MODELING EMOTION DYNAMICS IN INTELLIGENT AGENTS

A Thesis

by

MAGY SEIF EL-NASR

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

May 1998

Major Subject: Computer Science

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Approved as to style and content by:

John Yen (Chair of Committee)	Thomas R. Ioerger (Member)
J. Grau (Member)	W. Zhao (Head of Department)

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ABSTRACT

Modeling Emotion Dynamics in Intelligent Agents. (May 1998)

Magy Seif El-Nasr, B.S., American University in Cairo

Chair of Advisory Committee: Dr. John Yen

Emotions were shown to have a leading role in the human decision-making process, and thus they play an important role in human intelligence. Intelligent agents' research produced many models of emotional agents. However, most of these models focused on agent's behavior rather than its internal states, and thus, these agents tend to produce emotions according to some rules or predefined domain knowledge. Throughout the history of research on emotions, memory and experience were emphasized to be the main sources of the beating heart of the emotional process. More recently, the term "emotional intelligence" was introduced. Its introduction further emphasized the importance of experience in the emotional process. We are proposing a model of an agent that produces emotions according to its experience. Moreover, it simulates the emotional intelligence process. Research on human psychology has long considered the notion of an emotion to be a matter of degree; however, most of the existing research on emotional intelligent agents treats emotion as a black-and-white matter. We used fuzzy rules to explore the capability of fuzzy logic in modeling emotions. Fuzzy logic helped us to capture the fuzzy and complex nature of emotions. Experience and learning also helped in evolving our model to create a better illusion of reality. We chose to simulate a PET rather than a human or a creature, because pets have a limited set of goals that can be defined in a simple structure. Humans are more complex than pets. The emotional process in human beings is not a clear-cut process by itself, but rather it is intermingled with many other processes in the brain, including planning, self-perception, etc. Therefore, in order to simulate a human, one will have to simulate the other processes as well, while in pets it was much simpler. However, we will argue that our model could also be used to simulate human emotions.

I dedicate this thesis and work to

my mother and father who stood by me all the way

and to my brother who helped me in so many ways

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I would like to thank my advisor, John Yen, who stood by me and supported my ideas. When I entered Texas A&M as a master's student, I had no idea what field to go into or which field will best suit my abilities. I started looking for interesting areas and topics; my choice was modeling emotions. Even though emotion was considered a new topic in the Computer Science Department, Dr. Yen stood by me and supported the idea. He is the best. Through his visions I was able to capture many ideas and form a useful and interesting research work, which I think presents a major contribution to the field.

While working on my research, I had the pleasure of having Dr. T. Ioerger on my Committee. He helped me in developing a more research-oriented mind. Through the many hours that I took out of his time, he helped me in writing research papers and in looking at other alternatives. He had helped me in so many ways; I do not think I can thank him enough for that.

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I would like to thank the people who have been involved with me in projects concerning emotions and who have made this work more fun that it already was, including Sanaa, Jianwen, Linyu, Yi and Anna. I would also like to thank Dr. Daugherity, Michael Miller and Brent Cox for reading the thesis and making comments and suggestions. I would like to thank all the graduate students who have made my stay at Texas A&M so much fun.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER I

INTRODUCTION

1. WHAT IF …

What if a computer can learn and further predict the user's emotional state at any given moment? It has been shown that the user's emotional states affect perception, thinking and learning [7, 17]. However, many training and tutoring systems did not incorporate these factors in their systems' architecture [22]. For a training system to understand the user's learning status it may be useful to represent and predict his/her emotional state at any given time. Additionally, the system may use this knowledge to plan its next lesson, and decide on how to formulate the information in a way that will be easier for the user to understand and visualize. Tutoring or training systems are not the only systems that can benefit from modeling and using emotions. Systems and their applications will be further explored in detail in Chapter V.

This thesis focuses on modeling emotions in intelligent agents. We chose to concentrate on simulating emotions as opposed to predicting or understanding emotions. In part this decision was due to the fact that simulating emotions leads to effectively understanding emotions. Moreover, for a computer to understand or predict an emotional state of a subject, a quantitative measure of the emotional state must be calculated. Since we lack the experience and the equipment to measure emotion [34], we felt obliged to purse other avenues. Thus, we chose to concentrate on simulating emotions rather than understanding emotions. Even though the goal we set out to accomplish is only a part of a higher goal, we found out that it stands by itself to open a new area of research.

What if an agent can simulate certain emotional states and emotional behavior? Moreover, what if an agent can simulate emotional intelligence? Agents have been

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This thesis follows the style of *IEEE Transactions on Robotics and Automation*.

divided into several types, including interface agents, information agents, software agents and autonomous agents [28]. Modeling emotions will probably improve and further enhance the performance of several of these agent types. For example, if interface agents can form a better understanding of the user's moods, emotions, and preferences at any given moment, it can adapt itself and improve its services to match a particular user's needs. Software agents may use an emotion as a fitness function or an evaluation criterion for cooperation and coordination of certain tasks between multiple agents. In fact, emotion was used to help in the communication process of robots that collaborate on a certain task [44]. This particular application will be discussed in more detail in Chapter II.

Believable agents heavily rely on emotions to create believable responses. Believable agents were defined to be agents that create the illusion of life [3, 36]. The concept of believability is often used in theater. In theater, a character is created by completing a character study, which is formulated into a manifestation of the real character's behaviors. This manifestation is not necessarily real. In productions such as *Lion King or Pocahontas*, the characters were not real. Nevertheless, in these productions the characters evoked emotional responses from the audience as if they were real. This is the illusion of life. Thomas and Johnston [50] stated that sometimes the emotional responses need to be exaggerated to create the scene that you want to convey to the audience. In other words, at times it might be necessary to slow the response and the emotional expression for the audience to grasp the message. Creating believable agents might involve many other factors such as staging, animation and speed. Nevertheless, believable agents rely on emotional states and emotional responses as a foundation of their creation. In theater, emotions and emotional expressions were shown to be the determining factors that separate good artists' performances from others [50].

2. HISTORICAL PERSPECTIVE

Research on emotions started out with theories and views. The Greek philosophers established a theory on emotions. “Plato, for example, said that passions and desires and fears make it impossible for us to think [18].” Thus, emotions were viewed as obstacles to the human rational thinking. Centuries later, by the sixteenth century, Descartes [9] reinforced this theory by yet another theory. With his famous statement “I think therefore I am,” he formulated a theory of the emotional process that separates the mind from the body. In his book, *The Passions of the Soul,* he outlined the differences between passions and rational thinking. He regarded emotions as “passions of the soul,” which were defined as urges and needs that the body creates. In his view, the body holds all the needs and urges, while the mind is the heart of the rational thinking process [9].

After three centuries, new theories of emotions were established. By 1884, William James [15] published his article “What is Emotion?” At that time, there were no psychology journals. James set out to answer his question by proposing the following question: do we run from the bear because we are afraid or are we afraid because we run? His answer was that we are afraid because we run. He said, “my thesis on the contrary is that the bodily changes follow directly the perception of the exciting fact, and that our feeling of the same changes as they occur is the emotion [15].” His idea was that emotions are often accompanied by some bodily responses (e.g. tight stomach, tense muscles, etc.), and that different bodily responses trigger different emotions. Our reaction to these responses makes us feel an emotion.

Years later, different views and theories were formulated [18]. Cannon refuted James’ theory about emotions, which had dominated the psychology field for about thirty-six years. According to Cannon, James’ theory would not hold because almost all emotions have the same bodily responses. Thus, the idea that different bodily responses trigger different emotions was proven wrong. The era of the 1920’s saw the rise of the appraisals’ theory, which originated with Arnold. Schachter and Singer then took it up in the 1960's. In 1980 Zajonc raised the issue about conscious versus subconscious emotions. Zajonc had done some experiments and realized that the subjects, without recognition of the object in question, produced some affection for it. He then argued that the absence of conscious recognition meant that emotions were formed without the aid of cognition. Thus, he claimed that emotion and cognition were two separate areas. As a result, emotional research was rejected from the area of cognitive science, which emerged in the 1950's. However, by the mid-90's LeDoux opposed this rejection by stating that some cognitive processes occur in the subconscious level. Thus, it is premature to reject emotion from the field of cognition just because it includes subconscious level process [18].

Nevertheless, Zajonc's findings contributed to another view of the emotional process that was not yet explored. The idea of subconscious level emotional activities was new. Thus, the earlier view that regarded the emotional process as just a need or an urge was automatically refuted by the foundation of subconscious emotions, which was further expanded by Ohman [29].

3. EMOTIONAL INTELLIGENCE: A MYTH OR REALITY?

Searching for a complete definition for the emotional process, some psychologists tried to further explore its role in human intelligence. Howard Gardner [11] was one of the pioneer researchers in this field. In 1973 Howard Gardner wrote his book, *Frames of Mind,* to explain the concept of Multiple Intelligence [11]. The idea of Multiple Intelligence originated long before Gardner's time; however the theory was not well accepted at the time. He was formulating a new theory of intelligence. The idea of a single IQ test that could determine a person's intelligence and therefore speculate on the future of a person's life was rejected. Gardner divided intelligence into six types: linguistic, musical, logical-mathematical, spatial, bodily kinesthetic and personal intelligence [11].

The importance of Gardner's work became apparent a few years later. By the 1990's, many theories were formulated to describe a phenomenon that was later called "emotional intelligence." Emotional intelligence was part of Gardner's Personal Intelligence category, as indicated by the following quotation from his book, *Multiple Intelligence*,

> *Interpersonal* Intelligence is the ability to understand other people: what motivated them, how they work, how to work cooperatively with them. Successful salespeople, politicians, teachers, clinicians, and religious leaders are all likely to be individuals with high degrees of interpersonal intelligence. Interpersonal intelligence is a correlative ability, turned inward. It is a capacity to form an accurate, veridical model of oneself and to be able to use that model to operate effectively in life [12].

By 1994, emotions were further shown to have a clear and important role in the decision-making process. Evidence was uncovered to further emphasize the existence of "emotional intelligence." A. Demasio [8], a neurologist and philosopher, reviled new neurological evidence that emphasized the importance of emotions in the design-making process. Through his work with patients suffering a myriad of disorders, including brain damage, problems with memory, language, and reasoning, he was led to believe that mental activities need both the mind and the body [8]. A patient named Elliot was referred to Demasio after others had failed. Elliot had been diagnosed with a brain tumor. The tumor grew in his brain and it put enormous pressure on both frontal lobes. After what the surgeons called a successful surgery, in which the tumor and the damaged tissues were removed, Elliot experienced a radical personality change. He went from a successful businessman with a happy and stable family life to a person who could not hold a job and had to be in the custody of a sibling. This was the point when Elliot thought of seeking help. Elliot was a person who could not follow a schedule, motivate himself enough to get dressed in the morning, and was incapable of making the most basic decisions. For instance, he would spend an entire afternoon at work deciding whether to classify a group of data by date or place. He lost his job, his business and his marriage. Demasio describes his observations as follows:

> The machinery for his decision making was so flawed that he could no longer be an effective social being. In spite of being confronted with the disastrous results of his decisions, he did not learn from his mistakes… In some respects Elliot was new Phineas Gage [another case like Elliot, who was found at the time 1848], fallen from social grace, unable to reason and decide in ways conductive to the maintenance and betterment of himself and his family, no longer capable of succeeding as an independent human being [8].

After observing him talking about his situation, Demasio said, “I never saw a tinge of emotion in my many hours of conversation with him: no sadness, no impatience, no frustration with my incessant and repetitious questioning [8].” Elliot was given tests, including IQ tests, memory tests and decision-making tests. He passed every test that they could give him, even morality tests. His IQ was above average. However, Demasio argued that real-world decisions are far more complex than the tests which were given to him. In the real world we are faced with many uncertainties and we have to employ fast ways of making decisions rather than going though vast probability calculations.

With this case Demasio then formalized his findings into a theory. He noted that the emotional process is the leading catalyst in the decision-making process. He explained that emotions allow for a simple elimination process, which people call “gut feeling.” He argues that the “high reasoning,” advocated by Plato, Descartes and Kant, who employ formal logic and pure reasoning, rejecting emotions and feelings from their formulas, is flawed. Pure reason is what Elliot was bound to, and that did not lead him to a successful life.

Demasio’s findings proved the existence of emotional intelligence. Emotional intelligence was further explored and formulated by D. Goleman [12]. In his book, *Emotional Intelligence: why it can matter more than IQ* [12], he said:

> … what career to pursue, whether to stay with a secure job or switch to one that is riskier but more interesting, whom to date or marry, where to live, which apartment to rent or house to buy – and on and on through life. Such decisions cannot be made well through sheer rationality; they require gut feeling, and the emotional wisdom garnered through past experiences. Formal logic alone can never work as the basis for deciding whom to marry or trust or even what job to take; these are realms where reason without feeling is blind [12].

4. FOUNDATION OF EMOTION AND EI

Emotion. Science has been and still is looking for a complete definition of the term emotion. Even though there is no complete definition, there are some theories established to formalize the concept of emotion. In the following paragraphs, we will explore some of the definitions formulated in the early literature of research on emotions. Through these definitions, we will try to formulate a description of the concept of emotion as it stands today.

Emotion was defined as a feeling [46]. Not all feelings are emotions. For example, you can feel hunger, you can feel pain, but hunger and pain are not emotions. They are called motivational states [6]. Motivational states are feelings that might drive the brain to interrupt its normal activity to concentrate on a higher need. All the states that affect the survival goal of an agent are called motivational states, such as hunger, thirst, pain, exhaustion and sometimes fear.

Descartes defined emotions as passions [9]. He gave some examples of emotions, including anger, joy and fear. He further identified different facial expressions for each of these emotions. Emotions, among other feelings, can change the facial expressions. Feelings and emotions are part of the same process. In fact, feelings, emotions and reasons are all intermingled [25].

While there has been questions about what an emotion is and how an emotion can be formulated into a feeling, there exist a few other attempts to define the concept of emotion. Izard [14], using some tests on various subjects, formulated a list of innate emotions, i.e. emotions that are common through various cultures and social groups. The list he produced is similar to Descartes' list produced ages earlier [9]. Ortony et al. [30] produced a model of emotions where they defined emotions to be clusters or chunks. For example, there might be five or six different levels of anger, but these levels are all classified under the emotion anger. Rosman et al. [39] produced another model of emotions. The model was used to trigger emotions according to events, which were divided into categories according to the cause. These categories include (1) self-caused, (2) other-caused and (3) uncertain-cause events. Ekman [10], one of the leading psychologists in the area of emotions, listed six basic emotions: anger, fear, sadness, enjoyment, disgust, and surprise. He composed this list by looking at the various facial expressions among cultures and ethnic groups. He was trying to find the common or basic set of emotions that were shared by most cultures.

The idea of emotional intelligence became the groundwork of much of the research work done on the theory of emotions. Thus, the focus went from the definition of the concept of emotion and the emotional expression to the definition and modeling of the emotional intelligence phenomenon. Goleman [12] stated, "one aspect of emotional intelligence, 'social' intelligence [is] the ability to understand others and 'act wisely in human relations' [12]." Thus, he formulated and defined emotional intelligence to include the following:

1. *Knowing one’s emotions*. Self-awareness - recognizing the emotion as it happens.

2. *Managing emotions*. The ability to handle the feelings and emotions when they happen. This ability builds on the self-awareness step.

3. *Motivating oneself.* Redirecting emotions in the service of a goal is one of the essential ingredients for attention, self-motivation and creativity.

4. *Recognizing Emotions in Others.* The ability to recognize the other’s emotions, for example Empathy, is considered a fundamental “people skill. ”

5. *Handling relationships.* Handling relationships is the ability to manage emotions in others through leadership, popularity and interpersonal effectiveness [12].

Moreover, experience plays an important role in the simulation of emotional intelligence. Experience helps in shaping the personality and emotional behavior. As Goleman says:

> Such decisions cannot be made well through sheer rationality; they require gut feeling, and the emotional wisdom garnered through past experiences. Formal logic alone can never work as the basis for deciding whom to marry or trust or even what job to take; these are realms where reason without feeling is blind [12].

Therefore, to provide a good model of the emotional concept we have to simulate experience.

5. PROBLEMS IN EMOTIONAL MODELING

By the 1980’s, several appraisal models of emotions had been formulated. Ortony [30] and Rosman [39] tried to solve the problem of the synthesis of the emotional process given the occurrence of certain events. Both of these models formalized some variables that might affect the synthesis of emotions, including expectations, predictions of the occurrence of an event and effort of achieving a goal. In Ortony's [30] model, emotions were defined in terms of rules. For example, joy was defined as the occurrence of a desirable event [30]. In contrast, Rosman's model formalized emotions according to event categories [39]. These categories depend on many factors, including the likelihood of the event to occur and the consistency measure of an event in terms of the goals. In addition, he further refined the synthesis process to include self-perception. The idea of whether the subject perceives him/herself as weak or strong in terms of a given event might trigger different emotions. These two models show how two or three variables could effectively trigger different emotions. It should be noted that these models simulate fourteen or fewer emotions. Thus, more variables might be required if totally different or new emotions are added to the model. An implementation of an expert system followed these models to further extend the number of variables involved [41]. The list of variables include goal significance (concern relevance, outcome probability, expectation, conductiveness, urgency), novelty (suddenness, familiarity, predictability) and intrinsic pleasantness [41]. However, questions about the quantity and identity of the variables involved in the emotional process are still open.

These models consider only a subset of the emotional process. For example, it is clear that at a given moment different emotions may be triggered with different intensities. However, it is unclear how other emotions or other motivational states like thirst, hunger, pain, etc., affect emotions. These models are also limited to conscious emotions; subconscious emotions were not discussed. Since these models were not really developed for emotion simulation, they did not provide an explanation of how the internal states or variables used can be computed. If we are going to simulate emotions in a computer, we need to know how to compute these internal states.

Other models, like the Bolles and Fanselow's [6] model, tend to take a few emotions or motivational states like "fear" and "pain" and determine how they affect each other. They found that fear might inhibit pain and vice versa. Even though some conditioning was incorporated in the model, the model still represents one element of the bigger picture. Nevertheless, it outlines a very important point that the other models did not take into consideration; emotions and motivational states do affect each other in various situations. Thus, for example pain might inhibit other emotional states such as pride, shame, and fear.

D. Price et al. [35] showed that internal states such as desire and expectation can affect or even predict the emotional state of various subjects [35]. They based this conclusion on the data obtained by asking various subjects to quantify their experience of a certain emotion by answering some questions on a score from one to ten.

Due to the emergence of the believable agents, a number of models simulating the emotional process have been proposed. Two major models evolved out of this area, the OZ project [3, 4, 5, 36, 38] at CMU and Simon [51] at MIT. These models follow different agent architectures. These architectures will be detailed along with other models in Chapter II. The OZ project simulated agents, some of which were animated and others text based, with an emotional state and a behavior. Each agent initially has preset attitudes towards certain objects in the environment. Further, each agent has some initial goals and a set of strategies that it can undertake to achieve a specific goal. The agent senses or perceives an event in the environment. This event is then evaluated according to the agent’s goals, standards and attitudes. After an event is evaluated, special rules are used to produce an emotion with a specific intensity. The OZ project uses Ortony’s model as a basis for these rules. The emotions triggered are then mapped according to their intensity to a specific behavior. This behavior is then expressed in the form of text or animation [36]. One of the problems of this model is its mapping function. A specific emotion with a specific intensity is mapped to a behavior. The researchers rely on interval-based mapping. For example, they map the emotion of “anger” with the intensity of ten to twenty to a behavior like “rage out.” There will always be a question of where to set the cutoff for the boundaries. What happens if the anger intensity was nine and a half? The need for a smoother mapping and modeling of the emotional intensity and behavioral mapping is essential.

