Implementation of Millenson's Model of Emotions in a Game Environment

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Abstract. Emotions, arguably, impact our perception and decision-making. Modelling emotions and emotional responses in non-player characters is an active field of investigation. Our work centres on the implementation of psychological models through fuzzy logic, as a way of informing agent decision-making in video games. This paper presents an emotion model proposed by Millenson, and the demonstration of this model in a game environment. We shall include an outline of the psychological background to our work, the specifics of the implementation, and some discussion of our conclusions.

1 INTRODUCTION

The development of interactive games, and video/computer games in particular, has provided an outlet to examine the subtle intricacies of human interaction and non-verbal communication. An important factor in these interactions is the emotional state.

The accurate modelling of the emotional state of any agent, and changes to that emotional state, has long been the subject of extensive research [15, 27, 29, 5, 2, 1, 14]. 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 [6, 30]. Within computing sciences, such debate has tended to revolve around the practical questions regarding the mimicry of emotional responses and modelling of emotional state.

Within psychology, there are many schools of thought regarding the nature of emotions and how they are best modelled. We have performed an extensive review of these approaches, and further to this concerned ourselves with how they have been previously implemented in the field of artificial intelligence.

Recent publications in psychology have expressed a growing view that, rather than emotion being impedance to human creativity and decision-making, it is indeed an asset, if not a fundamental basis to the cognitive process [22, 21, 18, 19, 34, 23]. As this viewpoint begins to garner wider acceptance, it is expected that a renewed interest in emotion modelling and representation, from an academic standpoint, will follow, along with an exploration of emotion models that are not inherently linked to elementary control.

Our model is built upon the viewpoint that the emotion model itself should have the capacity to be wholly independent of the elementary control systems of the agent, instead being a construct to determine ongoing emotional state which is then called upon to inform decision-making.

A potentially key implementation of this concept lies in the decision-making capacities of non-player characters in game environments. These agents, being arguably the foremost means of direct human-agent interaction in the modern world, are naturally of significant interest to us. Bearing this in mind, our implementation in a game environment has been kept both simplistic, so as not to overshadow the theoretical implications, and intuitive, so as to ensure the work is clearly understood.

Within this paper we shall present some preface, discussing currently accepted approaches to modelling the emotional state of an agent, and how this work has fed into our own. We shall then proceed to outline the psychological emotion model we have selected, namely Millenson's theory of the behavioural school of emotions [4]. We shall present a method of applying fuzzy logic to the model itself, and the game implementation outlining the model's application through a simple, emotion-driven decision-making agent.

2 PSYCHOLOGICAL BACKGROUND

2.1 Preliminaries

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]. 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 in the nature of the models they propose.

The view of emotions as an evolutionary construct was initially proposed by Darwin in 1872 [8]. Over the past century, this has ultimately given rise to a school of thought which maintains that there are several fundamentally defined emotions, and that any given emotional state is a function of, or defined by, these emotions.

The exact number of 'fundamental' emotions widely varies. Plutchik first proposed his system of emotion classification in 1980 [24], containing eight fundamental emotions. In contrast, Ekman proposed a system consisting of six fundamental, or basic, emotions in 1982 [9]. Within this school of thought, the maximum number of basic emotions is generally thought to be fourteen [26].

Following on from the definition of basic emotions comes the definition of more complex emotions. Often these categories are divided using nomenclature indicating primary and secondary emotions as in the structure proposed by Parrott [20]. 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

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function, or construct, of less than a dozen named emotions [12, 11, 10, 13].

An alternative to this view, first proposed by Wundt in 1904, suggested that emotions could be better defined in the context of experience than crisp linguistics [33]. Research based on this principle has 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 labelled '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 inherently contextual 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 clearer definition of 'pleasantness', and arousal.

More recently it has been suggested that these views are not necessarily 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 [25]. A geometric application of a Darwinian idea has been viewed as a reasonable progression [26].

It is upon this idea of a hybrid of the two major psychological schools of thought that we have focussed our attentions. In particular, on the works of Millenson in the context of his geometric model of emotions that combines specific, named emotional states with a three-axis geometric model.

