applied to the Millenson implementations. Primarily, those differences lay in error definition as a function of the codependence present between the GEW's axes. We defined the criteria for success as follows: for any input values within the operational input range of the implementation, a numerical return was considered a success, saving in cases where it accompanied an error return in the MATLAB Technical Computing Environment. Error results were anticipated for all inputs outside the specified operational range of the system.

We recall that only one input variable was adjusted for each run of tests, the other being fixed at -1 for all experimental iterations. Table 7.17 presents the results of these tests under the header of the adjusted variable.

Table 7.17: Type-1 Geneva Emotion Wheel: Boundary Value Analysis Test Results

Input Value	x	y
-1.1	Error	Error
-1.0	Error	Error
-0.9	Error	Error
-0.8	Success	Success
-0.7	Success	Success
-0.6	Success	Success
-0.5	Success	Success
-0.4	Success	Success
-0.3	Success	Success
-0.2	Success	Success
-0.1	Success	Success
0.0	Success	Success
0.1	Success	Success
0.2	Success	Success
0.3	Success	Success
0.4	Success	Success
0.5	Success	Success
0.6	Success	Success
0.7	Success	Success
0.8	Success	Success
0.9	Error	Error
1.0	Error	Error
1.1	Error	Error

Of the 46 software engineering tests, 4 results returned unanticipated errors. These were present when the system was in a state of extremis, with one input at absolute minimum, and the variable input near or at absolute maximum or absolute minimum. Investigation revealed these to be a weakness in the implementation brought about by the manner in which the circumplexial geometry was represented in coordinates of x and y, coupled with the method the MATLAB Fuzzy Logic Toolbox handled inputs that provided no membership return.

While a significant weakness in the implementation, it was determined to proceed with exhaustive testing in order to determine the extent to which these anomalous results permeated the system. This flaw is considered both in the discussion of contextual testing results, and in the subsequent Critical Review.

Table 7.18: Type-1 Geneva Emotion Wheel: Error-Generating Values of **J**

x	y
1.0	1.0
1.0	0.9
1.0	-0.9
1.0	-1.0
0.9	1.0
0.9	0.9
0.9	-0.9
0.9	-1.0
-0.9	1.0
-0.9	0.9
-0.9	-0.9
-0.9	-1.0
-1.0	1.0
-1.0	0.9
-1.0	-0.9
-1.0	-1.0

Analysis of White Box Defect Testing

The list of results generated by the type-1 implementation of the Geneva Emotion Wheel is impractical to present in print format, far moreso than is the case with any implementation of the Millenson model. Indeed, even the representative ease with which an abridged version of Millenson can be presented is not manifest in the context of the Geneva Emotion Wheel. As such, discussion of these results will be more targeted and less abstract than in the prior cases. As always, an exhaustive list of results is provided within the appendices.

The first important result of experimentation with our implementation of the Geneva Emotion Wheel was the revelation of its weakness in cases of extremis. Specifically, 16 cases of the 441 tested input cases within operational limits of the system returned error results and a value of 0.5 membership for all sixteen basic emotions. This provided an inherent error probability of 3.6% in scenarios where the probability distribution of input values was uniform across the range. The list of **J** values at which this error occured is included as table 7.18. These results are included in the appendices, but not discussed further in our assessment of the psychological soundness of the implementation.

These aberrations aside, the fuzzy geometry used in the representation of the Geneva Emotion Wheel demonstrated interesting behaviour when con-

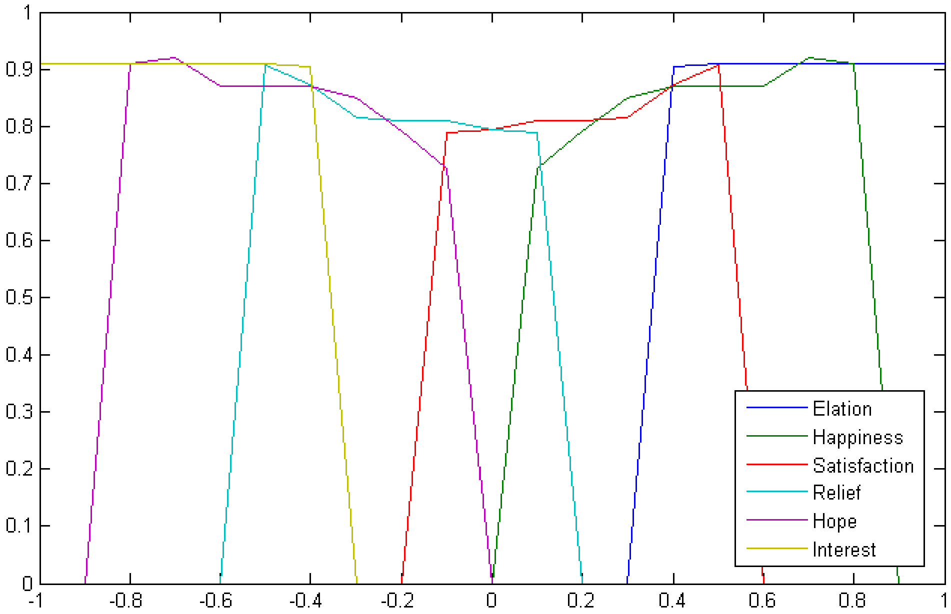

Figure 7.9: Type-1 Geneva Emotion Wheel: Cross-Section vs. Control, Valence Fixed @ 0.8

sidered across a range of named emotions with similar ratios of Valence to Control. Rather than discuss exhaustive results in the context of each named emotion, as is possible with Millenson, instead we focus upon four cross-sections and the implications of the non-trivial results each presents. In each case, the figures represent membership grades for the named emotions at the input values presented, with one input value remaining static while the other varies across the range.

Figure 7.9 presents an example where Valence is fixed at 0.8, and Control varied from -1.0 to 1.0. Figure 7.10 presents its corrollary, Control fixed at 0.8 while Valence varies from -1.0 to 1.0. In an effort to provide additional evidence of the implementation's behaviour, figure 7.11 presents emotion memberships where Valence is fixed at 0.5, with Control varied across the range of inputs. Similarly, figure 7.12 presents the corrollary, with Control fixed at 0.5 and Valence varied from -1.0 to 1.0.

The purpose of these figures is to demonstrate two things. Firstly, that the Scherer geometry is obeyed within the constraints of the model, and within the context in which the implementation is presented. Secondly, that the geometry is consistent inasmuch as behaviour is maintained across the operational region. Let us first consider figure 7.9.

Figure 7.9 presents a case where Valence is both positive and of high magnitude. That being the case, referring back to Figure 2.2, and taking

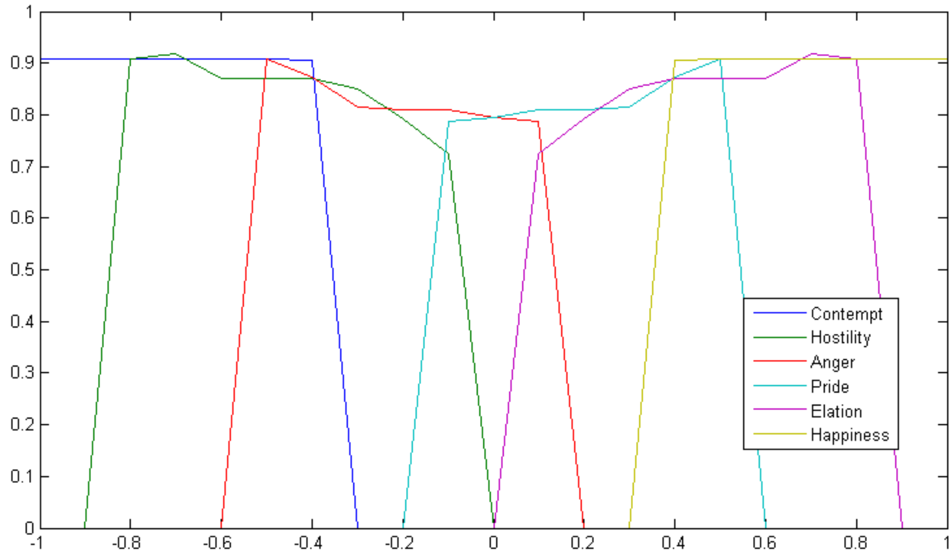

Figure 7.10: Type-1 Geneva Emotion Wheel: Cross-Section vs. Valence, Control Fixed @ 0.8

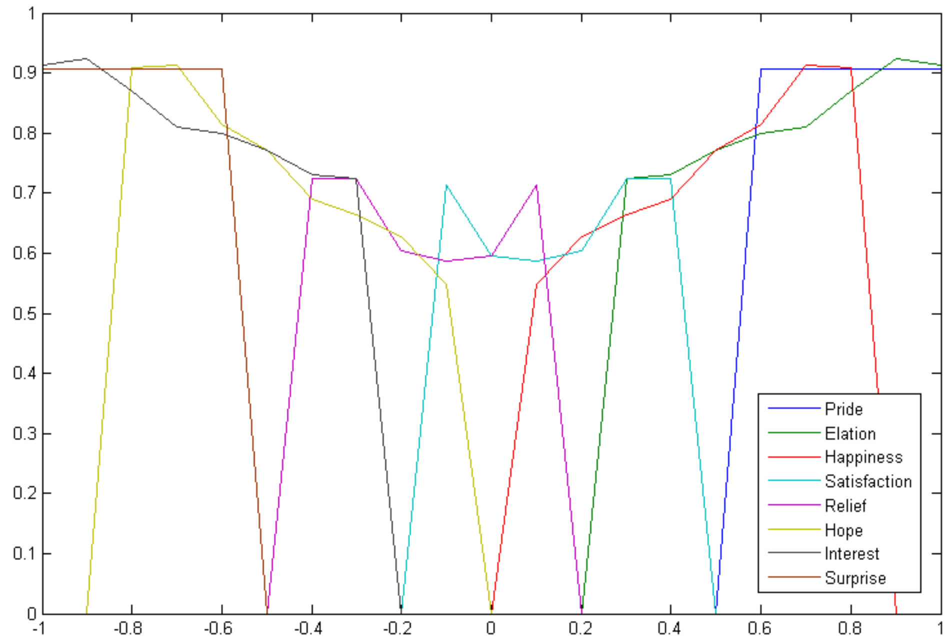

Figure 7.11: Type-1 Geneva Emotion Wheel: Cross-Section vs. Control, Valence Fixed @ 0.5

into account the trailing edges of our fuzzy geometry, we should expect the emotions triggered by a variance in Control across the range to be Elation, Happiness, Satisfaction, Relief, Hope and Interest. Figure 7.9 confirms that to be the case.