The model [51] developed at MIT includes of some internal states such as: neural states (brain temperatures, neurotransmitters, etc.), sensorimotor (facial expressions, body gestures, etc.), motivation (emotions, hunger thirst, etc.), and cognitive (appraisal, interpretation of events, etc.). The researchers used Rosman's [39] model to build the event appraisal and emotion triggering process. Essentially, the model monitors the internal states and the environment. The emotional state is periodically updated according to Roseman's rules. Emotional intensity is determined in terms of many factors, including the intensity of the same emotion in the previous time step. A mixture-filtering step proceeds by inhibiting opposite emotions. For example, sadness and happiness do not make sense to be felt at the same moment with the same intensity. Thus, one of these emotions is inhibited according to the intensity values. A behavior is triggered according to the highest intensity emotion. The mixture of emotions will be fed back to the system after being decayed by a certain amount α, where α is a constant value that is used throughout the process. The model poses many questions about how the internal states change and what changes them. Also, the idea of smooth transition from an emotional state to a behavior was not incorporated. Despite the fact that the model provided some guidelines such as the inhibition of opposite emotions, it is still unclear which emotion filter out the others. Moreover, it is unclear why the emotion with greater intensity rule over the other; what if depression had a value of five and happiness a value of six? Some researchers claimed that negative emotions have a much more profound impact on a subject than positive emotions. Thus, if the intensity values were close, probably the negative emotion should inhibit the positive emotion. Furthermore, questions about the inhibition process, including inhibition among positive emotions, were left unanswered. None of these questions were answered in any of the previous models. Although we will not provide answers to these questions in our model, we will present a better way of handling these parameters.

6. AN ALTERNATIVE

We propose an alternative model that better addresses the questions above using fuzzy logic and machine learning. In this section, we will outline how our model solves the problems highlighted in the previous section. Furthermore, we will also provide a high level design of the model and a summary of the results and the experiments taken. In conclusion, we will state the major contributions of the proposed model as opposed to other models.

To illustrate our model, we simulated a pet -- a dog named PETEEI. We chose a dog instead of any other pet type, because dogs seem to have more awareness of a person's emotions. It acts according to both its emotions and the owner's needs and emotions. The choice of a pet was two-fold, (1) many people have expectations about what a pet should act like, thus they will be able to test the model's believability more effectively; and (2) pets are simpler than humans. With pets we do not have to simulate a global tree-structure of goals, desires and conflicts. Additionally, a human's personality involves social interaction and social comparison processes that we did not incorporate. We also did not take the concept of self-esteem into account. Self-esteem is considered the stem of many of the human emotional problems. Nevertheless, the model still captures part of the human emotional system; it is not a complete model, but it is a step in the right direction.

A. OVERVIEW OF THE IDEAS OF THE MODEL

There are three major issues that are inadequately addressed by the previous models of emotions:

(1) No quantitative measure of internal states, including expectations, likelihood of events and a measure of event desirability, was described. Humans normally have different expectations for different events. These expectations result from an ongoing learning process. For example, if John went to work late and his boss did not say

anything, then John will tend to expect the same behavior from his boss the next time he comes in late. The levels of expectation will then be increased or decreased according to how many times the expectation was met and how many times it was not. There are other forms of learning that may affect expectations. For example, conditioning is another form of experience in which an agent develops an association between an object and a specific emotion or motivational state. This form of learning was modeled and implemented earlier [48], but most models do not account for it.

(2) There was no empirically based filtering method for inhibiting or enhancing emotions discussed. Combining emotions with motivational states and further filtering them with a more profound method can potentially affect the realism of a behavior. Motivational states such as hunger, pain and thirst can drastically affect the emotions triggered, and so can change the emotional behavior of the agent. For example, consider a subject who is experiencing pain and joy at the same time. If both emotions are very strong, he will probably act on the pain and inhibit the joy. A subject may also experience contradictory or opposite emotions, such as sadness and happiness, at the same time. Such mixed emotions can occur at various times and situations. To model emotions and emotional behavior, a model will have to take into account these mixtures and explore the effect of different emotions and motivational states on each other. We essentially combined different models, including Bolles and Fanslow's model [6] and Bower and Cohen's model [7] to provide a more believable behavior.

(3) The mappings from emotions to behaviors are not gradual. Most of the previous models use a threshold-based mapping technique. For example, they may have a rule that says if the agent is feeling 90% of sadness, then make him act aggressively. The sharp cutoff of 90% may present some problems during the character behavior process. For example, if sadness is triggered with an 85% or an 89% then how will the agent react? Will he be more or less aggressive? Fuzzy logic and fuzzy sets can potentially solve this problem. Instead of having sharp threshold such as the 90%

threshold described in the example above, we will use fuzzy sets that are defined as overlapping boundaries of terms such as *high, low* and *medium*. The use of fuzzy logic modeling, in our research, will be detailed in Chapter III.

B. OVERVIEW OF THE MODEL ARCHITECTURE

Figure 1 shows our architecture of the agent's internal cognitive mind. Even though the figure seems complex, in reality it is an overly simplistic model of the pet's mind. In essence, the architecture has three major components: a model of the emotional process, a model of cognition process, and a model of the learning process, shown in the figure as the experience model. The emotional model triggers emotions and generates emotional behavior. An emotion is triggered by an event. As soon as an event is perceived it is passed to the experience model for assessment. The experience model is one of the major contributions of the thesis. Most computational models of emotions have been built using the appraisal models such as Ortony & Collins [30], or Rosman [39]. Although these models use internal variables, such as expectations and the level of effort exerted, to produce emotions, the computational models that evolved out of these models (e.g. OZ [4]) did not use experience to trigger these internal variables. As Figure 1 shows, we propose an agent architecture that uses past experiences to guide its emotional process. The experience model uses reinforcement learning to calculate the maximum reward that the agent can get given the situation. The path, created by the reinforcement learning, is used to calculate the expectation values of events that might happen in the next time step. These expectation values depend on the mood of the agent. Therefore, if the agent is in a good mood, it will favor the expected good events more than the expected bad events; the favoring factor will heavily depend on how good the mood is and will directly impact the level of expectation. These expectation levels along with the event-goal association, which can also be obtained from the experience model, will be used to trigger certain emotions. The emotion generation phase, shown in the figure, uses certain rules, for example hope is defined as the occurrence of an unconfirmed desirable event.

The desirability measure is calculated using the event-goal association, which is obtained from the learning process, as shown in the figure. The desirability measure of the expected event will trigger the emotion to a certain degree depending on the expectation value. Different emotions will be triggered in similar ways; thus at any time step we may end up with a mixture of emotions with different intensities.

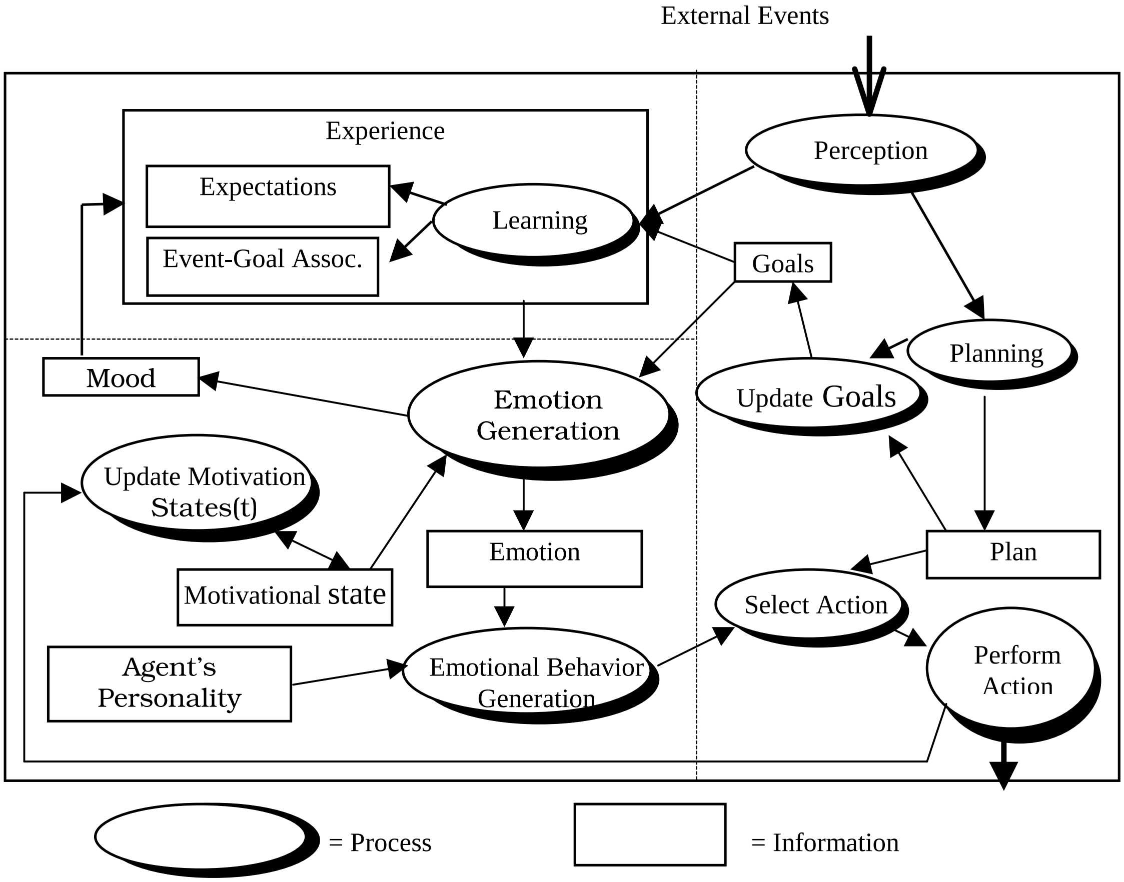

FIGURE 1. AGENT'S ARCHITECTURE – AN OVERVIEW

Emotional states are affected by the motivational states of the agent, as shown in the figure. Motivational states are updated through the agent's lifetime according to the agent's actions and time. For example, thirst is calculated using a number of factors, including the number of movements and the time when the agent drank last. Thirst may inhibit other emotions such as joy, pride or shame in certain situations. A filtering process, that inhibits or enhances certain emotions or motivational states, was implemented. The filtering process will produce an emotional state.

An emotional behavior generation process will then proceed by using fuzzy mapping. To simulate a smoother boundary, we are using fuzzy logic modeling [52]. Instead of having specific ranges or numbers for the intensity of a given emotion, we simulated the intensity in terms of fuzzy sets of *high, medium* and *low*. Instead of having a sharp boundary measure of emotional intensity, fuzzy sets give us the capability to simulate the intensity in overlapping regions. In other words, *medium* intensity overlaps with *high*, and *low* with *medium*. The mapping will then take a specific intensity and map it to a particular behavior. For example, we have rules like:

IF mood is *GOOD* and Joy is *HIGH* and Ball is *there* THEN RUN & PLAY

where *GOOD* and *HIGH* are fuzzy sets, and *there* is a singleton (either true or false). The appropriate rule will be fired accordingly, provided that there is another rule that tests if the mood was bad and does some other behavior.

Furthermore, the agent may not always act on its emotional process. Some situations may arise that obligate the agent to act according to its plan, ignoring its emotional state. Thus, an action selection process is used to select an action according to the situation, emotional response and the plan.

The model uses many parameters in the learning and filtering processes. We had to set these parameters to the right ranges. It should be noted that the end product for us is an emotionally intelligent agent. Therefore, these parameters should be set to a value that simulates the most realistic emotional states in a given situation. Instead of trying to derive these parameters from some philosophical theory, these parameters were set dynamically by a trial and error process. We ran the simulation on different parameter ranges to develop a definite range that produces the best impact on the realistic measure of the emotional process produced by the agent.

C. A PREVIEW OF SIMULATION AND RESULTS

The model was simulated as a Java application. It consisted of a garden scene with a pet house and a pet. The user is represented as a cursor. The user can interact with the scene through functions, including looking at various objects, taking various objects, hitting objects, or putting objects in the scene (the user will have an inventory item that he can click on and he can then put the items he collected from other scenes or that were initially in the inventory to the scene). The simulation was built to have the look and feel of other RPG (Role-Playing Games). A picture as well as a brief description of the interface and the various windows in the system is presented in Appendix A. The implementation followed the model that was discussed above.

Since believable agents are not necessarily real agents but are agents that can pass as a simulation of an intelligent lifeform, we chose to evaluate the model by having the user walk through several scenarios and answer a questionnaire. The questions involved assessment of intelligence, adaptiveness, naturalness of response, etc. To be able to examine the impacts of various aspects of the model, we provided scenarios that demonstrated learning, fuzzy logic and emotional filtering. We evaluated four variants of the system. First, we evaluated a model that produced a random set of behavior and emotional responses to create a baseline for the other experiments. Second, we evaluated the system with no fuzzy logic and no learning. Third, we evaluated a system that models fuzzy logic with no learning to see the impact of fuzzy logic on the emotional process. Fourth, to quantify the impact of the learning process on the model, we evaluated a model with both learning and fuzzy logic. We were able to show that users could reliably detect the improvement in the emotional responses of the pet when both learning and fuzzy logic were included in the model.

D. CONTRIBUTIONS

We can summarize the contributions of this thesis into three main areas:

(1) We are providing a way by which models of emotions can evolve to capture the dynamic nature of emotions. Adaptability is critical to realistic models of emotions. The complexity of the dynamics of the emotional process can only be captured through situations, time and experience. Various expectations and desires change by time and experience.

(2) Instead of using clear cut ranges or boundaries to map emotions to behaviors, we propose the use of fuzzy logic modeling to smooth the transitions.

(3) We combine the motivational states with the emotional states and provide a filtering technique that inhibits or enhances emotions according to the intensity and the values of the various emotional and motivational states.

7. STRUCTURE OF THE THESIS

This introductory chapter provides an overview of the thesis. It introduces the reader to the various motivations for developing a simulation of the emotional process. It provides a summary of the previous models, which are further explored in Chapter II. It also provides an overview of the model proposed by the thesis, which will be further detailed in Chapter III. Additionally, it summarizes some of the experiments that we ran in the process of evaluating the model. These results and experiments will be discussed in greater detail in Chapter IV. Moreover, this chapter gives the reader an introduction to the various terms used in the thesis and it also provides the reader with a historical perspective on the research of the evolving emotional process. Chapter V will expand on the motivations, discussed in this chapter, to introduce the applications and the future directions in modeling the emotional process. Chapter VI concludes the thesis by giving a brief summary of the contributions.

CHAPTER II

PREVIOUS WORK

1. PSYCHOLOGICAL MODELS

Psychological models of emotions were built to explore the concept of emotions from different viewpoints. Some models were built to emphasize the role of motivational states and their effect on the emotional and behavioral process. Some others were built to model emotions according to the occurrence of events; these models are called event appraisals. In contrast, some other models were produced to tackle different questions and directions in modeling emotions. For example, D. Price and J. Barrell [35] developed a model that describes emotions in terms of desires and expectations. Unlike the appraisal models, they did not limit an emotion to an event. They linked an emotion to the internal thinking process, which were reflected in expectations and desires. They gathered some participants and asked them questions about their experience with some emotions, including anger and depression. One of their questions was formalized as: "rate your experience of this emotion in a number from one to ten [35]." They took a number of answers from different participants and quantified them to fit a mathematical curve that showed the relation between expectation, desire and emotional intensity. However, the model did not provide a method for calculating expectations and desires. In fact, the model presented about five emotions and showed the impact of desires and expectations on determining these emotions. Even though the model was small and did not tackle but a small portion of the concept of emotion, it does have many merits. It presented an idea that we then used and enhanced to form our model. It also proved the importance of experience in determining and simulating emotional responses. Details on the calculation of expectations and their further use in determining the emotional state will be discussed in Chapter III.

A. MOTIVATIONAL STATES

Models of motivational states, including pain, hunger and thirst were explored in varies areas in psychology and neurology. A model of pain was developed by R. Schumacher and M. Velden [42]. However, most of these models tend to formulate the motivational states into a pure physiological reaction, and thus the impact that these motivational states have on other states such as the emotional states was not conceived.

A model was proposed by Bolles and Fanselow [6] to explore the relation between the motivational states and the emotional states, more specifically the relation between “fear” and “pain.” Their idea was that the motivational states such as “fear” and “pain” sometimes inhibit or enhance each other. Thus, in some situations, pain can inhibit fear and in some others fear can inhibit pain. They developed a model, which they called the PDR (Perceptual-Defensive-Recuperative) model. The PDR model consisted of three phases. The first phase, the perceptual phase, was defined as the phase where the subject perceives an object. At this instance, the subject would typically have some expectations from the stimulus presented. Expectation values were calculated as a result of the classical conditioning process, where the subject learned to associate certain stimulus with a certain response or with a certain emotion. They defined phase two as the defensive phase. In this phase, the subject would, according to his/her expectations, have some fear, provided that the stimulus presented a cause or was associated with pain expectation. The intensity of fear depended on the level of pain expected. Thus, the subject would tend to inhibit the pain (if it had any pain at the time), to act on the fear. In phase three, the recuperative phase, the intensity of fear would typically drop as a result of the disappearance of the cause of fear. Pain would then take over if there was any damage, and thus pain would inhibit fear [6]. The model emphasized the role of inhibition and how the brain or essentially the human body could inhibit or enhance some motivational states or emotions over others. This model was simulated and added as a part of our model. Clearly, this model presents only one spectrum of the filtering process. In our attempt to find better solutions, we reviewed other models.

B. APPRAISAL MODELS OF EMOTIONS

Appraisal models had been developed by the 80's and the early 90's to model emotions in terms of event occurrence [30, 39]. In the next couple of sections, we will detail two models that evolved around the 1980's.

i. ROSMAN'S MODEL

Rosman's model [39] is illustrated in Table 1. In this model, an emotion is generated according to an event assessment procedure [39]. Events were divided into motive-consistent and motive-inconsistent events. Motive-consistent events were defined as events that are consistent with one of the subject's goals. On the other hand, a motive inconsistent event denoted an event that threatens one of the subject's goals. Events were further categorized with respect to other categories. For example as shown in the table, the event can be caused by other, self or circumstance. Nevertheless, the knowledge of the cause was not sufficient. They further defined events according to a certainty measure. In other words, if it already happened then the subject would be certain that an event, *x*, had occurred by *y*. However, if the subject expected an event with a certain probability to occur by a certain cause then the model would identify that. As it is illustrated in the table, events of a certain cause, say other-caused were divided into certain or uncertain events. Another category that was used to differentiate some emotions was whether an event was motivated by obtaining a reward or avoiding a punishment. To illustrate the importance of this category, we will take relief as an example. As shown in the table, relief was defined as an emotion that was triggered by the occurrence of a motive-consistent event that was motivated by avoiding punishment. In other words, an occurrence of an event that was meant to avoid punishment or an event that prevented a goal-threatening event from occurring.

TABLE 1. ROSMAN'S MODEL

	Motive-consistent		Motive-inconsistent		Self
Circumstance-caused	Appetitive	Aversive	Appetitive	Aversive	
Unknown	Surprise				
Uncertain	Hope		Fear		Weak
Certain	Joy	Relief	Sadness	Distress, Disgust	Weak
Uncertain	Hope		Frustration		Strong
Certain	Joy	Relief	Frustration		Strong
Other-Caused					
Uncertain/certain	Liking		Dislike		Weak
Uncertain/Certain	Liking		Anger		Strong
Self-Caused					
Uncertain/certain	Pride		Shame, Guilt		Weak
Uncertain/Certain	Pride		Regret		Strong

Another important category that was also emphasized was self-perception. The fact that a subject might regard him/herself as weak in some situations and strong in some others may trigger different emotions. For example, if the subject expected a motive-inconsistent event to occur with a certainty level of 80% and he/she regarded him/herself as weak in the face of this event, then he/she would feel fear (as shown in the table). However, if the same situation occurred and the subject regarded him/herself as strong, then frustration would be the emotion triggered (as shown in the table) [39].