2.2 Millenson Model

Millenson's model (1967) was presented as a standalone concept, rather than in conjunction with a particular theory of emotion as was common at the time. It is similar in construction to modelling of Watson's three-factor theory, and finds basis in the technique of conditioned emotional responding [31, 32, 28].

In his model, Millenson presents a three-axis representation of emotional state. Along each axis he places what he considers to be a basic facet of emotional experience. He abstracts three emotional factors which he believes represent the sum total of human emotion, the axes being defined, arguably, as emotions relating to anger, anxiety and elation, respectively.

Understanding that three emotions cannot truly represent emotional experience in explicit terms, he extends his behavioural analysis based upon two key ideas. Firstly, that some emotions are indistinguishable from each other, save in terms of their relative intensities. Secondly, that the emotions he presents are basic emotions, and other emotions are simply compounds of these [17, 16]; in this, his work carries noticeable analogue with that of Plutchik and Ekman.

The nine emotions Millenson lists as fundamental are divided into three groups, one group per axis, and can be summarised as follows:

Anger-related Axis
Annoyance
Anger
Rage

Anxiety-related Axis
Apprehension
Anxiety
Terror

Elation-related Axis
Pleasure
Elation
Ecstasy

From our perspective, Millenson essentially proposes that, based on his second condition, any given emotional state may be represented by a point within this three dimensional model or, as we are wont to refer to it, emotional statespace.

3 FUZZY MODELLING OF MILLENSON

3.1 Method Outline

We dub our system 'Fuzzy Millenson Emotion Model', or FMEM. The emotional statespace, while it can be visualised as a cubic region, can just as easily be described as a collection of three general factors, one for each axis, each containing three membership functions, one for each linguistically defined emotion. We follow from our previous work [4] in defining the mathematical representation of FMEM.

Let us consider these variables in terms of **A**, **B**, **C**.

$$\Re = \{\mathbf{A}, \mathbf{B}, \mathbf{C}\} \tag{1}$$

where

$$\mathbf{A} \subset \Re; \mathbf{B} \subset \Re; \mathbf{C} \subset \Re \tag{2}$$

Each of these variables contains one membership function for each linguistically defined emotion. We shall define these emotions in algebraic terms of consistent form. For example, a_1 is the first membership function within the **A** variable. This expands to:

$$\begin{gathered} a_i \subset \mathbf{A} \text{ for } i = 1,2,3 \\ b_i \subset \mathbf{B} \text{ for } i = 1,2,3 \\ c_i \subset \mathbf{C} \text{ for } i = 1,2,3 \end{gathered} \tag{3}$$

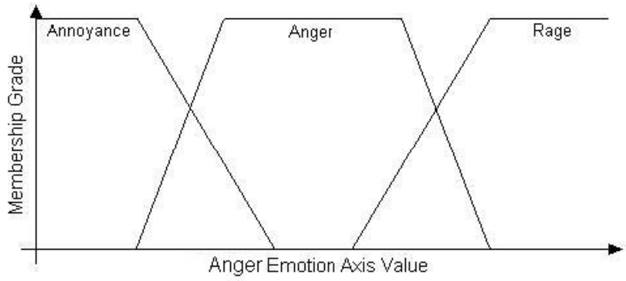

Figure 1. This figure shows the hypothetical form of an emotion variable in terms of individual fuzzy membership functions

An example of a potential makeup of the ‘Anger’-related emotion axis is included as Figure 1. Any point within the emotional statespace is a column vector with values for all three axes, and a membership for each determining its applicability to the current manifestation of the statespace membership functions. We define this as an *emotional experience*. Hereafter, emotional experience shall be referred to as **e**, and defined

$$\mathbf{e} = \begin{bmatrix} x \\ y \\ z \end{bmatrix} \tag{4}$$

where x, y and z are coordinates along the ‘Anger’, ‘Anxiety’ and ‘Elation’-related axes, respectively, and where

$$x \in \mathbf{A}; y \in \mathbf{B}; z \in \mathbf{C} \tag{5}$$

The membership grades obtained from a given e, are defined as follows.

$$\begin{aligned} \mu_{a_1} &= f_1(x) \\ \mu_{a_2} &= f_2(x) \\ \mu_{a_3} &= f_3(x) \\ \mu_{b_1} &= f_4(y) \\ \mu_{b_2} &= f_5(y) \\ \mu_{b_3} &= f_6(y) \\ \mu_{c_1} &= f_7(z) \\ \mu_{c_2} &= f_8(z) \\ \mu_{c_3} &= f_9(z) \end{aligned} \tag{6}$$

We should stress that the functions defining membership grades are not necessarily different across variables; the notation is written such as to provide the option if necessary.