A quick examination of figure 7.9 confirms several key features. Firstly, that the emotions triggered follow the Geneva Emotion Wheel geometry in abstract terms. That is to say, Interest, being the emotion in the above

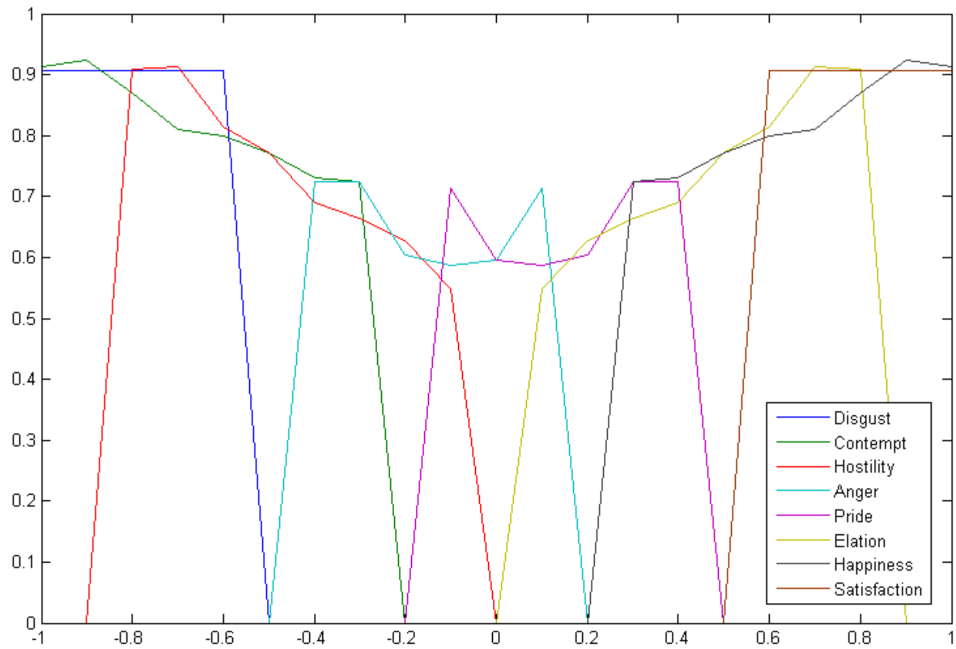

Figure 7.12: Type-1 Geneva Emotion Wheel: Cross-Section vs. Valence, Control Fixed @ 0.5

list associated with the lowest relative Control, is triggered at lower levels of Control than any other. Similarly, the order of triggering follows the geometry of the Geneva Emotion Wheel.

Secondly, figure 7.9 demonstrates symmetrical membership relationships for emotions across the midpoint of the Control range. This is important from a consistency perspective. The Geneva Emotion Wheel is a circumplex and, as such, any attempt to represent it geometrically must adhere to the symmetry inherent in its structure.

Lastly, the application of fuzzy logic, and the nature and structure of our particular implementation, should give rise to situations where multiple emotions have non-zero memberships simultaneously. Note that unlike Millenson, Scherer does not include as a function of the Geneva Emotion Wheel's structure an intrinsic property of compound emotions. Rather, in this case, it is the fuzziness associated with environmental perception which gives rise to these complex solutions. Figure 7.9 demonstrates that the implementation provides such results, with over 80% of samples providing non-zero results for two or more named emotions.

Considering figure 7.10, the important features are predominantly shared with figure 7.9, save that figure 7.10 demonstrates through it's complete consistency with figure 7.9 that the symmetrical consistency is observed across both variables at the values presented. Once again, the named emotions triggered remain consistent with the structure outlined in figure 2.2, as is the order in which they are triggered.

Moving on to consider figure 7.11, we present the case where Valence is both positive and of middling magnitude. In this case, we would anticipate across the range of Control values, all eight emotions associated with positive Valence to be triggered to a certain degree, which is to say Pride, Elation, Happiness, Satisfaction, Relief, Hope, Interest and Surprise. Figure 7.11 confirm this to be the case.

Setting Valence as 0.5 prevents the *prima facae* analysis possible with figures 7.9 and 7.10 in terms of which emotions should be triggered at the highest intensity. As is shown when considering Surprise and Interest, it is Interest which enjoys a higher, earlier peak. This makes sense, however, when one considers the geometry of figure 2.2, whereby Interest more closely relates to a point of middling, positive Valence and extreme, negative Control.

Of particular interest are the membership spikes in Satisfaction and Relief, which occur when the point of input moves outside the third fuzzy region of each, while remaining within the extremes of the fourth, triggering a brief, sharp increase in membership. This is, again, a function of the squared membership functions that lie at the root of the aberrations discussed at the beginning of this subsection.

That aside, figure 7.11 behaves much as we would expect. Unlike the case in figure 7.9, there are no positions within figure 7.11 which provide less than two emotions non-zero memberships at any given time. This is a result supported by the structure of the Geneva Emotion Wheel's geometry, which demonstrates greater concentration of like emotions as input magnitude decreases. Similarly, in accordance with the geometry, membership of the named emotions behaves symmetrically about the Control midpoint.

Figure 7.12, as with figure 7.10, provides useful information in the context that it supports all of the previous assertions regarding figure 7.11, while at the same time verifying that the symmetry of behaviour remains consistent across both input variables. Again, this is important as it demonstrates geometrical consistency with the Geneva Emotion Wheel upon which our implementation is based.

Exhaustive results are included within the appendices, and they bear out our assertion that barring the 3.6% of cases where abberant results are produced, our implementation of the Geneva Emotion Wheel pays due deference to the psychological theory upon which it is built, and behaves as one would

Table 7.19: Type-1 Geneva Emotion Wheel: Contextual Testing Data

–	Anger	Anxiety	Elation	Ang-Anx	Ang-Ela	Guilt
x	-0.2	-0.2	0.6	-0.2	0.1	-1
y	1.0	-1.0	0.9	0.3	0.7	-0.1
μe_{Pride}	0.000	0.000	0.000	0.091	0.786	0.000
μe_{Elation}	0.000	0.000	0.923	0.091	0.725	0.000
$\mu e_{\text{Happiness}}$	0.000	0.000	0.000	0.091	0.000	0.000
$\mu e_{\text{Satisfaction}}$	0.000	0.000	0.000	0.091	0.000	0.000
μe_{Relief}	0.000	0.000	0.000	0.091	0.000	0.000
μe_{Hope}	0.000	0.000	0.000	0.091	0.000	0.000
μe_{Interest}	0.000	0.000	0.000	0.091	0.000	0.000
μe_{Surprise}	0.000	0.000	0.000	0.091	0.000	0.000
μe_{Anxiety}	0.000	0.925	0.000	0.091	0.000	0.000
μe_{Sadness}	0.000	0.908	0.000	0.091	0.000	0.000
μe_{Boredom}	0.000	0.000	0.000	0.091	0.000	0.000
$\mu e_{\text{Shame/Guilt}}$	0.000	0.000	0.000	0.091	0.000	0.925
μe_{Disgust}	0.000	0.000	0.000	0.091	0.000	0.910
μe_{Contempt}	0.000	0.000	0.000	0.234	0.000	0.000
$\mu e_{\text{Hostility}}$	0.908	0.000	0.000	0.373	0.000	0.000
μe_{Anger}	0.925	0.000	0.000	0.353	0.789	0.000

expect a representation of that theory to so do.

Analysis of Test Cases

In terms of this contextual testing, erroneous results discussed above were not considered when determining values of **J** which best satisfied the selection criteria. The six selected **J** vectors are outlined in table 7.19. The table includes the name of the emotion or hybrid-pairing represented, the x and y components of **J**, and the individual membership grades of the emotions that make up $\mathbf{E}'_{\mathbf{S}}$. We are mindful of the definition of $\mathbf{E}'_{\mathbf{S}}$, as presented in equation 4.39, being a column vector with sixteen elements, each with values ranging from 0 to 1. Table 7.19 presents each element of $\mathbf{E}'_{\mathbf{S}}$ explicitly, for the sake of clarity.

While all proposed permutations of contextual testing were performed, we direct our attentions to a single experiment for the purposes of this report. Complete numerical results of other contextual tests are included within the appendices.

The scenario we focus upon is that of an agent, whose emotional state is modelled by the type-1 implementation of the Geneva Emotion Wheel, beginning the simulation in an emotional state defined by the vector **J** identified

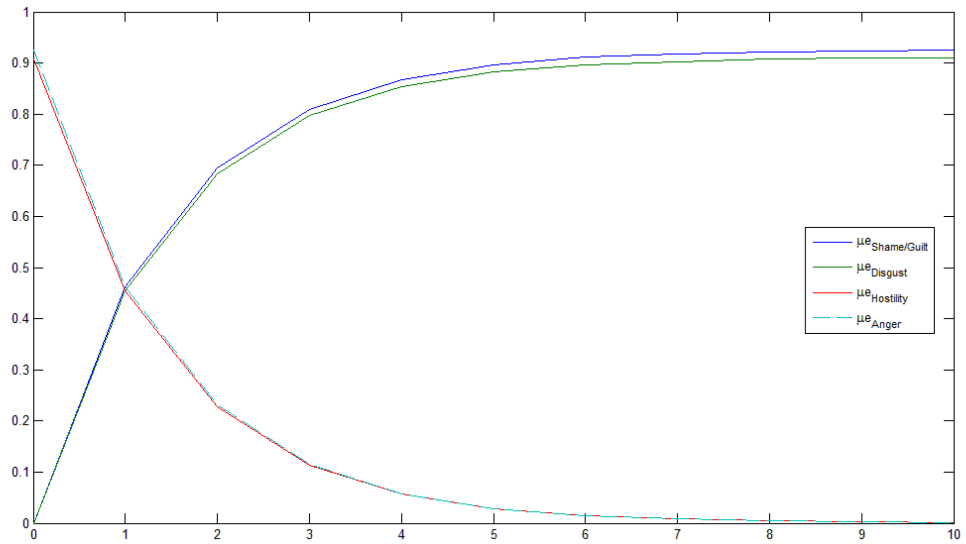

Figure 7.13: Type-1 Geneva Emotion Wheel: Emotion Membership over t Iterations

Table 7.20: Type-1 Geneva Emotion Wheel: Emotion Membership over t Iterations

t	$\mu e_{\text{Shame/Guilt}}$	μe_{Disgust}	$\mu e_{\text{Hostility}}$	μe_{Anger}
0	0.000	0.000	0.908	0.925
1	0.463	0.455	0.454	0.463
2	0.694	0.683	0.227	0.232
3	0.810	0.797	0.114	0.116
4	0.868	0.854	0.057	0.058
5	0.897	0.882	0.029	0.029
6	0.911	0.896	0.015	0.015
7	0.918	0.903	0.008	0.008
8	0.922	0.907	0.004	0.004
9	0.924	0.909	0.002	0.002
10	0.925	0.910	0.001	0.001

with Anger in table 7.19. This agent is serially exposed to environmental events defined by the input vector associated with 'Guilt' in the same table. The simulation continues for 10 system cycles, or iterations, using the unweighted mean method of determining $\mathbf{E_S}$ presented in Chapter Four.

Figure 7.13 provides a visual representation of non-trival elements of $\mathbf{E_S}$ (those elements with non-zero memberships), while table 7.20 provides this data in numerical form for clarity. The exhaustive values of $\mathbf{E_S}$ obtained during this experiment, including trivial memberships, are included within the appendices.

When the simulation begins, Anger possesses the highest membership grade within the system, narrowly superior to Hostility. Both Shame/Guilt and Disgust have zero membership. Within two iterations, Anger and Hostility have been overtaken by Shame/Guilt and Disgust, as should be expected from the method we use to determine $\mathbf{E_S}$. While Anger is initially of higher membership than Hostility, their memberships begin to descend along an identical gradient from the fifth iteration onwards. Conversely, the gap between Shame/Guilt and Disgust has widened by this point, there being a clear distinction between them despite the small difference in their membership grades.