This model, like most of the event appraisal models of emotion, is still not complete. The model did not formulate a method by which the categorization processes of events are calculated or measured. Calculating a probability factor of the occurrence of certain events still represents a big challenge. Furthermore, some events are perceived as both motive-inconsistent and motive-consistent. In this case, we will end up with different emotions. Therefore, a filtering mechanism by which emotions are inhibited or enhanced is needed. Moreover, the emotional process is rather deeply immersed in the thinking process and thus, not all emotions are triggered by external events. This fact uncovered an important limitation in the emotion event appraisal models.

ii. ORTONY, COLLINS AND CLORE'S MODEL

Ortony et al. [30] developed another model that was quite similar to Rosman's model [39]. They divided goals into three types: A-goals, which were defined as implicit goals or preconditions to a higher-level I-goal; I-goals, which were defined as implicit goals such as life preservation, well being, etc.; and R-goals, which were defined as explicit and short-term goals such as food, sleep, water, etc. They also defined some global and local variables that can potentially affect the process by which an emotion is triggered. Local variables were defined to be: the likelihood of event occurrence, effort to achieve some goal, realization of a goal, desirability for others, liking of others, the strength of cognitive unit, expectations and familiarity. Global variables were defined as sense of reality, arousal, and unexpextedness. After defining these terms, they formalized emotions into equations or formulas that can be realized as a computational model. For example: joy = the occurrence of a desirable event, relief = occurrence of a disconfirmed undesirable event. Sixteen emotions were formalized in this form, including relief, distress, disappointment, love, hate and satisfaction [30]. In fact, the model was employed as a computational model by the OZ group, a group working on believable agents at CMU (Carnegie Mellon University) [4, 5, 38, 36, 37].

Nevertheless, the model is not complete. As stated earlier the equations are intuitive and seem to capture the process of triggering one emotion really well, but often emotions are triggered in a mixture. The model did not show how to filter out the mixture of emotions triggered to obtain one emotional state. It is not clear how the model handles the calculation of the internal local and global variables that they said affected the emotions triggered, such as the expectation or the likelihood of the event occurrence.

2. ARTIFICIAL INTELLIGENCE AND EMOTION

Since the rise of AI, many models were proposed to simulate the human mind. Throughout the history of AI research, many models were proposed to simulate the emotional process, each of which presented a mark in the history of emotions. Simon [47, 46], one of the founders of AI, developed one of the earliest models of emotions in AI [46]. Essentially his model was just a simulation of motivational states, including hunger and thirst. He simulated these states as interrupts, thus whenever, for example, the hunger level goes beyond a certain limit the brain will be interrupted. Models of emotions from early 1960’s till the 1980’s were summarized by R. Pfeifer [31]. However, since the psychology of emotions was not yet complete at that time, it was not easy to find a computational model that described the whole emotional process. Instead of looking through these models, we will look at the more recent models. In the following sections we will take a look at the various models of emotions that had either employed several techniques from the AI world or applied emotions to various AI fields.

A. EMOTIONS IN ROBOTICS

A model was developed by S. Sugano and T. Ogata [48] on an electronically mapped robot. They set out to duplicate the idea of a “mind” in an electronic robot. Their hypothesis was:

> If a system has
>
> > the Survival Instinct
> >
> > the function to continue to live
> >
> > the self-preservation
> >
> > and has the communication function
>
> Then there is a possibility that mind emerges[48].

The robot had some external and internal sensors. External sensors were listed as: (1) a sensor for color, (2) a sensor for brightness, (3) a sensor for range, (4) a sensor for sound, (5) a sensor to sense shock (on or off), (6) a sensor to sense touch (on or off), and (7) a sensor to sense energy taste (3 levels). Internal sensors were listed as: (1) an energy consumption sensor and (2) voltage of the battery sensor. The output of the robot was either a motion or an emotion. The robot could move in the form of body and head rotation, arm extension or full body motion. Emotion was expressed in the form of colors, including blue for fear, red for anger, and yellow for expectation and pleasure.

Furthermore, the robot was developed to perform classical conditioning. We will illustrate the concept of conditional learning by giving an example that they illustrated in the paper. The robot initially expressed his pleasure when charged by showing the yellow color, but it did not show the yellow color at the sound that came before charging. Thus, the sound was defined as the unconditioned stimulus in this experiment. They repeatedly charged him and the sound always came before the actual charging began. After some time, the robot reacted to the sound with a yellow color expressing expectation and pleasure. Thus, the sound became a conditioned stimulus; in effect it symbolized being charged [48].

The robot performed learning, but it still was not performing emotional expression and emotional behavior. Being able to react to certain blocks or objects by expressing anger or pleasure is not considered as a valid model of the emotional process. Nevertheless, the model represented the conditional learning process that not many computational models of emotions incorporated. Therefore, the model by itself is a valuable asset to add to. However, the simulation of emotions was not accurate and it was not grounded on any of the psychological models. The model assumed that if the robot learned that a certain block x is bad, then it would automatically react to the block x with anger. This concept is true in some cases. However, the emotional process is a much more complex concept than what was presented in the paper.

Another system was developed not to model emotions, but rather it was developed to use some emotions for robot cooperation and collaboration [44]. A certain task was divided among a set of robots. Each robot initially had a set of strategies that it could employ. At any given time, the robot would test the situation and then it would choose a strategy that represented a best fit to the given situation. The selection of a strategy was based on a Q-learning algorithm. For more information on the Q-learning algorithm the reader is referred to [26]. The Q value was modified using an evaluation function that depended on the level of cooperation. The strategy with the best Q value would then be followed. A frustration function was introduced. The function served as a conflict resolution factor. Therefore, if the robot was pursuing a strategy and he failed to fulfill the goal in some amount of time, then it would go back to its learning model and choose the strategy with the second best Q value.

Even though they emphasized the importance of emotions and emotional intelligence, it was not clear how and why they modeled the different emotions that they mentioned. They did not show how the level of frustration was actually measured or calculated. Nevertheless, the system, as we understand it, illustrates a use of emotions in a multi-robot application.

B. MACHINE LEARNING IN EMOTIONS

An expert system was developed by K. Scherer [41] to "develop a computer program that would allow a user to enter information on a situation in which a strong emotion had been experienced and have the program predict or diagnose the nature of that emotional state [41]." According to Scherer, the emotional appraisal occurred in an invariant sequence. Thus, the appraisal process was constantly operative with evaluations being continuously performed to update the subject's information on an event. Scherer developed a predictive vector for 14 different emotions. This vector was later used by an expert system to predict emotional states given some information. A part of the predictive vector is presented in Table 2. As you can see from the table, there are many other factors considered for a given emotion. Unlike the other appraisal models described above, this model presents yet another dimension to all of them. The table shows, over ten variables that can elicit different emotions. Actually the table only provides some of the features that were selected for emotion prediction. For more information about the model and about the predictive vector used the reader is referred to [41]. The following are examples of questions asked by the expert system:

> Did the situation that elicited your emotion happen very suddenly or abruptly?
> (0) not pertinent (1) not at all (2) a little (3) moderately (4) strongly (5)extremely
>
> Did the situation concern an event or an action that had happened in the past, that had just happened or that was to be expected for the future?
> (0) not pertinent (1) the event had happened a long time ago (2) it happened in the recent past (3) it had just happened at that moment (4) it was to be expected for the near future (5) it was to be expected in the long run [41].

TABLE 2. PREDICTIVE VECTOR FOR SCHERER'S EXPERT SYSTEM

	Enjoyment/ Happy	Elation/Joy	displeasure/ disgust	contempt/ scorn	sadness/ dejection
Novelty					
Suddenness	low	hi/med	open	open	low
familiarity	open	medium	low	low	open
predictability	medium	low	low	open	open
intrinsic pleasantness	high	open	v.low	open	open
Goal Significance					
Concern relevance	open	self/relation ships	body	relationship s/order	open
Outcome probability	v.high	v. high	v. high	high	v. high
Expectation	consonant	open	open	open	open
Condunciveness	conductive	v. conductive	open	open	obstruct
Urgency	v. low	Low	medium	low	low

The model does not really model the emotional process. It predicts the emotional state given some information about the state of the user, but that does not mean that the model can essentially recreate or simulate an emotion. However, the model provides a more important view. It gives a more enhanced image of the emotional process that can be used to simulate and model the complete emotional process. The variables that were provided can essentially provide a good scheme for simulating emotions provided that we know how to compute them. Variables, including expectation, concern relevance, and predictability may require more than just a computation. It requires some sort of an experience track. As we will show in Chapter III, experience plays an important role in modeling emotions and further developing the emotional process. In essence, this is one of the major contributions of the thesis.

Another system was developed that made use of yet another learning algorithm, namely "Neural Networks [13]." Neural Networks were discussed in [26]. The system simulated a virtual environment where some herbivorous animals and carnivorous animals lived. Of course, the carnivorous animals were considered natural enemies of the herbivorous animals. The herbivorous animals selected their next actions by their own decision making process, while the carnivorous animals acted randomly. Within the virtual environment the grass increased with time. Only herbivorous animals had sex and could reproduce. Lifetime was simulated by an energy level that was increased by eating and was decreased by action, time and movements. If the energy level reached zero then the animal dies. The decision-making system was simulated as a three layered neural net. The input layer had about 171 units of environmental information. The environmental information was measured in the form of on or off signals. Every animal had a vision area of about two squares in each direction. The vision area was fed into the neural net in the form of 0 if no animal was there or 1 if there was an animal. The neural net would then output an action. The actions that the animals could take were *move to*, *attack*, *eat*, *do nothing*, and *copulate*. Additionally, a GA algorithm was used to mutate and crossover species. Although the system did not really model emotions, it behaved as if the animal was feeling some emotions. For example, one of the scenarios that was traced out of the system was presented as follows:

> the virtual herbivorous animal has moved as if it has been escaping from the carnivorous animal. We consider this action is caused by Fear. Fear is the most simple and primitive mental software that determines the best action for escaping from danger [13].

To achieve believability in simple actions is very trivial. Actually these animals can pass as believable for very simple behavior animals. However, when we look at more complex animals such as, pets or humans or even birds, achieving believability turns out to be a completely different story. In these cases, a complete model for simulating the emotional process is needed.

C. AFFECTIVE WEARABLES

Affective wearables were developed at the MIT media lab [33, 34, 32]. As Picard said, "one of the distinguishing features of wearable computers, as opposed to merely portable computers, is that they can be in physical contact with you in a long-term intimate way [32]." A wearable can potentially learn to recognize different physical and physiological patterns and then predict your mood, your emotional states, etc. Since it can stay with you for a long term, it can potentially learn some essential elements of your personality, your preferences, your friends, and your opinions. It can use the knowledge it gathered about you to serve you in the best way possible.

A prototype was developed at the MIT media lab to recognize patterns of corresponding affective states. They had set up a medical device that they attached to the wearable. The medical device was used to monitor the respiration, skin conductivity (GSR), temperature, blood volume pressure (BVP), heart rate (from BVP), and EMG (electromyogram, for muscular electrical activity). They measured stress through average heart rate, average respiration rate and skin conductivity or a combination of these. They gathered five subjects and ran some experiments involving reading from the physical devices while they were performing other specific tasks. These tasks involved sitting on a chair, walking around the room, etc. They found out that some of these emotions overlap on the readings. Stress involved accelerated heart rate, raised blood pressure, increased skin conductivity and constriction of the peripheral blood vessels; while heart variability, pupillary dilation and right and left hemispheric activation in the brain were associated with like/dislike.

Even though their system is not modeling or simulating emotions, it represents another variation of emotion prediction through measuring various physiological signals. Physiology had established yet another approach in modeling emotions. However, since we are dealing with simulating emotions, this model did not really provide any contribution or answers to the model we are trying to build.

D. AGENTS

Research on intelligent agents is divided into several agent types. Interface agents are developed to facilitate the communication between the user and the computer. Software agents are built to tackle some tasks with the help of other agents of the same type. These agents are built to cooperate, communication and collaborate among each other. Believable agents are built to create the illusion of life. These agents are typically used in entertainment products or theatrics animation. We will concentrate on the later type of agents in this section, because it is almost the only type that has made an extensive use of emotions in its architecture [3]. There are two different architectures for intelligent agents: the broad agent architecture and the distributed agent architecture. The broad agent architecture has three important properties: it has a broad set of capabilities, each capability is typically somewhat shallow, and all the capabilities are tightly integrated [38]. Thus, we will have an architecture that integrates all the internal states of the agent within it. The other type was based on Brook’s subsumption architecture. This architecture consists of a set of distributed agents with no internal states. These agents interact with each other in a way that achieves global intelligence.

i. BROAD AGENTS & BELIEVABLE AGENTS

J. Bates is building a believable agent (OZ project) [38, 4, 5] using the model that was described in *The Structure of Emotions* by Ortony, Clore and Collins [30]. The aim of the OZ project was to provide the users with the experience of living in dramatically interesting micro-worlds that include moderately competent emotional agents. They formalized emotions into types or clusters, where emotions within a cluster share similar causes. For example, the distress type describes all emotions caused by displeasing events. The appraisal of the displeasingness of events is based on the agent's goals. They also linked some emotions to some actions.

They actually deviated a little from the OCC [30] model. They did not model hope or fear. Joy and distress were modeled according to goal success and failure, respectively. The agent architecture is presented in Figure 2. As the figure shows there are three major models. TOK, presented in the figure, is the broad agent within which there are two models: HAP is a planner and EM models the emotional process. In fact, HAP does not plan for an action, but it chooses a specific plan from its repository of plans and carries it out. HAP takes emotions and attitudes as inputs from the EM model and outputs an action to the environment. It also passes back to the EM model some information about its actions such as information about goal failure or success. EM produces the emotional state of the agent according to different factors, including the goal success/failure, attitudes, standards and events. The emotional state is determined according to the rules given by Ortony's model [30]. These emotions are then passed to HAP, which determines the behavior according to the emotion and its plan. Sometimes emotions override the plan and vice versa. The outcome of the plan will then be fed back to the EM model that will then recreate and reevaluate its emotions and actions. This process will then iterate through the lifetime of the agent [38].

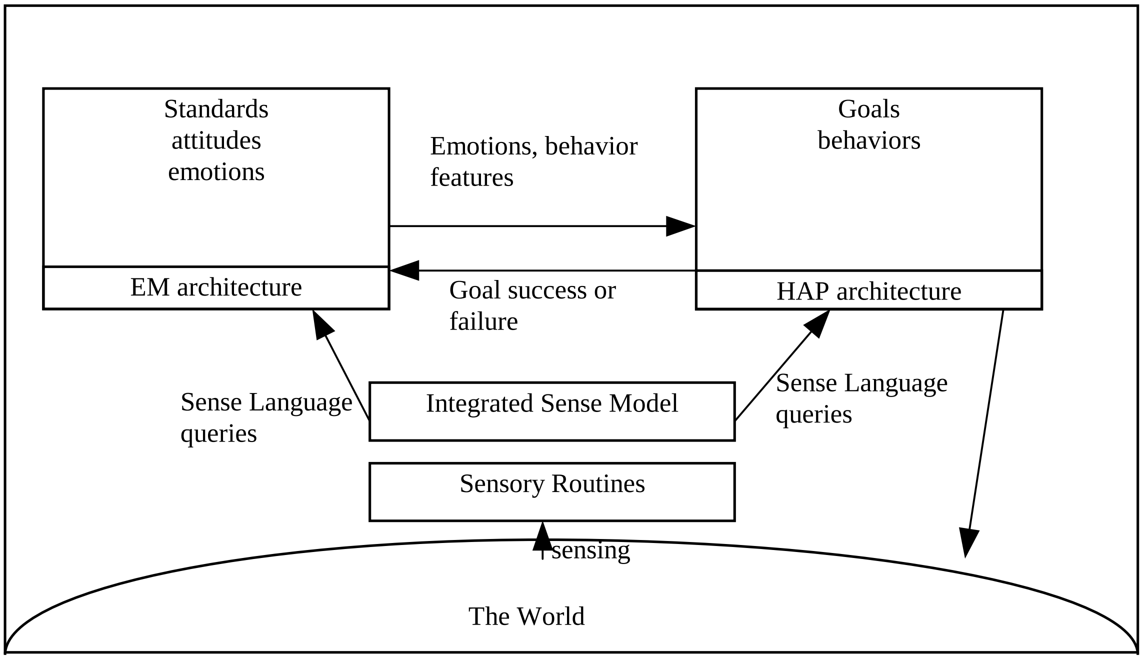

FIGURE 2. OZ PROJECT ARCHITECTURE

Many interesting points were considered in this project; however, there still are some problems. The emotional-behavior mapping process was designed as an interval-based mapping. To see the problem with that kind of mapping, we will adopt the following example:

if anger is between 3.5 and 7 then hit any object

The problem becomes more apparent with the question: what happens if the anger was 3.4. Fuzzy-logic can provide smoother transitions as it will be explained in more detail in the next chapter.

Even though this model employed Ortony’s emotional synthesis process [30], which emphasized the importance of expectation values, the model did not simulate any expectation values. Emotions were changing only according to the change of situations in time. There was no learning employed. Learning and experience can provide an additional dimension. Experience and learning in modeling emotions will be discussed in the next chapter.

ii. DISTRIBUTED AGENTS ARCHITECTURE

The MIT lab had also produced an emotional multi-agent project by 1997 [51]. The model only described basic emotions and innate reactions, however it presented a good starting point for building computer simulations of models of emotion. Some of the emotions proposed were Anger, Fear, Distress/Sadness, Enjoyment/Happiness, Disgust, and Surprise.

The model simulates the emotional process in several aspects, including (1) neural aspect, which simulates effects of neurotransmitters, brain temperatures, etc, (2) sensorimotor aspect which simulates facial expressions, body gestures, postures and muscle action potentials, (3) the model also includes a simulation of motivational states and emotional states, and (4) a cognitive aspect which includes event appraisals, interpretation of events, comparisons, attributions, beliefs, desires, memory and so on. The appraisal model used was Rosman's model, which was discussed above. In addition, emotions are decayed by the end of the emotional process.

Furthermore, the model also handles mixtures of emotions. Even though the paper does not show how the mixture of emotions is handled, it essentially stated that when simple contradictory emotions such as sadness and happiness occur at the same time then the more intense emotion will inhibit the other. The algorithm can be described as follows:

1. Both the internal variables (i.e. motivations) and the environment are sensed.
2. The values for all of the agent's motivations (both derived and emotions) are updated as described above.
3. The values of all behaviors are updated based on the current sensory stimuli (external stimuli and internal motivations).

4. The behavior with the highest value becomes the active behavior. Its expressive component is used to modify the agent’s expression and its experiential component is evaluated in order to update all appropriate motivations [51].

However, there are other motivational states that can affect the emotional life and sometimes inhibit some emotions, as in the case of “pain [6].” This factor is discussed in more detail in Chapter III. Moreover, the model did not represent the learning factor in modeling emotions. Experience and learning has been proven to change and shape the emotional process [12]. Our model further expands this concept in Chapter III. Furthermore, the idea of mapping emotions to behavior and emotional intensity is still simulated in a sharp edged fashion. Thus the introduction of fuzzy logic for the purpose of smoothing the transition will probably enhance the model. We will also introduce and detail this factor in Chapter III.

CHAPTER III

PROPOSED MODEL

In this chapter we will describe the proposed model. The model will be detailed in three major sections, including sections on fuzzy logic, emotional states/motivational states and learning. We will conclude this chapter by providing a summary of the model and its contributions. Chapter IV will further discuss the simulation and results attained.