Following on from Millenson’s proposal that emotional state was a combination of these basic emotions, we may proceed to infer emotional state in terms of non-zero membership grades. Further to this, we should consider the factors defining how the emotional state **e** changes over time.

Our rationale for choosing to fuzzify the individual emotions rather than the emotional state is two-fold. Firstly, fuzzifying the emotions themselves gives us some measure of accounting for linguistic inconsistency in their definition as determined by intensity; in other words, fuzzifying the emotion Anger permits us to address the question ‘how angry is angry?’. Secondly, by fuzzifying the emotions rather than the emotional state, we are able to obtain greater overlap between individual emotions across the same spectrum, making for a more varied and intricate fuzzy inferencing system and a more fluid change from one dominant emotion to the next.

For the purposes of clarity, the steps of the idealised model are illustrated below. Let us confine our axes to values between 0.0 and 100.0 Further to this, let us assign arbitrary values for **e** within these limits.

$$\mathbf{e} = \begin{bmatrix} 10.0 \\ 50.0 \\ 30.0 \end{bmatrix} \tag{7}$$

These values might produce the following membership grades.

$$\begin{aligned} \mu_{a_1} &= 0.4 \\ \mu_{a_2} &= 0.0 \\ \mu_{a_3} &= 0.0 \\ \mu_{b_1} &= 0.0 \\ \mu_{b_2} &= 1.0 \\ \mu_{b_3} &= 0.0 \\ \mu_{c_1} &= 0.8 \\ \mu_{c_2} &= 0.2 \\ \mu_{c_3} &= 0.0 \end{aligned} \tag{8}$$

This would give us the following non-trivial results from which to determine the subsequent behaviour of the system:

Annoyance: 0.4
Anxiety: 1.0
Pleasure: 0.8
Elation: 0.2

This is, of course, an idealised form of the model. For the purposes of our experimentation, the model is presented in a simplified form for ease of implementation on the chosen platform.

3.2 The Changing Emotional State

In the example we shall later present, we adopted a method of changing emotional state that created contextual relationships between environmental factors and specific axes of the model.

It is arguable as to whether this is preferable to a system that identifies specific events within the environment and attributes an emotional component relevant to all three axes to each event, since it necessitates the assumption that each axis is only affected by a specific environmental factor.

In an idealised system, each environmental factor would have an impact on all of the emotional axes, and those relationships would be exhaustively calculated such as to ensure that any event within the environment – which must, by definition, be measured in terms of its impact on the environment – is completely represented, even though not in specific terms addressing it.

For the purposes of this paper, however, we choose to link environmental factors to specific emotional axes. In the general case, we assign the environmental factors variables *L*, *M*, and *N*. This is true where

$$\begin{aligned} x &= f(L) \\ y &= f(M) \\ z &= f(N) \end{aligned} \tag{9}$$

which leads to

$$\begin{aligned} \mu_{a_i} &= f_i(f(L)) \\ \mu_{b_i} &= f_{(i+3)}(f(M)) \\ \mu_{c_i} &= f_{(i+6)}(f(N)) \end{aligned} \tag{10}$$

Thus with numerical values for the environmental variables, it is possible to define the agent's complete emotional state in general terms.

4 APPLYING FMEM TO GAMES

4.1 The Game Environment

For our game implementation, we opted to model an environment where an agent governed by the emotion model interacted with both a user-controlled element and an element governed by random path generation. To this end, using Game Maker™ 7.0, we generated a simple two-dimensional game. Figure 2 shows the starting layout of the game.