This trend continues to the end of the simulation, with Shame/Guilt narrowly exceeding the membership of Disgust, and both Anger and Hostility tending towards zero. Psychologically, this provides an interesting insight into the application of the Geneva Emotion Wheel from a computational control perspective.

While other implementations discussed in this work generate axial families of emotions, our implementation of the Geneva Emotion Wheel does not; and, indeed, the Geneva Emotion Wheel's own geometry is designed such that axial families as a concept are anathema to its makeup. Instead, our implementation through fuzzy logic, requiring as it does the fuzzification of the boundaries of the individual emotions and their intensity markers, establishes a pattern of sympathetic emotional triggering.

This is particularly evident at mid-range values, as discussed in the exhaustive testing section of this work, but also as regards the contextual testing outlined here. An event that marks highest possible membership of Shame/Guilt shall also trigger a Disgust response. Psychologically, we could argue that this might represent disgust at the environmental situation that has prompted the agent to feel guilt, or indeed self-disgust on the part of the agent for performing whichever action has prompted the reinforced Shame/Guilt response.

Chapter 8

Critical Analysis

8.1 Chapter Overview

In this chapter we compare and contrast the type-1 implementations of the Millenson Theory and Geneva Emotion Wheel, with the type-2 implementations of the Millenson Theory. We discuss the strengths and weaknesses of each, both computationally and psychologically, in the context of the others. In so doing, we seek to draw conclusions about the work we have undertaken, and set direction for the future of this and similar efforts.

Considering the Millenson theory on its own for the time being, we first consider the behaviour of the implementations of Millenson A with the implementations of Millenson B. Subsequently, we discuss the differences in performance between the type-1 and type-2 implementations, and consider whether the addition of the layer of uncertainty provided by type-2 fuzzy logic benefited its implementations.

8.2 Comparison of Millenson A with Millenson B

First, let us consider the type-1 implementation of Millenson A. We are reminded of figure 7.1, defined by the elements of table 7.2. We are further reminded that the memberships provided may be projected across all three axes of the Millenson theory.

The relative surface areas beneath the three named emotions along an axis were calculated based on the area beneath the curve. This information is useful in determining the relative membership magnitudinal probabilities of the three emotions, which is to say how 'strongly' they are represented within the boundaries of the system.

In such terms, we choose to recognise the area under the Pleasure emotion, as calculated using the geometry of figure 7.1, as representing Unity. The justification for this assertion is to facilitate ease of comparison between the three named emotions, in the context of their relative membership densities. By assigning the value Unity to the area under the Pleasure emotion, we are able to draw comparison with the Elation and Ecstasy emotions in the context of the membership density they possess across the operational breadth of the system. The Elation emotion has a surface area, then, equal to 1.337 times Unity. The Ecstasy emotion, similarly, has a surface area equal to 1.330

times Unity.

In terms of chance of firing for random data input, however, we must instead consider range of non-zero values. Again, we choose to recognise the operational range of the Pleasure emotion as shown in figure 7.1 to signify Unity. In this case, the Elation emotion's active range is equal to Unity, while the Ecstasy emotion's active range is equal to 0.429 of Unity.

Taking both into consideration, the central emotion, Elation, which Millenson uses to describe the entire axis, is the most strongly represented for any given random input. By contrast Ecstasy, which is considered the extremis emotion, while having very great membership when fired is the least likely to be so for any random input.

The general shapes of the graphs display trends we anticipated on the basis of the two-tier nature of the Millenson A representation. In accordance with the limitations we sought to place upon the structure, lower-level emotions trail into higher-level emotions in terms of membership. That is to say that an Elation-response is more likely to trigger residual Pleasure than a Pleasure response is likely to trigger residual Elation.

Next, let us consider the type-1 implementation of Millenson B. Again, we first determine the relative surface area beneath the curve. Taking the area under the Pleasure curve as Unity, for the same reasons as outlined previously, we can determine the area under the Elation curve to be 0.865 of Unity, and the area under the Ecstasy curve to be 0.480 of Unity. There can be no comparison of range of relevance when considering the results provided by the Millenson B implementation as non-zero results are provided for all three named emotions across the entire operational range of the system.

Looking at the membership area, however, it is clear that the Millenson B implementation weights in favour of the lower-level emotions over the higher. In terms of trailing edges, this is visually apparent in the system when considering the length of the trailing edge of Pleasure relative to the leading edge of Ecstasy. It is also visible when comparing the descending trends of Elation with the ascending trends of Elation.

In order to permit a clearer comparison of the two type-1 implementations of the Millenson theory, figure 8.1 demonstrates a superposition of figures 7.1 and 7.3.

Moving to the type-2 representations of Millenson, let us first consider Millenson A. Considering the area under the membership curves, if we again

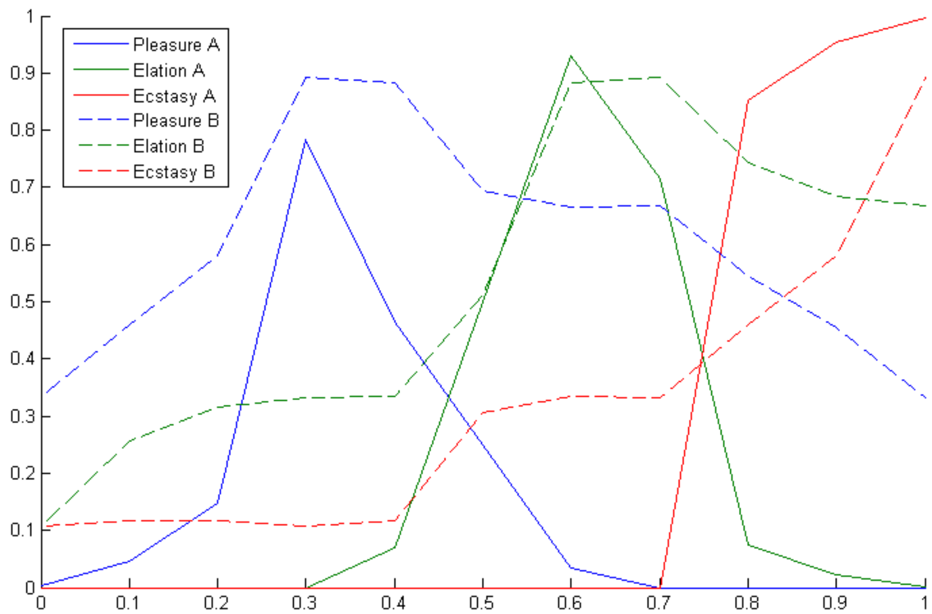

Figure 8.1: Type-1 Millenson A & B Membership of $S+\$$—-related Emotions for Increasing Z

define the area under the Pleasure curve as Unity, then Elation possesses an area equal to 1.382 of Unity, while the membership area of Ecstasy is 0.698 of Unity. Considering once again the operational input range of the implementation, defining the operational range of Pleasure as Unity, we see that the operational range of Elation is similarly Unity, and that the operational range of Ecstasy is 0.375 of Unity. In these aspects, the type-2 implementation of Millenson A adopts a similar shape to the type-1 implementation, to be expected given their shared two-tier nature.

Let us next consider the type-2 implementation of Millenson B. Taking the area under its Pleasure curve as Unity, then the membership area of Elation becomes 0.890 of Unity, and the membership area of Ecstasy becomes 0.649 of Unity. As a function of its shared characteristics with the type-1 implementation, comparison of active surface area is meaningless since non-zero results are provided for membership grades of all emotions associated with a given input. For ease of comparison, figure 8.2 is provided as a visual aid.

In overall terms, when comparing the behaviours of the two intepretations of Millenson's theory, it is appropriate that we consider their structural differences, in particular their rules structure. The key differences between the models come in two parts, rule structure and tier structure.

In the Millenson A implementations, each rule in the fuzzy inferencing

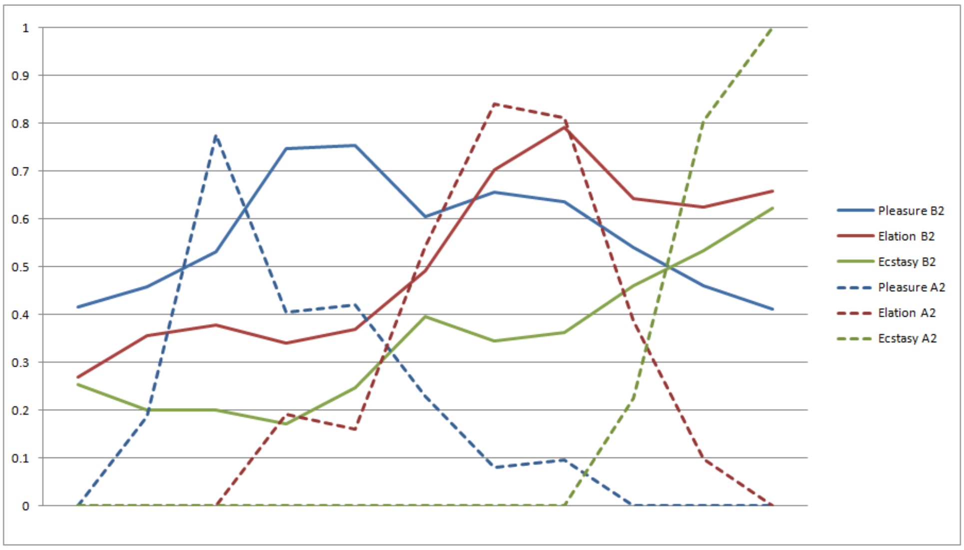

Figure 8.2: Type-2 Millenson A & B Membership of $S+$\$$-$-related Emotions for Increasing Z

system makes a connection between a single input and a single output. That is to say association is drawn between a specific input membership function, and a specific output membership function. In the Millenson B implementations, by contrast, each rule in the fuzzy inferencing system connects a specific input to three associated outputs, meaning that a connection is drawn between a specific input membership function and three output membership functions.

Similarly, while the Millenson B fuzzy inferencing system has an output for every named emotion, Millenson A produces instead a three-part vector which is then converted, geometrically, to generate values for the nine named emotions. This is the role of its second tier. Taking these differences into consideration, the magnitude of variation in the results should not be considered surprising.

A key and instantly discernable difference lies in the variety of compound emotional results presented by each implementation. While Millenson A never provides non-zero results for more than two named emotions, Millenson B provides non-zero results for all three named emotions at all times.

Connected to this are the differences in membership surface area between the two models. Summing the membership surface area of all three named emotions, and defining the summed surface area of the type-1 implementation of Millenson A results as Unity, the summed surface area of the type-1 Millenson B results would equate to 2.281 of Unity. Similarly for type-2, if the summed areas under the curves defined by type-2 Millenson A were defined as Unity, then the summed areas of the type-2 Millenson B results would equate to 2.120 of Unity.

This enables us to say that in average terms, for both modes of fuzzy logic, implementations of Millenson B shall return a higher summed membership across the three named emotions for a given input value.

Taking the global view, while both interpretations have justification in Millenson's theory, the broader-brush approach of Millenson B provides a greater variety in its psychological blend of emotions for a given stimulus event **J**. That said, the type-2 implementation of Millenson B failed to remain true to the criteria we set to determine adherence to the psychological theory. Millenson A, on the other hand, provides a narrower view as a function of a structure that minimises cases where all nine emotions fire, but both implementations met the criteria set for adherence to the psychological theory.

