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Fuzzy Computational Model for Emotion Regulation Based on Affect Control Theory

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Fuzzy Computational Model for Emotion Regulation Based on Affect Control Theory

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Fuzzy Computational Model for Emotion Regulation Based on Affect Control Theory

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Declaration of Co-Authorship / Previous Publication

I. Co-Authorship Declaration

I hereby declare that this dissertation incorporates material that is result of joint research. In all cases, the key ideas, primary contributions, experimental designs, data analysis and interpretation, were performed by the author, and the contribution of co-authors was primarily through the proof reading of the published manuscripts.

I am aware of the University of Windsor Senate Policy on Authorship and I certify that I have properly acknowledged the contribution of other researchers to my dissertation, and have obtained written permission from each of the co-author(s) to include the above material(s) in my dissertation.

I certify that, with the above qualification, this dissertation, and the research to which it refers, is the product of my own work.

II. Declaration of Previous Publication

This dissertation includes 10 original papers that have been previously published/submitted for publication in peer reviewed journals and conferences, as follows:

Section	Full Citation	Publication Status
2.3	A. Soleimani and Z. Kobti, "Toward a Fuzzy Approach for Emotion Generation Dynamics Based on OCC Emotion Model", IAENG International Journal of Computer Science, 2014, pp. 48-61 [116]	Published

Table 1 – Continued on next page

Section	Full Citation	Publication Status
3.2	A. Soleimani and Z. Kobti, "An adaptive computational model of emotion regulation strategies based on Gross theory", in Proceedings of the fifth C* Conference on Computer Science & Software Engineering, Montreal, QC, Canada, 2012, pp. 9-17 [112]	Published
3.3	A. Soleimani and Z. Kobti, "A fuzzy logic computational model for emotion regulation based on Gross theory". Proceedings of the 26th International Conference of the Florida Artificial Intelligence Research Society. May 2013, Florida, USA, pp. 142-147 [119]	Published
4.2	A. Soleimani and Z. Kobti, "Toward a Computational Model for Collective Emotion Regulation Based on Emotion Contagion Phenomenon", Proceedings of the 27th Canadian Conference on Artificial Intelligence, May 2014, Montreal, QC [116]	Published

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Abstract

Emotion modeling is a multi-disciplinary problem that has managed to attract a great deal of research work spanned to a wide spectrum of scholarly areas starting at humanistic science fields passing through applied sciences and engineering and arriving at health care and wellbeing.

Emotion research under the umbrella of IT and Computer Science was extensively successful with a handful of achievements especially in the last two decades. Affective Computing is an IT originated systematic research area that strives to best model emotions in a way that fits the needs for computer applications enriched with affective component.

A comprehensive Affective Computing based system is made of three major components: a component for emotion detection, a component for emotion modeling, and finally a component to generating affective responses in artificial agents.

The major focus of this dissertation is on developing efficient computational models for emotions. In fact most of the research works presented in this dissertation were focused on a sub problem of emotion modeling known as emotion regulation at which we strive to model the dynamics of changes in the emotional response levels of individuals as a result of the overt or covert situational changes.

In this dissertation, several emotion related problems were addressed. Modeling the dynamics for emotion elicitation from a pure appraisal approach, investigating individualistic differences in emotional processes, and modeling emotion contagion as a type of social contagion phenomena are a few to name from those conducted research works.

The main contribution of this dissertation was to propose a new computational model for the problem of emotion regulation that is based on Affect Control Theory. The new approach utilized a hybrid appraisal-dimensional architecture. By using a fuzzy modeling approach, the natural fuzziness in perceiving, representing

and expressing emotions was effectively and efficiently addressed. Furthermore, the combination of automata framework with the concept of bipolar emotional channels used at the heart of the modeling processes of the proposed model has further contributed to promote the behavior of the model in order to exhibit an accepted degree of human-like affective behavior.

Dedication

I am truly grateful to my parents for their limitless giving since the moment that I first opened my eyes and noticed the light of their love and kindness that had always shielded me from all negatives.

I am sincerely thankful to my loving, patient and hard- worker wife who was always beside me during all the happy and hard moments that we spent together during my PhD studies, where she did all the best to create an atmosphere of love and convenience for our family; without her sincere efforts, this dissertation would have never seen the light.

Besides, I do not forget naming my three angels who always and by their innocent acts gave me the energy and power to carry on in achieving something that would make them feel proud of their daddy.

This dissertation is lovingly dedicated to my dear parents, wife and children for their continuous support, encouragement and true love.

Acknowledgements

I would like to take the opportunity at the beginning of this dissertation document to acknowledge those who played an important positive role in my doctoral studies journey.

First and foremost, I would like to thank my PhD advisor, Dr. Ziad Kobti for his continuous support, kind and professional guidance during almost 5 years of my doctoral studies. His remarks and advises always illuminated the pathway to fulfill one of my major dreams to get to this level of expertise.

Besides, I would like to express my gratitude to the respected members of my PhD committee, Dr. Christine Thrasher, Dr. Dan Wu, Dr. Xiaobu Yuan for their valuable time, interest and comments about my research work. Furthermore, my special thanks go to the external examiner, Dr. Myounghoon (Philart) Jeon for his interest and valuable feedbacks about this dissertation.

In addition, I would like to acknowledge the efforts and support from my friend and roommate Pooya Moradian and appreciate the nice discussions and moments that we shared together.

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Preface

This dissertation document highlights a summary of the major components of my PhD research work performed at the School of Computer Science, University of Windsor, during the period of September 2010 and December 2014.

Considering the fact that my research area was a true blend of Computer Science with humanistic sciences especially Psychology, I started my research work with a dedicated assignment of my time and endeavor to deeply investigate the state-of-the-art approaches toward addressing the problem of emotions modeling.

That was not an easy job to perform knowing that it was being done by an IT researcher with quantitative mentality equipped with computing tools and methodologies that had to deal with a purely qualitative- nature problem yet still controversial among scientific communities with its special complexities and challenges. Hence, I spent my first year in my PhD program in studying a variety of methods and hypothesis with respect to modeling emotions and to set the appropriate framework for approaching this problem from an IT perspective.

Due to the wide recent and prospect applications for affect-enabled software and hardware products, emotion modeling has managed to create a solid systematic research within the field of Computer Science and in particular Artificial Intelligence (AI) and Human-Computer Interaction (HCI).

Coming from an AI background, I was able to present my first computational model for emotion regulation which included modeling the dynamics and processes

involved in the mechanism of changes in the emotional states of an individual in the second year of the PhD program. That model was an expansion of a previous model that had been developed based on a pure appraisal approach for modeling emotions. The newer version strived to address some open problems within the original model. Some augmented models were proposed later.

Considering the differences between different individuals in the perception, interpretation and expression of emotions, I investigated using a fuzzy approach in modeling the emotional processes where better results were obtained in the experiments. Hence, a fuzzy approach was adopted in all successive models.

Beside the traditional appraisal approach, another important direction in modeling emotions is the dimensional methodology at which distinct emotion labels lose their importance and a multi-dimensional space to measure and reflect the affective states of the individual is utilized instead.

Accordingly, some dimensional models for emotions were proposed. An important achievement was made in this regard where a dimensional computational model for emotion dynamics was proposed at which a fuzzy automata framework was used in the modeling architecture.

The major contribution of my PhD research work that can be mentioned in this brief summary was a computational model for emotion regulation that was developed based on a hybrid approach of appraisal and dimensional theories of emotion. This model which was built according to Affect Control Theory (ACT) managed to exhibit a high degree of human-like affective behavior. The title of "Fuzzy Computational Model for Emotion Regulation Based on Affect Control Theory" that is given to this dissertation was inspired from that contribution.

Chapter 1

Introduction

1.1   Problem Statement

Emotion is a subjective state or feeling that is a result of a complex interplay between personality traits, mood, context, conscious and subconscious mind, external stimuli and other factors. At the beginning of this thesis document and in order to have a well-defined problem statement for this research work, two essential questions need to be addressed. The first question briefly argues the necessity for studying and modeling emotions, whereas the second discusses how an emotion related study fits in a doctoral dissertation in Computer Science.

Emotion is an important component of the human mind and constitutes a non-detachable element of the personality of different individuals. During our daily life, emotions play a clearly visible role in affecting our beliefs and manipulating our cognitive activities such as perception and decision making. Furthermore, they reflect ready responsive patterns to be used in adapting our thoughts and behaviors to events and other changes in the environment [4].

Another important aspect of emotions is their dominant role in our social lives. Most of the different emotions that we experience are rooted in the interactions with

others including family members, friends, coworkers, strangers and even those people that might be physically thousands of miles away from us. In such an affective relationship, each individual plays a dual role of conveying emotional messages to other parties while keeping the ability to identify and cope with the emotional responses of the others.

According to the above brief description about emotions and their role in our lives, it can be stated that emotions have the required capacity to coordinate the numerous sophisticated somatic and mental processes in humans and to direct them to effectively respond to the changes of the world in a coherent fashion [96].

With respect to modeling emotions within the field of computer science beside what it might initially looks as the standard channel for studying emotions within the fields of humanistic sciences such psychology, cognitive science and neuroscience, it needs to be stated that computational models of emotions proposed by IT researcher do not constitute alternatives for traditional models. In fact, the majority of these computational models are often grounded in theories originated in psychology or cognitive science but enhanced and redesigned using a more robust scientific method. It is the case that traditional theories of emotions often use linguistic descriptions to dissect concepts and to describe the affective processes involved in emotions. Such linguistic models clearly lack several aspects and the detailed processes that are required for possible implementation. Furthermore, these informal descriptions of emotional dynamics are usually computationally intractable which makes it extremely difficult to use them directly in autonomous affective systems where non-human agents mimic the affective behavior of humans. Besides, the original models are usually very sensitive to the data gathered from case studies used in building them. That fact makes these models susceptible to errors associated with data collections from surveys and questionnaires or due to special lab arrangements, which all lead to validation issues of the proposed models.

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Hence, a crucial step towards developing models with the capability of exhibiting an acceptable degree of emotional intelligence would be to uncover the hidden details and assumptions of the emotional experiences, and to have a well-defined framework for the interactions between different modules involved in affective processes. It is exactly this point where Computer Science methodologies and AI techniques can step in to positively reshape the research in this area.

IT based emotion modeling is in fact the process of transforming informal theories of emotions into detailed concrete and tractable processes that are essential components in any computational architecture. Besides, addressing the details and hidden assumptions in such computational models indirectly extends the scope of the theory. Therefore, theses models will be a mean for not only making the theories concrete but also a framework for theory construction [72].

Accordingly, many researchers within the community of computer science and in particular AI sub fields started looking at this problem in a systematic way during the last two decades. The main drive behind such a huge research work done recently in this area by IT specialists needs to be attributed to the phenomena of ubiquitous computer-based systems and the astonishing widespread of internet applications. These easy to use tools have managed to invade almost all affairs of people lives regardless of their social group or age category. Such popularity along with the emergence of social networks made the enhancement of computer and Internet-based applications to exhibit maximal degree of human-like behavior, inevitable. The huge amount of research work about emotions among AI specialists managed to create a solid research field in the final years of the last century which was named *Affective Computing (AC)* [88].

AC is the study and development of systems that can recognize, interpret, process and simulate human affects. Calvo and DeMello in [21] argue that "Affective Computing aspires to narrow the communicative gap between the highly emotional human

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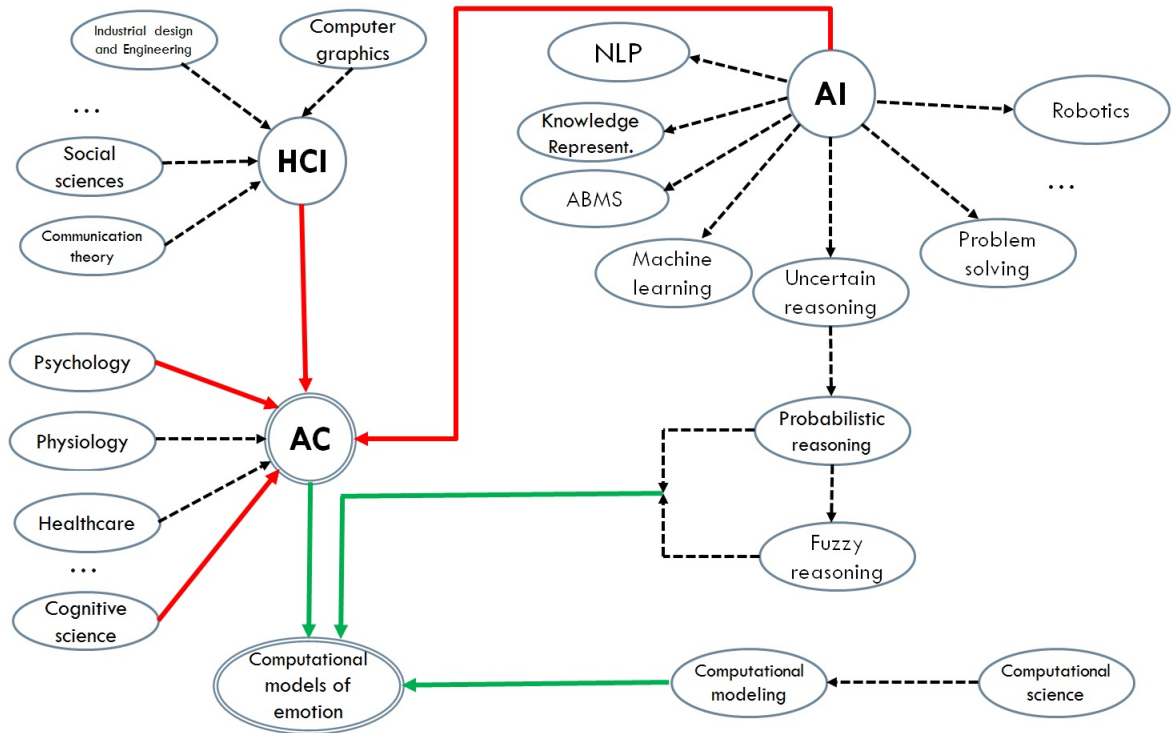
Figure 1.1: the Inter-disciplinary architecture of Affective Computing

and the emotionally challenged computer by developing computational systems that recognize and respond to the affective states (e.g., moods and emotions) of the user". The overall structure of an AC based system will include three major components; a component to recognize different emotions (e.g., from a person's facial expressions); a component to model affect dynamics (e.g., by means of computational models); and a third component to respond to affective states (e.g., in avatars, robots).

The main goal for AC is to enhance the human-computer interaction experience by enriching computer applications with an affective component that is capable of autonomously recognizing and intelligently responding to affective states of the user. Such a promotion is intended to make the interaction between the user with the computer agent (e.g., robot, avatar or a simple GUI application) more believable, usable and enjoyable.

It can be argued that AC is the fruitful result of the interplay between multiple disciplines. It uses the methods and techniques of Computer Science and in par-

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ticular AI in order to enhance the interaction between humans and computers by means of enriching such relationship to include affective aspects. This augmentation process entails deep study and concretization of emotional theories and emotion modeling. Fig. 1.1 shows the big picture of the inter-disciplinary architecture of affective computing.

1.2 Research Goal

The main research goal for this thesis is to build a relatively realistic agent-based model that simulates the dynamics of affect changes in humans as a result of the occurrence of situation-changing events. In particular, it investigates how an affect-enabled agent will adapt to new situations and how to regulate hyper negative emotions triggered in response to undesired and goal threatening events. Moreover, other aspects of human's affective functioning such as emotion generation mechanisms, emotion contagion phenomena as a special type of social contagion, and affective reasoning were thoroughly studied and modeled.

1.3 Research Methodology

The methodology that has been used to study and model the underlying processes of each research topic covered in this thesis was often made of three stages:

- Getting insight about the problem by identifying the properties of the basic processes that are involved in the problem under investigation through literature review and possible informal models obtained by empirical studies.

- Creating an executable model of each process through the computational formulation of those local properties.

- Simulation of the dynamics of the system, followed by results analysis and discussion.

This thesis document comprises several research studies that were conducted to address different topics under the umbrella of emotion modeling problem. Different computational techniques and methods proportionate to the nature of the problem under study were used to effectively and efficiently model the associated processes of each problem. In most of these research works, a hybrid appraisal-dimensional approach was used as the main framework for analyzing the affective influence of the entities that exist in the system. In addition, the proposed models utilized some solid mathematical modeling techniques such as fuzzy logic and state machines to study and model the dynamics of the behavior of affective agents.