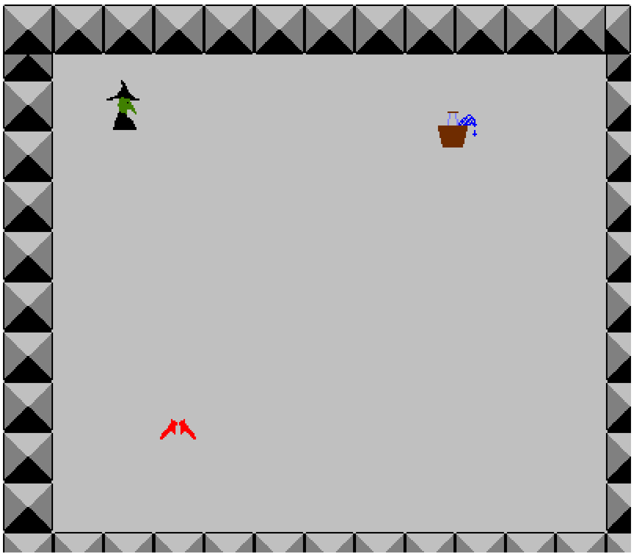

Figure 2. Screenshot of Starting Layout

We adapt the pedagogic case outlined by Ayesh [3] in the context of an agent, its food, and a predator.

- Bucket (Predator). The object in the upper right quadrant of Figure 2. This object is controlled by the player and moves in 25 pixel steps according to player input from the keyboard. The Bucket has an 80% chance to destroy the Elphaba object on contact, which is the player goal.
- Slippers (Food). The object in the lower left quadrant of Figure 2. This object is governed by a simple random pathing algorithm that causes it to spontaneously change direction, on average, every five movements of the Bucket. The Slippers have no objective.
- Elphaba (Agent). The object in the upper left quadrant of Figure 2. This object is governed by the emotion model (implementation specifics are outlined in the next section). The goal of this object is to come into contact with the Slippers, while avoiding contact with the Bucket. The speed and pathing of this object are managed entirely by the emotion model, with one exception; an override code ensures that the object will turn to a right angle leading it away from the Bucket if it impacts a wall.

4.2 Implementing FMEM

As has been indicated previously, the most straightforward implementation of the emotion model in a game environment requires us to connect environmental factors to each emotional axis. Now that our game outline is clarified, these factors can be outlined in context of the goals of the agent in question: Elphaba.

The first emotional axis we shall address is that concerning itself with elation-related emotions. Mindful that our agent's goal is to reach the Slippers, it makes sense for us to connect the proximity of the Slippers to the agent's sense of elation; the further away the Slippers, the lower the intensity of these positive emotions.

The second emotional axis we shall address is that which concerns anxiety-related emotions. Since contact with the Bucket will kill Elphaba, proximity to the Bucket should generate a heightened sense of these emotions; the closer the Bucket, the closer the agent comes to Terror.

The final emotional axis represents emotions relating to anger. That being the case, we opt to connect this emotion to an environmental factor extraneous to the activities of the other to objects: time. The longer it takes the agent to obtain the Slippers, the higher the value along this axis.

To simplify the implementation of our emotion model in this system, we choose to discretise our fuzzy membership functions and define our membership grades according to bands of values of x, y, and z such that multiple potential values of x share the same membership grade.

Figure 3 shows an outline of the implemented function of fuzzy membership for the pleasure-related axis. In this case, the value determining membership is distance from the Slippers; as such, the lower the value, the higher the membership of the more intense emotions on the axis. The solid line represents the emotion "Elation"; the dotted line represents the emotion "Ecstasy"; and the dashed line represents the emotion "Pleasure".

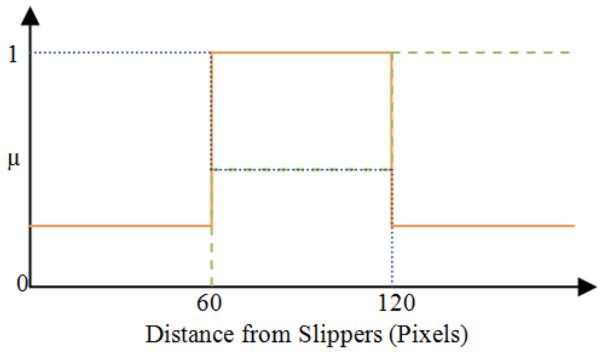

Figure 3. Fuzzy Membership Function (Elation-related Axis)

In implementing the rules for our fuzzy system, we used a method of scoring each rule for each iteration of the system, with the agent selecting the rule with the highest overall score. This is analogous to the process of a true fuzzy inferencing system, the key difference being the complexity of implementation due to inherent limitations within the development platform, and the crispness of the output.