It could be argued, therefore, that both implementations of Millenson A would be suited to applications where knowledge of the dominant emotion generated by a stimulus event is the key aspect. As such, Millenson A might serve suitably as a governor for a finite state machine desirous of including an emotional component. Conversely, the type-1 implementation of Millenson B might be suitable for exploration of the effect of blends of emotions upon control of an agent's behaviour; indeed, this is explored in our subsequent chapter concerning prototyping.

8.3 Comparison of Type-1 and Type-2 Implementations

In consideration of the differing behaviours of our type-1 and type-2 systems, irrespective of their interpretation of Millenson's psychological theory, we return first to discussion of their membership areas. Rather than speaking in general terms of Unity, where Unity is defined by the implementation in question, however, we instead consider the raw numerical values of their summed membership areas. Table 8.1 provides this information in a relative scale, in the context of emotions associated with the $S+\$-$ axis, which may be projected onto both alternative axes. Figures 8.3 and 8.4 provide the comparative resultant memberships visually.

From these figures, we determine that despite the increased level of fuzzi-

Table 8.1: Membership Areas for Type-1 and Type-2 Implementations of the Millenson Theory

Emotion	Type-1 A	Type-1 B	Type-2 A	Type-2 B
Pleasure	1.7311	6.1777	2.1901	5.7965
Elation	2.3143	5.3414	3.0268	5.1565
Ecstasy	2.3030	2.9644	1.5289	3.3475
Total	6.3485	14.4835	6.7458	14.3005

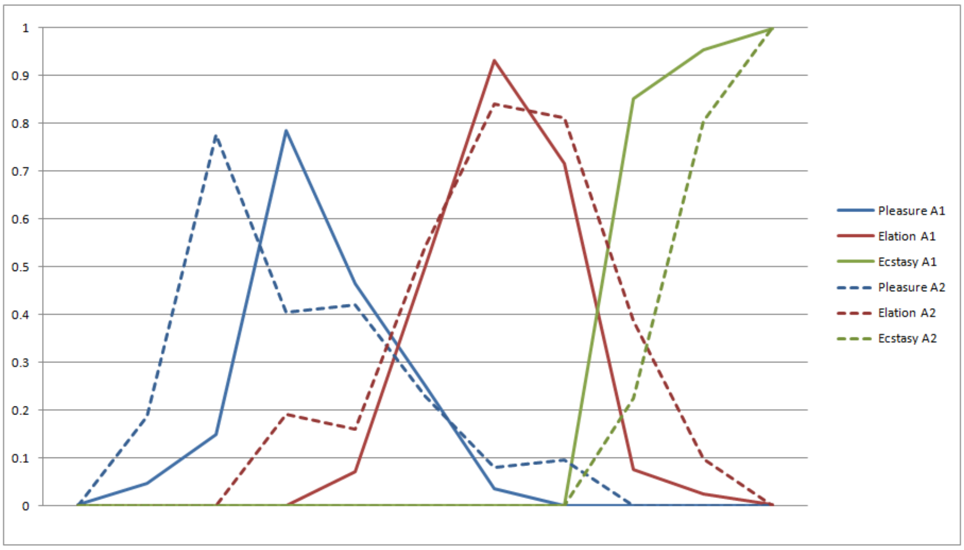

Figure 8.3: Type-1 and Type-2 Millenson A Membership of $S + \$—$-related Emotions for Increasing Z

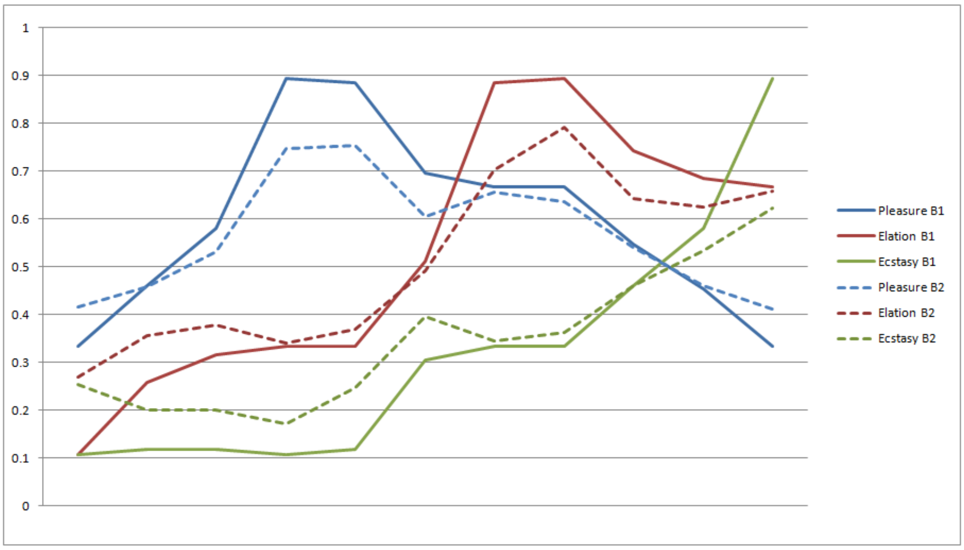

Figure 8.4: Type-1 and Type-2 Millenson B Membership of $S + \$—$-related Emotions for Increasing Z

fication type-2 enjoys over type-1 fuzzy logic, application of type-2 fuzzy logic only prompts a 6.26% increase in membership area in the context of Millenson A, and prompts a 1.26% reduction in membership area in the context of Millenson B. This should not be surprising, however, as the application of type-2 fuzzy logic inherently reduces membership peaks as a function of the nature of secondary membership functions, peaking as they do somewhat below the primary membership grade Unity.

First let us draw comparisons in the context of Millenson A. The most marked difference achieved by the implementation of type-2 fuzzy logic comes in the stepped ascents and descents of membership grade. Whereas in type-1 Millenson A, membership increases to peak, and decreases from peak, dependant upon input value, in type-2 the gradiant changes sign on multiple occasions over the course of the input range. Another difference comes in the location of the peak of Pleasure, which occurs at a higher input value for the type-2 implementation of Millenson A than it does for the type-1 implementation.

There are, however, marked similarities between the two implementations. The uppermost peaks of Elation and Ecstasy remain consistant. The membership areas do not deviate significantly, and the general 'form' of the output graph is consistent.

Let us move on to compare the type-1 implementation of Millenson B with the type-2 implementation. Here, again, the most noticeable differences revolve around the commonality with which the gradiant of membership grade changes sign over the course of the input range.

The key difference, however, is the failure of the Ecstasy membership grade to exceed the Elation membership grade at any point across the input range. In this, increased fuzzification has not necessarily let to greater psychological analogue as was hypothesised. Instead, in this instance, it has had the opposite effect.

In terms of similarities, there are several. The locations of the peaks of the three output emotions are consistent across models. The general shape of the graph remains consistent, and the membership areas are constant to within 1.26%.

In general comparison between type-1 and type-2 fuzzy logic as we have applied them in the field of emotion modelling, the additional layer of complexity provided by type-2 has not demonstrated significant difference in the performance of the implementations. This is not to say type-2 does not have a place in future work, however, and it is entirely feasible that a more focussed attempt to implement a type-2 emotion model in an affective agent, undertaken as some form of future work, could yield significantly positive results.

We are also mindful that only fuzzy logic of second order, or higher, can represent true uncertainty. And it should be noted that while the type-1 systems based upon Millenson's theory showed general consistency in trends associating input with emotion membership, type-2 demonstrated in its alterations of gradiant the uncertain fashion in which an agent might react to a stimulus that a quantifying algorithm might define as 'lesser' or 'greater'.

8.4 Comparing Millenson with the Geneva Emotion Wheel

Direct, numerical comparison between our implementations of these two models being impossible to render consistent and rigorous, we instead consider the observational differences and similarities between the behaviour of our type-1 implementation of the Geneva Emotion Wheel, and behaviours of our implementations of the Millenson theory.

Firstly, let us consider the behaviours of the type-1 implementation of the GEW across a range of inputs. As was observed in our implementations of type-2 fuzzy logic, the cross-sections we present and discuss with respect to the Geneva Emotion Wheel include scenarios where the gradient of an emotion's membership alters, seemingly irrationally. In addition, where the highest number of non-zero memberships obtained by any Millenson implementation is nine, the Geneva Emotion Wheel can return significantly more than that, as shown in our exhaustive testing results within the appendices.

Computationally, our implementation of the Geneva Emotion Wheel is more complex than that of the type-1 Millenson implementations. And, conceptually, the inputs associated with the Geneva Emotion Wheel are far more abstract by nature, and thus more complex to quantify.

That said, the Geneva Emotion Wheel produces more varied outputs, psychologically speaking, and as such associates a greater number of discrete emotions to a given experiential event than any implementation of Millenson could. Further to this, whereas Millenson's model generates three families of associated emotions, Scherer's provides sixteen distinct emotions to blend and contrast as one attempts to define the emotional impact of an event.

To that end, in view of our numerical experimentation, it would be suggested that further computational explorations of Scherer be targetted at human-like agents, where the subtle context of the model might have greater impact. In contrast, implementations of Millenson are rugged and robust and, as such, can be made suitable for most control tasks seeking an emotional component in their governance (as shown in Chapter 9).

Chapter 9

Prototype Case Study

9.1 Chapter Overview

It was reasoned that some application prototyping to demonstrate potential implementations of the systems discussed and researched over the course of this project was desirable. To that end, the type-1 implementation of Millenson B, presented in Chapter Six, was utilised to govern navigation of an agent existing in a predator-prey scenario. This implementation was selected for several reasons. Firstly, that as a type-1 implementation it was capable of being called from command line, which would be essential for its application in a real-time system. Secondly, the Millenson Model, as has been discussed previously, is conceptually simpler to integrate with a simple predator-prey scenario than the Geneva Emotion Wheel, the latter using inputs that require more subjective analysis to quantify than the former. Lastly, the type-1 implementation of Millenson B was a single-stage process, where the type-1 implementation of Millenson A was a dual-stage process, making the technical aspects of the integration of Millenson B more straightforward.

The brief in this case was that MATLAB would be used to process realtime updates to the emotional state of an agent within a Java game environment. This implementation was developed in association with Université du Havre, France, utilising a predator-agent-prey simulator created by researchers within their department, with this project's contribution being, as is proper, limited to the provision of the emotion model, and mutual determination of how the model should guide the agent's behaviour.

The chapter first presents the role of the emotion model in the structure of the control system for the agent. Next, the Java game environment itself is outlined for the purposes of clarity. Finally, two simulations are presented and the agent behaviours discussed from a psychological perspective.

9.2 The Role of MATLAB and the Emotion Model

An M-File was written which periodically obtained values for X, Y and Z, defined as they are in Chapter Four, from a delimited text file "Input.txt" generated by the Java predator-agent-prey simulator, and passed them to the emotion model within MATLAB. At the same time, the model obtained the previous emotional state, $\mathbf{E_M}$ from a delimited text file "Output.txt" that the M-File maintained and updated with each iteration.

These discrete values were processed by the fuzzy inferencing system, following the processes outlined in Chapter Six, to generate a resultant vector $\mathbf{E_J}$. The mean of this vector $\mathbf{E_J}$ and $\mathbf{E_M}$ was then calculated, and saved to the delimited text file "Output.txt". The agent simulation programme then used the nine elements contained in "Output.txt" to amend its behaviour, before generating a new set of values saved to "Input.txt".