1.4 Dissertation Overview

The structure of this dissertation is as follows. Following this introductory chapter, the problem of emotion modeling in general along with some of the existing major approaches to address this problem is reviewed in the next chapter. At the end of that chapter, a full computational model for emotion elicitation dynamics is proposed. Chapter 3, discusses the problem of emotion regulation in details as the main research area for this thesis. Chapter 4 studies the phenomena of emotion contagion as a type of social contagion where. The dynamics of population transitions between emotional and neutral states are modeled. Chapter 5 describes a novel approach to model the dynamics of emotion regulation based on Affect Control Theory which constructs the key contribution of this dissertation. The dissection of the proposed model is followed by a test case at which the model is verified and partially validated. This thesis document ends by a general conclusion and a few remarks with respect to the prospects of the future directions of the research.

Chapter 2

Emotion Modeling

2.1 Introduction

Emotion modeling research work within the field of IT constitutes a sub field that lays at the edge of Affective Computing and HCI (Human Computer interaction). Computational models of emotions are generally intended to incorporate an affective component into computer applications. This research area uses the techniques and methods from a variety of other major research areas in computer science such as machine learning, uncertain reasoning, robotics, NLP, Multi-agent systems, and Game theory in order to promote the mechanisms of interaction between machines and their human users. By injecting a component of affect into the interfaces of interactive web applications (e.g., avatar guides) or to the physical machines (e.g., humanoid service robots), the nature of communication in terms of quality, believability and enjoyment will be enhanced.

The necessity for enriching current computer applications especially in the fields of robotics and HCI with an affect component was accelerated due to the findings from different studies which showed the important role that emotions play in human cognitive tasks and in particular in the process of decision making. Hence, the ultimate

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goal for this research work is to add a comprehensive component of affect (emotion) to artificial agents in order to enable them to reason about and mimic the emotional behavior of humans to a high extent.

Prospect applications for emotion models span to a wide spectrum of science and engineering fields such as psychology, physiology, sociology, computer gaming, HCI and healthcare. At least two major broad lines can be considered with respect to this matter. The first would be to track and identify the emotional level of a human agent at any time to be used as the input to emotionally intelligent applications, such as those in the fields of robotics, computer gaming and HCI. In such applications, identifying the affective state of the user is a key item in establishing a successful affective relationship with the machine. The other direction would be to use these computational models in the process of emotion regulation, where internal or external interventions are applied as coping strategies utilized by specialists such as social behavioral therapists in order to regulate hyper emotional states and their negative consequences.

The rest of this chapter includes a brief review of some of the major approaches towards addressing the problem of emotion modeling from different perspectives. Cognitive approaches and in particular appraisal and dimensional theories are dissected with more details due to the fact that most of the existing IT based computational models of emotions were built based on such approaches. At the end of this chapter a computational model of emotion generation that models the elicitation of all 22 emotions proposed in OCC theory [83] is presented. That model was published under the following reference:

- Ahmad Soleimani, and Ziad Kobti, Toward a Fuzzy Approach for Emotion Generation Dynamics Based on OCC Emotion Model, IAENG International Journal of Computer Science, 41:1, pp48-61, 2014

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2.2 Modeling Approaches

Neural models In affective neuroscience (e.g., [27]), the purpose of modeling emotions is to help us understand the neural circuitry that underlies emotional experience. These models offer new perspectives about the manner in which emotional states influence our health and life outcomes. It is clear that this modeling approach is beyond the context of this thesis.

Communicative models The communicative approach to model emotions (e.g., [102]) is based on a sociological perspective where emotion processes function as a communicative system. Accordingly, emotions are mechanism for informing other individuals of one's mental state; and means for expecting or requesting changes in the behavior of others. The recent tremendous expansion of social networks has paved the way for the emergence of numerous applications that analyze emotions and other affective states of individuals using the easy to access data available through daily conversations in social networks.

Cognitive models Arnold[4] is considered to be the pioneer of the cognitive approach to emotions which is the leading view of emotion in cognitive psychology [7]. According to cognitive modeling of emotions, in order to experience an emotion, an object or event is appraised as directly affecting the person in some way. In this approach, appraisal processes that involve a few dimensions such as the novelty of the experiences, consistency with goals, expectedness, urgency and ability to cope, are at the heart of the modeling procedure. Cognitive modeling can be divided itself into three major categories as follows:

- Appraisal models

- Dimensional or core affect

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- Regulation and coping

2.2.1 Appraisal Models

The key idea in appraisal theories is the fact that there exist a strong relationship between cognition on one side and the affective states and emotions that people experience on the other side. In other words, emotions are manifestations of often non-deliberate but complex analysis of the relationship between an individual and his/her environment. The analytical processes often called appraisals are deeply coupled with some cognitive processes such as perception, memory, explanation and planing which are required for an agent in order to understand the relationship between itself and the environment and to interact effectively with its relevant entities [39]. According to the approach taken in appraisal modeling of emotions, the complexity of different situations raised as a result of the occurrence of external events and other types of interactions between an individual and its environment can be eased through expressing the person-environment relationship in term of a set of dimensions. These dimensions referred as appraisal variables are often track-able and measurable. Hence, it can be stated that events by themselves are not the true factors that elicit certain emotions but rather the way that these events are interpreted according to the believes, desires and intentions is what shapes the tendencies that beside other internal interactions yields to the generation and experience of different emotions.

Although different sets of appraisal variables were used in some emotion models that were built based on an appraisal approach (e.g., [83, 33, 43]), Scherer [103] and Frijda [Frijda1989] argue that these appraisal variables should be able to address the following matters in order to be effectively used in the process of emotion generation.

- Relevance (importance) of the situation to the individual.

- Implications on individual's own goals. (beneficial or harmful)
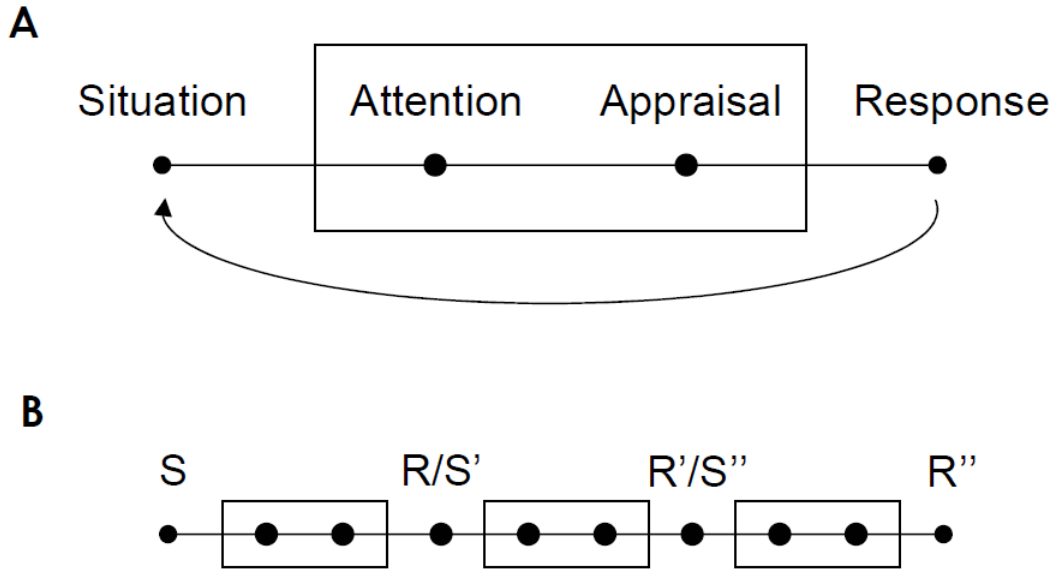
Figure 2.1: A- recursive property of situation-response relation. B- temporal representation of figure A. here, three cycles are drawn back-to-back [42]

- Self/other responsibility of the situation (agency)

- Situation's degree of controllability over the situation and possible reversibility.

- Degree of expectedness by the individual. (occurrence probability)

- Potentials of coping for the new situation.

On the other hand, an equivalently important aspect beside appraisals themselves, are the affective responses generated by the agent itself in order to cope with the new situations arose in the environment. In general, two major categories of coping strategies exist. Problem-focused and emotion focused [61]. Problem-focused are those strategies that are aimed at changing the environment in a way that is in-line with the goals of the agent. Whereas, emotion-focused are those strategies that strive to influence the internal affective states of the agent in a positive way. Considering the fact that an emotional response or action will create a new situation which will be fed back to the appraisal module of the agent, there will be an ongoing chain of these situation-response cycles. Gross [42] describes this approach in Figure 5.1.

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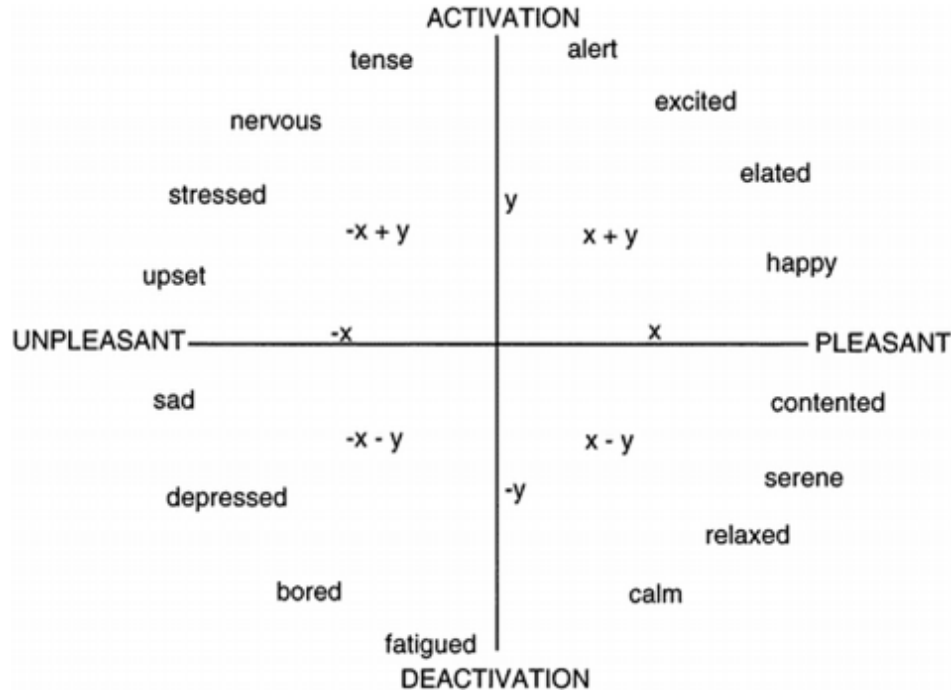
Figure 2.2: The two dimensional space for core affect [99]

Appraisal theory was adopted in several psychological hypothesis for emotion modeling such as [83, 33, 43]. The computationally tractable attribute of the OCC model proposed by Ortony *et al.* [83] was taken by numerous researchers within the field of affective computing [88] as the basis for developing a number of computational models for emotional processes. Later on in this chapter, a computational model for emotion elicitation processes based on OCC theory is presented.

2.2.2 Dimensional Models

According to dimensional approaches for modeling emotions, affective states and emotions are expressed in terms of the components of a multidimensional space. Russell [99] considers two dimensions of pleasure and arousal in order to represent and interpret different affective states. He differentiates between simple primitive feelings which he calls them *core affects* and other emotional states. Russell argues that core affects are unlabeled affective tendencies which are often unrelated to specific causes

or events; whereas events and other types of stimuli are considered to be the major triggering cause for other emotions such as fear, anger and surprise. These core affects usually reside in the subconscious mind when they remain neutral or stable but become active when there is an alteration in their levels. Consequently a corresponding cognitive function such as perceptual/attentional process will be triggered to identify the source of alteration. The idea of core affects is depicted in Figure 2.2 . In this figure, the affective evaluation process of each internal state or external event is performed based on its dual components of pleasure and activation (arousal) in this dimensional system.

Another widely used dimensional approach to emotions is the so called PAD system. Introduced by Mehrabian [76], PAD interprets different emotional states in terms of the components of a three dimensional affective space. These affective dimensions are pleasure (valence), arousal (activity) and dominance (controllability). Each emotional state will occupy a point in this coordinate system based on its PAD values. For instance, Figure 2.5 depicts the position of emotion *pride* based on its vector of $\overrightarrow{PAD} = (0.4, 0.3, 0.3)$. As another instance, the PAD vector for emotion *fear* is $\overrightarrow{PAD} = (-0.64, 0.60, -0.43)$. These values indicate that fear is a highly unpleasant emotion with substantial level of arousal along with a considerable degree of uncontrollability (i.e., the sentiment of submissiveness). In addition, longer lasting affective tendencies such as mood and personality traits are considered in this model also. Accordingly, the mood of an individual is considered as a mid-term affective state that is derived by summing and averaging the PAD components of the emotional states of the individual within a certain time interval. With regards to the personality traits of individuals, a mechanism to link the personality traits such as extra-version, agreeablity, etc., that are introduced in the five factor model [74] to the PAD space has been proposed. The PAD space approach has been widely used by several computational models of emotions.
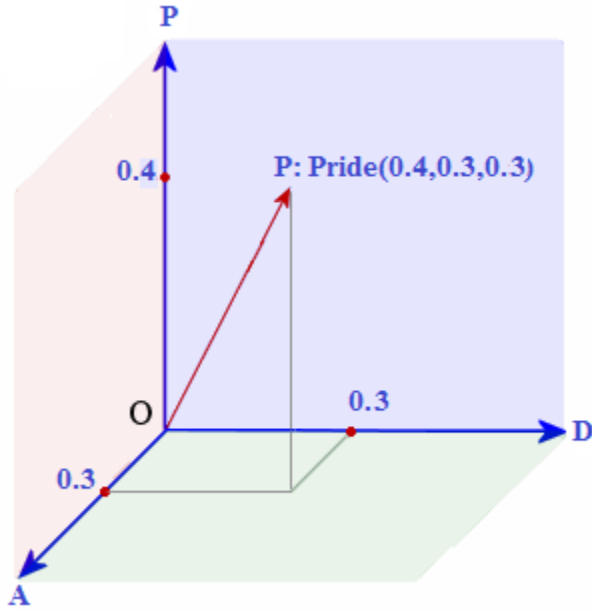
Figure 2.3: PAD vector for emotion pride

2.2.3   Emotion Regulation and Adaptation

In emotion regulation, the basic idea is how to regulate exaggerated emotional responses and to control their intensity levels. Strong evidences (e.g., [27]) have shown that hyper negative emotions can create serious mental as well as physical problems. The main focus in emotion regulation is to study the mechanisms of adaptation in elicited emotions. Different regulation and coping strategies are considered by researchers within this field. According to Gross [43], two categories of regulation strategies exist; antecedent-focused and response-focused. These two categories are discriminated from each other based on the timing at which a certain strategy can be employed during an emotional episode. Accordingly, antecedent-focused strategies are those that can serve the regulation process before an emotional state has been fully activated. In other words, they target those emotional tendencies that are most likely to elicit a certain emotional response in a later time. Response-focused, on the other side, are those strategies applied to regulate a fully triggered emotional response

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Figure 2.4: A process model for emotion regulation. According to this model, emotion may be regulated at five points in an emotional experience: (a) selection of the situation, (b) modification of the situation, (c) deployment of attention, (d) cognition change, and (e) modulation of experiential, behavioral, or physiological responses. [45]

as a result of some stimuli or an internal state. Figure 2.4 depicts the full picture for Gross emotion regulation strategies.

2.2.4 Computational Models of Emotion

Computational models of emotions are often grounded in theories originated in psychology, neuroscience or cognitive science. Such theories use linguistic descriptions to dissect concepts and to describe the affective processes involved in emotions. These informal descriptions of emotional dynamics are often computationally intractable which makes it extremely difficult to use them directly in autonomous systems where non-human agents mimic the affective behavior of humans. Hence, a crucial step towards developing models with the capability of exhibiting an acceptable degree of emotional intelligence would be to uncover the hidden details and assumptions

involved in emotional experiences, and to have a well defined framework for the interactions between different modules involved in affective processes.

Emotion modeling in fact is the process of transforming informal theories of emotion into detailed concrete and tractable processes that are essential components in any computational architecture. Besides, addressing the details and hidden assumptions in such computational models indirectly extends the scope of the theory. Therefore, these models will be a mean for not only making the theories concrete but also a framework for theory construction [72].