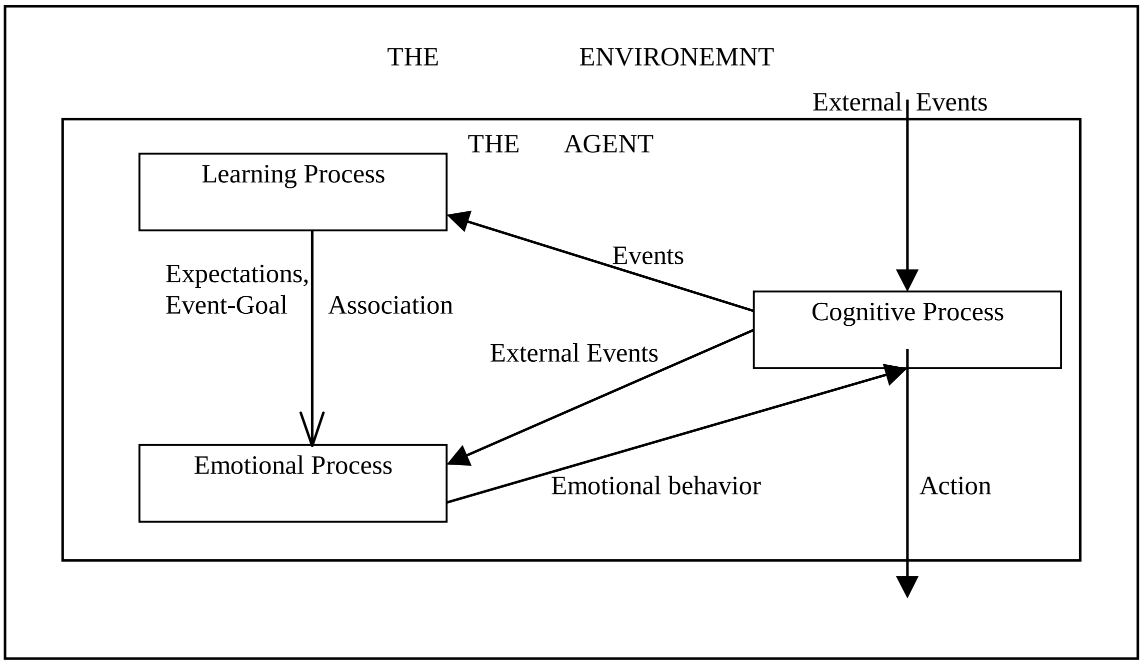

FIGURE 3. ABSTRACT AGENT ARCHITECTURE – AN OVERVIEW

1. OVERVIEW ON THE SYSTEM'S ARCHITECTURE

The model consists of three major processes: the learning process, the emotional process and the agent's cognitive process. Figure 3 illustrates the abstract view of the agent's architecture. As the figure shows on the right-hand side, the agent first perceives certain events from the environment. These events are then passed to both the emotional process and the learning process (on the left-hand side). The emotional process will take the perceived event from the cognitive process; in addition, it will use some of the learning process outcomes, including expectations and event-goal associations, to produce a behavior. The behavior is then returned back to the cognitive process to make a decision. The decision is made according to the situation, mood, the emotional states and the emotional behavior; an action is then triggered accordingly.

A. OVERVIEW OF THE EMOTIONAL PROCESS

The emotional process is shown in more detail in Figure 4. In this figure, boxes represent different processes within the model. Information is passed from one process to the other as shown in the figure. The perceived event taken from the cognitive process is first evaluated. The evaluation process consists of two sequential steps. Firstly, the experience model determines which goals are affected by the event and the degree of impact that the event holds on these goals. Secondly, fuzzy modeling proceeds to get a desirability level of the event according to the measure calculated by the first step and the importance of the goals involved. The event evaluation process depends on two major criteria: the importance of the goals affected by the event and the degree by which the event affects these goals. Fuzzy implication rules are used to determine a desirability measure of the event according to these two criteria.

The desirability measure, once calculated, will be passed to an appraisal model to further determine the emotional state of the agent. The model uses a combination of Ortony [30] and Rosman's [39] models to trigger emotions. An emotion or a mixture of emotions will be triggered using the event desirability measure. The mixture will then be filtered to produce an emotional state. The filtering process uses a variation of Bolles and Fanslow's [6] model to produce a coherent mixture of emotions. In essence, the emotional state will be a list of emotions that apply at a specific time given a certain situation. The emotional state is passed to the behavior selection phase. Through this phase, a behavior is chosen according to the situation assessment and the emotional state. The behavior selection process is simulated using fuzzy implication rules. The emotional state will then be decayed and fed back to the system for the next iteration. Additionally, there are other paths by which a behavior is produced. Some events or objects may trigger a conditioned behavior, and thus these events will not pass through the normal paths of the emotional process, but rather an emotion and a behavior is automatically triggered by the conditioning process [18]. A further discussion of this process will be given in Section 4.

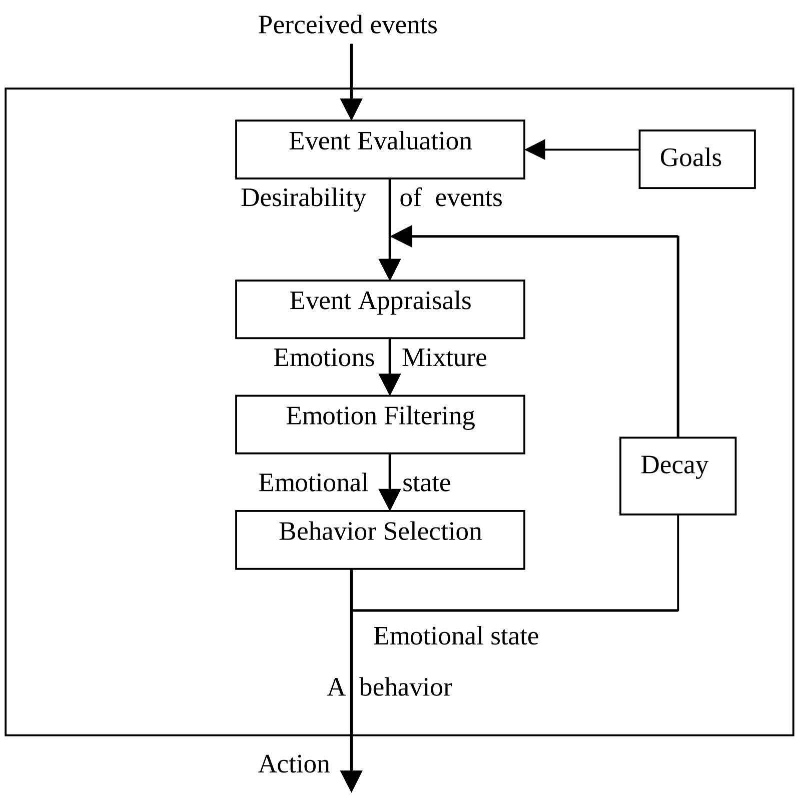

FIGURE 4. EMOTIONAL PROCESS

Instead of discussing the emotional process step by step in terms of the order of execution, different steps will be reviewed from the various contribution viewpoints. Therefore, we will devote a section to explain fuzzy logic and its motivations. We will detail the emotional filtering process, outlining the method by which some emotions may inhibit or enhance each other. However, before getting into the detailed discussions, the reader will be introduced to the learning process, outlining its importance in the emotional process. The learning process will have its own section describing how learning is designed and used to trigger certain responses and emotions.

B. OVERVIEW OF THE LEARNING PROCESS

In the early stages of this research, we expected that the only type of learning associated with the emotional process would be conditioning, which forms the emotional memory [18]. However, we found that there are other types of learning that directly relate emotions to the emotional intelligence process. These include learning about the subject's moods, and learning the actions that pleases or displeases the subject. A variation of reinforcement learning is used to assess events according to the agent's goals. Conditioning is used to associate an emotion to an object that was experienced and had triggered the emotion in the past. The agent learns features that discriminate things around it such as patterns of action, moods, and actions that please or displease the agent or the user. These features are used to determine: (1) an action that will please or displease the agent or the user if a situation arises where this information may be used for the agent's benefit, (2) an expectation value detailing what and how much to expect from the user or other agents. The first use presents one aspect of emotional intelligence process. The second determines the emotions triggered. As we shall see in the next few of sections, many rules trigger emotions using expectations. Expectations may be triggered solely by conditioning. However, when the agent interacts with other agents or users, conditioning will not be the only factor that determines the expectations of the agent. Moreover, events are judged as desirable or undesirable events according to the degree by which an event affects a goal or a set of goals. The question of how the agent knows that a particular event causes a particular goal to fail or succeed was previously unsolved [34]. However, our model demonstrates that the knowledge about the causal effects of events can be a product of the learning process.

2. FUZZY LOGIC IN EMOTIONS

One of the problems with the previous models, as discussed in Chapter II, is the mapping procedure by which these models map a given emotion or set of emotions to an action. The approach we take with our model is to use fuzzy logic. In this section our solution will be described and detailed. However, describing the fuzzy logic concept and its uses is beyond the scope of this thesis. For more information on fuzzy logic the reader is referred to [52]. This section will describe how and when to use fuzzy logic as opposed to normal interval mapping or functional mapping.

A. WHY FUZZY LOGIC

Even though we have pointed out in general the weak points or problems in previous models, to understand the motivations of fuzzy logic we still need to further explore these problems. Thus, we will take one of the previous models and follow it through to point out some of these problems. We have chosen Reilly's [36] Ph.D. thesis on believable social and emotional agents, which is the part of the OZ project that concentrated on the emotional and social side of intelligent agents. The model first assessed the event as being desirable or undesirable with respect to the agent's goals. A desirable event was defined as an event that causes goal success, while an undesirable event was defined as an event that causes goal failure. The desirability of an event was measured as a true or false concept [36].

Ortony's [30] model was used to trigger emotions such as joy, sadness, etc. Emotions were triggered at different intensities. Intensities are degrees, say a number between 1 and 10, that measure the degree of an emotion. The intensity degree was used to map the emotional state to a behavior. They followed an interval mapping technique to get an accurate personality.

There are two major problems in the techniques employed.

- Desirability was measured as a binary concept. This approach is not sufficient to handle a situation where an event satisfies a goal to an intermediate degree. The concept of partial goal successes or failures was not employed. Moreover, the idea of an event satisfying multiple goals or satisfying some goals and not others was not incorporated. It is often the case in real life scenarios that an event helps achieve a goal to a partial degree.

- The mapping of emotional states to behaviors was made according to an interval based technique. To get a clearer picture of the problem, we will employ the following example:

$$\text{Aggressiveness(a):=} \begin{Bmatrix} anger(a) > 0 \wedge fear(a) > 5 & anger(a) + fear(a) \\ anger(a) > 0 \wedge fear(a) < 5 & anger(a) \\ otherwise & 0 \end{Bmatrix}$$

Where a denotes a particular agent. The statement implies that if the anger level of the agent a is greater than 0 and the fear value of the agent a is greater than five then the aggressiveness will be a function of both anger and fear [36]. However, if anger is greater than 0 and fear is less than 5 then the aggressive value will be a function of anger. A problem might occur in situations where the fear value of the agent a is 4.9, or 4.7; will that make the agent less aggressive even though it is very close to 5?

Fuzzy logic could substantially enhance the system's performance by eliminating the two problems outlined above. We propose a fuzzy logic model to handle the following concepts:

Fuzzy Goals: this concept introduces a degree of success and failure in achieving certain goals.

Fuzzy Membership: the membership of an event to a goal is modeled as a matter of degree, thus an event can be affecting two or more goals with different degrees.

Fuzzy Mapping: the mixture of emotions is mapped to a behavior through the use of a fuzzy mapping technique.

B. THE USE OF FUZZY LOGIC IN THE MODEL

To understand the whole process of the emotional modeling, we will illustrate the whole process in Figure 5, shading the steps where fuzzy logic is used.

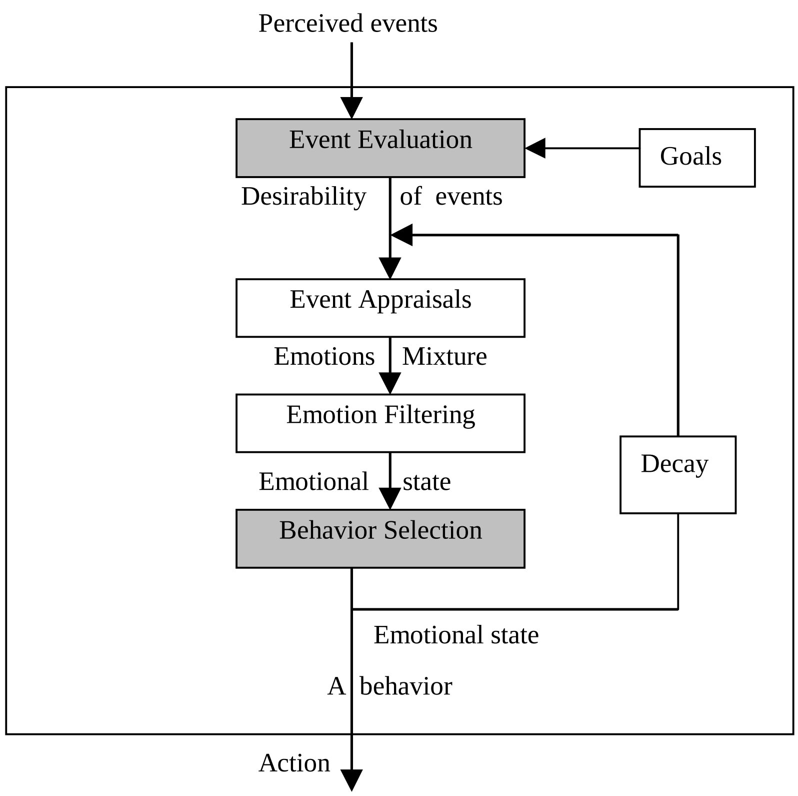

FIGURE 5. FUZZY LOGIC IN THE EMOTIONAL PROCESS

i. EVENT EVALUATION

Fuzzy mapping rules are defined according to the degree by which an event affects certain goals and the importance of these goals. The impact that a certain event has on a goal is defined as five fuzzy sets with triangular membership functions. These fuzzy sets are as follows: *NoImpact, HighPositiveImpact, LowPositiveImpact, LowNegativeImpact,* and *HighNegativeImpact*. The importance of a goal is dynamically set during the simulation according to the agent's assessment of a particular situation. Thus, the importance measure of a goal is also represented as three fuzzy sets using triangular membership functions. These fuzzy sets are defined as follows: *NoImportance, SomeImportance* and *ExtremeImportance*. In addition to these fuzzy sets, a desirability measure is defined using five fuzzy sets, which are *NegativeHighDesirability, NegativeLowDesirability, NoDesirability, PositiveLowDesirability* and *PositiveHighDesirability*.

We used the rules in the form given below:

IF Affect(G_1,E) is A
AND Affect(G_2,E) is B
…..
AND Affect(G_k,E) is H
AND Importance(G_1) is D
AND Importance(G_2) is F
….
AND Importance(G_k) is I
THEN Desirability(E) is C

where *k* is the number of goals simulated in the system. This rule reads as follows: if the goal, G_1, is affected by an event, *E*, to a degree *A* and goal, G_2, is affect by an event, *E,* to a degree *B*, etc., and the importance of the goal, G_1, is *D* and the importance of goal, G_2, is *F*, etc., then the desirability of the event, *E*, will be of degree *C*. We are using Mamdani's model, discussed in [52], with centroid defuzzification to get a desirability degree, which will be sent to the next process. Mamdani's model uses sup-min to get the matching degrees for the *n* rules. For example, if the rule is as follows:

If X is A_i Then Y is C_i

where *X* is an input variable, *Y* is an output variable, A_i and C_i are fuzzy sets, and *i* is the number of rules. In this simple example, if the input is fuzzy represented by $\mu_{A'}(x)$ then the matching degree will be calculated as follows:

$$\sup_x(\mu_{A'}(x) \wedge \mu_{A_i}(x))$$

where x is the input, and $\mu_{A'}(x)$ is the membership function of the input if it is fuzzy. If the input is not fuzzy then it will be a point or a number. $\mu_{A_i}(x)$ is the membership function presented by the rule. The $\wedge$ operator gets the minimum of these membership functions and then a *sup* operator is applied. The result will be a matching degree for the rule i. All the rules will then be aggregated using the *max* operator. A defuzzification process will then proceed using the following formula:

$$COA(A) = \frac{\int \mu_A(x) \quad x \quad dx}{\int \mu_A(x) \quad dx}$$

where $\mu_A(x)$ is the membership function resulting from the aggregation, and x represents the possible values of the membership function. For more information about Mamdani's model and how it aggregates the rules, the reader is referred to [52].

The defuzzification process will return a number that will then be used as a measure of the event desirability.

ii. EMOTIONAL STATES SIMULATION

Once an event desirability measure is calculated, rules can be fired to identify an emotional state. The rules used for firing the emotions are formulated from Ortony's model [30]; an example is shown below:

Joy = the occurrence of a desirable event.

Some emotions, including hope, fear and relief need more than just the measure of desirability discussed above; expectations and likelihood play an important role in simulating these emotions. For example, hope is defined as: the occurrence of an unconfirmed desirable event. We are using experience to guide the calculation of the likelihood of the occurrence of an event. This expectation value can be used along with the desirability measure, discussed above, to trigger an emotion. The intensity of an emotion is defined in terms of both the desirability and expectation values.

iii. BEHAVIOR SELECTION

Fuzzy logic is used once again to determine a behavior given a set of emotions. The behavior depends on the emotions of the agent and the situation or the event that occurred. For example, consider the following rule:

If Anger is *High*
AND *dish-was-taken-away*
THEN behavior is *Bark-At-user*

The behavior *barking at user* depended on what the user did and the emotional intensity of the agent. If the user did not take the dish away and the agent was angry for some other reason, he would not be inclined to bark at the user, because the user might not be the cause of his anger. Thus, it is important to identify both the event and the emotion. It is equally important to identify the cause of the event. In this case, we are assuming that non-environmental events such as *dish-was-taken-away*, *throw-ball, ball-was-taken-away,* etc. are all caused by the user. To generalize the rule shown above, we used the following fuzzy rules:

IF $emotion_1$ is A
AND $emotion_2$ is B
…..
AND $emotion_k$ is C
AND Event is E
THEN BEHAVIOR is F

where *k* is the number of emotions in the system. *A, B* and *C* are fuzzy sets defining the emotional intensity as being *HighIntensity, LowIntensity* or *MediumIntensity*. Behaviors are simulated as singletons, including *Bark-At-User* and *Play-With-Play.* Likewise, events are also simulated as singletons such as *dish-was-taken-away*, *throw-ball, ball-was-taken-away,* etc.

At the end of each cycle, a feedback process will decay the emotions and feed them back to the system. Very few research studies have addressed the emotional decay process [51]. A constant, ϕ, was given for the decay of the negative emotions and another constant, δ, was given for the decay of positive emotions. We set $\phi < \delta$, to decay positive emotions at a faster rate. These constants along with the constants used in the learning algorithm are passed as parameters to the model. We used a trial and error process to find the best settings for these parameters. We found that there is no single best setting. However, we came up with a range of settings that produced a more realistic behavior for the agent. These ranges were: $0.1< \phi <0.3$ and $0.4 < \delta <0.5$.

3. EVENT APPRAISALS AND EMOTION FILTERING

A. EVENT APPRAISALS

Once a desirability degree is set for an event, rules can be fired to determine the emotional state given an expectation and a desirability measure of the perceived event. The expectation value is taken from the learning model, which is detailed in a later section. A variation of Ortony's [30] model is used to define the rules used. These rules are documented in Table 3. Fourteen emotions are simulated using these rules. Other emotions like love and hate towards a subject *x* are measured according to the actions of *x* and how *x* helps the agent to achieve its goals. To apply the rules shown in the table, we need a few more components. These components are summarized as follows:

TABLE 3. RULES OF EMOTIONS

Emotion	Rule
Joy	occurrence of a desirable event
Sad	occurrence of an undesirable event
Disappointment	occurrence of a disconfirmed desirable event
Relief	occurrence of a disconfirmed undesirable event
Hope	occurrence of an unconfirmed desirable event
Fear	occurrence of an unconfirmed undesirable event
Pride	action done by the agent and is approved by standards
Shame	action done by the agent and is disapproved by standards
Reproach	action is done by the other and is not approved by the agents standards
Admiration	action done by the other and is approved by the agents standards
Anger	Complex emotion → sad + reproach
Gratitude	Complex emotion → joy + admiration
Gratification	Complex emotions → joy + pride
Remorse	Complex emotions → sad + shame

(1) the desirability measure of the event, which is taken from the event evaluation process discussed in the previous section, (2) standards and event judgment, which are taken from the learning process featured in Figure 3, and (3) expectations of events to occur, which are also taken from the learning process.