The Millenson Model was selected for this prototyping effort because it was, as has been discussed previously, the model requiring least abstraction in its representation. From a psychological standpoint, the following assumptions were made:

- That a reduction in the distance between the agent and food (a prey individual) was considered the application of positive stimulus.
- That an increase in the distance between the agent and food (a prey individual) was considered the removal of positive stimulus.
- That a reduction in the distance between the agent and danger (a predator individual) was considered the application of negative stimulus.
- That an increase in the distance between the agent and danger (a predator individual) was considered the removal of negative stimulus.

Recollecting our definitions of the variables X, Y and Z in the context of Millenson's model of emotion, these four assumptions provide us with absolute quantifications of all three as contextual concepts. The fashion in which the Java Implementation quantified these in specific terms is outlined later in this Chapter.

From the perspective of the MATLAB implementation, the defining feature was that these elements were presented as single precision floating point values between 0 and 1, that they could be utilised to generate a new emotional output, which subsequently formed a constituent of an updated emotional state for the agent.

9.3 The Java-Based Agent Environment

The Java Simulation itself followed four basic principles consistent with the Predator-Agent-Prey environment:

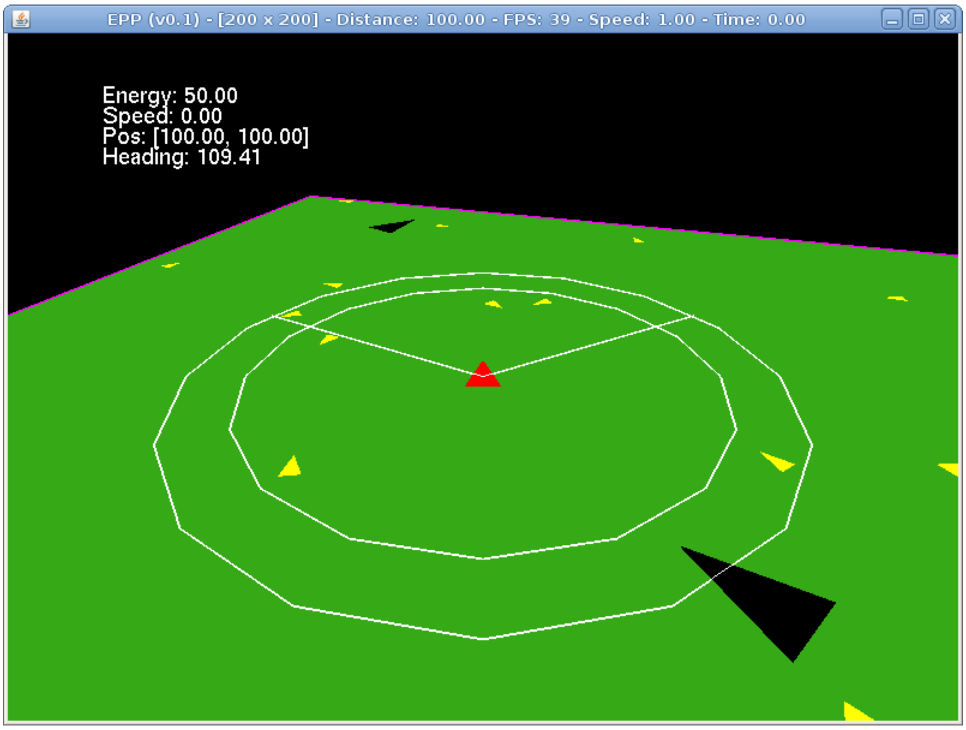

Figure 9.1: Java Environment, Developed in its Entirety by Karim Mahboub

- That the agent should die if caught by a predator.
- That the internal energy level of the agent should diminish over time.
- That the consumption of prey would replenish a portion of the agent's internal energy level.
- That the agent should die if its internal energy level reduced to zero at any point over the course of the simulation.

Figure 9.1 shows the three-dimensional nature of the environment, and is included for illustrative purposes. Within the environment, the agent is represented by a red triangle, the prey by smaller yellow triangles, and the predators by large, black triangles.

The environment itself, and all Java-related programming undertaken during this prototyping, was produced by Karim Mahboub and we claim no credit for it. For the purposes of this work, our focus is upon the practical application of the Type-1 fuzzy logic implementation of Millenson B, rather than the Java Environment. Such technical descriptions of the environment as are present are included solely to faciliate better understanding of the scenario.

The prey are simulated as boids [73]. As such, they move around the environment and have a tendency to maintain their trajectory. They move as a flock, or school, wherever possible and flee at the appearance of their predator, the agent. The Predators of the agent, who ignore the boids, follow a random path around the environment until they detect the agent. Whilst a predator detects the agent, it shall give chase.

All three species within the simulation had two methods of detection, represented as sight and hearing. Sight had a limited viewing angle, but high range. Hearing functioned at all angles, but with a lower range. This represented any given species' capacity to sense objects behind it.

Within the environment, the Millenson-governed agent was required to determine its reaction to a given situation in the context of the types of agent which surrounded it and, as a consequence of the modes of detection, their trajectories. To do so, first was read the "output.txt" file which provided the vector $\mathbf{E_J}$ as produced by the MATLAB module, in terms of the nine output variables x_{1-3}, y_{1-3}, and z_{1-3}.

In relating these nine distinct emotions to behaviour, the system associated each triplet of emotions with a facet of behaviour. Let us consider x_{1-3}, or, in explicit terms, Annoyance, Anger and Rage. In this prototype, following from Millenson's psychology, these three emotions were linked with the removal of positive stimulus. As such, we associated these three emotions with the increasing desire of the agent to obtain food. As these distinct emotions represented differing intensities of removed positive stimulus, the fashion in which they were applied weighted each emotion differently, and with increasing magnitude in line with increasing numeric identifier. Thus the weighting of Anger was greater than the weighting of Annoyance, and the weighting of Rage was greater than that of Anger.

These concepts were then merged into an overall weighting value that was applied to the agent's attraction to prey. This weighting value, X_e, was determined by the weighting values of each distinct emotion w_{1-3}. Thus X_e was explicitly defined

$$X_e = \frac{w_1x_1 + w_2x_2 + w_3x_3}{w_1 + w_2 + w_3} \tag{9.1}$$

or

$$X_e = \frac{\sum_{n=1}^{3} w_nx_n}{\sum_{n=1}^{3} w_n} \tag{9.2}$$

This representation was projected across all nine distinct emotions in order to generate similar variables Y_e and Z_e, of the form

$$Y_e = \frac{\sum_{n=1}^{3} w_n y_n}{\sum_{n=1}^{3} w_n} \tag{9.3}$$

$$Z_e = \frac{\sum_{n=1}^{3} w_n z_n}{\sum_{n=1}^{3} w_n} \tag{9.4}$$

thus defining the emotionally-informed behavioural weighting vector $\mathbf{B_e}$

$$\mathbf{B_e} = \begin{bmatrix} X_e \\ Y_e \\ Z_e \end{bmatrix} \tag{9.5}$$

$\mathbf{B_e}$ was a concept devised specifically for this prototype. As this new vector represented the behavioural impact of the new emotional state coming from the MATLAB module, it was used as a weighting value for the agent displacement. Agent displacement was handled by way of gravitational attraction and repulsion, with B_e acting as a moderator to the force applied to the agent by the other species within the environment.

Having clarified the application of X_e, and its psychological justification, we now outline the other two inputs required. Y_e, application of negative stimulus, was informed by the proximity of predators. As such, its component of $\mathbf{B_e}$ informed the repulsive quality of predators, prompting the agent to flee from danger. Lastly, the variable Z_e, representing the current levels of pleasure, elation and ecstasy felt by the agent, acted as a retardant force against the overall output vector. Psychologically, this represented the idea that the more pleasurable the agent's current situation, the less likely it would be for it to want to change that situation. These informed the *dir* direction vector.

The *dir* direction vector was calculated from each of the prey and predator positions, prey consisting of an attraction *att* compound and predators having a repulsing effect *rep* on the *dir* vector:

$$\overrightarrow{dir} = (X_e \overrightarrow{att} + Y_e \overrightarrow{rep}) \times (1 - Z_e) \tag{9.6}$$

where

$$\overrightarrow{att} = \sum_{f \in F} (\overrightarrow{Pos_f} - \overrightarrow{Pos_{agent}}) \tag{9.7}$$

Table 9.1: Representation of the local situation

	f_1	f_2	p_1	p_2	Total
$\delta dist$	2	-1	3	-2	
$weight$	0.5	1	1	0.5	
$X = \sum\{\$+\}$	1	–	–		1.0
$Y = \sum\{S-\}$	–	–	–	1	1.0
$Z = \sum\{S+, \$-\}$	–	1	3	–	4.0

$$\overrightarrow{rep} = \sum_{p \in P} (\overrightarrow{Pos_{agent}} - \overrightarrow{Pos_p}) \tag{9.8}$$

F representing the set of prey (or 'food'), P denoting the set 'predators', and Pos signifying the position of the considered member of the simulation. This provided the new displacement vector for the agent and allowed the updating of each individual's position in the world.

Following this, the future stimulus input vector, which was to be sent back to MATLAB as a new "input.txt" file, was calculated. In Millenson's theory, emotion is directly linked to the agent's local situational stimuli. In the case of this prototype, these referred to the relative positions of local prey and predators.

Consider a local situation with two prey, identified as f_1 and f_2, and two predators, p_1 and p_2. From their proximities could be computed the new emotional output vector compounds, X representing the removal of positive stimuli ($\sum\{\$+\}$), Y the addition of negative stimuli ($\sum\{S-\}$), and Z both the removal of negative stimuli and addition of positive stimuli ($\sum\{S+, \$-\}$), in line with figure 2.1 and equations given in Chapter Four.

As shown in table 9.1, $\delta dist$ value, corresponding to the difference between the current distance and the previous one for a given individual, would require calculation. Were this value negative, the corresponding individual would be coming closer to the agent, hence applying fear-related emotions if the individual were a predator, or pleasure-related emotions if the individual were prey.

Before computing the three stimulus compounds, weighting values corresponding to the difference between the senses used to detect the individual are necessary to consider. In the example presented in table 9.1, 1 was given for individuals in the viewing of the agent, while 0.5 was assigned to those located only within hearing range. In practical terms, this meant that a viewed predator was considered to have twice the stimulus impact of a heard one. We concede that observationally this point is open to debate: things that are only heard, for example, can be frightening until they are seen to be harmless. In this simulation, however, the environment and agent interactions were not complex enough to justify such an exhaustive approach. Indeed, attempting to do so would likely have required so many exceptions that it would have diluted the value of the emotion model's inclusion.

The weightings themselves were situationally subjective and could hypothetically be amended depending upon the importance one wished to place upon specific sensory stimuli. The weightings included in table 9.1 are provided for illustrative purposes only.

The elements of the stimulus vector **J** were then determined as follows

$$X = \sum_{f \in F} \delta dist_f \quad \text{if } \delta dist_f > 0 \tag{9.9}$$

$$Y = \sum_{p \in P} \delta dist_p \quad \text{if } \delta dist_p < 0 \tag{9.10}$$

$$Z = \begin{cases} \sum_{f \in F} \delta dist_f & \text{if } \delta dist_f < 0 \\ \sum_{p \in P} \delta dist_p & \text{if } \delta dist_p > 0 \end{cases} \tag{9.11}$$

before being fed back into the MATLAB module to obtain a revised emotional state.