The qualitative nature of the emotion theories proposed within humanistic sciences such as psychology or human cognition poses an important challenge that impedes the implementation and broad use of these informal models. Such qualitative models do not address some key elements such as intensity and duration of an emotional experience that are required for most of affect-enabled applications. Therefore, building quantitative models for emotions is inevitable.

2.3 Toward a Fuzzy Approach for Emotion Generation Dynamics Based on OCC Emotion Model

Abstract. This paper investigates using a fuzzy appraisal approach to model the dynamics for the emotion generation process of individuals. The proposed computational model uses guidelines from OCC emotion theory to formulate a system of fuzzy inferential rules that is capable of predicting the elicitation of different emotions as well as tracking the changes in the emotional response levels as a result of an occurred event, an action of self or other individuals, or a reaction to an emotion triggering object. In the proposed model, several appraisal variables such as event's desirability and expectedness, action's praise-worthiness and object's degree of emotional appealing were considered and thoroughly analyzed using different techniques. The output of the system is the set of anticipated elicited emotions along with their intensities. Results from experiments showed that the proposed OCC-based computational model for emotions is a an effective and easy to implement framework that poses an acceptable approximation for the naturally sophisticated dynamics for elicitation and variation of emotional constructs in humans.

2.3.1 Introduction

Emotions are inseparable building blocks of human personalities. They are deeply rooted in most of our desires and tendencies, and influence to a large extent our intentions and shape our actions. Conversely to the tenet adopted by most past philosophers, such as Descartes and Paolo who looked at the evil side of emotions and believed in an eternal conflict between intellect and emotions, contemporary research

findings (e.g., [10, 28, 31, 62]) emphasize the important role of emotions and their direct involvement in the process of decision making. Furthermore, emotions help us to develop an effective coping system that is inevitable to adapt our behaviors to the different situations that arise from events and continuous changes in the environment. According to some studies in the field of neuroscience, those individuals who were unable to feel and experience emotions due to a possible brain damage, have a clear impairment in making rational decisions [27]. These findings clearly rule out the tenet that emotions adversely affect the wisdom of individuals and prevent them from being rational. In short, it can be stated that an emotional component is existent in most cognitive activities [96].

Considering the fact that human behavior including emotional behavior is a complex and multifaceted construct [16, 81], it is necessary to look at the problem of modeling emotional behavior from different perspectives and consider as much as possible all its psychological, physiological, neurological and cognitive states and aspects in order to efficiently model such a complex interplay between the mind, brain, and the body of humans as well as the interaction between them and the environment.

Beside the traditional theories of emotions by philosophers and psychologists such as Aristotle, Freud and Darwin that can be tracked in the early stages of human civilization, studying emotions has recently attracted a great deal of research works across a variety of domains from applied sciences and engineering to commerce and business and arriving at public wellbeing and healthcare. A great deal of affect-enabled applications and commercial products started to emerge in the market as a result of the recent "affect-awareness" research campaign that showed the high influence of emotions in almost all cognitive activities, e.g., decision making, within a broad spectrum of life affairs from entertainment and gaming to healthcare [117].

Within the field of information technology and computer science, an increasing number of rich research works in the area of emotions can be seen nowadays. Accord-

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ing to Gratch et al. [72], computational models of emotions proposed by computer scientists are beneficial in three directions. First, they provide an effective framework for theorizing, testing and refining of emotion hypotheses often proposed within the field of psychology; second, they can promote the general research work in artificial intelligence (AI) by enriching it with new techniques and approaches derived from emotion dynamics modeling; and third, they provide a very effective mean for improving the facilities and methodologies used in human-computer interaction (HCI) [72].

Affective Computing (AC) can be considered the fruitful outcome of the vast endeavor of computer scientists in the field of studying emotions. Despite AC's relatively young age, it has managed to turn into a robust well-established research area with its own professional meetings and scholarly journals. According to its founder, R. Picard [88], AC is "computing that relates to, arises from, or deliberately influences emotions" [88].

An AC system strives to fill up the gap between highly emotional people and emotional challenged machines [21]. Hence, AC is about building computer artifacts that are more emotionally intelligent, i.e., to recognize (e.g., from person's facial expressions or physiological signals emitted from wearable sensors), represent (e.g., by building computational models) and respond to (e.g., in service robots or avatars) affective states.

In the process of building a computational model for emotions, different approaches such as appraisal (e.g., [83, 44, 81]), dimensional (e.g., [36], [99]), adaptation and coping (e.g., [73],) can be used. The proposed model is an appraisal based model that is inspired by the emotion theory suggested by Ortony, Clore and Collins known as OCC [83]. The essence of the proposed model, is to use fuzzy appraisal systems that evaluates the elicitation mechanisms for all the three sets of OCC emotions and

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by using guidelines from the background theory, it would be possible to anticipate the emotional behavior of the agent in different circumstances.

Fuzzy logic principles were applied by ElNasr *et al.* [30] to build their fuzzy computational model of emotion, FLAME. FLAME uses the concept of fuzzy sets in order to represent and quantify different emotions. At the core of this model, a set of learning and coping algorithms exist to be used for the purpose of adaptation performed by the agent in response to the changes of some aspects of the environment. Some of these aspects are event expectations, patterns of user actions and rewards. In [68], a fuzzy system was used to map some physiological signals into a point on a core affective space of arousal and valence. This point then is mapped again into a set of five emotions using a second fuzzy system.

With respect to the possible applications for the proposed model, two trajectories are possible. The first direction would be to track and come up with patterns for the affective responses in the subject individual as a result of the occurrence of a series of events or reactions to self or other agent's actions or possible exposures to emotion triggering objects. Such affective patterns pose the input to emotionally intelligent systems, e.g., interfaces used in HCI, robotics and computer gaming at which recognizing the affective state of human users is a crucial piece of information that is required in order to establish an efficient affective rapport between artificial agents and their human users [128, 39]. The other direction is the potential usage of such systems in the fields of neuro-therapeutics and social behavioral therapies through applying deliberate interventions to control and regulate hyper negative emotional responses as well as psychological complications [45, 41].

In brief, this article proposes a fuzzy computational model for anticipating the type and intensity of emotional states experienced by a subject individual as a result of the occurrence of an emotion triggering event; an action of self or other agent(s); or facing an emotion triggering object. Furthermore, it investigates the potentials

for applying some regulatory mechanisms for emotion interventions at which external stimuli can be used as a mean for controlling negative hyper emotions. It would appear that this objective is of high importance considering its promising utilization in psychotherapy where these interventions can be some auxiliary elements such as audio or video clips similar to those used by Chakraborty et al.[23].

The rest of this article is organized as follows: in the next section, a breif review of some of the recent computational models of emotions that were built based on an appraisal approach is presented. Section III reflects the architecture of the proposed model and it dissects the appraisal processes in details. In section IV, a general formulation of the problem is presented along with the associated emotion computation modules and algorithms. Next, a detailed description of some of the simulation experiments that were conducted to verify the functionality and evaluate the performance of the system is given, followed by discussion and conclusion sections.

2.3.2 Computational models of emotions

An important challenge for psychological theories of emotion is their qualitative nature. A qualitative model of emotion does not address some key characteristics that are essential for a practical implementation in affect-enabled applications and affective agents. Some of these important aspects are the intensity level of emotional experiences, the duration of emotional experiences, the interplay between an elicited emotion and the behavior of the agent as well as the temporal dynamics for such influence, possible decay patterns for triggered emotions, etc. Such quantitative parameters are an inevitable part for a formal computational model of emotions.

As mentioned earlier in this article, computational models of emotions have managed to find their own way to many interdisciplinary applications. With respect to humanistic sciences such as psychology, biology and neuroscience, computational models of emotions have manifested themselves through models and processes that

were used to test and improve the formalization of the hypothesis and background theories [130]. In the field of robotics and in the computer gaming industry, an increasingly number of affect-enabled applications built based on these computational models can be seen. These computational models are essential for improving the performance of Human-Computer Interaction (HCI) applications in order to develop intelligent virtual agents (e.g., avatars or service robots) that exhibit a maximal degree of human-like behavior [13]. A large number of these computational models were build based on an appraisal approach to emotions constructs. At this point, a brief description of the appraisal theory is presented.

2.3.2.1 Appraisal theory

Appraisal theory, non-arguably is the most widely used approach in the recent computational models of emotion [125]. Based on this theory, emotions are outcomes of previously evaluated situations attended by the subject individual and have the connection between emotions and cognition is highly emphasized. Therefore, emotional responses are generated based on an appraisal or assessment process performed continuously by the individual on situations and events that take place in the environment and are perceived relevant by the individual.

According to the appraisal theory which was formally proposed by Smith and Lazarus [110], in order to evaluate the different situations that arise in the relationship between an individual and its environment, a set of appraisal variables or dimensions needs to be considered. Scherer [103] and Frijda [33] argue that these appraisal variables should be able to address the affective-relevant aspects of the situation, such as those listed below, in order to be effectively used in studying the emotion elicitation process and the dynamics of changes in the emotional behavior of individuals as well as building computational models.

Appraisal variables

- Relevance of the situation and its implication on individual's own goals, (i.e., beneficial or harmful)

- Self or others responsibility of the situation

- Degree of the situation expectancy by the individual

- Coping and adjustments potentials for the situation

- Changeability or reversibility of the situation

2.3.2.2 Examples of appraisal computational models

EMA Emotion and Adaptation (EMA) [72] is a computational model of emotions that is built based on the emotion theory proposed by Lazarus[61]. In EMA, the agent-environment relationships are represented using causal rules that interpret the emotion elicitation dynamics as well as different adaptation and coping strategies. In this model, beliefs, desires and intentions of the agent beside past events, the current state, and possible future world states are all important role players in the emotional processes. In EMA, two types of causal interpretation exist. One type is a cognitive process that is slow and deliberative whereas the other is fast and reactive. Furthermore, it includes a highly detailed system for emotion adaptation and coping strategies which enables the emotionally intelligent agent to regulate its hyper negative emotions. In EMA, four categories of such regulation strategies were considered according to have either attention, belief, desire or intention of the agent to be the targeted of the regulation process [73].

ALMA A Layered Model of Affect (ALMA) [36] is an OCC [83] based model that combines three affective components of emotion as short-term, mood as medium-term and personality as long-term factor to express the affective state of individuals.
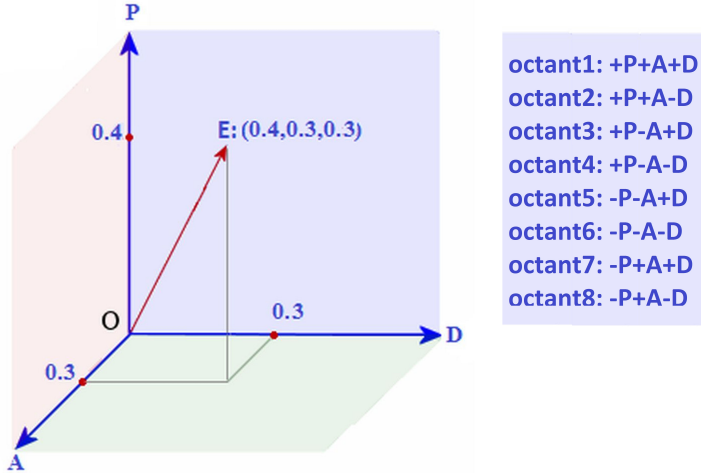
Figure 2.5: PAD vector and mood octant [113]

ALMA adopts the approach of Mehrabian [76] in which he describes the mood with the three traits of pleasure (P), arousal (A) and dominance (D). Hence, the mood state of the agent is described based on the classification of each of the three mood dimensions: +P and −P to reflect pleasant and unpleasant, +A and −A for aroused and unaroused, and +D and −D for dominant and submissive states. These three discrete components build the so called PAD space where each point represents a mood state called mood octant (see Fig. 2.5).

Furthermore, in order to initialize the mood states, ALMA uses a mapping between OCC emotions to the PAD components of the mood octant. Table 5.3 depicts such mapping between OCC emotions and the PAD space. In the proposed model, this approach is exploited to calculate the overall mood state of the agent. As dissected in the next section, this quantity is widely used in the calculations of emotion intensity levels.
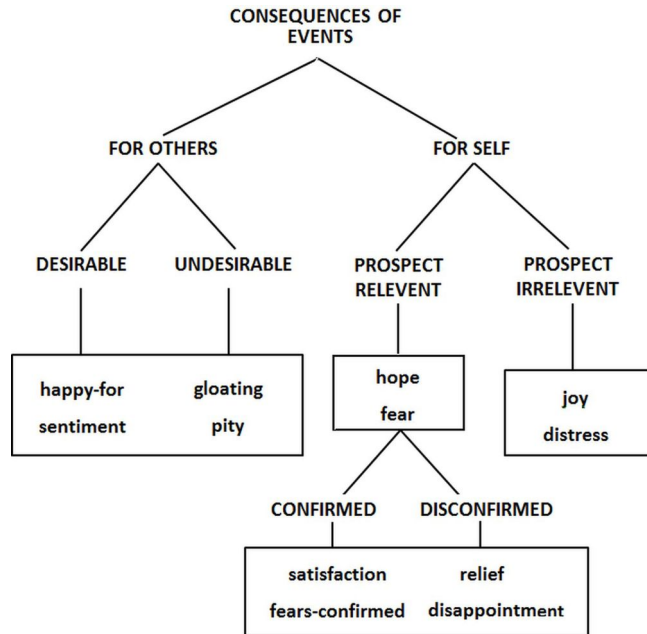
Figure 2.6: OCC action-originated emotions. Adopted partially from [83]
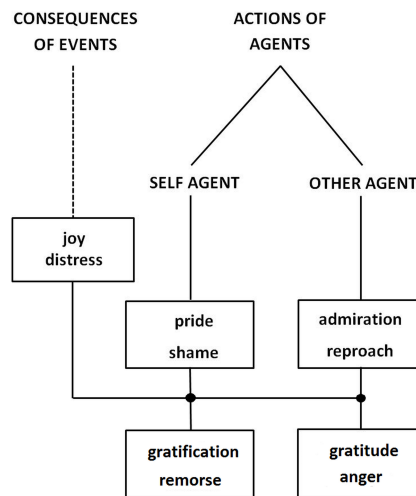
Figure 2.7: OCC event-originated emotions. Adopted partially from [83]
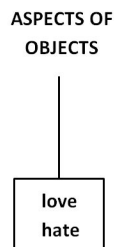
Figure 2.8: OCC object-originated emotions. Adopted partially from [83]

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Table 2.1: Mapping of OCC emotions into PAD space [36]

Emotion	P	A	D	Mood octant
Admiration	0.5	0.3	-0.2	+P+A-D Dependent
Anger	-0.51	0.59	0.25	-P+A+D Hostile
Disliking	-0.4	0.2	0.1	-P+A+D Hostile
Disappointment	-0.3	0.1	-0.4	-P+A+D Anxious
Distress	-0.4	-0.2	-0.5	-P-A-D Bored
Fear	-0.64	0.6	-0.43	-P+A+D Anxious
FearsConfirmed	-0.5	-0.3	-0.7	-P-A-D Bored
Gratification	0.6	0.5	0.4	+P+A+D Exuberant
Gratitude	0.4	0.2	-0.3	+P+A-D Dependent
HappyFor	0.4	0.2	0.2	+P+A+D Exuberant
Hate	-0.6	0.6	0.3	-P+A+D Hostile
Hope	0.2	0.2	-0.1	+P+A-D Dependent
Joy	0.4	0.2	0.1	+P+A+D Exuberant
Liking	0.4	0.16	-0.24	+P+A-D Dependent
Love	0.3	0.1	0.2	+P+A+D Exuberant
Pity	-0.4	-0.2	-0.5	-P-A-D Bored
Pride	0.4	0.3	0.3	+P+A+D Exuberant
Relief	0.2	-0.3	0.4	+P-A+D Relaxed
Remorse	-0.3	0.1	-0.6	-P+A-D Anxious
Reproach	-0.3	-0.1	0.4	-P-A+D Disdainful
Resentment	-0.2	-0.3	-0.2	-P-A-D Board
Satisfaction	0.3	-0.2	0.4	+P-A+D Relaxed
Shame	-0.3	0.1	-0.6	-P+A-D Anxious

2.3.3   Proposed approach

2.3.3.1   OCC theory

The emotion process model suggested by Ortony, Clore and Collins known as OCC [83] is a robust and well-grounded appraisal theory for emotion dynamics that was highly influential in the field of studying emotions. This theory has managed to inspire many researchers in the field of affective computing. As a result of such influence, a considerable number of computational models of emotions can be seen today where OCC was the basis for them (e.g., [36, 73, 30]).