To illustrate this process, we will employ the emotion of relief as an example. Relief is defined as the occurrence of an unconfirmed undesirable event, which means that the agent expected some event to occur and this event was judged to be undesirable, but this event did not occur. In essence, this means that the agent was in a fear state in the time step before, because fear is defined as expecting an undesirable event to happen. A history of emotions and the corresponding events are kept in what is called the short-term emotional memory. Thus, once a confirmed event occurs, it is checked with the short-term emotional memory; if a match occurs, a relative emotion is triggered. For example, if the emotion in the previous time step was fear, then relief will be triggered. The intensity of relief is then measured as a function of fear.

While some emotions may depend on other emotions in their definition, others do not. For example, hope is defined as the occurrence of an unconfirmed desirable event, i.e. the agent was expecting a desirable event with a specific probability. For example, a student who is repeating a course is expecting to get an A grade with a probability of 80%. It should be noted that the hope intensity is not proportional to the expectation value, as is the case with other emotions. On the contrary, the higher the certainty, the less the hope, as is noted in [35]. Thus, the hope intensity is defined as :

$$Hope(expectation, desirability) = (1.7 \times expectation^{0.5}) + (-0.7 \times desirability)$$

The formulas calculating the intensity of emotions were taken from a study done by Price et al. [35]. These are illustrated in Table 4. The table shows the method by which intensities are calculated for various emotions given an expectation value and an event desirability measure.

TABLE 4. CALCULATING INTENSITIES

Emotion	Intensity
Joy	$Joy(expectation, desirability) = (1.7 \times expectation^{0.5}) + (-0.7 \times desirability)$
Sad	$Sad(expectation, desirability) = (2 \times expectation^{2}) - desirability$
Disappointment	$Diappointment(Hope, desirability) = Hope \times desirability$
Relief	$Relief(Fear, desirability) = Fear \times desirability$
Hope	$Hope(expectation, desirability) = (1.7 \times expectation^{0.5}) + (-0.7 \times desirability)$
Fear	$Fear(expectation, desirability) = (2 \times expectation^{2}) - desirability$
Pride	$Pride(standards, event(x)) = value(x, standards)$
Shame	$Shame(standards, event(x)) = value(x, standards)$
Reproach	$Reproach(standards, event(x)) = value(x, standards)$
Admiration	$Admiration(standards, event(x)) = value(x, standards)$

B. EMOTION FILTERING

Emotions usually occur in a mixture. For example, the feeling of sadness is often mixed with shame, anger or fear. However, what distinguishes one emotion from another is the intensity value. Furthermore, emotions are sometimes inhibited or triggered by other states such as the motivational states. Bolles and Fanslow's [6] work gave an insight on the impact that motivational states have on other emotions. In their work the highest intensity state takes over [6]. Nevertheless, with emotional states it may not be the case, for example a certain mixture of emotions may produce different actions or behaviors as shown by the fuzzy rules in Section 2. In the following paragraph we will provide a description of how we simulate and further filter the interaction between the motivational states and the emotional states. However, the model does not put a determined theory on how this filtering technique should be followed. We found that many of these interactions were influenced by the personality and the domain. Therefore, we can only provide an example of how these interactions are simulated in our simple implementation. It should be noted that different filtering mechanisms could be employed to simulate different personalities.

Motivational states are states that interrupt the cognitive process to satisfy a higher goal. These states include, hunger, thirst, pain and fatigue. Table 5 shows the different motivational states simulated, and their calculation methods. It should be noted that these motivational states have different fuzzy sets representing level, e.g. *low*, *medium* and *high*. Once these states reach a specific level, say *medium*, they send a signal to the cognitive process telling it to pay attention to a specific need that has developed. These motivational states can then block the reasoning process and sometimes the emotional process to produce a plan for getting the agent what he/she needs, whether it is water, food, sleep, etc. The plan depends on the agent's situation at a particular time step. For example, if the agent already has access to water, then it will drink, but if it does not have access to water and knows where to get it then it will form a plan to get it. However, if the agent must depend on another agent to satisfy its needs then it would use the learned model of the other agent to try and manipulate him/her. Nevertheless, it is not always best for the agent to inhibit the emotional states to achieve the goal or satisfy a need. For example, sometimes the agent will be acting on fear and inhibiting other motivational states. The cognitive process always looks for the best emotion to enhance or inhibit in various situations. In some situations, it might be best if fear inhibits pain, but in some others it might be the opposite [6]. Thus, before inhibiting emotions, we make a situation assessment and an emotional versus motivational states assessment, whichever is best for the agent to act on, in the given situation, will take precedence while the others will be inhibited.

TABLE 5. CALCULATING MOTIVATIONAL STATES' INTENSITIES

Motivational State	Intensity
Pain	Function (Number of Hits, the intensity of the hits)
Tired	Function(Level of movement, time last slept)
Thirst	Function(water loss [calculated as a function of frequency of movement, intensity of movement (running is higher than walking ..etc.), time last drank, quantity that was drunk])
Hunger	Function (intensity of movement, frequency of movement, time last ate, the quantity of food ate)

It can be clearly seen that motivational states can inhibit emotional states and vice versa. This kind of filtering might occur on the emotional level as well, i.e. sadness or anger may inhibit joy or pride in some situations. Some models employed techniques, which tend to inhibit opposite emotion [51]. For example, an emotion like *sadness* will tend to inhibit *joy* if *sadness* was more intense than *joy*. Likewise, if *joy* was more intense than *anger* or *sadness* then *joy* will inhibit both. Nevertheless, we found that negative and positive emotions will tend to influence each other only when the mood is on the boundary between states [7]. The mood is simulated as either positive or negative depending on the number of positive and negative emotions in the last five time periods. We calculate the frequency of positive and negative emotions as follows:

$$pos = \frac{\sum_{t}^{t-5} numberofPositiveEmotions}{\sum_{t}^{t-5} numberofemotions}, \; neg = \frac{\sum_{t}^{t-5} numberofNegativeEmotions}{\sum_{t}^{t-5} numberofemotions}$$

If $pos > neg$ then the mood is positive, otherwise the mood will be negative.

To illustrate the importance of the mood, we will employ an example. In this example, we will have the mood as negative, calculated as an average of three negative emotions and two positive emotions all with a medium intensity. The mixture of the emotions triggered was as follows: (1) a positive emotion, *l*, with a high intensity and (2) a negative emotion, *k*, with a relatively lower intensity than that of *l*. The negative emotion, *k*, will inhibit the positive emotion despite the fact that the positive emotion was triggered with a higher intensity. Since there are no published methods on how the emotional states can be inhibited or filtered, we had to formulate some answers ourselves. Thus, we used a trial and error method, where we brought in three users to evaluate the agent's behavior. The experiments were set up with different techniques to explore the best technique to adopt. After analyzing the experimental data, we found that the method illustrated above was favored over other methods tested. It should be noted that there might be other methods to achieve the filtering process. However, this method is sufficient for creating a realistic behavior for our agent.

4. EXPERIENCE IN MODELING EMOTIONAL DYNAMICS

Learning has a major impact on the emotional process. The importance of learning will become very clear when we detail the learning section to explore the various ways that learning can change the emotional and behavioral state. There are four components to the learning process: (1) learning about events and likelihood of events to occur given a situation, (2) learning about the user, (3) learning about actions and categorizing them as good or bad, and (4) an associative learning technique that associates objects to certain motivational states or emotions. We have used different inductive techniques to develop a working model out of these four learning dimensions. In the next few subsections we will detail these four learning types.

A. LEARNING ABOUT EVENTS AND EXPECTATIONS

The agent will need to know what event to expect, how much to expect it and how bad or good it is. This information is crucial for the emotional process. As it was discussed in Section 2 and 3, the identification of emotions and emotional intensity heavily rely on expectations. Furthermore, events are normally measured by their impact on a set of goals. It is often the case that a given event does not have any impact on any specific goal directly, but some sequence of events may eventually have an impact on some goals. Thus, identifying the link between an event and the corresponding goals was noted to be a very complex task to accomplish [38]. The agent can potentially learn this by using a reinforcement learning algorithm [16, 26]; we will briefly outline one of the reinforcement algorithms, namely the Q-learning algorithm. The reader is referred back to [16, 26] for more detail.

It is often the case that an agent does not know the consequences of a given action until a complete sequence of actions is finished. The agent, therefore, faces the problem of temporal credit assignment, which is defined as determining which of the actions in its sequence are responsible for producing the eventual rewards. To illustrate the solution that reinforcement learning offers to this problem, we will look at reinforcement learning in more detail. The agent represents the hypothesis or the problem space using a table of Q-values in which each entry corresponds to a state-action pair. The table can be initially filled with default initial values (we used 0). The agent will begin from a state s. He will take an action, a, which takes him to a new state s'. The agent may obtain a reward r for his action [26]. If it receives a reward it updates the table above using the following formula:

$$Q(s,a) \leftarrow r + \gamma \max_{a'} Q(s',a') \quad [26]$$

where r is the immediate reward, γ is a discount factor, s' is the new state, and a' is an action from the new state s'. Thus, the Q value of the previous state-action pair depends on the Q value of the new state-action pair.

This algorithm is guaranteed to converge only for deterministic Markov Decision Processes (MDP). However, in our application there is a one-to-one alteration between the agent and the user. It is almost impossible to predict the reward given a state and an action, because it may change according to the user and environment. For example, at a state, s_0, the agent may do an action, x, and as a consequence the user gives him a positive reward. At a later time step, the agent is in the same state, s_0, so he takes action, x, again but this time the user rewards him negatively. Therefore, as you can see from this simple example, the user introduces a non-deterministic response to the agent's actions. In this case, we treated the reward as a probability distribution over outcomes based on the state-action pair. Figure 6 illustrates this process in more detail. The agent starts off in state, s_0, and takes an action a_0 then the user can take either action, a_1, that puts the agent in state, s_1, or action, a_2, that puts the agent in state, s_2. The dotted lines show the nondeterminism induced by user's actions, while the straight black lines shows the state-action transition as represented in the table. The way we get the probability of the user's actions is by either using a count of the number of times the user did this action given the state-action pair, (s_0, a_0), divided by the number of actions the user took given that the agent was at state, s_0, and did action, a_0. Another way for determining the probability of the user's actions is using the user action patterns detailed in the next subsection.

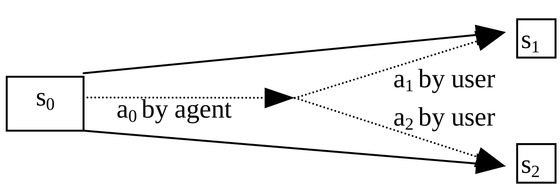

FIGURE 6. NONDETERMINISTIC REWARDS

We then used a new formula for calculating the Q-value, which is defined as follows:

$$Q_n(s,a) \leftarrow E[r(s,a)] + \gamma \sum_{s'} P(s'|s,a) \max_{a'} Q(s',a')$$

where $P(s'|s,a)$ is the frequency count that was described above, and $E[r(s,a)]$ is the expected probability of the $\max_{a'} Q(s',a')$ [26].

At any given time, the agent will be faced with different actions to take with the possibility of different outcomes and different rewards. The formula and the algorithm described above gives the maximum expected reward given that the agent is at a particular state. Since we are trying to simulate a believable agent, we looked at how humans make decisions. We found that emotions and moods have a great impact on their decisions [7, 8, 11, 12]. Thus, we used moods to guide the expectation values of the next state, s', given that the agent is in state s. Instead of calculating the value of a state by maximizing the reward we are using the mood as a determining or averaging factor for the different new states. As noted in [7] when the agent is in a good mood it will tend to look at the good side, and otherwise it will look at the bad side. Thus, we refined the expectation mechanism to capture this phenomenon. In a particular situation, the agent will be looking at numerous alternative paths, some of them may lead to failure and some of them may lead to success. If the agent's mood is good then the agent will look at the good side and expect the good events with a degree of β more than the bad events and vise versa. We modified the equation above to include the β value. Thus, the formula would be as follows:

$$Q_n(s,a) \leftarrow E[r(s,a)] + \gamma \times \sum_{s'} \begin{cases} \mathit{match} & (1+\beta) P(s'|s,a) \max_{a'} Q(s',a') \\ \mathit{otherwise} & P(s'|s,a) \max_{a'} Q(s',a') \end{cases}$$

For all the actions that match the mood, the value will be incremented by a β degree, otherwise the previous equation holds. We will take an example to illustrate this idea. For example, the agent is trying to decide between two actions. These actions are illustrated in Figure 7. If he plays with the ball then there is a 70% chance that it will end up in state, s_2, which has a reward of 2.5, but there is also a 30% chance of ending up in state, s_1, which has a reward of -1.5. While if it ignores the ball then there is an equal chance of getting to state, s_4, which has a reward of -3, or state, s_5, which has a reward of 6. Thus, if we use regular probability calculation, action *IgnoreBall* will have a value of 1.5 and *playWithBall* has a value of 1.3, so the agent will ignore the ball. However, if we take the mood into account then the calculation will be different, because the agent will expect different outcomes with different moods. So if for example, the agent is in a good mood, he will expect positive rewards with a degree β more than the negative rewards. If we set β to 10%, then play with ball will have a value of 1.475 and ignore ball will have a value of 1.8.

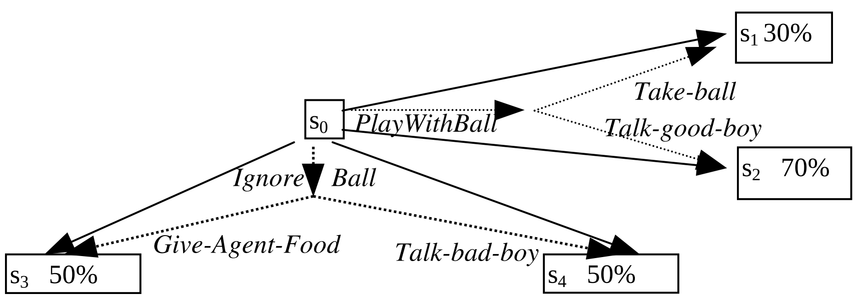

FIGURE 7. AN EXAMPLE OF REINFORCEMENT LEARNING

B. FORMING A USER MODEL

Since the agent is interacting with the user, the agent will have to learn about the user's patterns of actions. A heuristic approach is used to define a pattern and to further define a probability of an action, a_1, to occur given that an action, a_2, has occurred. We focused on patterns of length three, i.e. the user did action a_1, then action, a_2, and finally action, a_3. This concept can be further illustrated using the pet and the owner example. The owner goes into the kitchen *(a_1)*, takes out the pet's food from the cupboard *(a_2)* and feeds the pet *(a_3)*. These three consecutive actions led to the pet being fed. Thus, if the owner goes to the kitchen again, the pet would probably expect to be fed to a certain degree. As it can be seen from the example, learning sequences of actions can be very useful in predicting other people's actions.

A sequence of two actions would not capture a meaningful pattern, because most of the actions are very small, quick and specific such as *throw-ball*. An action or two consecutive actions by themselves are not meaningful. Therefore, in order to capture a meaningful pattern, we set the length of the pattern to a lower bound of. On the other hand, an upper bound of seven plus or minus two was made under the assumption that the short-term memory can hold only seven plus or minus two chunks [24]; i.e. the agent's mind may not handle more than a length of 7±2 consecutive action comparisons. Considering a pet's mind, we think that handling a pattern of three consecutive actions is more suitable. In other words, we think it will require a high cognitive load on the pet's brain if it has to deal with a pattern with more than three actions. Therefore, we decided to make the agent more realistic rather than more intelligent by limiting the length of the patterns learnt. However, we did not limit the number of patterns learnt, because the number of patterns learnt will be directly related to the long-term memory rather than the short-term memory, as in the case of the length of the pattern.

There are two different operations done with a pattern. Firstly, the pattern is created or reinforced by the number of times it is repeated. Every pattern, p, will have a default value, v_0, when it is created. As soon as an action is taken, the history of actions is checked against the patterns stored in the agent's pattern tables. If a pattern exist then it is incremented by one unit. If it does not exist then a pattern is created and initialized to the initial value, v_0. We set v_0 to a one unit.

Secondly, a probability of an event is calculated according to the expected action given a sequence of the two previous actions that occurred. To illustrate the second operation, we will employ the following algorithm:

> Given: action, B, is taken by the user and a pattern, p, does exist in which B is a member.

1. If B is the first action then
   expect NextAction(p, B)
   probability = value(p)/ n
2. If B is the second action then
   expect NextAction(p, B)
   probability = (value(p) * ∂) / n

where *NextAction* is a method that gets the next action in the pattern, and *value* is a method that gets the value of a pattern. It should be noted that the pattern is initialized with an initial value, v_0, which is then incremented whenever the pattern is repeated. The probability is calculated, as the value of the pattern divided by n, where n is the total number of actions that the user can do at any given time.

C. LEARNING PLEASING AND DISPLEASING ACTIONS

External reinforcement was used to learn what actions are pleasing or displeasing for the user. Thus, we are letting the user give the agent some feedback on his actions by saying *bad* or *good*. Then the agent assesses actions in terms of a function: $Quality(x, s)=v$, where x is an action that happens in a particular situation s, and v is the value given to the action-situation pair. When externally reinforced the agent searches its knowledge base for the action-situation pair. If they were not found, a value, v_a, is given to the action-situation pair. We set this value to 1.5. However, if the action-situation pair was found and the Quality matches the Quality that was documented then the pair is reinforced by a 1.5 unit, otherwise the agent becomes confused and decrements the pair by a 1.5 unit.

This type of learning is two folded. (1) It creates a basis by which the agent can please or displease the other when the situation arises, and (2) it creates the baseline by which the agent can set its own standards. These standards are then used to determine emotions like pride or shame. In addition, these standards are used to evaluate the user’s actions and trigger emotions, including admiration and reproach. The intensities of these emotions are calculated as a function of the value, *v*, of the learnt rule.

D. CLASSICAL LEARNING OR CONDITIONING

Associating objects to emotions or to a motivational state, forms yet another type of learning which is closely integrated with the reinforcement learning discussed above [18]. For example, if the agent experienced pain when an object, *g*, touches it, then the motivational state of pain will be associated with the object *g*. This kind of learning does not depend on the situation per se, but it depends on the object-emotion/motivational state association.

Each of these associations will have a count, which is incremented by the repetition of the object-emotion occurrence. This type of learning will provide the agent with another type of expectation triggered by the object rather than the event. Using the frequency count and the intensity of the emotion triggered, the agent can calculate the expectation level. We used the formula shown below:

$$Expectation(e) = \frac{intensity(e)^{*} \times \Pr ob(o|e)}{\Pr ob(o)}$$

where *e* is the emotion triggered, *Prob(o)* is a method that calculated the number of times an object, *o*, was introduced to the agent, and *Prob(o|e)* is a method that calculates the number of times an object, *o,* was introduced and caused the emotion *e*. To illustrate this process we will adopt the following example. Consider a needle, which was introduced to the agent. The first time the needle was introduced it caused the agent 30% pain. So the agent will associate the needle with 30% pain. The next time we introduced the needle, the agent will expect pain with a level of 30%. Let’s say that we did not inflict any pain on the agent, and we introduced the needle about 90 times without inflicting any pain. Thus, the next time the needle is introduced, the agent will expect pain with a level of (30%/90). As you can see, the level of expectation of a particular emotion, *e,* is decreasing by the number of times the object, *o*, was introduced without inflicting the emotion, *e*. If, however, we shocked the agent with the needle 90 times and only introduced it 10 times without inflicting any pain, then the expectation of pain will be increasing.