9.4 Testing of Game Implementation

The system was tested several times for stability. Generally, stability tests were simple, single-predator, single-prey environments. Such environments being explored at length in the context of Millenson already [6], however, this work directed its attention specifically towards more complex environments with multiple predators and multiple prey. Two such tests are discussed and analysed at length within this work from the context of perceived behaviours the emotion model applied to the agent.

The testing environment for Tests 1 and 2 had several uniformities:

- The agent began each simulation with a given amount of energy, which decreased at a constant rate over time.
- The maximum speed of predators and prey was consistant across both

experiments.

- The maximum speed of the agent was consistent across both experiments. Each simulation began with five predators and twenty prey present within the environment.

- The relative size of the environment was consistent across both experiments.

- The starting position and orientation of each of the predators and prey were determined randomly for both simulations.

- The maximum rate of change of orientation of the agent was consistent for both simulations.

Log files of the elements of stimulus vector $\mathbf{J}$ were recorded, along with the elements of the emotional state vector $\mathbf{E_M}$ and the emotionally-influenced behaviour vector $\mathbf{B_e}$. In addition, the agent's orientation and displacement were recorded. In order to grant some measure of understanding regarding the agent's behaviour, graphs of $\mathbf{J}$, $\mathbf{B_e}$, and a graph of the agent's rate of change of orientation $\delta\theta$, are provided in the subsequent behavioural analyses in an effort to demonstrate the urgency the agent felt at any given moment to alter course.

9.5 Analysis of Prototype Tests

9.5.1 Experiment 1

Figure 9.2 illustrates the positions and orientations of the agent, predators and prey at the start of this experiment; figure 9.3 indicates the stimulus vector $\mathbf{J}$; figure 9.4 indicates the emotional behaviour vector $\mathbf{B_e}$; and, figure 9.5 indicates the rate of change of orientation, $\delta\theta$, all over time. Note that each unit of time equates to 0.2s, the testing refresh rate of the system.

The agent begins this run with nothing present in its field of vision, and five prey within alternative sensory detection range. This prompts a hard about-face from the agent, at maximum magnitude of $\delta\theta$, shown in figure 9.5 as the plateau from $t = 0$ to $t = 20$. It is also noted that during this process, the fact that the agent is initially forced to move away from the prey in order to make a pursuit turn increases his anger, which then trails off and pleasure

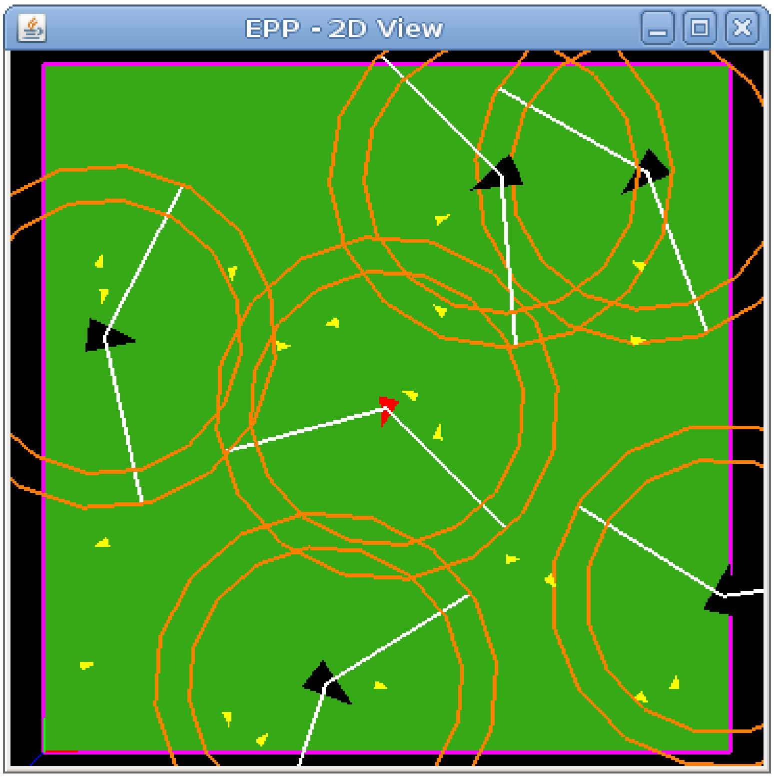

Figure 9.2: Experiment 1: Starting Positions and Orientations

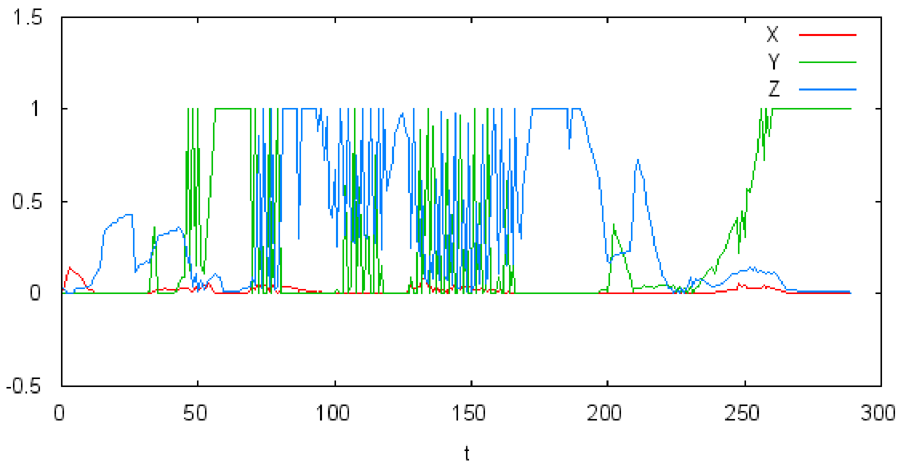

Figure 9.3: Experiment 1: Stimulus Vector **J** over time

increases as he begins to close the gap and briefly spikes as he consumes one of his prey.

The initial spike in Y, applied negative stimulus shown in figure 9.3, indicates the pursuit path of the agent leading to detection by a predator. This forces the agent to alter course slightly, pursuing two prey but abandoning the third; this causes an increase in all emotion-informing stimuli, again, in line with expectations.

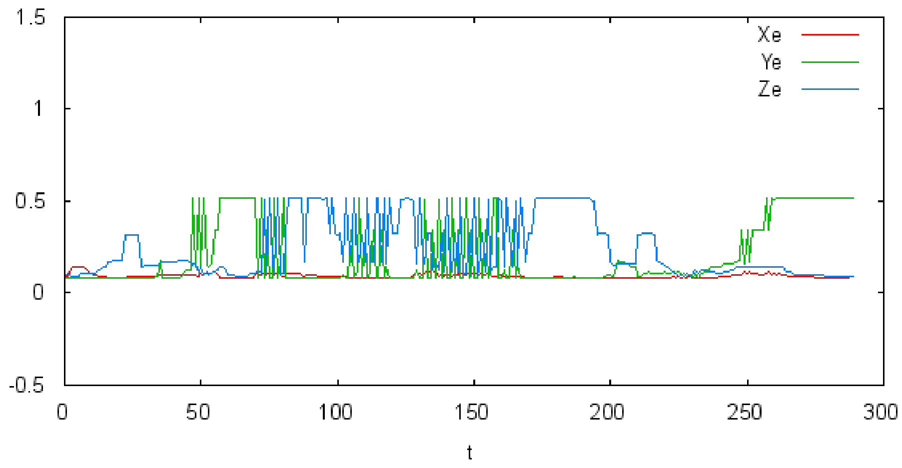

Figure 9.4: Experiment 1: Emotional Behaviour Vector $\mathbf{B_e}$ over time

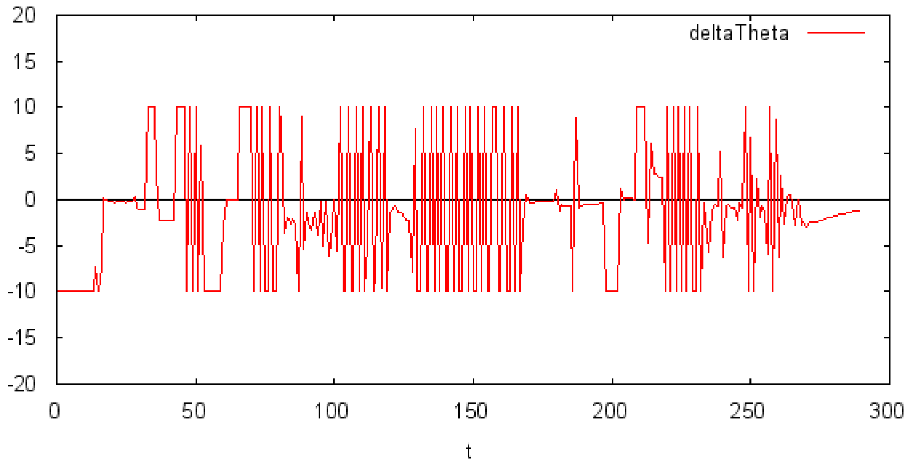

Figure 9.5: Experiment 1: Rate of Change of Orientation $\delta\theta$ over time

The next major spike in applied negative stimulus occurs when a second predator encounters the agent, at $t = 46$. As figure 9.3 illustrates, through the highly variable nature of the anxiety-inducing experience, two predators are both hovering in the edge of the agent's vision. Figure 9.4 indicates the impact this has on agent behaviour, increasing the repulsive weighting of predators along similar lines, and figure 9.5 indicates the agent's path darting from side to side, each time attempting to escape a predator only for the other to move into it's field of vision. This could be considered as simulating terror-induced confusion.

As both predators fall in to pursue the agent, it reacts by running between them, outpacing their advance. This path also decreases the distance, albeit slightly, between the agent and his prey, indicated by the increased application of positive stimulus shown in figure 9.3, which is then reinforced by the removal of negative stimulus caused by his outpacing the predators.

The noisy, but comparatively steady turn indicated just prior to $t = 100$ on figure 9.5 marks the agent's pursuit course of his prey, moderated by the proximity of the nearest predator. The agent takes a sweeping path, slightly increasing the removal of positive stimulus, as shown by the increase in X in figure 9.3, the result of which increases the attraction of the prey, leading the agent to make an increase in rate of change of orientation to make a run towards them. This tactic succeeds, allowing the agent to devour two more prey by $t = 160$, and a third by $t = 190$. This, combined with the fact his path has let him make ground on the pursuing predator, gives significant reinforcement to the Z stimulus component, as shown in figure 9.3.

Shortly after $t = 200$, another predator begins pursuing the agent. The introduction of this predator on the agent's flank, outside his field of vision, prompts the slight increase in Y shown in figure 9.3 at this time. The sharp indecision in angle seen in the spiking oscillations in figure 9.5 circa $t = 220$ to $t = 240$ are caused by conflicting desires to escape the predator, and consume the one remaining prey of the small party the agent began the simulation chasing.

The increase in pleasure seen prior to $t = 250$, however, is caused by another entire school of prey swarming into the agent's field of vision. These five prey, which soon merge with another four, distract the agent entirely from the lone prey he had been pursuing, allowing it to escape.