The popularity of OCC among computer scientists can be attributed to the fact that this theory was founded on a well-defined constraint-satisfaction architecture

approach with a finite set of appraisal dimensions used as criteria for classifying different emotions. Such an approach taken in OCC makes it computationally tractable and hence, understandable by computer specialists.

The essence of the proposed model is to provide a computational method for the elicitation dynamics of all 22 emotions included in the OCC emotion theory [83]. The first step toward building a computational model for emotions was to split them into three categories according to their elicitation causes; those emotions elicited as a result of some occurred events (see Fig. 2.6); those emotions elicited as reactions to self or others actions (see Fig. 2.7); and those emotions elicited as a result of being exposed to emotion triggering objects (see Fig. 2.8).

The elicitation dynamics along with the intensity level calculations were designed using guidelines from the background theory beside a set of techniques and assessment processes made on the group of previously selected appraisal variables. An important point that must be clarified here is the fact that in the proposed computational model, positive or negative affective reactions or feelings are not considered emotional states unless they are above certain thresholds. According to such approach, an individual might feel pleased about an event but that feeling does not elevate to a realistic joy emotion due to below the threshold level for pleasure. This was the reason behind eliminating such intermediate feelings from the original OCC model.

With respect to event-originated emotions, according to Fig. 2.6, the first appraisal variable that differentiates the emotions of this group into two sets is the orientation of the event that take place in the system; meaning that whether the utility of the event is oriented toward the agent itself or some other agent(s). This evaluation process yields to a first level of classification of the emotions into *for self* or *for others* categories. Another classification takes place for *self* emotions group based on the prospective appraisal variable that indicates if the event has already taken place (prospect=False) or would possibly take place in the future (prospect=True).
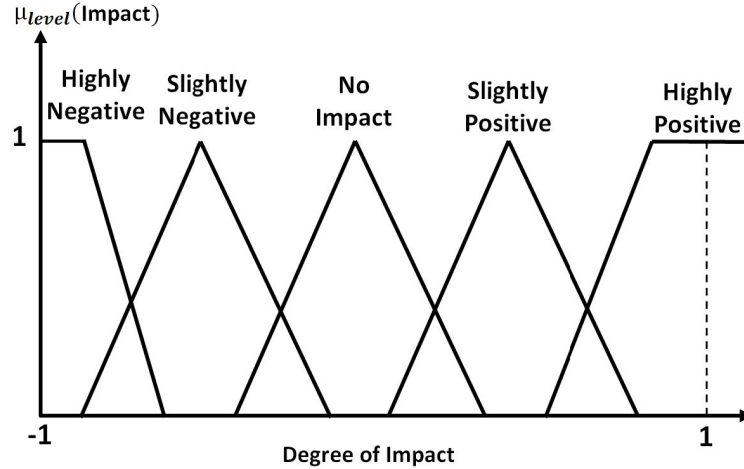
Figure 2.9: Event's fuzzy degree of impact on individual's goals [117]

A prospective emotion, e.g., hope transforms into a post-prospect emotion of *satisfaction* in case of confirmation or *disappointment* in case of disapproval according to some temporal dynamics explained in section 2.3.4.

2.3.3.2 Events

The event-originated branch of OCC theory contains emotion types whose eliciting conditions are directly linked to an appraisal process performed on external events that take place in the environment and are perceived relevant events by the agent. Relevance appraisal variable is in fact an indicator for the degree of impact that an occurred event has on the set of agent's goals.

In order to present a quantifiable measure for this variable, the term desirability of events was used in the proposed model. Hence, desirability is a central variable accounting for the impact that an event has on an agent's goals, namely how it helps or impedes their achievements.

An event in the proposed approach, is a situation-changing condition that often takes place without explicit interventions by other agents. This definition differentiates this type of events from another group of conditions that still might be called events where they are caused by an agent or they are direct consequences of a de-

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liberate and intentional action. According to OCC theory an event can have several aspects, each of them possibly triggering a different emotion. In this article it is assumed that what OCC calls *different aspects of an event* can be considered as consequences of the primary event.

Event's desirability   In OCC theory, the desirability of events is close in meaning to the notion of utility. When an event occurs it can satisfy or interfere with agent's goals, and the desirability variable has therefore two aspects; one corresponding only to the degree to which the event in question appears to have beneficial (i.e. positively desirable) consequences; and the other corresponding to the degree to which it is perceived as having harmful (i.e. negatively desirable, or undesirable) consequences.

The desirability of an occurred or prospective event poses the most influential factor in the specification of the emotion type that will be triggered along with its intensity. A fuzzy approach is adopted to determine the desirability level of an event. Accordingly, a fuzzy scale for the desirability consists of five fuzzy sets is considered as follows:

$$Desirability = \{HighlyUndesired, SlightlyUndesired,$$
$$Neutral, SlightlyDesired, HighlyDesired\}$$

The above desirability level is linked to an evaluation process that takes into account the impact (either positive or negative) of the event on the set of goals of the agent. Two other fuzzy variables are used to express this impact. Variable *Impact* that indicates the event's degree of influence on one or more goals of the agent (see Fig. 5.5); and variable *importance* that reflects the importance or preference of each goal. Hence,

$$Impact = \{HighlyNegative, SlightlyNegative,$$
$$NoImpact, SlightlyPositive, HighlyPositive\}$$

$$Importance = \{ExtremlyImportant,$$

$$SlightlyImportant, NotImportant\}$$

Considering the fact that an event can have an impact on multiple goals whereas each goal has its own importance level, the problem of measuring the desirability of an event would turn into solving a system of fuzzy rules [30].

With regards to the composition of the fuzzy rules in the resulted fuzzy system, a combination of the sup_min composition technique proposed by Mamdani [67] and the weighted average method for defuzzification [97] is considered. Using the composition approach explained in [30], we can apply the sup_min operator on *Impact*, *Importance* and *Desirability*, and hence, the matching degree between the input and the antecedent of each fuzzy rule can be determined. For example, consider the following set of n rules:

$IF \qquad Impact(G_1, E) \ is \ A_1$

$\qquad AND \ Impact(G_2, E) \ is \ A_2$

$\qquad ...$

$\qquad AND \ Impact(G_k, E) \ is \ A_k$

$\qquad AND \ Importance(G_1) \ is \ B_1$

$\qquad ...$

$THEN \quad Desirability(E) \ is \ C$

Where k is the number of agent's goals and A_i, B_i and C are fuzzy sets. This rule reads as follows: if event E affects goal G_1 to the extent of A_1 and it affects goal G_2 to the extent of A_2, etc., and that the importance of goal G_1 is B_1 and for goal G_2 is B_2, etc., then event E will have a desirability value of C.

It is clear that C will have a fuzzy value and hence needs to be defuzzified (quantified). In order to do so, we adopt the approach taken in [30] based on Mamdani model [67], but instead of using centroid defuzzification, the weighted average method for defuzzification was used in the proposed model. Hence, using the sup_min composition operator between the fuzzy variables of *Impact*, *Importance* and *Desirability*,

the matching degree between the input and the antecedent of each fuzzy rule will be computed. For example, consider the following set of n rules:

$IF\ x\ is\ A_i\ THEN\ y\ is\ C_i$

...

$IF\ x\ is\ A_n\ THEN\ y\ is\ C_n$

Here, x and y are input and output variables respectively. A_i and C_i are fuzzy sets and i is the *ith* fuzzy rule. If the input x is a fuzzy set A', represented by a membership function $\mu_A(x)$ (e.g. degree of desirability), a special case of A' is a singleton, which represents a crisp (non-fuzzy) value. Considering the definition of the *sup_min* composition between a fuzzy set $C \in F(X)$ and a fuzzy relation $R \in F(X \times Y)$ which is defined as:

$$C \ o \ R(y) = \sup_{x \in X} \min \{C(x), R(x,y)\} \quad \text{for all } y \in Y$$

We can calculate the matching degree w_i between the input $\mu_A(x)$ and the rule antecedent $\mu_{A_i}(x)$ using the equation below:

$$\sup_{x \in X} \min \{\mu_A(x), \mu_{A_i}(x)\}$$

which can be rewritten as:

$$\sup_{x}(\mu_A(x) \wedge \mu_{A_i}(x))$$

The $\wedge$ operator calculates the minimum of the membership functions and then we apply the *sup* operator to get the maximum over all $x's$. The matching degree influences the inference result of each rule as follows:

$$\mu_{C_i'}(y) = w_i \wedge \mu_{C_i}(y)$$

Here, C_i' is the value of variable y inferred by the ith fuzzy rule. The inference results of all fuzzy rules in the Mamdani model are then combined using the max operator $\vee$ as follows:

$$\mu_{comb}(y) = \mu_{C_1'}(y) \vee \mu_{C_2'}(y) \vee ... \vee \mu_{C_k'}(y)$$

Based on the definition of the $sup\,min$ composition between a fuzzy set $C \in F(X)$ and a fuzzy relation $R \in F(X \times Y)$, we have:

$$C \circ R(y) = \sup_{x \in X} min\left\{C(x), R(x,y)\right\} \quad \text{for all } y \in Y$$

We use the following formula based on the weighted average method for defuzzification in order to defuzzify the above combined fuzzy conclusion:

$$y_{final} = \frac{\sum \mu_{comb}(\overline{y}).\overline{y}}{\sum \mu_{comb}(\overline{y})}$$

where $\overline{y}$ is the mean of each symmetric membership function. Hence,

$$Desirability_f(e) = y_{final}$$

The result of above defuzzification process, y_{final} will return a number that is the value for the input event's desirability.

On the other hand, in order to enable the agent to make a good estimation for event expectation measure, we let it learn patterns of events. Next section describes briefly the function of the learning component in our model.

Events prospect As discussed earlier in this article, a group of OCC emotions are prospective emotions, meaning that they are some transient emotional states that reflect a kind of uncertainty with respect to the occurrence possibility of some events. Hence, these emotional states eventually turn to a more stable emotions once the uncertainty factor was removed. The prospective attribute is directly linked to the degree of occurrence possibility perceived by the agent. In other words it reflects a mechanism for event expectedness by the agent. Event's expectedness is a sophisticated construct which involves several factors [62].

In the proposed model, a simple but acceptable estimation for this measure, similar to the one used in [30] is adopted. Based on this approach, a learning module is used to enable the agent to learn patterns for the events that take place in the environment and consequently to expect the occurrence of future events based on those identified patterns of events using a probabilistic approach. The event's patterns are constructed

based on the frequency with which an event, say, e_1 is observed to occur right before previous events of e_2, e_3, etc.

A table data structure is used to count the number of iterations for each event pattern. The conditional probability of $p(e_3 \mid e_1, e_2)$ indicates the probability for event e_3 to happen, assuming that events e_1 and e_2 have just taken place. The first time that a pattern is observed, a corresponding entry for the event's pattern will be created, and the count is set to 1. This flag will be incremented for each future observation. These count flags can be used to compute the conditional probability for a new event Z to occur, given that events X and Y have already occurred. Therefore, The expected probability for event e_3 is:

$$Likelihood(e_3 \mid e_1, e_2) = \frac{C[e_1, e_2, e_3]}{\sum_i C[e_1, e_2, i]}$$

Where c denotes the count of each event sequence. Here, a length of three for the sequence of the event patterns was considered.

In case that the number of observations is low, only one previous event can be considered in the conditioned probability, hence:

$$Likelihood(Z \mid Y) = \frac{\sum_i C[i, Y, Z]}{\sum_j \sum_i C[i, Y, j]}$$

However, if the priori for event Y occurring right before event Z was never been observed, then we can use unconditional prior based on the mean probability for all events to calculate the probability of event Z as follows:

$$Likelihood = \frac{\sum_{i,j} C[i, j, Z]}{\sum_{i,j,k} C[i, j, k]}$$

For the sake of brevity, we refrain from providing a full detailed description of this approach and interested readers are referred to the above mentioned reference.

2.3.3.3 Actions

Another type of emotions in OCC theory are those originated by the consequences of purposeful actions. Some events that take place in the environment of an agent

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can be attributed to the actions of self or some other agent(s). Hence, the intentional and deliberate factor of the event is what differentiate this kind of events from those natural,non-purposeful, non-attributable or with unknown source that are involved in the elicitation of event-originated emotions. This distinction is close in meaning to the variable of attribution or responsibility introduced in Lazarus theory of emotion [61], that is required to describe the behavior and justification for a group of emotions such as anger that are closely linked to an assessment process of an action.

According to this approach, a measure for the *praiseworthiness* attribute of the action needs to be defined. With respect to the valence of this attribute, it will be assigned a positive value when the action is in-line with the contextual standards or values, e.g., saving a drowning person which will elicit pride or admiration emotions; whereas it will be assigned a negative value if the action violates those standards or values, e.g., mocking a handicapped person which will trigger an emotion of shame or reproach (in this case it can be called the degree of blameworthiness). It is presumed though that these standards are adopted by the agent itself and are active in the evaluation process of the actions. It is important to be clarified that the proposed model keeps itself independent from these standards and for the sake of providing higher generality for the model, it is assumed that they are simply given to the system.

Other parameters that affect the value of *praiseworthiness* are the the degree of unexpectedness for the action being performed by the class type of the actor agent as well as the degree of the agent involvement in the action or its outcome.

2.3.3.4   Compound Emotions

According to OCC model, some emotions can be considered compound emotional states due to the fact that they are related to the consequences of regular events as well as actions-originated events. A compound emotion such as anger is triggered when

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the evaluating agent appraises both the desirability of the event and the attribution of the action led to the event. Hence, a state of anger is interpreted as a combination of distress and reproach emotions. Therefore, for this type of emotions, the appraisal parameters would include praiseworthiness of the performed action as well as the desirability of the occurred event.

2.3.3.5 Objects

The final set of emotions in the OCC model is a pair of complex states that indicates love and hate emotions. Love and hate can be considered as the hyper states of the general feelings of liking and disliking states toward an object [122]. The appraisal dimensions for this set of emotions are the degree of emotional attraction of the object and the degree of familiarity with the object by the evaluating agent. Emotional attraction can be considered as a function of dispositional attitudes toward a category or class that the object belongs to. Accordingly, appealing is set to value 'attractive' if the object has a positive 'object valence' along with a 'familiarity valence' less than a certain threshold; Conversely, it is set 'not attractive' if the object has a negative 'object valence' along with a 'familiarity valence' above a certain threshold [110].

In the next section, we use the above general hierarchy and the given approach of modeling emotion elicitation dynamics along with other guidelines from the base theory to formulate the problem formally in order to come up with the framework of the intended computational model.

2.3.4 Problem formulation

As discussed earlier, emotions in OCC model are divided into three major groups. We strive to keep the formulation of this problem and the calculative modules in line with the original classification of emotions. At this point, it is affirmed that with each elicited emotional state, it would be necessary to apply its impact on the

overall (global) emotional state of the agent according to some temporal dynamics. In emotion literature, this associated overall emotional state is often referred as the mood state of the individual. Mood is mid-term affective state [42] that stays for a longer period than an emotional state and it can be considered as the average valence of recent emotional states [75] along with some other attributes such as the personality traits [74]. According to research findings, the mood state influence to a large extent the way that an individual perceives his environment and reacts to an emotion-eliciting situation. Therefore, this measure was widely considered in the proposed model at which it is called mood-impact-factor.

2.3.4.1 Mood-impact-factor

According to [36], there exists a relationship between different emotions and the previously described PAD components of the agent's mood (see Fig. 2.5 and table 5.3). Therefore, in order to calculate the mood of the agent, the following equation is proposed:

$$\Delta Mood_{Global} = \alpha.\sqrt{P^2 + A^2 + D^2}$$

Where α is a signed adaptation coefficient that would be positive if the experienced emotion was positive and it enhances the generic mood state of the agent, whereas a negative emotion will yield in a negative α with an adverse impact on the global mood state of the agent. the exact value for this quantity is left for the experiment phase.

2.3.4.2 Emotion calculations

In this section, a set of computational equations is proposed for each emotion in order to anticipate the elicitation of the competent emotion as well as its intensity level. These modules were designed based on the approach presented in the previous section along with some guidelines from the OCC emotion theory. In these formulas, e is an

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occurred event, subscript $_p$ stands for *potential* and subscript $_t$ stands for *threshold*, p_i reflects an agent and t is an indicator for time, a is an action performed by self or some other agent, and *obj* is an encountered object.