As it can be seen from the discussion above, another set of expectations and possibly emotions can be triggered directly from the model above. If we take the example of the needle, then when the needle is introduced, automatically an emotion of fear will be triggered, because the agent will be expecting pain. However, if the object was associated with sadness or joy, an emotion of sadness or joy may be triggered in these cases respectively. The intensity of these emotions will be calculated using the formula described above.

5. SUMMARY

This chapter presented and discussed the proposed model. The model forms a more complete version of the emotional process through proposing various additions and extension to the traditional believable agent models:

- Using fuzzy logic as a tool to provide smooth overlapping regions or levels. These regions were used to simulate the emotional intensity, the degree that an event affects goals and the degree of the goals' importance. Fuzzy mapping was used to calculate the event desirability measure. In addition, fuzzy mapping was also used to map an emotional state to a behavior.

- To complete the emotional process, a method should be formulated to filter out the mixture of emotions either by inhibiting or enhancing other emotions or motivational states to produce an emotional state which is applicable in the given situation.

- The emotional process is not a static process. However, the dynamic nature of emotions does not occur only from the manifestation of change of situations through time. The dynamic nature of emotions evolves out of experience and learning. Thus, the emotional process is better simulated as a manifestation of learning and change of situations through time.

CHAPTER IV

SIMULATION AND RESULTS

1. SIMULATION

In this section, we will describe how the model, presented in the previous chapter, was actually implemented. We chose to model emotions in a pet. Our decision was based on the following reasons:

- Pets are simpler than humans. They do not require sophisticated planning. Concepts of identity, self esteem, self-awareness and self-perception do not exist in animals. In addition, the goal structure of pets is much simpler than humans'.

- To evaluate the realism of the pet's behavior, we will have to appeal to the user's judgment. We thought it would be better to have a model of a pet rather than some other creature, because most people have some expectations about what a pet can or cannot do, and thus the evaluation will take advantage of the common knowledge that we assume is shared among people.

The model was given the name PETEEI, which stands for a PET with Evolving Emotional Intelligence. PETEEI was designed to have the look and feel of a typical Role Playing Game interface. It has five major scenes: a garden, a bedroom, a kitchen, a wardrobe and a living room. The garden scene is illustrated in Appendix A. In fact, Appendix A, shows one of the scenarios that we ran in the evaluation process.

In order to anticipate the various behaviors and situations that needed to be simulated, story boards were designed for various scenes in the simulation. A list of user actions was defined, summarized as follows:

- Walk to different scenes. The user can walk from one scene to the next by clicking the cursor on the walk button and then clicking on the direction he wants to go to. The cursor will then change to an arrow with the destination name on it. For example, if the user clicked left and if the next scene to the left is the bedroom, then the cursor will be shaped as an arrow with the word bedroom on it. This would give the user a quick feedback on where he/she is going.

- Object Manipulation. The user can take objects from a scene. This action will automatically add the object to the user inventory from which objects can be taken and introduced to the scene.

- Talk aloud. The user can initiate a talk with objects (including the pet). Talk is done by selecting words from a predefined set of sentences, which are defined within the main window for the application. After setting what the user wants to say, he/she can then click on talk. This will initiate a global talk to all the objects in the scene as if the user was talking aloud.

- Opening and closing doors. The user can open and close doors or other objects that may be opened or closed in the environment.

- Miscellaneous actions. The user can save the environment. This action will automatically save the information PETEEI learned about the user so the user would not have to start all over the next time. We have this feature as an option in case the user wants to start over after really torturing the pet.

2. EVALUATION METHOD AND VALIDITY

A. EVALUATION PROTOCOL AND VALIDITY

Evaluation methods were explored in Baecker's book [2]. Evaluation techniques were summarized as heuristic evaluation, cognitive walkthroughs, usability testing, usability engineering, and controlled experiments. For more information on these evaluation techniques the reader is referred back to [2]. All these techniques involve users or experts evaluating the usability of the system. Nevertheless, there were other techniques discussed as: think aloud - work aloud, videos, questionnaires, etc. From all of these methods we chose to use questionnaires with scenario walkthroughs. The reasons for our choices are summarized as follows:

- Questionnaires provide us with already quantified answers to the questions that we are looking for.

- Questionnaires deal with users directly. We did not want to ask experts to test our system for many reasons, including feasibility and validity of judgment criteria.

Other alternatives include running two experiments (with the same parameters, procedure, etc.) in parallel; one experiment running on a real pet and the other experiment is running on our simulated pet. This would probably give us an exact measure of reality for comparison. However, this method was rejected for the following reasons. (1) Our model was built to simulate experience and it's impact on behavior. Therefore, without knowing or quantifying the real pet's experience, the experiment will always be biased, because there will always be another factor playing in the background, and that is experience. (2) It was highly impractical to run such experiments, especially ones exerting pain and fear on real pets.

i. SELECTION AND SOURCES OF SUBJECTS

Participants in the evaluation were recruited from an email alias pool that is maintained by the Computer Science Department at Texas A&M University. We recruited 21 subjects from this pool. The ages of the subjects were in the range of eighteen to twenty six years old. Most of the participants were first year undergraduates. This choice was done to discount the bias factor inflicted by the background knowledge of the users within the sample. Normally, users with different backgrounds will try to fit the simulation to their experience. Thus, users with sociology background will look at the social side of the agent, people with HCI background will look at the usability side and people with biology background will compare the agent to a real biological being. In order to diminish this effect, we selected users, first year undergraduates, who do not have specific background knowledge tied to any field.

ii. EXPERIMENTAL PROCEDURE

Participants were asked to meet with the principle investigator for a period of two and one-half hours in a computer science lab at the Texas A&M campus. The participants were first given a fifteen-minute introduction to the system and the simulation. Participants were notified that their responses will be used to further enhance the system and not as a measure of how good the system is. This way the users were encouraged to criticize the system and the model in a less biased way. Most of the time, users would be assessing the system in a positive fashion because they are either trying to be nice knowing how much work went into it or they are impressed by the interface, etc. Thus, we thought telling them that we need their advice for improving the system would potentially reduce the effect of this problem.

The participants were handed some instruction sheets. These sheets walked them through different scenarios showing them the different functionalities of the model. These scenarios are shown in Appendix C. They were then asked to fill out a questionnaire about what they have seen in the simulation. While answering the questionnaires, the subjects were asked not to write their name or mark the papers in any way that might be used to identify them at a later time period. This precaution was taken to ensure anonymity of response. The questionnaire is shown in Appendix B.

The protocol described above was repeated for the four different models. (1) We evaluated a simulation where the pet produced a random set of emotions and random behaviors. This experiment provided a baseline for the other experiments. Sometimes the users were impressed by the pictures and sound, and the fact that the pet in the pictures had emotions and reacted to the user's actions might drive some users to answer some questions with a positive feedback. For example, just by noticing that the pet has emotions, the users might give the pet three points of intelligence. Three points of intelligence might mean somewhat intelligent to the user or not intelligent. Thus, we had set up this experiment with the random behavior and emotions to establish the real zero scale of the evaluation. (2) We evaluated a simulation with no fuzzy logic nor learning. This model was done using crisp interval mapping instead of fuzzy mapping. (3) A simulation with fuzzy logic but no learning was evaluated to see the effect of fuzzy logic on the system. We added fuzzy modeling to this model; however, the emotional synthesis process uses only the rules mentioned in Chapter III. The expectation values were simulated as constant probabilities with no dynamic effect. (4) A simulation with fuzzy logic and learning was then evaluated to establish a validation of our hypothesis.

We had difficulty getting a bigger sample of users to commit for a two-hour evaluation process. Therefore, we carried out the experiments so that the same user would walk through the different models. The problem with this method is that the user might be driven to make direct comparisons between the different models. To eliminate this problem, we employed a counter-balanced Latin square design, where the order of execution of the different models was shuffled for the different users.

B. RESULTS

The questionnaires were collected and analyzed. The questions, shown in Appendix B, were designed to evaluate the different elements of the model. In this section, we will show some questions and analyze the corresponding user's answers.

i. Expectations

We devoted two questions to measure how many actions met or did not meet users' expectations and why. Users were first asked the following question:

> Do you think that the actions the pet does through the simulation meet your expectation?
>
> ☐ Yes ☐ No

This question was meant to give us an estimate on which model the users thought best met their expectations in terms of the pet's reactions and emotions. We gathered users' answers to the question above.

TABLE 6. EXPECTATIONS OF USERS

Model	**Yes**	**No**
Random	4.8%	95.2%
No learning /no fuzzy	19%	81%
Fuzzy/ no learning	95.2%	4.8%
Learning/ fuzzy	100%	0%

Table 6 shows the users' answers in a percentile scale for the different models tested. As it can be seen from the table, 95.2% of the users answered No for the random model. Since it is a random model, it could happen that the user expected the pet to wiggle his tail and the pet wiggled his tail by coincidence. However, the most common response was, "I feel that his actions are not 'real' but programmed to produce some unrelated and contradictory actions when some buttons are pushed." As for the non learning and non fuzzy model, people thought that he acted in a kind of edgy behavior. As one of the users said, "he is moody. I can see from the emotional levels scale that his emotions are rising gradually, but his behavior is not really done that way, I guess.." As a result of this observation, the fuzzy model that was incorporated to smooth the behavioral mapping increased the percentile results to 95.2%. Most of the users rated the fuzzy model higher in terms of expectations, but they could not map their answers to words. Most of them, when asked to rate their answer, said that the actions seem real, more convincing, more gradual like what you would expect from a pet. It should be noted that the scenarios given to users include two or three scenarios that would show this gradual and smooth mapping of the behavior. We were able to find these scenarios from a test case that we ran with some users earlier. As the table shows, the learning model further enhanced the average of these results to a 100%. However, the difference between the fuzzy and the learning model was only a count of one user, thus we think that the improvement induced by the learning model is not of any real significance. To prove this intuition, we used the following formula to calculate the statistical significance of the average above using a 95% confidence interval.

$$\pm 1.96\sqrt{\frac{p*(1-p)}{n}}$$

where n is the sample size, p is the percentage of Yes or No answers and 1.96 represent the 95% confidence. The confidence interval of the fuzzy model is, 86.1% to 104.4% for the Yes answers and 24.8% to -15.2% for the No answers. These intervals overlap with the mean of the learning model shown in the table above. Thus, we conclude that the improvement shown by the learning model is not of any real statistical significance.

We further asked the users to rate the answers above on a scale from one to ten according to how many actions were or were not met. The question was divided into two questions as follows:

A. Rate your answer in the scale of one to ten in terms of how many actions were not met by your expectation. (1| one → 10| more than ten actions). Explain your rating.
B. Rate your answer in the scale of one to ten in terms of how many actions you considered out of the ordinary. (1| one → 10| more than ten actions). Explain your rating.

TABLE 7. EXPECTATION RATINGS

Model	Question A		Question B	
	mean	**interval**	**mean**	**interval**
Random	9.52	9.01-10	8.76	7.47 - 10.1
No learning /no fuzzy	4.9	4.22 - 5.59	0.33	0.09 - 0.58
Fuzzy	0.76	0.19 - 1.33	0	0 - 0
Learning	0.14	0 - 0.3	0	0 - 0

Answers were collected for the questions above and an average is calculated, shown in the Table 7 as the mean. We also calculated the confidence interval for a 95% confidence with a sample size of 21. This measure was calculated using the following formula:

$$\bar{x} \pm 1.96(\frac{\sigma}{\sqrt{n}})$$

where $\bar{x}$ is the mean, the σ is the variance and n is the size of the sample which is 21 in this case. The confidence interval is shown in the table. Thus, as you can see from the table above, the number of actions that were not met by users expectation (represented by Question A) decreased drastically by the incorporation of the fuzzy model. Additionally, it further decreased with the incorporation of the learning component, as was expected from the explanation given in the previous paragraph. Question B was looking for the number of outrageous actions that the users thought the pet did in the different models. As you can see from the table above, the random model had an average of 9.52 actions (remember that we asked users to write a number between one and ten). Some users commented that the pet was confused and his actions/emotions were very contradictory. This number of outrageous actions decreased with the incorporation of the nolearning/nofuzzy model. The incorporation of the fuzzy and learning models further decreased the number of outrageous actions to zero.

As you can see from the results given above, the measure by which the pet met users' expectation increased by adding the fuzzy model and it further increased by adding learning. Most of the people expect the pet to learn from the feedback given to it and they further expect it to react with a normal and smooth behavioral mapping.

ii. Intelligence

To explore how users perceive the pet's intelligence in the four models, we asked the users to rate the intelligence of the pet given some definitions. Thus, we formulated the questions as follows:

> The concept of intelligence has been defined and redefined many times. For the purpose of our experiment we will evaluate intelligence from two different perspectives.
>
> A. Intelligence was also defined as exerting behaviors or actions that are goal oriented.
>
> Do you think that PETEEI has this form of intelligence?
>
> ☐ Yes ☐ No
>
> If yes, rate your answer in the scale of one to ten. (1| the pet is has only minor goal-directed intelligence→ 10| the pet is very goal-directly intelligent). Explain your rating.
>
> B. Another definition to intelligence is the ability of the agent or the subject to adapt to a certain environment or situation.
>
> Do you think that PETEEI has this form of intelligence?
>
> ☐ Yes ☐ No
>
> If yes, rate your answer in the scale of one to ten. (1| the pet is has only minor adaptability→ 10| the pet is very adaptable). Explain your rating.
>
> C. Overall how would you rate the pet's intelligence using the three criteria above? Explain your answer. *(1| not intelligent → 10|very intelligent).*

We evaluated the answers and calculated the mean and confidence interval. Table 8 shows these results.

TABLE 8. INTELLIGENCE RATINGS

Model	Question A		Question B		Overall	
	mean	interval	mean	interval	mean	interval
Random	0.14	-0.1 - 0.35	0.33	0 - 0.67	1.143	0.863 - 1.423
No learning /no fuzzy	0.3	0.1 - 0.6	1.1	0.4 - 1.8	3.19	2.87 - 3.511
Fuzzy	0.5	0.2 - 0.9	0.5	0.4 - 0.9	3.05	2.68 - 3.42
Learning	7	6.17 - 7.83	5.1	3.9 - 6.4	7.05	6.678 - 7.417

The ratings of the random model were between one and zero. It should be noted that the scale goes from 1 to 10, and thus zero means that the pet is not intelligent. However, one or two users rated the pet's intelligent in the random model as two and they explained that by saying "PETEEI knew about his surroundings like he knew if there was water around him or not." In contrast, you can see that by using the nolearning/nofuzzy model the level of intelligence increased a little bit. Nevertheless, we think that this increase is negligible compared by the increase that came about by adding the learning component to the model. As you can see, the overall intelligence went from a 3 or 3.2 to a 7.05. Additionally, an increase of 6.5 and 4.6 was noted for questions A and B, respectively.

It should be noted that from looking at the table, a slight difference can be seen between the fuzzy and no learning/nofuzzy model. However, it can also be seen that the confidence interval overlaps greatly between these two models. Therefore, we came to the conclusion that fuzzy logic did not improve the intelligence perceived by the audience. The difference noted in the table was too small to be conclusive.

iii. Learning

To explore how the users perceived the learning component in each model, four questions were formulated. The questions were as follows:

Learning can be measured in many different aspects.

A. A subject x can learn about the other people's behavior to know what to expect and from whom.

Do you think PETEEI learns about you?

Yes ☐ No ☐

If yes, rate your answer in the scale of one to ten. (1| the pet leans only a few things about me → 10| the pet learns a lot about me). Explain your rating.

B. A subject could learn more about the environment to plan for his/her actions.

Do you think PETEEI learns about its environment?

☐Yes ☐ No

If yes, rate your answer in the scale of one to ten. (1| the pet leans only a few things about the environment→ 10| the pet learns a lot about the environment). Explain your rating.

C. A subject could learn how to evaluate some actions as good or bad according to what people say or according to his own beliefs.

Do you think PETEEI learns about good and bad actions?

☐ Yes ☐ No

If yes, rate your answer in the scale of one to ten. (1| the pet leans about only a few actions→ 10| the pet learns to assess all its actions). Explain your rating.

D. Overall how would you rate the pet's learning using the four criteria listed above? Explain your answer. *(1| does not learn much → 10|learns a lot).*

TABLE 9. LEARNING RATINGS

Model	Question A		Question B		Question C		Overall	
	mean	**interval**	**mean**	**interval**	**mean**	**interval**	**mean**	**interval**
Random	0	0 - 0	0	0 - 0	0.1	-0.1 - 0.3	0.238	0.051 - 0.425
No learning /no fuzzy	0.5	-0.1 - 1.1	0.3	-0.2- 0.9	0.4	-0.2 - 1	0.91	0.44 - 1.37
Fuzzy	0.9	0.1 - 1.6	0.5	-0.2 - 1.2	0.29	-0.19 - 0.76	1.143	0.48 - 1.81
Learning	7.7	7.3 - 8.1	5.95	4.77 - 7.14	7.67	7.25 - 8.08	7.952	7.608 - 8.297

The results shown in Table 9 shows how learning was perceived by users. We think that sometimes even though the pet does not explicitly learn, the users might perceive the pet learning. However, the results shown in the table suggests the opposite. As it can be seen, the numbers for all the models without the learning component was between zero and two. There were some differences that can be noted from the table among these different models, however the difference is small and the confidence levels overlap greatly, leading us to believe that users did not really perceive learning in these models. In contrast, the learning model was observed to increase the learning perceived in all questions. In question A there was an increase of 6.8, in question B there was an increase of 5.49, in question C there was an increase of about 7.4, and in the overall question there was an increase of about 6.8. We think that this increase demonstrates that the users did perceive learning in the learning model, while they did not perceive the learning in any other model. We can also conclude that the increase in learning did increase intelligence perceived, as was shown in Table 8 described in the previous subsection.

iv. Behavior

The users were asked to rate the behavior of the pet in terms of how convincing it is. The users were told not to rate it in terms of animation or facial expression, but to concentrate on the behavior and emotion aspect. We analyzed users' answers and we got the results shown in Table 10.

TABLE 10. BEHAVIOR RATINGS

Model	Behavior	
	mean	interval
Random	1	0.67 - 1.33
No learning /no fuzzy	4.33	3.60 - 5.07
Fuzzy	5.43	4.86 - 6
Learning	8.095	7.65 - 8.542

As the table above shows, the random model did not convey a realistic or a convincing behavior to the user since the rating was on average one. In contrast, the introduction of the nolearning/nofuzzy model improved this measure by about 3.33 units on average. The fuzzy model also improved this measure by 1.1 units. The learning model further improved this measure by 2.6 to get an average of 8.1 units.

We conclude that the introduction of learning improved the system and created a closer simulation of a real pet. Even though the pet was not moving except maybe once or twice in the simulation, the users all agreed that the model behind the interface could further serve as a model to simulate more believable characters, provided that animation is added. As a matter of fact, one of our users noted that, "I like this model better than

Petz [a commercial product that simulates believable pets], because this model shows me more about how the pet learns and further displays his affection to me, while in Petz the dogs just animate and play around with no emotions, or if there were some I was not able to know what emotions they were feeling and how they learn from me."

CHAPTER V

FUTURE WORK AND APPLICATIONS

1. APPLICATIONS OF THE MODEL

Models of emotion and behavior are not restricted to the area of believable agents. In the next few paragraphs, we will enumerate some of the applications that can potentially benefit from modeling emotions. It should be pointed out that some applications may not need to simulate a complete model of emotions and emotional responses. Moreover, some applications do not even need any explicit model of emotion. Through our discussion in the following paragraphs, we will not only give examples of applications that can benefit from modeling emotions or emotional intelligence, but we will also outline some applications that will not benefit from modeling emotions as a part of their architecture.