Unfortunately for our agent, following this flock of prey leads him directly into the path of another predator, travelling in exactly the opposite direction. This causes the Y spike and plateau shown in figure 9.3 at $t = 260$. Regrettably, the number of prey beyond the predator is too great a temptation, and while he makes some attempt to skim past the predator, he fails and is devoured, ending the simulation.

9.5.2 Experiment 2

Figure 9.6 illustrates the positions and orientations of the agent, predators and prey at the start of this experiment; figure 9.7 indicates the stimulus vector $\mathbf{J}$; figure 9.8 indicates the emotional behaviour vector $\mathbf{B_e}$; and, figure 9.9 indicates the rate of change of orientation, $\delta\theta$, all over time. Again, it should be noted that each unit of time equates to 0.2s, the testing refresh rate of the system.

In this simulation, the agent begins with no predators in detectable range,

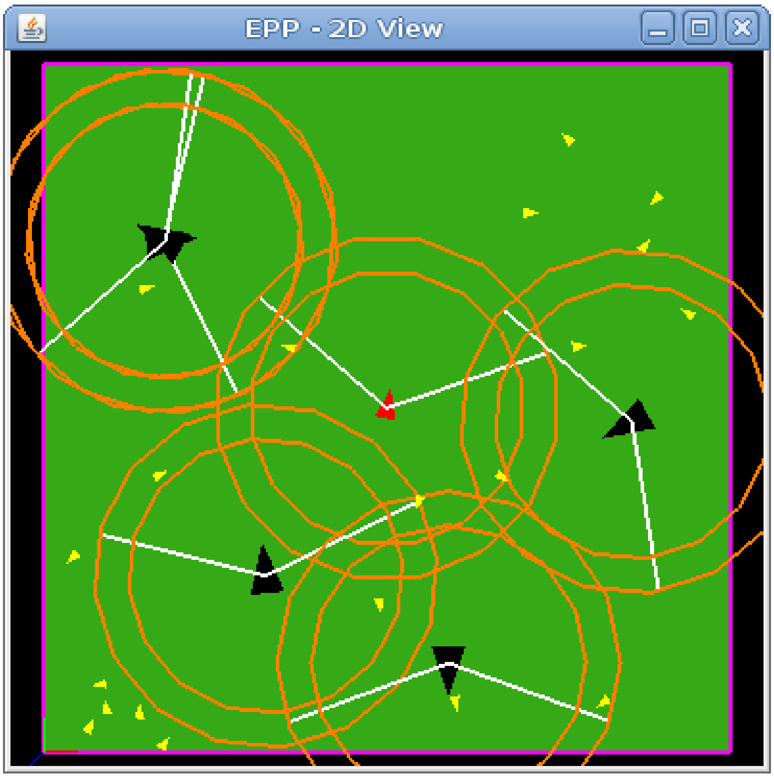

Figure 9.6: Experiment 2: Starting Positions and Orientations

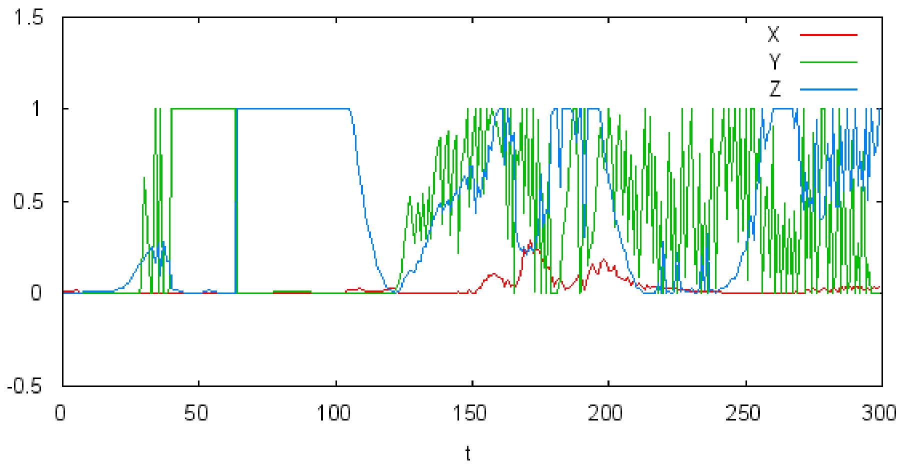

Figure 9.7: Experiment 2: Stimulus Vector **J** over time

and two prey, one nearer than the other. This leads the agent to make a sharp turn until $t = 10$, as shown in figure 9.9. The abandonment of one prey in favour of another causes a slight increase in the X variable of $\mathbf{J}$ that we consider to be mild annoyance, but it quickly tails off as the agent focusses on its pursuit.

At $t = 20$, the agent begins to close distance with the prey, leading to an expected increase in Z as shown in figure 9.7. After $t = 25$, however, figure 9.7 displays a spike in Y, followed in quick succession by another

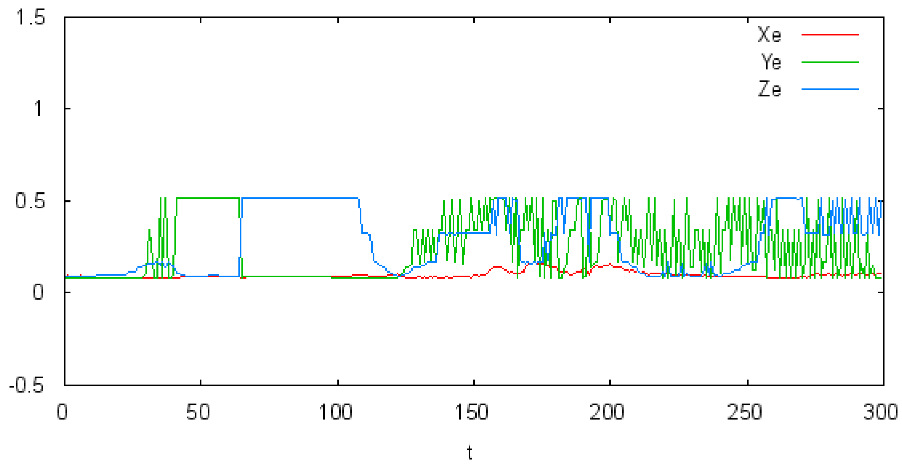

Figure 9.8: Experiment 2: Emotional Behaviour Vector $\mathbf{B_e}$ over time

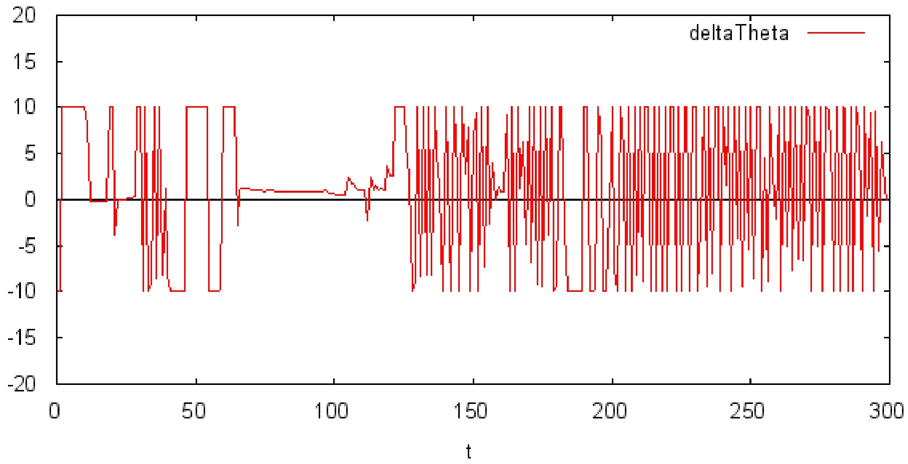

Figure 9.9: Experiment 2: Rate of Change of Orientation $\delta\theta$ over time

two. This is caused by two predators entering the agent's field of vision near-simultaneously, leading to the same terror-induced confusion response discussed in the previous experiment.

In this state of confusion, the agent turns away from one predator towards another, then veers in a swooping escape trajectory, managing to come up on the tail of the prey he was chasing, which by now has been joined by a second. This daring maneuvre explains the fear plateau from $t = 40$ to $t = 60$. The subsequent Z spike and plateau, caused by the urgent reduction of negative stimulus (escape from the predator) and application of positive stimulus (closing on the prey) might be considered ecstatic relief at the gambit paying off. Also, we note the steady, carefully modulated course the agent follows during this pursuit, as shown in figure 9.9.

This strong elation-related response tails off by $t = 120$, the prey altering their course to cross the path of the predators, thus forcing the agent to take a wider arc and increase distance from them, leading to the wavering X increase shown in figure 9.7; again, mild annoyance.

We witness, however, a steady increase in Z from $t = 125$ to $t = 155$ brought about by a school of new prey entering the agent's field of vision and closing with them. Parallel to this, we see an increase in Y, as the path of pursuit of the prey also leads to a decrease in range from the remaining pursuing predator.

By $t = 170$, the complexity of the environment, and the sheer number of potential prey, combined with the ever-present threat of the predator forcing course alterations, has prompted a decrease in Z as the agent is unable to close distance with any significant number of prey, nor open up distance with the pursuing predator, and an increase in X as the agent is forced to ignore an increasing number of prey just to avoid the predator.

Circa $t = 190$, the agent moves to an extremely close distance with the single prey it has managed to keep tracking, prompting a Z response, only to be denied its meal by the arrival of yet another predator which generates a spike in Y and forces the agent to abandon its meal by turning away, generating an increase in X, as shown in figure 9.7.

His new course, however, brings the agent to track another two prey. Opening distance on the predator and closing with the prey, remembering that the agent has not eaten since the simulation began, increases Z. However, the path ultimately requires the agent to cut across the path of the predator, prompting spikes in Y.

At $t = 250$, our agent's perseverence is apparently rewarded, as a school of prey move into view, on a trajectory that leads away from the predator, accounting for the increase in Z and sudden decrease in Y shown in figure 9.7 for this period. At the last, however, just Z makes a final peak and the agent is on the verge of consuming three prey at once, his energy reaches zero, and he dies of starvation.

Chapter 10

Conclusion

10.1 Chapter Overview

This work initially set out to explore the concept of emotion representation through fuzzy logic, with a view to establishing new inroads in terms of the application of psychologically sound, computationally consistent models of emotion to agent behaviour. In order to draw this work to a conclusion, it is necessary to consider every aspect of the programme of research, objectively, and consider whether or not it has contributed towards that goal.

To that end, this chapter seeks to draw the various threads that have run throughout this report together, and assess the success or otherwise of the project in the context of those goals outlined in the introductory chapter. Subsequently, we discuss each aspect in turn, beginning with discussions of the intended scope of the project, and whether or not those limits were adhered to.

Following this, the aims and objectives outlined at the outset of this work are considered individually. We then revisit the contributions this work sought to make to the field, before critically reviewing the overall project and outlining some of the future work that it prompts.

10.2 Scope

We recollect that the scope of the psychological aspect of this project was specifically set to exclude the incipient generations of new models of emotion. While this was adhered to, it is worth making brief observations regarding the multiple interpretations of Millenson's theory and clarifying why these in and of themselves were not beyond the scope of the project.

The differences between Millenson A and Millenson B, as we denote them in this work, came about due to alternative interpretations of vague linguistics in Millenson's own work. Both fundamentally adhere to the psychological structure and geometry of his model in terms of input and output; where they differ are the causal connections between the two. As such the difference is computational, rather than psychological, and without clarification from Millenson himself over which computational representation most closely observes the psychology of his model, we are left to draw our own conclusions on the basis of performance.