For the purposes of clarity, our axes were defined thus: elation-related emotions, axis 1; anxiety-related emotions, axis 2;

anger-related emotions, axis 3. The three rules governing our agent's behaviour were as follows:

- Rule 1: If axis 1 is Ecstasy, and axis 3 is Anger, move towards Slippers
- Rule 2: If axis 1 is Pleasure, and axis 3 is Rage, move towards Slippers
- Rule 3: If axis 2 is Terror, and axis 1 is Pleasure, move away from Bucket

All behaviour of the Elphaba object was governed by these three rules, save the override which caused the object to change direction when impacting a wall.

5 TESTING AND RESULTS ANALYSIS

The program was run ten times from the same starting positions.

Figure 4 is a screenshot taken 22s into test 3, as the Elphaba object veers away from the Bucket, as the Rule 3 score begins to outweigh Rules 1 and 2. Figure 5 shows the Elphaba object successfully avoiding the Bucket and approaching the Slippers.

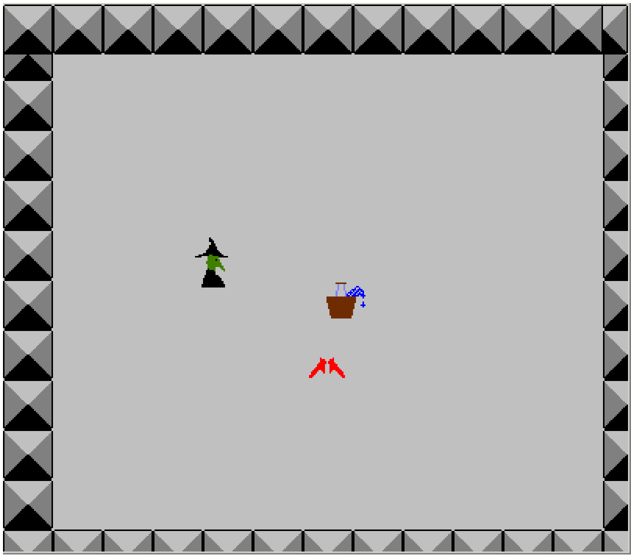

Figure 4. Screenshot of Test 3 as the Elphaba Object retreats

Six times, the Elphaba object was intercepted by the Bucket; the remaining four, the Elphaba object obtained the Slippers. The longest run of the program was test 6, where the Elphaba object was intercepted by the Bucket after 42s.

In this section we shall discuss notable behavioural patterns which were observed during testing.

Most notably, the Elphaba object reliably avoided the Bucket until Rule 2 overrode Rules 1 and 3, in all simulations where the Elphaba object was destroyed by the Bucket. This is due to the frustration effect that Rule 2 represents. Since play time is linear and has no ebb and flow, in the manner that proximity does, ultimately the rule governed by time will score higher than the others. In that situation, the Elphaba object could be perceived as being so frustrated as to gamble on the 20% chance that a collision with the Bucket will not destroy her. It should be noted that in test 6 this 'gamble' paid off and the Elphaba object passed through the Bucket and obtained the Slippers.