It is assumed that an emotional state will not be triggered unless its intensity is above a certain threshold level. This assumption was applied in accordance with the real world rule that not any desirable or undesirable feeling would yield into an explicit emotion [83]. Furthermore, according to the formalization of emotions proposed by Steunebrink *et al.* [120], it is necessary to differentiate between the actual experiences of emotions and those conditions that merely trigger emotions. Hence, a triggered emotion will not necessarily lead to a genuine experience of it, due to the fact that it was assigned an intensity below the minimum experience level.

$$Desirability(p, e, t) = Desirability_f(e) + \Delta Mood_{Global}(t)$$

$$Mood_{Global}(t) = Mood_{Global}(t-1) + \Delta Mood_{Global}(t)$$

Event-originated emotions   As elaborated before, according to the OCC model, event-originated emotions are classified into two groups of *self-related* and *others-related*. This classification was made by considering the consequences of an occurred event to be directed toward either the evaluating agent itself or some other agent. The diagram of Figure 2.6 shows that the first group includes the set of $\{joy, distress, hope, fear, satisfaction, disappointment, fearsconfirmed, relief\}$ emotions whereas the second group includes$\{happyfor, resentment, gloating, pity\}$ emotions.

Self-related   In this section, calculation modules for the self-related set of event-originated emotions are presented. Self-related addresses those emotional states that are being elicited in the evaluating agent itself.

Emotion Joy   An agent experiences joy emotion when it is pleased about a desirable event. Hence,

$$IF\ Desirability(p, e, t) > 0$$
$$THEN\ JOY_p(p, e, t) = Desirability(p, e, t)$$
$$IF\ JOY_p(p, e, t) > JOY_t(p, t)$$
$$THEN\ Intensity(p, e, t) = JOY_p(p, e, t,) - JOY_t(p, t)$$
$$ELSE\ Intensity(p, e, t) = 0$$

Emotion Distress   An agent experiences distress emotion when it is displeased about an undesirable event. Hence,

$$IF\ Desirability(p, e, t) < 0$$
$$THEN\ DISTRESS_p(p, e, t) = -Desirability(p, e, t)$$
$$IF\ DISTRESS_p(p, e, t) > DISTRESS_t(p, t)$$
$$THEN\ Intensity(p, e, t) = DISTRESS_p(p, e, t) -$$
$$DISTRESS_t(p, t)$$
$$ELSE\ Intensity(p, e, t) = 0$$

As discussed earlier, *Prospect* in the following equations is a binary logical variable that reflects the occurrence prospect for a future event e. Hence, it merely indicates if person p believes that such event will occur (Prospect=TRUE) or will not occur (Prospect=FALSE) in the future. In case of $Prospect(p, e) = TRUE$, the function of $Likelihood(p, e)$ will return the probability for the occurrence of event e.

Emotion Hope   An agent experiences hope emotion when the occurrence of a desirable event in the future is expected. Hence,

$$IF\ Prospect(p, e, t)\ AND\ Desirability(p, e, t) > 0$$

$$THEN\ HOPE_p(p, e, t) = Desirability(p, e, t) * Likeihood(p, e, t)$$

$$IF\ HOPE_p(p, e, t) > HOPE_t(p, t)$$

$$THEN\ Intensity(p, e, t) = HOPE_p(p, e, t) - HOPE_t(p, e)$$

$$ELSE\ Intensity(p, e, t) = 0$$

Emotion Fear   An agent experiences fear emotion when the occurrence of an un-desirable is expected. Hence,

$$IF\ Prospect(p, e, t)\ AND\ Desirability(p, e, t) < 0$$

$$THEN\ FEAR_p(p, e, t) = -(Desirability(p, e, t))*$$

$$Likeihood(p, e, t)$$

$$IF\ FEAR_p(p, e, t) > FEAR_t(p, t)$$

$$THEN\ Intensity(p, e, t) = FEAR_p(p, e, t) - FEAR_t(p, t)$$

$$ELSE\ Intensity(p, e, t) = 0$$

Emotion Relief   An agent experiences relief emotion when the occurrence of an expected undesirable event is dis-confirmed. Hence,

$$IF\ FEAR_p(p, e, t) > 0\ AND\ NOT(Occurred(p, e, t_2))$$

$$AND\ t_2 \geq t$$

$$THEN\ RELIEF_p(p, e, t_2) = FEAR_P(p, e, t))$$

$$IF\ RELIEF_p(p, e, t_2) > RELIEF(p, t_2)$$

$$THEN\ Intensity(p, e, t_2) = RELIEF_p(p, e, t_2) -$$

$$RELIEF_t(p, t_2)$$

$$AND\ reset\ FEAR_P(p, e, t_2) = Desirability(p, e, t_2)*$$

$$Likeihood(p, e, t_2)$$

$$ELSE\ Intensity(p, e, t_2) = 0$$

In the above rules it is simply assumed that once a prospective negative event was disproved, the relief level of the agent would be directly proportional to the level of fear that was experienced by the agent in an earlier time. It is clear that such an

assumption was made for simplicity and in reality the relationship between these two constructs is more sophisticated. In addition, although the agent has experienced some relief emotion at time t_2 as a result of dis-confirmed negative event e, but we would need to consider the possibility of its occurrence in a later time. This was the reason for re-computing the value of $Fear_p$ since at least one of its parameters (i.e., Likelihood) was changed.

Emotion Disappointment   An agent experiences disappointment when the occurrence of an expected desirable event is dis-confirmed. Hence,

$IF\ HOPE_p(p, e, t) > 0\ AND\ NOT(Occurred(p, e, t_2))\ AND$

$t_2 \geq t$

$THEN\ DISAPPOINTMENT_p(p, e, t_2) = HOPE_P(p, e, t))$

$IF\ DISAPPOINTMENT_p(p, e, t_2) >$

$DISAPPOINTMENT_t(p, t_2)$

$THEN\ Intensity(p, e, t_2) = DISAPPOINTMENT_p(p, e, t_2)$

$-DISAPPOINTMENT_t(p, t_2)$

$AND\ reset\ HOPE_p(p, e, t_2) = Desirability(p, e, t_2)*$

$Likeihood(p, e, t_2)$

$ELSE\ Intensity(p, e, t_2) = 0$

In the above rules, it was assumed that the level of disappointment emotion elicited as a result of dis-confirmed positive event is directly proportional to the level of hope that the agent had for that event. It would appear that such an assumption is in line with the rule of thumb, the higher the hope for an expected event, the higher the disappointment at its dis-confirmation.

Emotion FearsConfirmed   An agent experiences fears-confirmed emotion when the occurrence of an expected undesirable event is confirmed. Hence,

$IF\ FEAR_p(p, e, t) > 0\ AND\ (Occurred(p, e, t_2))\ AND$

$t_2 \geq t$

$THEN\ FEARSCONFIRMED_p(p, e, t_2) =$

$-(Desirabiklity(p, e, t_2))$

$IF\ FEARSCONFIRMED_p(p, e, t_2) >$

$FEARSCONFIRMED_t(p, t_2)$

$THEN\ Intensity(p, e, t_2) = FEARSCONFIRMED_p(p, e, t_2)$

$-FEARSCONFIRMED_t(p, t_2)$

$ELSE\ Intensity(p, e, t_2) = 0$

Emotion Satisfaction   An agent experiences satisfaction emotion when the occurrence of an expected desirable event is confirmed. Hence,

$IF\ HOPE_{pot}(p, e, t) > 0\ AND\ (Occurred(p, e, t_2))\ AND\ t_2 \geq t$

$THEN\ SATISFACTION_p(p, e, t_2) = Desirability(p, e, t_2)$

$IF\ SATISFACTION_p(p, e, t_2) > SATISFACTION_t(p, t_2)$

$THEN\ Intensity(p, e, t_2) = SATISFACTION_p(p, e, t_2) -$

$SATISFACTION_t(p, t_2)$

$ELSE\ Intensity(p, e, t_2) = 0$

Here, it can be argued that a simple approximation for the intensity of the above two emotions at the realization of the occurred event by the agent, is to remove the prospect factor from the calculations and link them directly to their initial desirability measures.

Others-related   In this section, calculation modules for the others-related set of event-originated emotions are presented. Others-related addresses those emotional states that are being elicited in a different agent from the evaluating one.

Emotion HappyFor An agent experiences happyfor emotion if it is pleased about an event presumed to be desirable for a friend agent. Hence,

$IF\ Desirability(p_2, e, t) > 0\ AND\ Friend(p_1, p_2)$

$THEN\ IF\ Desirability(p_1, e, t) > 0$

$THEN\ HAPPYFOR_p(p_1, e, t) =$

$(Desirability(p_2, e, t) + Desirability(p_1, e, t))/2$

$ELSE\ THEN\ HAPPYFOR_p(p_1, e, t) =$

$|Desirability(p_2, e, t) - Desirability(p_1, e, t)|$

$IF\ HAPPYFOR_p(p_1, e, t) > HAPPYFOR_t(p_1, t)$

$THEN\ Intensity(p_1, e, t) = HAPPYFOR_p(p_1, e, t,) -$

$HAPPYFOR_t(p_1, t)$

$ELSE\ Intensity(p_1, e, t) = 0$

Emotion Pity An agent experiences pity emotion if it is displeased about an event presumed to be undesirable for a friend agent. Hence,

$IF\ Desirability(p_2, e, t) < 0\ AND\ Friend(p_1, p_2)$

$THEN\ IF\ Desirability(p_1, e, t) < 0$

$THEN\ PITY_p(p_1, e, t) =$

$|(Desirability(p_2, e, t) + Desirability(p_1, e, t))|/2$

$ELSE\ PITY_p(p_1, e, t) = |Desirability(p_2, e, t) -$

$Desirability(p_1, e, t)|$

$IF\ PITY_p(p_1, e, t) > PITY_t(p_1, t)$

$THEN\ Intensity(p_1, e, t) = PITY_p(p_1, e, t,) - PITY_t(p_1, t)$

$ELSE\ Intensity(p_1, e, t) = 0$

For the above two emotions, we argue that in case of compatible desirability for both agents, the emotion level would be obtained by averaging the two desirability measures [117]. The other scenario would be when the two agents have opposite desir-

ability for event e at which the algebraic sum of the two would determine the intensity level of the resulting emotion. It needs to be clarified that these computational rules hold even when event e is irrelevant to agent p_1(i.e., $Desirability(p_1, e, t) = 0$).

Emotion Gloating   An agent experiences gloating emotion if it is pleased about an event presumed to be undesirable for an non-friend agent. Hence,

$IF\ Desirability(p_2, e, t) < 0\ AND\ NOT(Friend(p_1, p_2))$
$THEN\ IF\ Desirability(p_1, e, t) < 0$
$THEN\ GLOATING_p(p_1, e, t) =$
$|(Desirability(p_2, e, t) - Desirability(p_1, e, t)|$
$ELSE\ GLOATING_p(p_1, e, t) =$
$|Desirability(p_2, e, t) + Desirability(p_1, e, t)|$
$IF\ GLOATING_p(p_1, e, t) > GLOATING_t(p_1, t)$
$THEN\ Intensity(p_1, e, t) =$
$GLOATING_p(p_1, e, t,) - GLOATING_t(p_1, t)$
$ELSE\ Intensity(p_1, e, t) = 0$

Emotion Resentment   An agent experiences resentment emotion if it is displeased about an event presumed to be desirable for an non-friend agent. Hence,

$IF\ Desirability(p_2, e, t) > 0\ AND\ NOT(Friend(p_1, p_2))$
$THEN\ IF\ Desirability(p_1, e, t) < 0$
$THEN\ RESENTMENT_p(p_1, e, t) =$
$|(Desirability(p_2, e, t) - Desirability(p_1, e, t))|$
$ELSE\ RESENTMENT_p(p_1, e, t) =$
$|Desirability(p_2, e, t) - Desirability(p_1, e, t)|$
$IF\ RESENTMENT_p(p_1, e, t) > RESENTMENT_t(p_1, t)$
$THEN\ Intensity(p_1, e, t) =$

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$$RESENTMENT_p(p_1, e, t,) - RESENTMENT_t(p_1, t)$$
$$ELSE \ Intensity(p_1, e, t) = 0$$

Action-originated emotions

Non-compound emotions For this set of emotions, we consider a function called *Praise* that evaluates and sets the degree of praiseworthiness of an action. A negative value for this function indicates the degree of blameworthiness of the action.

Emotion Pride An agent experiences pride emotion if it is approving its own praiseworthy action. Hence,

$$IF \ Praise(p_1, p_2, a, t) > 0 \ AND \ (p_1 = p_2)$$
$$THEN \ PRIDE_p(p_1, p_2, a, t) = Praise(p_1, p_2, a, t)$$
$$IF \ PRIDE_p(p_1, p_2, a, t) > PRIDE_t(p_1, p_2, a, t)$$
$$THEN \ Intensity(p_1, p_2, a, t) =$$
$$PRIDE_p(p_1, p_2, a, t) - PRIDE_t(p_1, p_2, a, t)$$
$$ELSE \ Intensity(p_1, p_2, a, t) = 0$$

Emotion Shame An agent experiences shame emotion if it is disapproving its own blameworthy action. Hence,

$$IF \ Praise(p_1, p_2 a, t) < 0 \ AND \ (p_1 = p_2)$$
$$THEN \ SHAME_p(p_1, p_2, a, t) = -Praise(p_1, p_2 a, t)$$
$$IF \ SHAME_p(p_1, p_2, a, t) > SHAME_t(p_1, p_2, a, t)$$
$$THEN \ Intensity(p_1, p_2, a, t) =$$
$$SHAME_p(p_1, p_2, a, t) - SHAME_t(p_1, p_2, a, t)$$
$$ELSE \ Intensity(p_1, p_2, a, t) = 0$$

Emotion Admiration An agent experiences admiration emotion if it is approving a praiseworthy action of another agent. Hence,

$IF\ Praise(p_1, p_2, a, t) > 0\ AND\ NOT(p_1 = p_2)$

$THEN\ ADMIRATION_p(p_1, p_2, a, t) = Praise(p_1, p_2a, t)$

$IF\ ADMIRATION_p(p_1, p_2, a, t) >$

$ADMIRATION_t(p_1, p_2, a, t)$

$THEN\ Intensity(p_1, p_2, a, t) =$

$ADMIRATION_p(p_1, p_2, a, t) - ADMIRATION_t(p_1, p_2, a, t)$

$ELSE\ Intensity(p_1, p_2, a, t) = 0$

Emotion Reproach An agent experiences reproach emotion if it is disapproving a blameworthy action of another agent. Hence,

$IF\ Praise(p_1, p_2a, t) < 0\ AND\ NOT(p_1 = p_2)$

$THEN\ REPROACH_p(p_1, p_2, a, t) = -Praise(p_1, p_2a, t)$

$IF\ REPROACH_p(p_1, p_2, a, t) > REPROACH_t(p_1, p_2, a, t)$

$THEN\ Intensity(p_1, p_2, a, t) =$

$REPROACH_p(p_1, p_2, a, t) - REPROACH_t(p_1, p_2, a, t)$

$ELSE\ Intensity(p_1, p_2, a, t) = 0$

Compound emotions For this class of emotions, as stated earlier, we deal with two other implicit emotional states that are involved in the calculations and the intensity level would include an average-like operation between these two emotions. Therefore, beside the value of function *Praise* used in the above equations, it will be necessary to calculate the desirability of the resulted events in the same way that was performed for the set of event-originated emotions.