Thus neither is a novel psychological theory in its own right, merely two novel interpretations of an already published psychologically grounded theory of emotion. As such, their parallel development did not extend beyond the scope of the project. Other limitations in terms of psychological scope, such as the express developmental consideration of models combining situational input and emotional output, were observed; although, naturally, the literature review itself extends somewhat beyond this as it seeks to set overall psychological context for this work.

In terms of the computational scope of the work, all limits declared at the outset of this work were adhered to. Orders of fuzzy logic higher than second were not considered, and no calibration training was used in order to ensure results were not skewed in favour of an ideal outcome.

10.3 Aims and Objectives

Within this work, we have furthered the field of affective computing in the context of consideration of multi-value logic representations of psychologically grounded emotion models. The models have been presented in a general context, rather than in terms of any specifically associated control system, and can be taken on a modular basis in that light. We believe the work here shall prompt further exploration into the arena of psychologically consistent emotion modelling, and its place within the wider fields of affective computing and human-like agents.

This work has shown, from defined first principles, how psychologically grounded models of emotion might be extrapolated and represented through fuzzy logic systems. This process has been performed in such a way as to demonstrate that such abstractions can be made without sacrificing the conceptual nature of the psychological theories themselves, thus observing analogue across disciplines.

Each implementation presented within this work has been constructed in accordance with the fuzzy logic representations outlined in Chapters Four and Five. As such, they have been fashioned in a form that adheres to the psychological principles upon which they are built. While one implementation proved unsuitable for testing as a function of developmental limitations, even its structure is presented in a form drawn from the psychological geometry of its parent theory.

Of the five implementations this work provides testing data regarding, all were analysed in the context of the psychological meaning of their results. Through this process, consistency was maintained with the goals declared at the outset of this work.

10.4 Contributions of Thesis

In this section, we consider the original contributions discussed in Chapter One, and address them individually.

- Research of psychologically grounded models of emotional state suitable for computational representation.
- Construction of mathematical representations of one or more psychologically grounded models of emotional state, using type-1 fuzzy logic systems.
- Construction of mathematical representations of one or more psychologically grounded models of emotional state, using type-2 fuzzy logic systems.
- Computational implementations of these representations for the purposes of comparison and review.

The primary contribution of this work has been the conversion, representation and implementation of two wholly disparate, psychologically grounded theories of emotion. These theories have been implemented in a fashion that demonstrably adheres to the psychology upon which they are based, and using mechanism sympathetic to the abstract nature of the concepts they represent. As such, this work has presented novel methodologies to the field of emotion modelling, and established a firm foundation for future exploration of the role emotion might play in the behaviour of affective or human-like agents.

In addition, this work has approached representation of two psychological theories from the perspective of fuzzy logic. The representations and implementations presented herein are thoroughly unique to this work, but generated in a way that permits them to be projected onto a multitude of functional scenarios.

The work has presented the first two computational representations of a psychologically grounded emotion theory utilising higher-order fuzzy logic. Specifically they have utilised type-2 fuzzy logic which is in itself a growth area within artificial intelligence research.

Three implementations have been presented utilising type-1 fuzzy logic, and three implementations have been presented utilising type-2 fuzzy logic. Of those three type-1 implementations, all have been subject to a robust scheme of testing. Of the type-2 implementations, two were subject to an equally severe testing regime. The type-2 representations, and their implementations, have been compared and contrasted with like type-1 systems, and are presented in a fashion that it is expected shall make further comparisons between such systems more straightforward.

10.5 Critical Review

In this section of the conclusion, we are required to present a critical overview of all work produced over the course of this research project. Within this section, we also consider future work that is prompted by that already undertaken herein.

First, let us consider our mathematical representations of Millenson's theory. Contextually, the decision to pursue two different interpretations of Millenson's theory, based upon ambiguous linguistics, provided much scope for abstraction and consideration of the nature of the stimulus-emotion links he proposed. This decision generated a broader base of comparison, and forced a deeper level of internal comparison than would have been possible had our attentions focussed solely on one interpretation of Millenson and our interpretation of the Geneva Emotion Wheel.

Mathematically and, importantly, computationally, Millenson is more readily applicable to agent control systems than the Geneva Emotion Wheel. The simple connections between environmental stimuli and emotional output provide a model that can be easily applied in the context of any agent environment that includes both positive and negative stimulus.

One could draw the implied conclusion that Millenson's model is simpler because it is less psychologically sound than the Geneva Emotion Wheel. While this could be argued, the effectiveness of the implementation of Millenson B in type-1 fuzzy logic, in the context of our Chapter relating to prototyping would suggest that at the very least Millenson's theory can be used to generate sound, emotionally complex agent behaviour.

We should not consider the 'deaths' of the agents within that prototype as indications that the implementation failed in its task. The act of modelling the emotional state, and using it to inform decision-making, is not an act of optimisation. Emotionally governed responses are not necessarily rational or optimal, and to set optimisation of agent survivability as a criterion of success would be counterproductive and counter-intuitive. Instead, considering the agent's behaviours in the context of the emotions it is 'experiencing', the reasons behind the two deaths can be seen as verifications of the purpose of the model.

In the context of the implementations of Millenson's psychological theory, our representations largely held psychological analogue with the original theory, save in the case of the type-2 implementation of Millenson B. This loss in analogue could be fixed by simply rebalancing the membership functions that define the system's inputs and outputs, but to do so would have made meaningful comparison between it and the type-1 implementation of Millenson B less likely. In addition, significant redefinition of the membership functions might have given rise to an entirely incipient third interpretation of the Millenson theory. We intend to pursue this in future work.

Assessing the overall contributions of our investigations into Millenson's psychological theory, we conclude that this portion of the programme of research has provided a new approach to the concept of emotion modelling through fuzzy logic. Aside from that, it also includes the only known example of type-2 fuzzy logic being applied in the context of emotion modelling, at the time of writing.

Considering next our investigations into the Geneva Emotion Wheel, the picture is more mixed. The only successful implementation of our representational model of the Geneva Emotion Wheel generated an error return in 3.6% of cases, assuming uniform distribution of input value. The type-2 implementation, while we believe it to be numerically and psychologically sound, proved unsuitable for testing in the environment we selected for its development.

That said, if Millenson represented a 'plug and play' approach to emotion modelling for simple agents governed by fuzzy logic, the Geneva Emotion Wheel by its very nature provides a more cerebral definition of the emotional state. In this, we propose that our mathematical representation of Scherer's psychological theory lends itself particularly to the field of human behaviour simulation, where experience and reaction can be far more subtle than those observed in our prototype testing of Millenson's theory.

We assert that to truly determine the effectiveness, or otherwise, of any representation of the Geneva Emotion Wheel would require prototyping developed exclusively with the intention of assessing the subtle nuances of human/humanlike-agent interactions. Further to this, it is possible that rather than our mathematical representation of the Geneva Emotion Wheel being optimal for control purposes, it might instead be more usefully applied to assessment of user emotions, and in terms of anticipating emotional trends.

One interesting feature discussed during our contextual analysis was the concept of sympathetic emotions, where basic emotions that lie close to each other on the circumplex might be fired by an experience that would be seen to more directly define a different named emotion. The clearest example of this came in the corresponding triggering of a high Disgust response to a situation that made the agent feel Shame/Guilt. We hypothesise that this could either represent agent disgust at the situation that causes it to feel Shame/Guilt, or disgust with itself for whichever action has prompted the Guilt response. We assert that this warrants further exploration, from both a psychological and computational standpoint.

Taking into account the above, we maintain that our investigations into mathematical representation of the Geneva Emotion Wheel have yielded useful contributions to the field of computational emotion modelling at large, and in particular in the context of the application of fuzzy logic to the field. As such, this portion of the research programme served its purpose with as much validity as our investigations into Millenson' theory, just in a less pragmatic fashion.

Considering our own work with respect to recent research addressing the application of fuzzy logic in the context of representation of emotional state, we reference three appropriate and contemporary publications. Leon, *et al*, present work considering affect-aware behaviour modelling [47]. Their work specifically directs its attention towards demonstrating the value of a valence-based emotional component in the modelling of user emotional state. Focussing on architecture, they produce preliminary results supporting the benefits of including consideration of emotional state in affective agents. Our own work, generating several representations of emotional state that relate specifically to environmental factors, including valence in both cases, could be taken further in this direction. In particular, we might consider emotion determination with respect to a user, rather than defining an emotional state for an agent.

A more recent publication by Kazemifard, *et al*, [42] discusses specifically the value of emotions in terms of their place in decision-making. In particular, their work presents a computational model designed to map events within an agent's universe to resultant emotional states, with a view to making such an architecture scalable and versatile. Unlike our work, which considers the abstract case and bases application upon implementation-specific definitions of environmental input, their system is multi-layered and self-informing. The architecture they define could provide inspiration in the context of future, exploratory implementations of the emotional state models presented in our work. The abstracted nature of our own model makes this of particular interest to us, as the systems we define rely on no predetermined quantitative associations between environment and input, and as such can be tuned relatively easily.

Lastly, we consider the work of Su, [95], connecting emotion and personality to expressive character motion in a narrative environment. In his work, he presents an exhaustive analysis of the connection between emotion and expression and, by extension, affect. His focus being primarily on narrative is particularly interesting to us in the context of future exploration of our own, more abstracted work. In particular, the connections he presents between event and affect provide useful inspiration regarding potential software utilisation of our fuzzy logic implementations.

Before drawing our account to a close, we consider possible future research that might take inspiration from our initial forays into the field. The further implementation of mathematical representations of the Millenson theory, with a view to inclusion in more complicated environments is an obvious area that our initial prototyping suggests warrants further investigation. Having demonstrated psychologically justifiable behaviours in a pedagogic case, more detailed environments featuring multiple agents and multiple, disparate sources of stimuli may yield valuable insight into emotionally-governed multi-agent interactions.

Similarly, the prototyping of systems governed by type-2 implementations of Millenson's theory would allow for a greater level of contextual comparison between these and their type-1 counterparts, perhaps providing a more definitive answer as to the benefits higher order fuzzy logic can bring to the field. As has already been observed, redevelopment and redefinition of the type-2 implementation of Millenson B such that it meets our success criteria without sacrificing analogue with the type-1 implementation, mathematical representation or psychological theory is already underway.

In terms of future work relating to the Geneva Emotion Wheel, aside from the prototyping already mentioned, the development of a functional type-2 implementation of our mathematical representation may well provide a deeper insight into the impact of type-2 fuzzy uncertainty when applied in environments with a subtler emotional context. In addition, it would permit comparison of behaviour on a numerical level with the type-1 implementation.

As regards further development of the type-1 implementation, redesigning the system such that the aberrant errors no longer occur is an obvious first step in further development. Beyond this, we advocate a revisitation of the mathematical representation with a view to using fuzzy numbers as input values, and perhaps approaching the geometry through a system relating to polar coordinates rather than cartesians.

To conclude, this work has provided new insights into the application of fuzzy logic to emotion modelling, and presented entirely novel mathematical representations of two psychological theories of emotion. In so doing, it has provided a basis for future exploration, and contextual comparison, in an arena which it is anticipated shall continue to expand, as a fundamental aspect of the broader topic of affective computing, for many years to come.

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