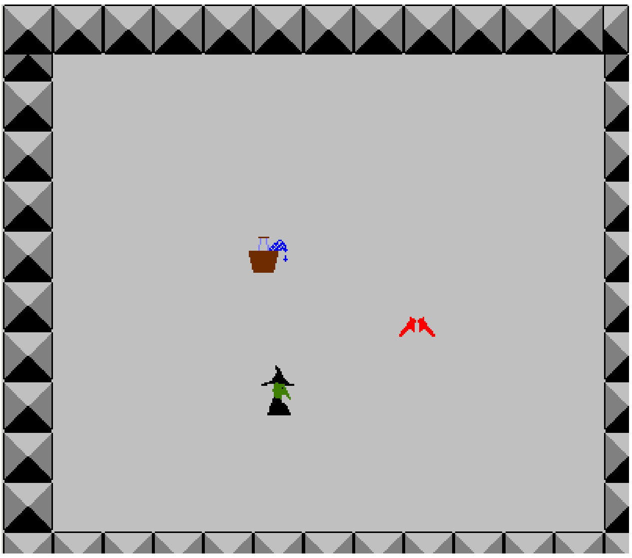

Figure 5. Screenshot showing the Elphaba object approaching the Slippers

Other repeated behaviours were highly predictable. When the Bucket was positioned next to the Slippers, the Elphaba object would hastily retreat, and then make another attempt. The same was observed when the Bucket was positioned between Elphaba and the Slippers.

An unexpected side-effect of the pathing override for wall collisions was that if the Elphaba object hastily retreated to a wall, it would follow the wall in whichever direction brought it closer to the Slippers, and make a beeline for the Slippers the instant Rule 1 outweighed Rule 3, circumnavigating the Bucket very effectively. This behaviour was observed in tests 2, 7 and 10.

6 CONCLUSIONS & FUTURE WORK

The paper has presented an emotion model for an AI-governed non-player character. The model has been shown to be grounded in psychological theory, and compatible with the general principles of a fuzzy inferencing system. The model has been implemented in a game format to govern the motion of an antagonist to the player (Elphaba).

The purpose of this research is to develop an emotion model that might serve as a guide to decision-making in agents that will experience ongoing interaction with users. This initial implementation has demonstrated that further investigation of this field has the potential to provide valuable insight. Time can now be devoted to expansion of the design of the system, and exploration of more advanced implementations that might better demonstrate its effectiveness.

The next stage in this research has two components. The first will be to explore the implications of two antagonistic agents whose movements are both governed by this emotion model. The second shall be a more traditional implementation of the model, with no simplifications, using a hardcoded fuzzy inferencing system and applying the model more extensively to an agent that would refer to it in multiple decisions, rather than simply pathing.

We shall also more extensively test the implementation of an emotion model to govern actions against alternative control methods, and in conjunction with alternative control methods, where the emotion model informs rather than dictates.

In addition, we shall continue to explore alternative psychological models of emotion that share the same basic groundings in psychological theory, and the potential implementation of higher order fuzzy logic systems [5], for comparison purposes. The increased level of fuzzification may permit a greater uncertainty of behaviour and, therefore, a closer analogue with emotionally erratic decision-making.

REFERENCES

[1] H. Ahn and R. W. Picard. Affective cognitive learning and decision making: The role of emotions. In The 18th European Meeting on Cybernetics and Systems Research, 2006.

[2] T. Archevapanich, B. Purahong, M. Klingajay, and P. Sooraksa. Facial visualization for robotic indicator by using fuzzy emotional system. In SICE-ICASE, 2006. International Joint Conference, pages 5634–5637, Oct. 2006.

[3] A. Ayesh. Perception and emotion-based reasoning: A connectionist approach. In Informatica, volume 27, pages 119–126, 2003.

[4] W. Blewitt, A. Ayesh, R. I. John, and S. Coupland, "A Millenson-Based Approach to Emotion Modelling" Conference on Human System Interaction (HSI'08), Poland, 2008.

[5] W. F. Blewitt and A. Ayesh, "Modeling the Emotional State of an Agent through Fuzzy Logic With Reference to the Geneva Emotion Wheel " European Simulation and Modelling (ESM'2008) Conference, Le Havre, France, 2008, pp. 279-283

[6] K. Boehner, R. DePaula, P. Dourish, and P. Sengers. How emotion is made and measured. International Journal of Human-Computer Studies, 65(4):275–291, April 2007.

[7] A. Camurri and A. Coglio. An architecture for emotional agents. Multimedia, IEEE, 5(4):24–33, Oct.-Dec. 1998.

[8] C. Darwin. The Expression of the Emotions in Man and Animals. Harper Collins/Oxford University Press, 1872/1998.

[9] W. V. Friesen, P. Ellsworth and P. Ekman. Emotion in the human face, chapter What emotion categories or dimensions can observers judge from facial behavior?, pages 39–55. Cambridge University Press, 1982.