Emotion Gratification   An agent experiences gratification emotion if it is approving its own praiseworthy action that led to a desirable event. Hence,

$IF\ Praise(p_1, p_2a, t) > 0\ AND\ (p_1 = p_2)\ AND$
$Desirability(p, e, t) > 0$
$THEN\ GRATIFICATION_p(p_1, p_2, a, t) =$
$(PRIDE_p + JOY_p)/2$
$IF\ GRATIFICATION_p(p_1, p_2, a, t) >$
$GRATIFICATION_t(p_1, p_2, a, t)$
$THEN\ Intensity(p_1, p_2, a, t) =$
$GRATIFICATION_p(p_1, p_2, a, t) -$
$GRATIFICATION_t(p_1, p_2, a, t)$
$ELSE\ Intensity(p_1, p_2, a, t) = 0$

Emotion Remorse   An agent experiences remorse emotion if it is disapproving his own blameworthy action that led to an undesirable event. Hence,

$IF\ Praise(p_1, p_2a, t) < 0\ AND\ (p_1 = p_2)$
$AND\ Desirability(p, e, t) < 0$
$THEN\ REMORSE_p(p_1, p_2, a, t) =$
$(SHAME_p + DISTRESS_p)/2$
$IF\ REMORSE_p(p_1, p_2, a, t) > REMORSE_t(p_1, p_2, a, t)$
$THEN\ Intensity(p_1, p_2, a, t) =$
$REMORSE_p(p_1, p_2, a, t) - REMORSE_t(p_1, p_2, a, t)$
$ELSE\ Intensity(p_1, p_2, a, t) = 0$

Emotion Gratitude   An agent experiences gratitude emotion if it is approving a praiseworthy action of another agent that led to a desirable event. Hence,

$$IF\ Praise(p_1, p_2 a, t) > 0\ AND\ NOT(p_1 = p_2)$$
$$AND\ Desirability(p, e, t) > 0$$
$$THEN\ GRATITUDE_p(p_1, p_2, a, t) =$$
$$(ADMIRATION_p + JOY_p)/2$$
$$IF\ GRATITUDE_p(p_1, p_2, a, t) > GRATITUDE_t(p_1, p_2, a, t)$$
$$THEN\ Intensity(p_1, p_2, a, t) =$$
$$GRATITUDE_p(p_1, p_2, a, t) - GRATITUDE_t(p_1, p_2, a, t)$$
$$ELSE\ Intensity(p_1, p_2, a, t) = 0$$

Emotion Anger   An agent experiences anger emotion if it is disapproving a blame-worthy action of another agent that led to an undesirable event. Hence,

$$IF\ Praise(p_1, p_2 a, t) < 0\ AND\ NOT(p_1 = p_2)$$
$$AND\ Desirability(p, e, t) < 0$$
$$THEN\ ANGER_p(p_1, p_2, a, t) =$$
$$(REPROACH + DISTRESS_p)/2$$
$$IF\ ANGER_p(p_1, p_2, a, t) > ANGER_t(p_1, p_2, a, t)$$
$$THEN\ Intensity(p_1, p_2, a, t) =$$
$$ANGER_p(p_1, p_2, a, t) - ANGER_t(p_1, p_2, a, t)$$
$$ELSE\ Intensity(p_1, p_2, a, t) = 0$$

Object-originated emotions   As discussed earlier in this article, this type of emotions are related to the attraction and aversion aspect of the emotion-eliciting objects from the perspective of the evaluating agent. This kind of emotions can be distinguished from the other two types (i.e., events-originated and actions-originated) with respect to the fact that they are directly experienced as a result of dispositional liking or disliking attribute toward the category or class that the object belongs to along with some self characteristics of the object itself. Although in the base theory, the attribute of familiarity (vs novelty) between the object and the evaluating agent was

considered as a factor that affects the elicitation and intensity of these emotions, but due to the complex and uncertain attitude of OCC with respect to relationship between this factor and the appealing of the object (e.g., directly or reversely proportional or being highly contextual), we refrain from considering this attribute in the calculations of this type of emotions and focus merely on the appealing attribute of the objects.

Emotion Love An agent experiences love emotion if it is attracted to an appealing and object (agent). Hence, we have

$IF\ Appealing(p, obj, t) > 0$

$THEN\ LOVE_p(p, obj, t) = Appealing(p, obj, t)$

$LOVE_t = k/Familiar(p, obj, t),\ k = constant$

$IF\ LOVE_p(p, obj, t) > LOVE_t(p, obj, t)$

$THEN\ Intensity(p, obj, t) =$

$LOVE_p(p, obj, t) - LOVE_t(p, obj, t)$

$ELSE\ Intensity(p, obj, t) = 0$

Emotion Hate An agent experiences hate emotion if it is attracted to an appealing and object (agent). Hence, we have

$IF\ Appealing(p, obj, t) < 0$

$THEN\ HATE_p(p, obj, t) = -Appealing(p, obj, t)$

$HATE_t = k/Familiar(p, obj, t),\ k = constant$

$IF\ HATE_p(p, obj, t) > HATE_t(p, obj, t)$

$THEN\ Intensity(p, obj, t) =$

$HATE_p(p, obj, t) - HATE_t(p, obj, t)$

$ELSE\ Intensity(p, obj, t) = 0$

2.3.4.3 Algorithms

Event-Track-State: to determine triggered emotions along with their intensities as a result of the occurrence of a series of events

Input: $q_0 = <m_0, I_0>$, $Mood_{global}$, $E = \{e_1, e_2, ..., e_k\}$, E is list of occurring events

$Q = \{<m_i, I_i>, m_i \in Event\_Competent\_Emotions, I_i \in Intensity_{fuzzy}\}$

Output: $q_f = \{<m_1, I_1>, <m_2, I_2>, ... <m_k, I_k>\} \subset Q$
Begin
   Defuzzify state $q_i = q_0$ using weighted average method
   For each event $e \in E$
      Begin
         Calculate $Desirability_f$ for event e
         Based on the variables of $Orientation$, $Prospect$ do:
         Determine possible emotional state $<m_i, I_i>$ from emotion derivation rules
         Obtain $\Delta MoodR_{global}$ for e using PAD look-up table
        Update $\Delta MoodR_{global}$
      End For;
   For each m_i where $I_i > 0$
      Begin
         Print $<m_i, I_i>$
      End For;
End.

Agent-actions emotions   Action-Track-State: to determine triggered emotions along with their intensities as a result of the occurrence of a series of actions

Input: $q_0 = <m_0, I_0>$, $Mood_{global}$, $A = \{a_1, a_2, ..., a_k\}$, A is list of actions

$Q = \{<m_i, I_i>, m_i \in Action\_Competent\_Emotions, I_i \in Intensity_{fuzzy}\}$

Output: $q_f = \{<m_1, I_1>, <m_2, I_2>, ... <m_k, I_k>\} \subset Q$
Begin
   Defuzzify state $q_i = q_0$ using weighted average method
   For each event $a \in A$
      Begin
         Based on the variables of $Degree\_involvement$, $Unexpectedness$ do:
         Calculate $Praiseworthiness$ for action a
         Determine possible emotional state $<m_i, I_i>$ from emotion derivation rules
         Obtain $\Delta MoodR_{global}$ for a using PAD look-up table
        Update $\Delta MoodR_{global}$
        If $a \in \beta$ set of actions
           Begin
              calculate compound emotions
           End;
      End For;

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Table 2.2: List of agent's goals and events along with their impact on each goal for both agents

Goal		G1	G2	G3
Importance		$HighlyImportant$	$SlightlyImportant$	$HighlyImportant$
Event/Person		$Impact$(G1)	$Impact$(G2)	$Impact$(G3)
e_1	p_1	$HighlyPositive$	$NoImpact$	$HighlyPositive$
	p_2	$SlightlyPositive$	$SlightlyNegative$	$NoImpact$
e_2	p_1	$HighlyNegative$	$SlightlyPositive$	$SlightlyNegative$
	p_2	$HighlyNegative$	$HighlyPositive$	$HighlyPositive$
e_3	p_1	NoImpact		
	p_2	$HighlyPositive$	$NoImpact$	$HighlyPositive$
e_4	p_1	$HighlyNegative$	$HighlyPositive$	$HighlyNegative$
	p_2	$HighlyNegative$	$SlightlyPositive$	$SlightlyNegative$
e_5	p_1	$HighlyPositive$	$HighlyPositive$	$NoImpact$
	p_2	$NoImpact$	$HighlyNegative$	$SlightlyPositive$

For each m_i where $I_i > 0$
    Begin
        Print $< m_i, I_i >$
    End For;
End.

2.3.5   Simulation experiments and discussion

In order to test the performance of the model and verify its functionality under different circumstances, a series of simulation experiments were conducted. For brevity, two of these experiments are considered here. The goal of the first experiment is study the emotional behavior of the agent as a result of the occurrence of some independent events. The second experiment includes those events where their occurrence was a result of some actions performed by the evaluating agent itself or some other agents. Situations at which the subject agent was exposes to emotion-eliciting objects are also included.

Table 2.3: Temporal dynamics of the occurring events

time	0	10	20	30	40	50	60	70	80	90
Occurrence			e_1		e_3	e_4	e_2		e_5	e_1
Prospect		e_2	e_5		e_4		e_5			
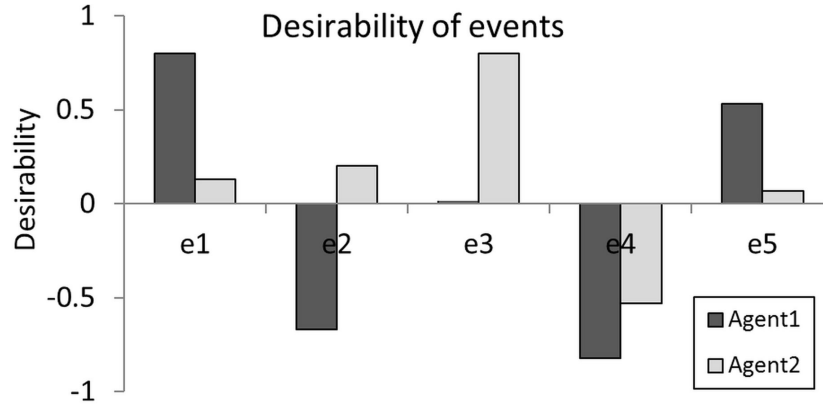
Figure 2.10: Calculated event's desirability for both agents

2.3.5.1   Scenario 1 unattributed Events

In this experiment, a scenario where the subject agent does not attribute the events to the actions of itself or other agents is considered. Consequently, the appraisal process is merely being performed based on the occurred events through their desirability and expectedness measures. p_1 is the subject (evaluating) agent, p_2 is the other agent, $G = \{G_1, G_2, G_3\}$ are the goals of the agents and $E = \{e_1, e_2, e_3, e_4, e_5\}$ is the set of possible events. The fuzzy values of *Importance* and *Impact* for these goals and events are described in Table 5.4. Table 2.3 shows the temporal dynamics of both real and prospect events that take place in the system during the simulation time. It is assumed that the time duration for a prospect event is 20 time-steps; meaning that the agent will experience the competent prospect emotion for 20 time-steps before it turns into a deterministic emotion. In addition, it is assumed that the life-time for each deterministic emotion is 20 time-steps as well; emotional responses start to deteriorate through a linear function due to normal decay and vanishes completely after that period.

As the first step, the desirability level for all events of E for both agents were calculated and the results are reflected in the graph of Fig. 5.8.

According to Table 2.3, at time-step=10, since there is a possibility for the occurrence of e_2 as a negative event, the agent experiences fear emotion. The actual occurrence of positive event e_1 at step=20, caused emotion joy to be triggered in agent p_1. In addition, at the same step, a certain level of emotion hope was elicited in the agent for the prospect positive event of e_5. At step=30, due to dis-confirmed e_2, the fear emotion will disappear and gives its room to the relief emotion. At step=40, the occurrence of e_3, which was initially an irrelevant event for agent p_1, but considering the fact that it is a positive event for a friend agent (p_2) will yield in triggering the emotion of *happyfor* in p_1. Furthermore, prospective event e_4 will cause p_1 to experience a relatively high level of fear emotion which converts into *fearsconfirmed* at step=50. At step=60, negative event e_2 took place and caused p_1 to experience a high level of distress emotion. Unlike the earlier prospective occurrence of this event, it was not proceeded by a fear emotion since it was not predicted by the agent. At the same step, the prospective event of e_5 resulted in some degree of hope emotion. This emotion was converted into satisfaction at step=80 when the occurrence of e_5 was confirmed. Finally, at step=90, positive event e_1 took place and caused the agent to experience a high level of joy. Fig. 5.9 depicts the changes in the global mood level of agent p_1 as a result of the occurred events. As elaborated before, the changes in the global mood of the agent is proportional to the PAD components of the triggered emotions which in turn were elicited as a result of occurred events. Fig. 2.11 shows a complete list of all events-originated emotions that were experienced by agent p_1 during the simulation time along with the intensity of each. For instance, it can be seen that the agent experienced emotion joy for the first time at step=20 with a high intensity of 0.7 as a result of the occurrence of event e_1. The joy emotion started to deteriorate due to the normal decay and it completely disappeared by step=40.

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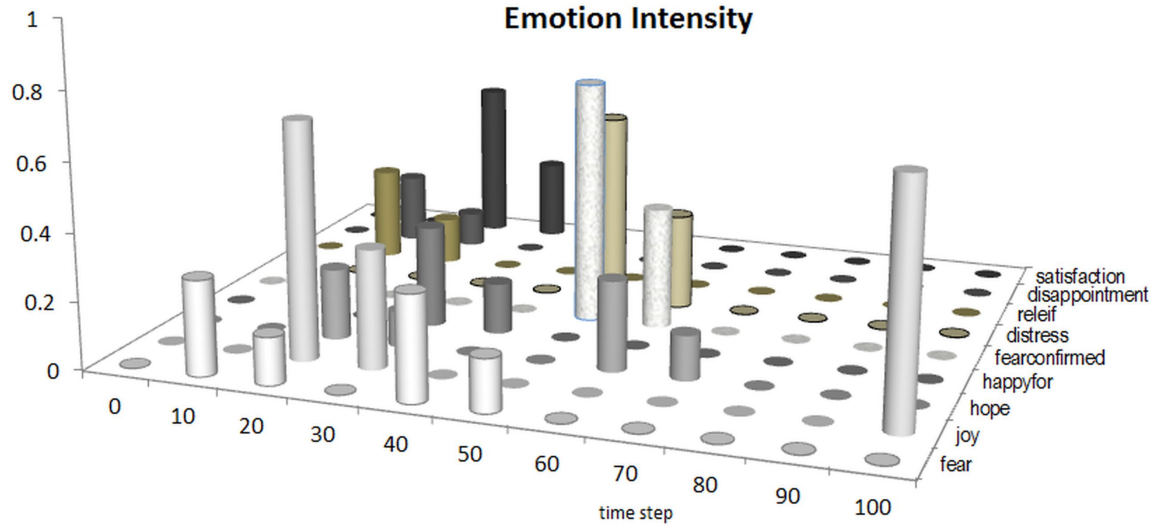
Figure 2.11: Intensity of all events-originated emotions for agent p_1 during the simulation
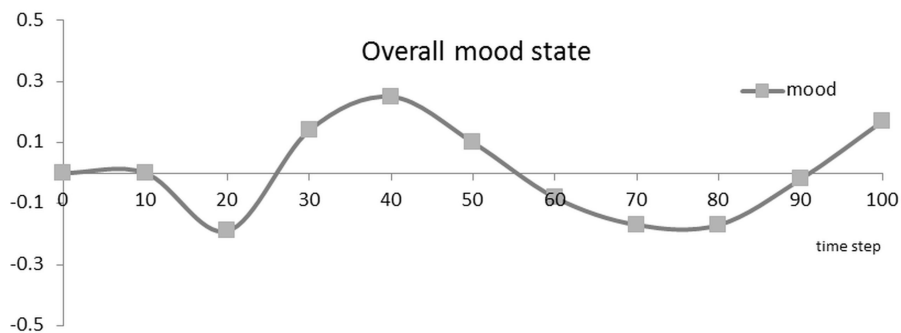
Figure 2.12: Global mood level changes as a result of occurred events

The agent ended the simulation with another wave of joy emotion as a result of the re-occurrence of e_1.

In this scenario, it can be noticed that the emotional behavior of the agent was directly influenced by appraisal processes performed by the agent itself on the set of events that took place in the environment and were perceived relevant by the agent. Furthermore, it can be clearly seen that the fact whether an event is directed towards the agent itself or some other agents, plays a critical role in the set of elicited emotions and their intensities.

2.3.5.2 Scenario 2 - attributed events and emotion-eliciting objects

In this scenario, the subject attributes the occurred emotion relevant events to the actions of self or other agents. Table 2.4 describes all type of actions that can be performed by both agent p_1 as the evaluating agent and agent p_2 as the other agent. According to this table, there are two sets of actions; set α_i where $i \in \{1, 2, 3\}$ which represents those actions that are not associated with regular events and hence will generate non-compound actions-originated emotions; and set β_j where $j \in \{1, 2, 3, 4, 5\}$ which represents those actions that generate compound emotions.