A. INTERACTIVE DRAMA - BELIEVABLE AGENTS

Development of believable agents emerged from the field of interactive drama. To simulate an illusion of life, we will first have to look into the factors that differentiate good simulations from others. In movies, for example, the main component that creates the situation is the emotion. Emotions and emotional expression is what differentiates good actors from bad ones. Therefore, if we are to create the illusion of life we need to simulate the emotional process. As Ian Maitlan, Emmy Award- winning director and editor said, quoted by Picard [34],

> “A film is simply a series of emotions strung together with a plot. …” Though flippant, this thought is not far from the truth. It is the filmmaker’s job to create moods in such a realistic manner that the audience will experience those same emotions enacted on the screen, and thus feel part of the experience [34].

There are important factors that should be taken into consideration when creating a believable agent. These factors can be summarized as follows:

(1) emotional exaggeration. One of the important aspects of believability is the idea of emotional expression. Some times these emotions and expressions have to be exaggerated to create the desired effect [3].

(2) staging. Creating the right emotion, the right movements at the right time and in the right situation are one of the elements that lead to a successful performance. In the pet example, we created a scene that is more or less within the users' expectations. Moreover, when the user expects the pet to bark the pet barks, and when the user expects the pet to play with the ball it does. The idea of meeting the user's expectation versus the suspension of belief theory in theater is closely related. However, not all the movements in theatrics performances meet user's expectations; when the performance deviates from the user's expectation, the user should be warned of this deviation in one way or the other. In movies the audience is automatically warned by the development of the situations. This way the suspension of belief theory may still be intact, while the user's expectations are not met.

(3) personality traits. Whenever users look at a believable agent, they will automatically map its personality to a model of personality traits that they developed through their experience. Thus, having a personality is not essential, but conveying a constant personality is. The agent will always be judged as if it has a certain personality even if it does not. It should be pointed out that the agent should not deviate from the personality that was set up.

To show the contribution of our model on a specific application, we will employ the Role Playing Game example. A role playing game is a game where the user takes the role of a specific character, a King, a Prince or a Warrior. Moreover, the user will be given a mission depending on the character played in the game. During the game the user will talk to other characters. In some games the user may even convince other characters to join him/her in pursing the mission that was established in the game. The characters within the game are all simulations of real characters. Therefore, they should convey a proper character and personality. Currently, the characters are simulated in a scenario-based method. At any given time, the user may choose to talk to any character within the particular scene that the user is in. During the user's interaction with the chosen character, the user is faced with a collection of sentences that he can tell the character. According to the sentences chosen, the character will react. Thus, essentially the developers will have to write different scripts and different storyboards according to the combination of the different paths that the user can take. The limitation of this method is that the characters tend to be unconvincing.

The OZ project [3] introduced another approach to simulating characters. By the use of believable agents, the characters are promoted from a collection of scripts that are triggered by some constant number of sentences to an intelligent being that can express and trigger emotions according to the different situations that it faces. Moreover, the character will also use its planning process to produce actions according to its own goals. Nevertheless, this introduction does not completely solve the problem of character interaction. During communication and interaction, we tend to learn about the other's emotions and character. This information will help us formulate some expectations about what others can do. Thus, as Chapter III and IV shows, experience plays a major role in the interaction process with other entities in the simulation.

B. INTELLIGENT TUTORING SYSTEM AND TRAINING SYSTEMS

The very first sentence of this thesis indicated the importance of emotion simulation and modeling in the area of tutoring or training systems. Traditionally, intelligent tutoring systems' architecture involved the following models: (1) a model of the concept being taught, and (2) a model of the system. There is a move towards adding a new dimension, a student model, to this architecture. A student model is essential to capture the qualitative and the quantitative aspect of learning. On the one hand, a quantitative aspect measures how much information the student conveyed and how much is left. This aspect can be effectively measured through tests and exercises. In contrast, the qualitative aspect measures the mood and the situation of the student from which we can formulate and order the lessons in a way that is easier for the student to understand and visualize. This model will be especially useful when more than one student is involved as in a group study or a group training system.

In computer simulations there is always a question about the amount of information needed. Various factors tend to gain major importance in computer simulations, including performance and computational costs. Therefore, there is always a trade off between the amount of information that we need to maximize and the performance/cost measure that we need to minimize. We found out that sometimes it was enough to simulate part of the mind. For example, we have developed a teacher training system as a class project. The system was meant to teach or rather train the teacher on how to communicate information to students in a way that keeps them all motivated. Thus, we studied different personalities and simulated them. These personalities include idiot savants, spiteful bullies, nerds and troublemakers. To simulate these personalities we did not need all the emotional states that were simulated in the pet. In fact we simulated only four emotions: joy, sad, depression and fear. We added some other states, including boredom and motivation. Students' learning processes depend on their attention span and motivations [17]. We found that these states were enough to simulate classroom agents. However, how much is enough is still an open question. The answer heavily depends on the application and the domain studied. However, the argument still holds, we still need a model that simulates or synthesizes part of the emotional process to increase the performance of a training or a tutoring system

C. INTERFACE ASPECT

We believe that any system that interacts with humans should have a user model of some sort. Humans have emotions and they always experience some mood change. To model the human mind in any given situation, the system will have to simulate emotions and moods among other processes of the human mind. We will adopt the email system as an example. There have been many confusions and miscommunications resulting from plain text email messages. People can not tell from an email if the person sending the email is serious or joking. Even though the use of Italics, bold letters, capital letters can serve this purpose, emotional expressions are missing from plain text emails. The emphasis that can be given in speech provides a much easier, faster and more effective method compared to what can be written in paper.

Users frequently become frustrated when learning a new package. Users, whether they are end-users or programmers, usually find themselves struggling with a piece of software trying to prepare a presentation, prepare a book, a document or even build some kind of a graphical model. They have an abstract idea of what they want to do. However, most of the time they do not know how to start. The help option or manuals do not usually offer much help, because the user him/herself could not put the abstract model of what they want to do in words relative to the index topics. Therefore, they get stuck; they search in the help, but do not find any answers. Looking for answers they sometimes turn to friends, but it might help if the system can sense the user's level of frustration and try to offer help accordingly.

Some agents have been built to learn and adapt to the user's needs [19]. Learning user's preferences can be predicted solely by the emotional state of the user. These agents may learn what news you like to read or what excites you and add a bookmark to it automatically. They may also learn how to filter your email throwing out what is not relevant to you. The problem with the current adaptable agents is that they are limited on the information that they collect on the user. By using wearable computers, more specifically affective wearable computers, information can be gathered about the amount of excitement and stress among other emotional states. Many applications were discussed in Picard's book, *Affective Computing* [34]. She provided some other aspects of the use of affective computing. For more details on the various applications that can benefit from modeling emotions the reader is referred to [34].

D. MODELING EMOTIONS AND CONTRIBUTIONS

Even though some applications may benefit from modeling emotions, some others may not. For example, modeling emotions may not affect applications like search engines. Search strategies may use some sort of relevance of information to the user and thus, it may use a user model that includes keyword relevance information. However, it will not need to model the user's emotional states or moods to get this information.

As we mentioned earlier, it all depends on the application and the domain studied. Some models may benefit from including a model of the emotional process, but some others may not. Even though there are some applications that may benefit from including a model of the emotional process in its architecture, these applications may not use all the emotional states described in the proposed model to enhance their performance and applicability. Thus, the question of how much information should we model is yet another aspect that have to be settled by the designers depending on the domain and application involved.

In this section, we have outlined some of the major application areas that need emotions. These models may benefit from the contributions outlined in the thesis. For example, any model that seeks to simulate emotions and emotional expressions can benefit from introducing the fuzzy logic modeling proposed in the model. Furthermore, learning can provide a step towards understanding the link between cognition and emotions. If we are modeling a student or a user, we can probably make use of this link. Additionally, the discussion about the filtering process of emotions and motivational states can provide another major implication that can be rendered to all the applications discussed to understand and predict the emotional state.

2. FUTURE DIRECTIONS

There are various directions for future work. There have been many points raised by users in the user evaluation. Some of the cases that the users gave might not apply to the model, but it might affect the believability of the agent, and thus it provided us with major points for enhancing the simulation. There are two major aspects in the future directions, future work related to the model itself and another related to the simulation. Even though the simulation was a fabrication of the model, the simulation addresses other issues that are related to the practical aspect of the model.

A. CHARACTER FEATURES

By interviewing users who evaluated the system, we were able to formulate some major character features that have to be there for the character to be believable. Some of these features were discussed such as emotions and emotional expressions. At the simulation level, we found out that there are other character features that may have a major impact on the believability of an agent. These features include animation, speed and environment. Animation by itself can create a realistic view of the character even if the character simulates random behaviors. Animation can create a more realistic manifestation of the agent studied. Thus, animation was regarded as a very important factor in believability. The speed by which the character reacts may also affect the believability of the character as pointed out in Chapter I. The complexity of the environment and the interactions between the user and the characters or the agent will provide yet another dimension for future research.

B. PERSONALITY

At the model level, we can extend the model to handle a more generalized aspect of human intelligence. The model did not really have a representation of the agent's personality; it was rather conceived by the user. Thus, even though the agent itself did not have an explicit representation of the pet's personality, the personality was implicitly presented by the model. It should be noted that even though a personality was conceived, the personality that was conceived was different from one user to the other. It heavily depended on the user's background and experience. Thus the need for a concrete personality is still important especially in mutli-agent projects.

Personality can be modeled according to personality traits, personality quirks and character studies. Character studies provide a good starting point for character animation and personality simulation. Some other models have added a personality model in their projects, however the personality was modeled within the mapping function from emotions to a behavior. However, other aspects of personality, including quirks, which do not specifically depend on emotions, have to be modeled. Thus, a personality model is essential to provide a more believable agent.

C. MULTI-AGENT SIMULATION

Another extension that is worthwhile to pursue is the multi-agent simulation. In the applications that were discussed above, we rarely see one agent by itself. Thus, it is always a group of agents that interact. As it was once said, the whole is greater than the sum of the parts. Thus, if we need to simulate a group of agents that interact with each other or with the user, we will have to extend our model. Our model was designed for one agent and a user. For an agent to interact with other agents then the architecture should be extended to model the communication process. Therefore, the model will not only have to simulate the user's needs, but it will include information about other agents as well. Some type of self-evaluation, self-perception will have to also be modeled.

Furthermore, categorization of the other agents' behavior, personality and emotion is essential to facilitate the communication process. In essence, the problem will then be extended from modeling emotions to modeling social behavior.

D. TOWARDS HUMAN INTELLIGENCE

Human intelligence certainly includes other small variables that can extend and further enhance the model, for example, the idea of an identity. The processes of self-realization, self-perception and self-awareness form the identity that can later shape the personality. These concepts provide yet another dimension to the model that we did not incorporate. Moreover, the idea of self-esteem can also be added to the model. It had been documented [12] that the process of self-esteem heavily depends on the experience process, and thus we can further extend the model to incorporate the link between emotions, experience and self-esteem. The idea of opinion formation about other objects and other people around us may also be added to the model.

Human intelligence includes cognition, learning, planning as well as emotional intelligence. We have provided an insight on some of the connections between some of these processes. We still have a long road to go to build these complete processes and to further establish the links between them.

CHAPTER VI

SUMMARY AND CONCLUSION

We have provided some of the major limitations of the previous models of emotion. We further discussed an attempt to provide a solution to all the limitations of these models. However, as it turned out we have some issues in the model that called for more future enhancements and extensions. In the next couple of paragraphs, we will attempt to summarize and conclude our work.

Important emphasis on the concept of emotional intelligence has led researchers to look into the idea of emotion simulations and synthesis, and to further understand its impact on the many areas within the computer science field. Effective wearables [34] are being developed at MIT to measure the emotional state of a user. This research can then produce a model that can be used as a catalyst in many other systems. By the use of this model, systems can measure the user's reaction to provide better services accordingly. Other systems were produced to predict the emotional states of the user by subjecting the user to answer certain questions about his/her situation. From these questions, the system was be able to predict the correct emotional state. In agent research, simulating emotions was proven to lead an important role in believable agents, interface agents and software agents. In software agents and robotics, models of emotions were developed to enhance the cooperation and collaboration between agents to carry out specific tasks [44].

Models of believable agents were developed using two main architectures. One of which, is the broad agent architecture that constitutes a big model, which includes several internal states [4]. These internal states are evaluated and an action evolves according to the resulting emotional state. The other architecture is closer to Brook's subsumption architecture, which consists of a set of different distributed agents with no internal states [51]. Every agent is responsible for calculating a specific state, and then all the emotional states are integrated, evaluated, decayed and fed back to the system. In evaluating the emotional states a behavior is triggered. This behavior is then carried out by the robot/subject.

However, these models were limited in what they could do. These limitations can be summarized as follows:

- Although these models simulated emotional states and emotional mapping to select a behavior, these models still did not include a substantial filtering system that takes into account some of the motivational states, including *pain*, *hunger* and *thirst* and their impact on the emotional states. Thus, we have built our model to simulate a filtering system that carries out the inhibition and enhancing process between emotional states and motivational states according to the situation at hand. The emotional state, which resulted from the filtering process, will constitute a mixture of emotions with different intensities.

- The next step is the mapping process of an emotional state to a behavior. The previous models built their mapping process upon intervals. However, the problem with intervals is that it produces a very edgy behavior. Interval based mapping, adopted by these models, and provides very sharp boundaries by which a behavior is mapped given an emotional intensity. Thus, there is a need to further smoothen these boundaries. We have proposed the use of fuzzy logic mapping and fuzzy sets to smooth the boundaries of emotional intensity.

- Lastly, emotions are not static entities, they are rather dynamic entities that change according to the learning process and change in situations through time. All the previous computational models looked at the dynamic process in terms of change of situations in time. None of them looked at the experience factor and how it changes the emotional process. Thus, we have taken it upon ourselves to implement a working model of the emotion dynamics. The model simulates the dynamic nature of emotions through time, situations and experience. Psychological models have viewed some of the learning aspects on the emotional process. However, our model reviews the different types of learning and how these learning types acquired by the agent help to formulate a closer picture to reality.

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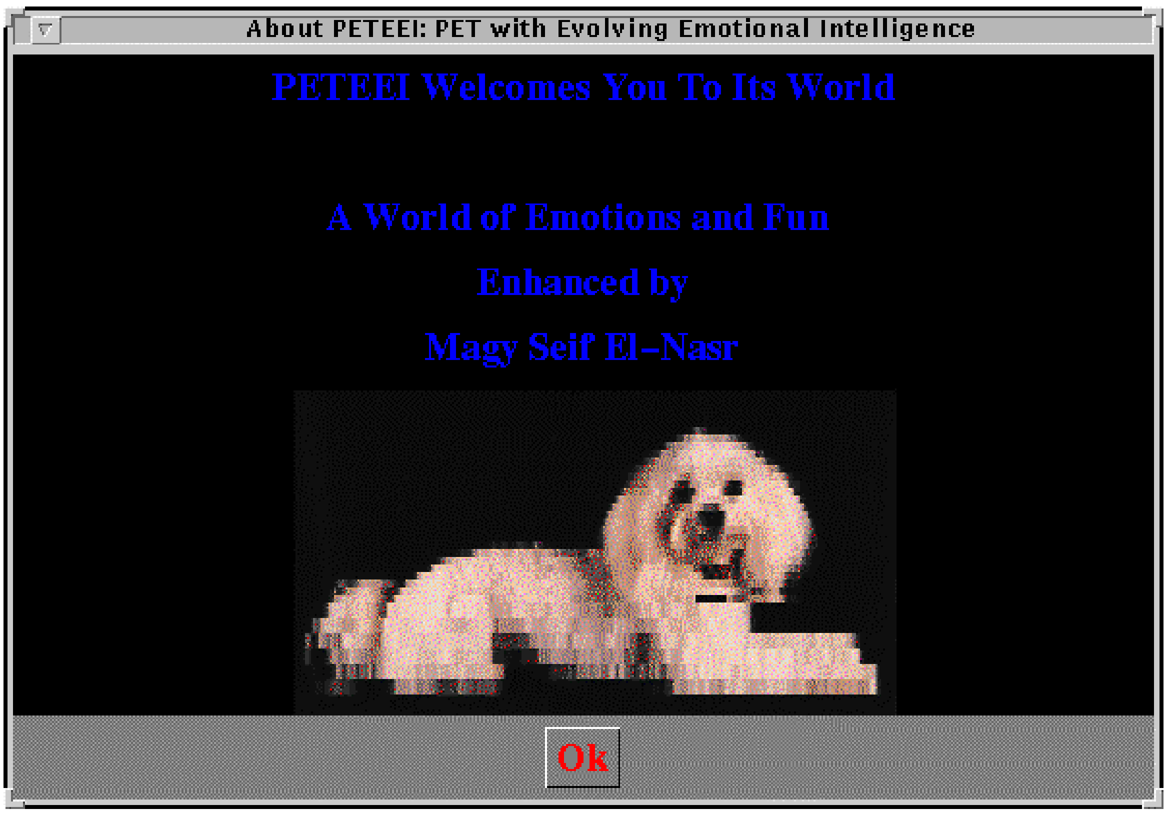
APPENDIX A

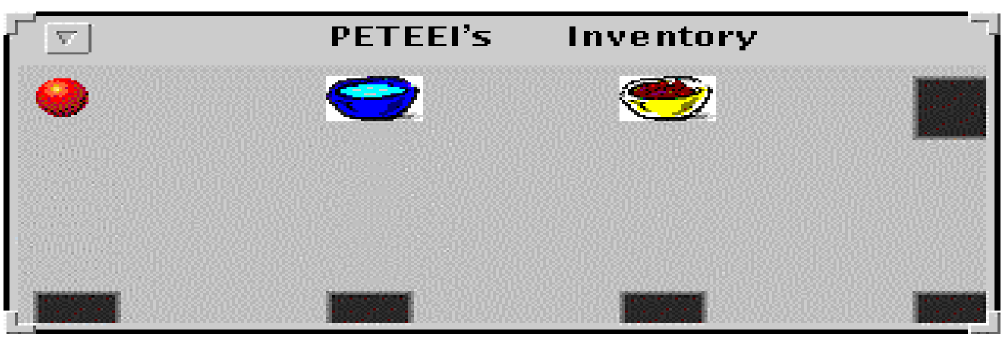
THE SIMULATION

In this section, we will go through a scenario and introduce the various windows of the system. In the next figure we will see the first window of the system.