[10] P. Ekman. Are there basic emotions? Psychological Review, 99:550–553, 1992.

[11] P. Ekman. An argument for basic emotions. Cognition and Emotion, 6:169–200, 1992.

[12] P. Ekman. Facial expression of emotion. American Psychologist, 48:384–392, 1993.

[13] P. Ekman. Genetic, Ethological and Evolutionary Perspectives on Human Development: Essays in Honor of Dr Daniel G. Freedman., chapter Expression or communication about emotion. American Psychological Association, 1997.

[14] N. Esau, E. Wetzel, L. Kleinjohann, and B. Kleinjohann. Real-time facial expression recognition using a fuzzy emotion model. Fuzzy Systems Conference, IEEE International, pages 1–6, 2007.

[15] C. Gershenson. Modelling emotions with multidimensional logic. In Fuzzy Information Processing Society, 1999. NAFIPS. 18th International Conference of the North American, pages 42–46, 10-12 June 1999.

[16] J. R. Millenson. Principles of Behavioural Analysis. New York: Macmillan, 1967.

[17] J. R. Millenson. The Psychology of Emotion: Theories of Emotion Perspective, chapter 4, pages 35–36. John Wiley & Sons, 1967.

[18] R. Muramatsu and Y. Hanoch. Emotions as a mechanism for boundedly rational agents: The fast and frugal way. Journal of Economic Psychology, 26(2):201–221, April 2005.

[19] N. Naqvi, B. Shiv, and A. Bechara. The role of emotion in decision making: A cognitive neuroscience perspective. Current Directions in Psychological Science, 15(5):260–264, 2006.

[20] W. G. Parrott. Emotions in Social Psychology. Psychology Press, 2001.

[21] L. I. Perlovsky. Integrated emotions, cognition, and language. In Neural Networks, 2006. IJCNN '06. International Joint Conference on, pages 1570–1575, 16-21 July 2006.

[22] L. I. Perlovsky. Toward physics of the mind: Concepts, emotions, consciousness, and symbols. Physics of Life Reviews, 3(1):23–55, March 2006.

[23] E. Peters, D. Vastfjall, T. Garling, and P. Slovic. Affect and decision making: A hot topic. Journal of Behavioural Decision Making, 19(2):79–85, 2006.

[24] R. Plutchik. Emotion: Theory, research, and experience: Vol. 1. Theories of emotion, chapter A general psychoevolutionary theory of emotion, pages 3–33. New York: Academic, 1980.

[25] J.A. Russell. A circumplex model of affect. Journal of Personality and Social Psychology, 39:11611178, 1980

[26] K. R. Scherer. What are emotions? and how can they be measured? Social Science Information, 44(4):695729, 2005.

[27] T. Shibata, K. Inoue, and R. Irie. Emotional robot for intelligent system-artificial emotional creature project. In Robot and Human Communication, 1996., 5th IEEE International Workshop on, pages 466–471, 11-14 Nov. 1996.

[28] K. T. Strongman. The Psychology of Emotion. John Wiley & Sons, 1996.

[29] J.D. Velasquez. An emotion-based approach to robotics. In Intelligent Robots and Systems, 1999. IROS '99. Proceedings. 1999 IEEE/RSJ International Conference on, volume 1, pages 235–240, 17-21 Oct. 1999.

[30] G. Wang, Z. Wang, S. Teng, Y. Xie, and Y. Wang. Emotion model of interactive virtual humans on the basis of mdp. Frontiers of Electrical and Electronic Engineering in China, 2(2):156–160, 2006.

[31] J. B. Watson. Psychology. From the Standpoint of a Behaviourist. Philadelphia: Lippincott, 1929.

[32] J. B. Watson. Behaviorism. Chicago: University of Chicago Press, 1930.

[33] W. Wundt. Principles of physiological psychology. New York, NY: Macmillan., 1904.

[34] Marcel Zeelenberg, Rob M. A. Nelissen, Seger M. Breugelmans, and Rik Pieters. On emotion specificity in decision making: Why feeling is for doing. Judgement and Decision Making, 3(1):18–27, 2008.