Furthermore, according to Table 2.4, each action is associated with four appraisal dimensions that are necessary for computing the praiseworthiness appraisal function. These four dimensions are: (1) a binary variable to determine compliance with the contextual standards with TRUE or FALSE values; (2) a pair of fuzzy variables to determine the degree of responsibility of each agent separately in the performed action which will take a fuzzy value from the fuzzy sets of $\{solely, highly, moderately, slightly\}$; (3) possible outcome event of the action; and (4) a pair of fuzzy variable that determines the degree of unexpectedness for the action being performed by any of the two agents which will take a value from the fuzzy sets of $\{highly, moderately, slightly\}$.

Additionally, Table 2.5 reflects all the actions that were performed by both agents during the simulation period.

It is clear that in the occasion of having actions of type β, it would be necessary to consider the desirability of the outcome emotions also, in a similar way to the experiment of scenario 1 beside evaluating the praiseworthiness function. Furthermore, considering the fact that β set of actions responsible for generating compound emotions are associated with the same set of events used in the previous experiment (i.e., e_is), there will be no need to calculate the desirability of those events this task was performed in the experiment of scenario 1. Therefore, these desirability quantities

Table 2.4: List of emotion-eliciting actions along with their valence, degree of involvement, possible outcome event and degree of action unexpectedness

Action	Stand. comp.	Degree of resp.		outc. event	Unexpectedness	
		p_1	p_2		p_1	p_2
α_1	✔	solely	highly	—	highly	highly
α_2	✗	highly	solely	—	mod.	highly
α_3	✔	solely	slight.	—	slightly	slightly
β_1	✔	solely	solely	e_1	highly	slightly
β_2	✗	sligt.	mod.	e_2	highly	mod.
β_3	✔	highly	highly	e_3	sligtly	highly
β_4	✗	mod.	mod.	e_4	mod.	mod.
β_5	✔	solely	highly	e_5	slightly	slightly

Table 2.5: Temporal dynamics of actions performed by both agents

time	0	10	20	30	40	50	60	70	80	90
A(p_1)			β_2		β_3				α_2	β_1
A(p_2)		α_2	α_3		β_5	α_1	β_1		β_2	

will be used along with the newly calculated praiseworthiness of actions to anticipate the type and intensity of the compound emotions in this experiment. For simplicity, other unaddressed conditions of this experiment were considered identical to those of the previous experiment.

The first step in this scenario will be to calculate the value of praiseworthiness for each action of α_i as well as β_i. Fig. 2.13 represents the actions praiseworthiness values calculated for both agents.

According to Table 2.5, at time-step=10, action α_2 was performed by p_2. Considering the fact that α_2 is a norm violating action, and also the fact that p_2 was highly involved in this action while it is highly unexpected to be conducted by this agent, a strong emotion of reproach was elicited in agent p_1 as a result of this action. At step=20, agent p_2 performed the positive action of α_3 but considering the weak role of agent p_2 in performing this action as well as its low unexpectedness to appear from the class type of agent p_2, a potential weak signal for emotion admiration was triggered

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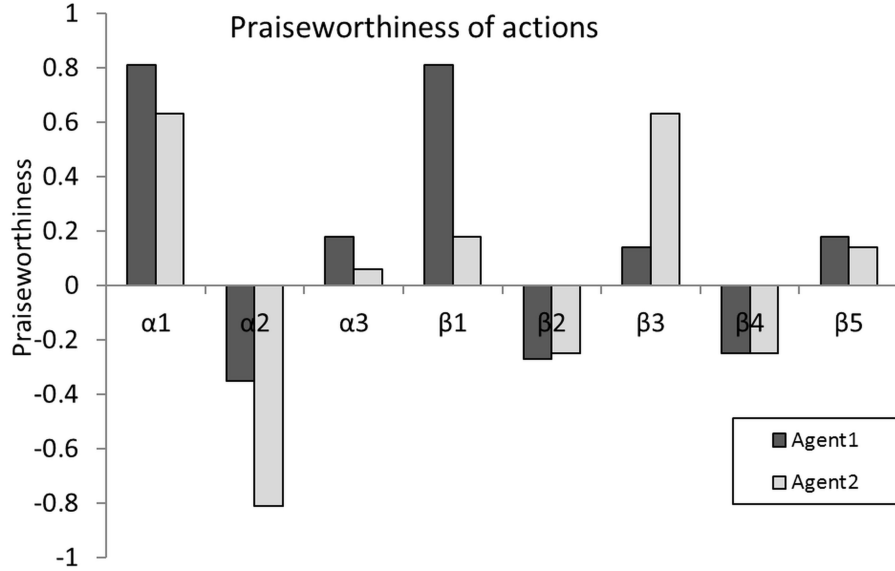
Figure 2.13: Calculated praiseworthiness of actions for both agents

in agent p_1 but it did not reach the threshold level of admiration, hence, no genuine admiration emotion was elicited in p_1 as a result of this action. Concurrently, action β_2 was performed by agent p_1 itself which is a norm-violating action and hence it triggers the emotion shame in , but since the responsibility of p_1 in this action was low, hence the intensity of shame will be low.

Furthermore, this action as expected will also generate emotion remorse considering its role in the occurrence of the negative event of e_2. The intensity level of emotion remorse will by high though since event e_2 is highly undesirable for agent p_1. at time step=40, all previously elicited emotions will be vanished due to the normal decay factor discussed earlier in first experiment. On the other hand, at this step two actions of β_3 and β_5 was performed by p_1 and p_2 respectively. Both of these actions are expected to generate compound emotions. With respect to action β_3, it generates a weak emotion of pride since the unexpectedness factor is low for the class of agents that p_1 belongs to. Furthermore, although this action is associated with event e_3 but since this event has no impact on the agents goals and consequently it is neither a
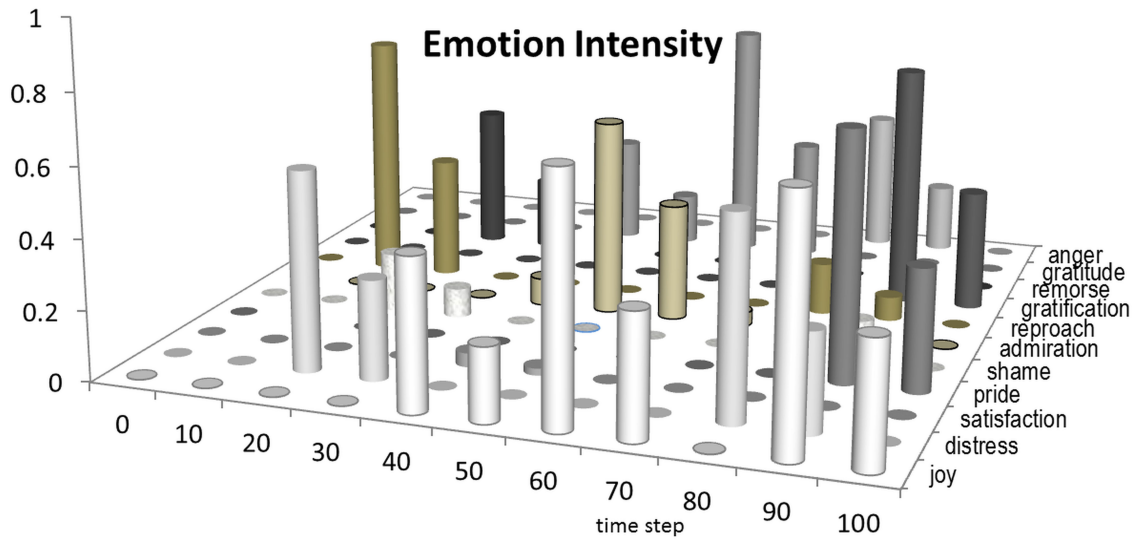
Figure 2.14: Intensity of all actions-originated emotions for agent p_1 during the simulation

negative nor a positive event for p_1 with desirability measure=0. Therefore, no emotion of events-originated type will be generated as a result of this action. Concurrently at this step, the positive action of β_5 by p_2 will create a weak admiration emotion in agent p_1 as well as a stronger gratitude emotion due to the occurrence of the highly desirable event of e_5 that took place as a result of this action. At step=50, action α_1 was performed by p_2 and as a result, emotion admiration was elicited in agent p_1.

The situation continues with the actions of β_1, β_2 performed by p_2 which elicit emotions of admiration, gratitude, reproach and anger in agent p_1 as well as actions α_2, β_1 performed by p_1 itself which elicit the emotions of shame, pride and finally gratification respectively. Fig. 2.14 shows a complete list of all actions-originated emotions that were experienced by agent p_1 during the simulation time along with the intensity level of each. With respect to all events-originated emotions, it is worth noted that they were generated with the same mechanism as described in the previous scenario.

In this scenario, it can be noticed that the emotional behavior of the agent was directly influenced by the praiseworthiness of the emotion triggering actions performed

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either by the agent itself or some other agents. It can be seen for instance, how the same action generated different emotions as a result of being performed by the evaluating agent itself or by another agent.

2.3.6 Conclusion

In this article a fuzzy appraisal approach for anticipating the emotional states that will be experienced by an individual based on OCC emotion theory was proposed. These emotions are elicited as a result of either the occurrence of some goal-relevant events; evaluating an action of self or other individuals; or a dispositional reaction to some emotion-eliciting objects. Emotion generation modules were formulated for all 22 emotions of the OCC model according to this ternary classification. The problem formulation was performed based on some guidelines from the OCC emotion theory along with different appraisal methods and techniques such as measuring the desirability of events, degree of event's expectedness, action's degree of compliance with standards, level of involvements, etc.

At the core of each assessment process in the proposed computational model there exist a fuzzy evaluation system that analyzes the competent appraisal variables and generates the value for the output parameters. Furthermore, a probabilistic learning approach was used to enable the agent to come up with an event prediction model based on the previously learnt patterns of events.

The proposed model was able to determine the set of triggered emotions along with their intensities at any point of time as well as the overall mood state of the agent during the simulation interval. The authors of this article believe that this work is still at the preliminary level and there is much room for further development and research that can use the obtained methods and results to bridge to the relevant disciplines, especially psychology and healthcare.

2.4   Conclusion

In this chapter, the principles for modeling emotions from the perspective of IT and in particular Computer Science were briefly dissected. Considering the huge challenges associated with this kind of research areas where the problem under study is mostly qualitative in nature and the fact that the existing models proposed by experts within the fields of humanistic sciences are expressed using informal linguistic descriptions that clearly lack the necessary details as well as a well-structured architecture of the internal processes which are all essential components for a possible implementation, we have adopted an incremental approach toward building a comprehensive computational model for emotions that fits the needs for computer applications. This chapter reflected a pure appraisal approach towards modeling the elicitation mechanisms of emotions at which each individual emotion was looked at as an independent affective construct.

Chapter 3

Emotion Regulation

3.1 Introduction

Emotion regulation represents an important open problem in emotion studies. The main focus in this field is on regulating hyper negative emotions. It articulates the "appropriate" level for emotional responses. In simple words it talks about where, when and how much emotion to have in order to make a "wise" decision. The importance of this problem lays in the strongly evidence-supported tenet [1,2,3] that hyper levels of emotions can be harmful and accompanied with distructive concequences. Unbalanced levels of emotions were tracked in many forms of psychopathology, social difficulties and even physical illness [42].

Emotion regulation targets this potential risk and is aimed at balancing the level of one's emotional responses in different situations.

The aim of this research work is not to come up with an independent hypothesis about emotion regulation but the focus is rather on building computational models based on existing hypothesis. This goal entails making major changes to the architecture of the original models in order to address the missing details as well as building a computational framework for the affective processes. We believe that a

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well-established computational model is capable of providing a much more stronger tool to test, verify, validate and eventually implement the model in real applications.

This chapter includes two computational models that were proposed to address the problem of modeling emotion regulation and were published as research papers as follows:

- A. Soleimani and Z. Kobti, "An adaptive computational model of emotion regulation strategies based on Gross theory", in Proceedings of the fifth C* Conference on Computer Science & Software Engineering, Montreal, QC, Canada, 2012, pp. 9-17 [112]:

  In this article, a computational model is proposed that models the dynamics of the underlying processes for emotion regulation according to Gross theory [45] for emotion regulation. It extends the dynamism of the original model by considering other factors that play a role in adjusting the levels of elicited emotions such as mood and personality of the individual. This research paper is presented in Section 3.2

- A. Soleimani and Z. Kobti, "A fuzzy logic computational model for emotion regulation based on Gross theory". Proceedings of the 26th International Conference of the Florida Artificial Intelligence Research Society. May 2013, Florida, USA, pp. 142-147 [119]

  In this research paper, a computational model for emotion regulation is proposed that was built based on a fuzzy logic approach. The model compares the regulation behavior of a knowledgeable agent that is capable of learning and adapting itself to the environmental changes versus a non-knowledgeable agent that does not adapt itself to different situations and concluded that the learning capability is critical in helping the agent to cope better with changes in the environment and consequentlt to exhibit a smoother regulation behavior. This research paper is presented in Section 3.3

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3.2 An adaptive computational model of emotion regulation strategies based on Gross theory

Abstract. Judgments, preferences, and other cognitive tasks entail an emotional foundation and cannot function in an emotional vacuum. Emotion regulation strategies target the potential risk of having inappropriate level of emotions in the process of decision making. This study is a follow-up on a previous computational model for emotion regulation strategies based on Gross theory and applies several enhancements to it. In particular, we extend the dynamism of the original model by considering a dynamic environment in which emotion eliciting events occur during the simulation period. Furthermore, some key parameters are made adaptive rather than constants. (e.g. the persistence factor was made adaptive to the individual's mood changes). Results obtained from the augmented model show further consistency with the base theory.

3.2.1 Introduction

Emotions are a major and non-detachable element of every individual's life. Contemporary studies emphasize the important role of emotions as ready to use behavioral responses, major adjusters in the process of decision making and an effective mean to ease the social interpersonal communications [42]. Conversely, emotion can have negative and sometimes destructive impacts if it is not applied at the right time and/or with appropriate level of intensity. This negative attribution can be tracked in many forms of psychopathology, social difficulties and even physical illness [42]. Therefore, a vital element in enjoying a successful social life with healthy physical and mental personality is to have a balanced level of emotions. Gross in [45] states that, "Emo-

tion regulation includes all of the conscious and non-conscious strategies we use to increase, maintain, or decrease one or more components of an emotional response". Considering the fact that the multi-componential processes of an emotional experience unfold over time, emotion regulation strategies would consist of "changes in emotion latency, rise time, magnitude, duration and offset of responses in behavioral, experiential or physiological domains" [43].

This article extends the computational model based on Gross theory for emotion regulation, proposed by Bosse & colleagues [13] and applies a set of enhancements in order to make it more dynamic and adaptive with regards to different circumstances. In next section, we overview the related work done in this area. Section 3, elaborates briefly on Gross informal process model of emotion regulation. Next, we review Bosse & colleagues proposed computational model for emotion regulation. In section 5, we address the shortcomings of Bosse and colleagues implementation and introduce our enhanced approach followed by simulation experiments, discussion and conclusion.

3.2.2 Related work

The role of emotions in the process of decision making was always controversial during the history of mankind and human related sciences. In most of emotion theories which go back to before the mid of last century, emotions were looked at as an adverse and sometimes neutral element in our decisions and thus should be avoided or kept at its minimum level [27]. It was up to a few decades ago when contemporary researchers proposed a different point of view towards this topic. In almost all recent theories of emotion (e.g., Lazarus [61], Ortony and colleagues [83], Scherer [102], and Frijda [33]), the functionality of emotions and affect in general is confirmed and the role of emotion as a major component in the process of decision making and other cognitional activities is emphasized.

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In some recent works, an increasing number of researchers have focused on building a process model for emotion regulation as an independent sub-model of a comprehensive model of emotions. They study different strategies and techniques that could be used to modulate and finally regulate emotional responses in order to utilize emotions more effectively in the process of decision making at different levels. (e.g., [44, 45, 82]). Gratch and Marsella in their detailed model of Emotion and adaptation (EMA)[73], assign a great deal of their work to the process of emotion regulation. EMA adopts the approach of Lazarus [61] in building its detailed computational model of coping (i.e., the regulation of negative emotions). They suggest four groups of such strategies: a) attention-related coping, such as seek/suppress information to monitor an unexpected or uncertain state. b) belief-related coping, such as blaming some other agent for a negative outcome rather than oneself. c) desire-related coping, such as ignoring a goal that is unlikely to be achieved. d) intention-related coping, such as avoiding strategy in which an agent takes an action (e.g., run away) from a looming threat [72].