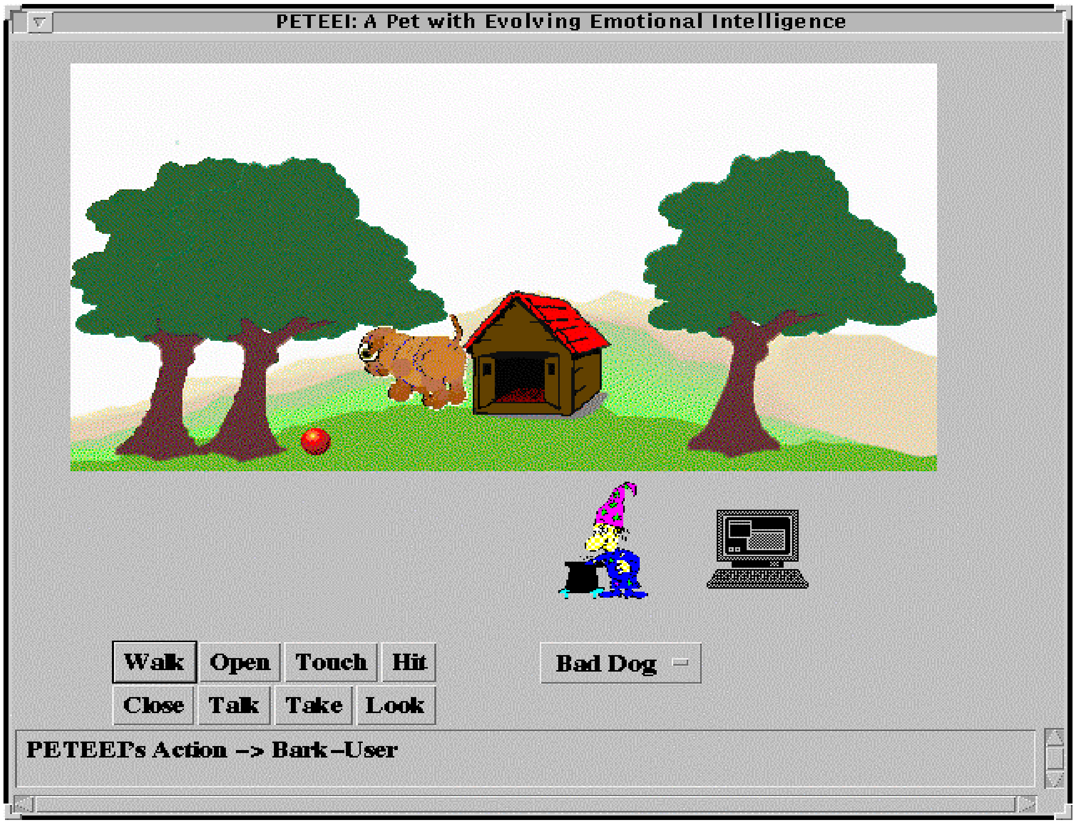


Then when the user presses the ok button, then the main scene window will be brought up. This window is illustrated below.

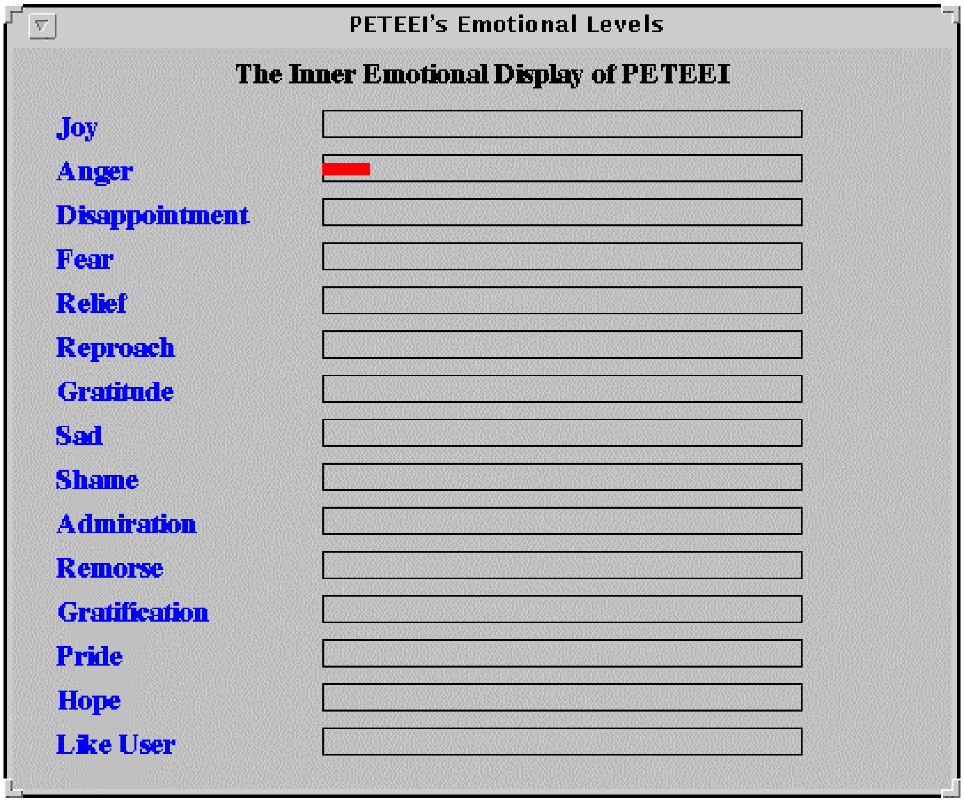
As you can see, there are many actions that the user can do in the environment as illustrated in the thesis. If I take out the food and the water by clicking on each with the mouse, this screen will appear.



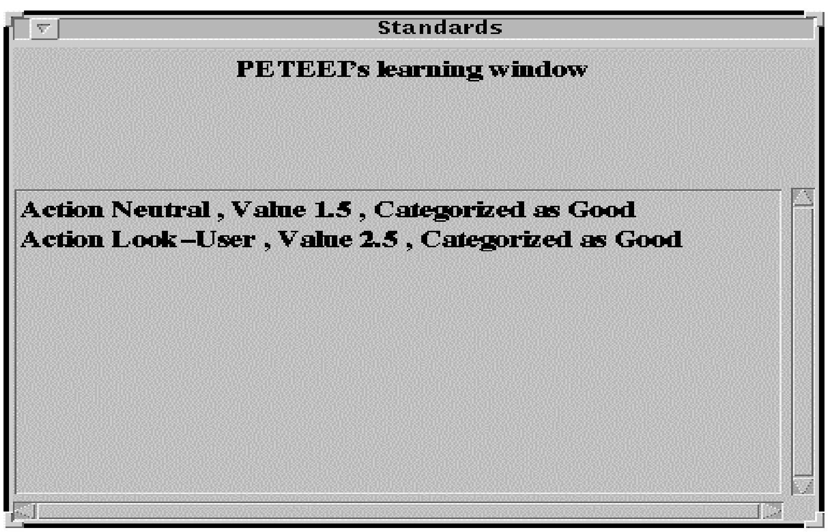
This screen is the inventory of the user. Thus, as you can see the food and the water will disappear from the main scene illustrated below and will appear in the inventory as illustrated by the picture above.



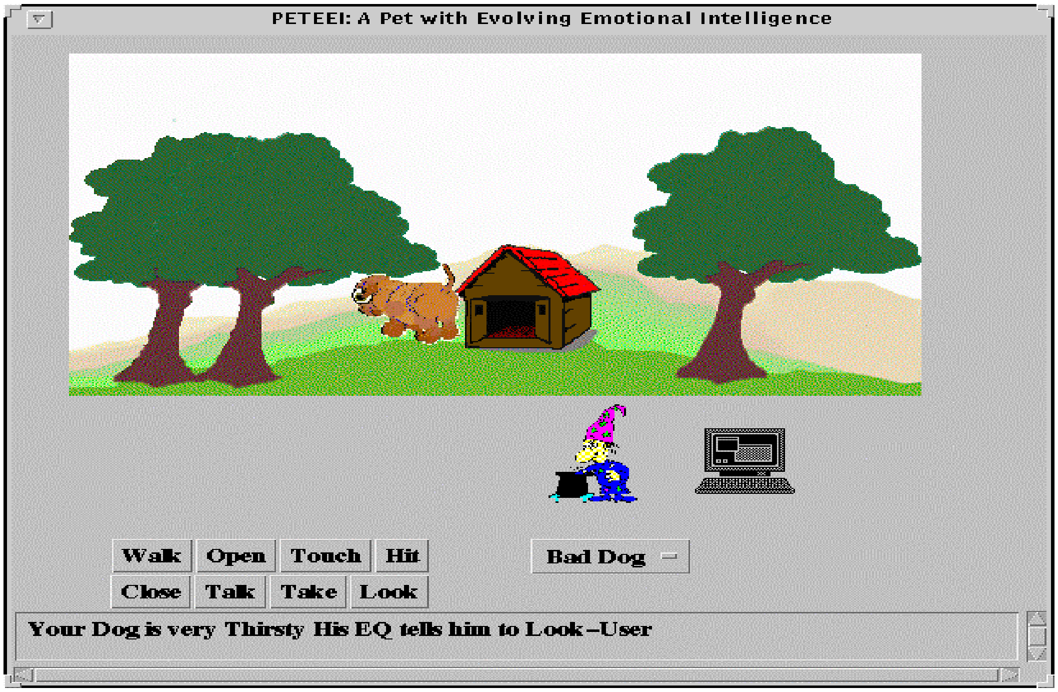
As you can see, the pet is barking at the me as is written in the box the end of the window. As you can see another window popped up with the information about the emotional process and the level of each emotion. This window is illustrated in the window below. As you can see, the pet is angry at the user for taking away the food and water from him and his liking of the user is 0%, while initially we starting by having the pet like the user about 20%. So these two actions produced the first impression of the user to the pet and thus, the pet will not listen or learn anything from the user. He basically hates the user now, so we considered to restart the simulation and show you another simulation.



We started the system again, tried to teach the dog some good and bad actions, i.e. actions that pleases the users and actions that does not. We got the following window.



As time passes his thirst level increases, when it increases to the limit, he will try to please you. Thus, he will search for the action that pleased you most, as shown above, it is Look-User. Thus, he will look at the user, as is illustrated by the figure below.



APPENDIX B

QUESTIONAIRE

Background: ______________________________
(State Major and degree)

Types of games played before: RPG ARCADE
(Circle all that applies)

Expectation:

Through your interactions with the pet you have seen it react and produce emotions.

A. Do you think that the actions the pet does through the simulation meet your expectation?

☐ Yes ☐ No

Rate your answer in the scale of one to ten in terms of how many actions were not met by your expectation. (1| one → 10| more than ten actions). Explain your rating.

B. Did PETEEI during the simulation or during its interaction with you produce any actions that you thought was outrageous or out of the ordinary?

☐ Yes ☐ No

If yes, rate your answer in the scale of one to ten in terms of how many actions you considered out of the ordinary. (1| one → 10| more than ten actions). Explain your rating.

Intelligence:

The concept of intelligence has been defined and redefined many times. For the purpose of our experiment we will evaluate intelligence from two different perspectives.

A. Intelligence was also defined as exerting behaviors or actions that are goal oriented.

Do you think that PETEEI has this form of intelligence?

☐ Yes ☐ No

If yes, rate your answer in the scale of one to ten. (1| the pet is has only minor goal-directed intelligence→ 10| the pet is very goal-directly intelligent). Explain your rating.

B. Another definition to intelligence is the ability of the agent or the subject to adapt to a certain environment or situation.

Do you think that PETEEI has this form of intelligence?

☐ Yes ☐ No

If yes, rate your answer in the scale of one to ten. (1| the pet is has only minor adaptability→ 10| the pet is very adaptable). Explain your rating.

C. Overall how would you rate the pet's intelligence using the three criteria above? Explain your answer.

(1| not intelligent → 10|very intelligent).

Learning:

Learning can be measured in many different aspects.

A. A subject x can learn about the other people's behavior to know what to expect and from whom.

Do you think PETEEI learns about you?

☐ Yes ☐ No

If yes, rate your answer in the scale of one to ten. (1| the pet leans only a few things about me → 10| the pet learns a lot about me). Explain your rating.

B. A subject could learn more about the environment to plan for his/her actions.

Do you think PETEEI learns about its environment?

☐ Yes ☐ No

If yes, rate your answer in the scale of one to ten. (1| the pet leans only a few things about the environment→ 10| the pet learns a lot about the environment). Explain your rating.

C. A subject could learn how to evaluate some actions as good or bad according to what people say or according to his own beliefs.

Do you think PETEEI learns about good and bad actions?

☐ Yes ☐ No

If yes, rate your answer in the scale of one to ten. (1| the pet leans about only a few actions→ 10| the pet learns to assess all its actions). Explain your rating.

D. Overall how would you rate the pet's learning using the four criteria listed above? Explain your answer.

(1| does not learn much→ 10|learns a lot).

Behavior:

How would you rate the pet's behavior?

Explain your answer.

(1| not realistic → 10| very realistic).

Personality: Explain in your own words what do you think the personality of PETEEI is? Rate your answer in terms of how did the character convey this personality to you.
(1| did not convey it → 10| conveyed it very well).

Improvement: Suggest one improvement for the system and explain why it is needed.

APPENDIX C

INSTRUCTIONS FOR WALK THROUGH SCENARIOS

Scenario 1 : User feedback

Click on the witch button *(to open the inventory window)*
A window of the several items that you have will appear *(inventory window is open)*
click on the food icon then click on the garden scene *(feed the pet)*
click on the water icon then click on the garden scene *(give water to the pet)*
Click on the button that says Bad Dog *(give the pet bad feedback on his last action)*
Highlight the Bad Dog phrase
Click on the Talk Button
See the effect on the learning window shown *(Pet learns the action is bad)*
See the action of the Dog now (shown in the bottom part of the garden scene window) *(Pet reacts)*
Click on the button that says Bad Dog *(give the pet good feedback on his last action)*
Highlight the Good Dog phrase
Click on the Talk Button
See the effect on the learning window shown *(Pet learns the action is good)*
See the action of the Dog now (shown in the bottom part of the garden scene window) *(Pet reacts)*
Click on the button that says Bad Dog *(give the pet good feedback on his last action)*
Highlight the Good Dog phrase
Click on the Talk Button
See the effect on the learning window shown *(Pet learns the action is good)*
See the action of the Dog now (shown in the bottom part of the garden scene window) *(Pet reacts)*
Click on the button that says Bad Dog *(give the pet good feedback on his last action)*
Highlight the Good Dog phrase
Click on the Talk Button
See the effect on the learning window shown *(Pet learns the action is good)*
See the action of the Dog now (shown in the bottom part of the garden scene window) *(Pet reacts)*
Click on the button that says Bad Dog *(give the pet good feedback on his last action)*
Highlight the Good Dog phrase

Click on the Talk Button
See the effect on the learning window shown *(Pet learns the action is good)*

Scenario 2 : Emotional Intelligence

Click on the water icon in the garden scene *(give water to the pet)*
Click on the food icon in the garden scene *(feed the pet)*
See the effect of these actions on the emotional state of the pet *(Pet changes his emotions)*
Click the Look button *(Look at the trees)*
Click on the tree in the garden scene window
Click on the Look button *(Look at the sky)*
Click on the sky in the garden scene window
See the effect of these actions on the emotional state of the pet *(Pet reacts)*
Keep looking at other objects by pressing on the Look button and then press on the object until you see an effective change in the text box shown in the bottom of the garden scene *(Ignoring the pet by looking at different objects)*
Note the change in the emotional state window *(Pet changes his emotions)*
Note the text box and see what the agent is doing *(Pet reacts)*
Click on the witch button until you get the inventory window *(open inventory window)*
Click on the water icon then click on the garden scene *(give pet water)*
Note the effect on the emotional window *(Pet changes his emotions)*
Click on the food icon then click on the garden scene*(feed the pet)*
Note the effect on the emotional window *(Pet changes his emotions)*

Scenario 3 : Effect of user's actions on the pet

Click on the food icon *(remove food)*
Click on the water icon *(remove water)*
Note the effect on the pet's emotional state (shown emotional states window) *(Pet changes his emotions)*
Note the pets reaction (shown in the bottom on the garden scene window) *(Pet reacts)*
Click on the ball icon in the inventory window then click on the grass in the garden scene window *(Throw the ball to the pet)*
Note the effect on the pet's emotional state (shown emotional states window) *(Pet changes his emotions)*
Note the pets reaction (shown in the bottom on the garden scene window) *(Pet reacts)*
Restart the application by clicking on the computer button and then choose quit from the menu *(Restart the emotions and learning experience of the pet)*
Click on the witch button *(Open the inventory window)*
Click on the water icon then click on the grass in garden scene window *(give the pet water)*
Click on the food icon then click on the grass in garden scene window *(feed the pet)*

Note the effect on the pet's emotional state (shown emotional states window) *(pet changes his emotions)*
Click on the ball in the inventory window then click on the grass in the garden scene window *(throw the ball)*
Note the effect on the pet's emotional state (shown emotional states window) *(pet changes his emotions)*
Note the pets reaction (shown in the bottom on the garden scene window) *(Pet reacts)*

Scenario 4 : Effects of the mood of the user

Click on Hit then click on the Tree *(hit the tree)*
Click on Hit then click on the grass *(hit the grass)*
Keep repeating these operations 5 or 6 times *(repeating hitting the grass and the tree)*
Note the effect on the emotional states *(pert changes his emotions)*
Note the effect on the pet's actions shown by the end of the garden scene window *(pet reacts)*

Scenario 5 : Ignoring the pet

Restart the application by clicking on the computer button and then choose quit from the menu *(restart pets emotional and learning experience)*
Click on the Look button then click on the sky in the garden scene *(look at the sky)*
Keep repeating the last two actions until you see a significant change in the pet's action (shown in the bottom on the garden scene window) *(keep looking at the sky)*
Note the effect of this action on the pet's action (shown in the bottom on the garden scene window) *(pet reacts)*
Note the effect of this action on the pet's emotional state (shown in the emotional state window) *(pet changes its emotions)*

Scenario 6 : Torturing the pet

Restart the application by clicking on the computer button and then choose quit from the menu *(restart pets emotional and learning experience)*

Click on Hit then click on the pet *(Hit the pet)*
keep repeating the hitting pet function (the previous two statements) until you hear
the pet moaning *(keep hitting the pet until it goes into a real serious condition)*
See the effect the emotional state of the pet seen in the emotional states window *(pet changes his emotions)*
Click on the witch button *(open the inventory window)*
Click on the water icon in the inventory window then click on the grass in the garden scene window *(give the pet water)*
Click on the food icon in the inventory window then click on the grass in the garden scene window *(feed the pet)*

Note the effect on the emotional state of the pet seen in the emotional states window *(pet changes his emotions)*
Click on the ball icon in the inventory window then click on the grass in the garden scene window *(throw the ball)*
Note the effect of this action on the pet's reactions (seen in the bottom of the garden scene window) *(pet reacts)*
Note the effect of the throw-ball action on the emotional states of the pet shown in the emotional states window *(pet changes its emotions)*

Scenario 7 : Effect of Motivational states on the pet

Restart the application by clicking on the computer button and then choose quit from the menu *(restart pets emotional and learning experience)*
Click on the Look button then click on the sky in the garden scene *(look at the sky)*
Click on the Look button then click on the tree in the garden scene *(look at the trees)*
Keep repeating these four last operations until you hear a sniffing sound *(keep looking at the sky and then at the trees until pet is thirsty)*
Note the effect of this action on the pet's action (shown in the bottom on the garden scene window) *(pet reacts)*
Note the effect of this action on the pet's emotional state (shown in the emotional state window) *(pet changes its emotions)*

Scenario 8 : Effect of user patterns

Restart the application by clicking on the computer button and then choose quit from the menu *(restart pets emotional and learning experience)*
Click on the Look button then click on the sky in the garden scene *(look at the sky)*
Click on the Look button then click on the tree in the garden scene *(look at the trees)*
Click on witch button *(open the inventory window)*
Click on the water icon in the inventory window then click on the grass in the garden scene (*give water to the pet)*
Click on the water icon *(remove water)*
Click on the Look button then click on the sky in the garden scene *(look at the sky)*
Click on the Look button then click on the tree in the garden scene *(look a the tree)*
Click on witch button *(open inventory window)*
Click on the water icon in the inventory window then click on the grass in the garden scene *(give water to the pet)*
Click on the water icon *(remove water)*
Click on the Look button then click on the sky in the garden scene *(look at the sky)*

Click on the Look button then click on the tree in the garden scene *(look a the tree)*
Click on the water icon in the inventory window then lick on the grass in the garden scene *(give water to pet)*
Click on the water icon *(remove water)*
Click on the Look button then click on the sky in the garden scene *(look at the sky)*
Click on the Look button then click on the tree in the garden scene *(look at tree)*
Click on the water icon in the inventory window then click on the grass in the garden scene (*give water to the pet)*
Click on the water icon *(remove water)*
Click on the Look button then click on sky in the garden scene *(look at the sky)*
Note the effect of this action on the pet's action (shown in the bottom on the garden scene window) *(pet reacts)*
Note the effect of this action on the pet's emotional state (shown in the emotional state window) *(pet changes its emotions)*

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