3.2.3 Gross model

Gross identifies two main streams in the formation of emotion regulation strategies, antecedent-focused and response-focused. Antecedent-focused strategies contribute in shaping the emotional response tendencies before they are fully activated while response-focused can be applied to the emotional responses which have already taken place.

The first antecedent-focused regulation strategy in Gross theory is *situation selection*. Here, the target is to choose a situation that would meet with the desired response levels for certain emotions. A person might stay away from a place which provokes a bad memory about a negative event which has had happened before at that specific place. This example depicts a down-regulating possible grief emotion.

The second antecedent-focused regulation strategy is *situation modification.* Based on this strategy, a person tries to modify some controllable attributes of a current situation in order to acquire a different level of emotion. A person who is watching his favorite football match decides to switch to another channel covering the same event but with a broadcaster in his native language to increase his excitement. This example depicts an up-regulating joy emotion.

The third antecedent-focused regulation strategy is *attention deployment.* Based on this strategy, emotions can be regulated without changing the world. Each situation has many aspects at which an individual can shift his/her attention to a certain one in order to manipulate his (her) emotion response level. A person who is watching a TV show might cover his eyes at a horrible scene.

The fourth antecedent-focused regulation strategy is *cognitive change.* This strategy is aimed at changing the cognitive meaning of an event and thus altering its emotional significance. A specific type of cognitive change, which is aimed at down-regulating a negative emotion is reappraisal. Reappraisal means that "the individual reappraises or cognitively re-evaluates a potentially emotion-eliciting situation in terms that decrease its emotional impact"[45].

As of the response-focused category, *response modulation* is an important strategy that can be applied after the manifestation of the emotion. Figure 3.1 depicts five different points at which above different emotion regulation strategies can be applied.

3.2.4 Bosse and colleagues computational model

In their approach, Bosse and colleagues argue that they have conducted a deep and detailed analysis of Gross model and performed several steps in order to formalize Gross theory which is expressed informally (without mathematical or computational notations). For simplicity, they have considered only one specific emotion (e.g., happiness, fear or anger) in their work. They argue that this approach is realistic in the
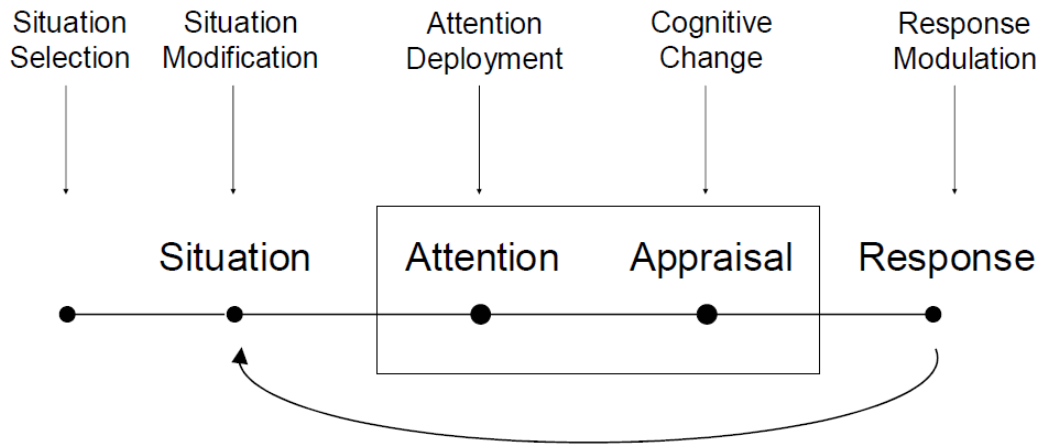
Figure 3.1: According to GROSS model, emotions can be regulated at five distinct points in the emotion generative process [42]

sense that in most cases and based on the circumstances, only one specific emotion is involved directly in the context or is the most dominant among other emotions. Furthermore, the latter approach makes the proposed model generic and applicable regardless of the emotion type that needs to be regulated. In the rest of this article, we refer to this model as "B-model".

3.2.5   Overview of the model

Based on Gross, a hyper emotional state (response) can be regulated using different strategies. Thus, the first step in the modeling process is to declare a set of variables corresponding to the available strategies. In their work, they consider antecedent-focused strategies only (i.e., situation selection, situation modification, attentional deployment and cognitive change). Although they emphasize on the generic attribute of their model which allows adding the other type of emotion regulation strategies (i.e., response-focused), they argue that the first set of strategies are more adaptive.

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In this model, at each point in time, it is assumed that for each element k a certain choice is in effect which has a an emotional value of v_k attached to it. Each emotional component v_k contributes to the emotion response level ERL with an associated weight of w_k. In order to include the momentum in ERL between two consecutive time steps (each time step = 1 time unit), a persistence factor β indicating the degree of persistence of the emotion response level (i.e., the slowness of adjusting) was considered. Someone who can switch between different emotional states rapidly (e.g., who stops being upset right after receiving an apology) will have a low β.

On the other hand, humans often and based on different circumstances look for a certain favorite level for each emotion. This optimum value for a certain emotion varies among different individual and also along the time. In the big picture, most people aim at a relatively high level of positive emotions (e.g., happiness, joy, etc.) while they target a lower level for negative emotions (e.g., fear, anxiety, etc.). In fact, the regulation process begins with a simple comparison between the current emotion response level ERL and the emotion response level aimed at ERL_{norm}. The difference d between these two components is the basis for the amount of adjustments required for each of the elements k. In other words, in each time step, we try to make ERL more convergent toward ERL_{norm} and hopefully make them overlap ($d = 0$) at the end of the simulation. Since different emotion regulation strategies can be applied at different intensities (frequencies) a modification factor α_n was considered to reflect the strength of the adjustments using different strategies. In fact, α_n can be look at as the flexibility or willingness (either conscious or unconscious) of an individual to change his/her emotional value using strategy n. In addition, another variable, γ_n appears in the calculating of the modification factors. In fact, γ_n indicates the personal tendency (flexibility) to adjust the emotion regulation behavior based for a certain strategy. Furthermore, changing behavior in favor of emotion regulation requires some effort. This effort of adjusting α_n for element n, is represented by

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Variable	Meaning
ERL	Emotion response level
ERL_{norm}	Optimal level of emotion
d	Difference between two emotion levels
β	ERLmomentum
w_n	Weight of element n in adjusting ERL
v_n	Chosen emotional value for strategy n
α_n	Modification factor for element n
γ_n	Personal tendency to adjust v_n
c_n	Adjustment cost for v_n
$\triangle t$	Time step

Table 3.1: Summary of model variables

cost c_n. Table 3.1 depicts a list of all related variables used in the model. Some of these variables were considered to remain constant at their initial values during the simulation experiments (particularly $ERL_{norm}, \beta, w_n, c_n, \gamma_n$). The other variables depend on the constant factors and also on each other.

3.2.6 Details of the computational model

The emotion response level and the emotional values are represented in a scale of real numbers between 0 and 2 (where 0 is the lowest emotion response level equivalent to No-emotion state while 2 shows the highest value possible or extremely emotional). Although, this assumption is a considerable simplification of the real problem, but, this approach is common in the area of Artificial Intelligence, especially in the field of Affective computing (e.g.,[52],[37]). The same scale was taken to express and measure the level of emotion that is aimed at for a given emotion. (i.e., ERL_{norm}). As a simple illustration, suppose one wants to influence its state of excitement by going to the wonderland. he/she will have the choice of riding a scary roller coaster or a Taxi Jam(milder ride). This can be represented by introducing two situations, sit_1 and sit_2 , for example with ride1 = 1.5 (since taking the ride of the roller coaster will increase the state of excitement) and ride2 = 0.7 (taking the second ride has

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a lower level of thrill). Moreover, we assume that ERL_{norm} can for instance be 1.2 (i.e., one aims at being excited, but not too excited). In that case, if one's current $ERL_{excited}$ is already high, one will be likely to take Taxi jam ride (i.e., choose sit_2), and vice-versa.

Updating the Emotion response level (ERL)   The following difference equation is used to calculate the new value for emotion response level at the end of each time step:

$$ERL_{new} = (1 - \beta) * \sum_n (w_n * v_n) + \beta * ERL$$

The new emotion response level (ERL_{new}) takes into account the emotional impact of each emotion component v_n after applying emotion regulation strategies This is calculated by the weighted sum of $\sum w_n * v_n$. By normalization, the sum of all weights w_n is taken to be 1. β is the persistence factor which is the proportion of the old emotion response level (ERL) that persists in the new emotion response level (ERL_{new}). Based on Gross[44], emotion regulation strategies applied at an earlier stage would have a larger impact on the ERL. In order to implement this fact, those emotion components that occur at an earlier point in time in the emotion regulation process were granted higher weights.

Updating the emotional values   The emotional components of each strategy v_n are on their turn recalculated at each time step by the following set of difference equations:

$$d = ERL - ERL_{norm}$$

$$\triangle v_n = -\alpha_n * \frac{d}{d_{max}} \triangle t$$

$$v_{n_{new}} = v_n + \triangle v_n$$

Adaptation of modification factors   The experience that we acquire over time by trying different strategies in different situations and evaluating the outcomes (either consciously or subconsciously) in a subsequent process poses a major and valuable component in everyone's cognitive and emotional knowledge. In the suggested model, this source of evaluation feedback was considered by letting the modification factors associated with emotional components (strategies) be assessed over a period of time. Therefore, the success of an emotion regulation strategy is evaluated, and based on this assessment, the willingness to change behavior in favor of that emotion regulation strategy can be adjusted. The following evaluation function is used:

$$Eval(d_{t-(t+p)}) = mean(abs(d_{t-(t+p)}))$$

Here $Eval$ function, takes the absolute difference between the actual and expected levels of emotion for all time points during the time interval of t until $t + p$ (where currently $p = 5$). The arithmetic mean value of these absolute differences gives the value of the evaluation function. Until the model has done enough steps to perform this evaluation function for two different periods of time, α_k's are kept constant. After that, the evaluation function is used to adjust the modification factors α_k using the following difference equations:

$$\triangle\alpha_n = \gamma_n * \left(\frac{\alpha_n}{\alpha_n+1}\right) * \left(\frac{Eval(d_{new})}{Eval(d_{old})} - c_n\right)\triangle t$$

$$\alpha_{n_{new}} = \alpha_n + \triangle\alpha_n$$

In these formulas, $\alpha_{n_{new}}$ is the new modification factor an and γ_n represents in a numerical manner the personal flexibility to adjust the emotion regulation behavior. When γ_n increases, in a proportional manner $\triangle\alpha_n$ will increase, and α_n an will change more. The part $\frac{\alpha_n}{\alpha_n+1}$ assures that $\triangle\alpha_n$ is more or less proportional to α_n. The denominator $\alpha_n + 1$ prevents α_n from under or over-adaptation when it gets very high. Furthermore, d_{new} is the mean value of d in the last time interval, and d_{old} is the mean value of d in an older time interval. The ratio $Eval(new_d)/Eval(old_d)$ will be

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smaller, if the actual level of emotion response deviated relatively more from the level of emotion aimed at in the older interval than in the newer interval. Currently, for the new interval the interval from $t-5$ to t is taken, with t the current time point, and for the old interval the interval from $t-10$ to $t-5$. if $Eval(new_d)/Eval(old_d)$ is smaller, $\triangle\alpha_n$ will be lower. Finally, c_n represents the costs of adjusting the modification factor for element n. When there are higher costs to adjust an, the value c_n is higher, and $\triangle\alpha_n$ will be lower. However, due to the prevention from under or over-adaptation, α_n will never reach a value under 0, even with high costs.

3.2.7   Our approach

The major motivation for our approach that inspired us to have a follow-up on B-model was the fact that, in several occasions it oversimplifies the processes involved in emotion regulation and lacks the dynamism in human adaptive assessments. This shortcoming is much related to several core parameters of the system that were considered constant. (such as the persistence factor). Furthermore, it underestimates the differences among different individuals in the process of emotion regulation. Their model clearly ignores such distinctions between different people (e.g., by considering a fixed strategy cost for all individuals). Therefore, in our model the main attention was given to the expansion of the dynamism and adaptivity of the proposed formulas in the original study as well as to some extent to take into account the relevant distinctions between different people.

In brief, we argue that some people might not be able to measure their emotional response level or they might not have a clear idea about their favorite emotion response level in different scenarios. We address this fact by adding a random number to both ERL and ERL_{norm} in order to shrink down the gap between our figures and the real ones. Furthermore, we believe that the persistence factor (β) can not be considered constant. Some people are capable of switching between different emotional states in

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a relatively short period while for some others it might take much longer. A person who did bad in an exam might decide to do his favorite sport right after the exam to get ride of his/her grief emotion while for another person it might inhibit him/her from positive feelings and even activities for the next several days. This is much related to the differences in personality and also mood of individuals. Therefore, in our model we consider the persistence factor as a function of mood and personality. In order to express mood and personality in a simple manner, we adopt the approach taken in ALMA (A Layered Model of Affect) [36] with some changes. With regards to the costs associated to each emotion regulation strategy, we argue that these costs can not be considered fixed as well. In our approach, we link those costs to domain knowledge of the individual. A detailed elaboration about this approach is provided in section 5.1.4.

The detailed model In this section, we propose an augmented version for the equations of B-model. In our model, an agent entity refers to an individual who tries to modulate his/her emotion response level. Also, base model refers to B-model. Furthermore, a time step in our model equals one time unit (i.e., second, minute, hour, day, etc.). Last, we assume that the environment will not change during the simulation time and thus no events are occurring. This assumption was made from the perspective that we are trying to simulate the modulation of an already existent emotional response based on the internal perception and assessment of the situation-response cycles involved in emotion regulation process made by the individual him/her self. Thus, this study is not intended to track the role of different events in eliciting or modulating certain emotions. Building such a model will pose an extension of our current model and is planned for future work.

Updating emotion response level In order to measure the emotional response level at each time step, the same formula of the base model was used with the differ-

ence that the persistence factor β is not a constant value but rather is a function of the mood and personality of the agent at each time step. Therefore,

$$ERL_{new} = (1 - \beta) * \sum_n (w_n * v_n) + \beta * ERL \qquad (1)$$

$$\beta = f(mood, personality) \qquad (2)$$

In order to incorporate a component of mood and personality in our model, we use the approach taken by Gebhard in his layered model of affect (ALMA)[36]. In ALMA, three types of affect are considered. Emotions as short term, mood as mid term and personality as long term affect all play a role in the formation of the agent affective states. ALMA adopts the approach of Mehrabian [76] in which he describes the mood with the three traits of pleasure (P), arousal (A) and dominance (D). In order to implement the PAD mood space, three axes ranging from -1.0 to 1.0 were used. Hence, the mood is described based on the classification of each of the three mood axises: +P and −P to reflect pleasant and unpleasant, +A and −A for aroused and unaroused, and +D and −D for dominant and submissive. These three discrete factors builds the so called PAD space in which each point and based on its coordinates in this three dimensional system, represents a mood state called mood octant (such as relaxed, bored, anxious, etc. see Table 3.2). Furthermore, in order to initialize the mood states, ALMA uses a mapping between the PAD space and the long term personality based on the five factor model of personality [74](i.e., Openness, consciousness, extra-version, agreeableness and neuroticism). Although emotions are not the only factor in mood changes and there are some other players in this field [80], for simplicity, we consider only the role of emotions in shaping the mood of the agent. Using this approach, a mapping between emotions and the PAD space of mood was suggested in ALMA. Table 5.3 depicts partial mapping between the OCC emotion model [83] and the PAD space. In our model, we exploit this approach to encode the mood of the agent into a single quantifier through calculating the Euclidean distance of each emotion to the origin of the PAD three dimensional space. This distance can

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+P+A+D Exuberant	-P-A-D Bored
+P+A-D Dependent	-P-A+D Disdainful
+P-A+D Relaxed	-P+A-D Anxious
+P-A-D Docile	-P+A+D Hostile

Table 3.2: Mood octants of the PAD space[36]

also be expressed as the magnitude of the PAD vector for each emotion. In Figure 2.2, vector $\overrightarrow{OP}$ shows the position of emotion pride on the PAD coordinate system.

In order to express β as a function of these mood quantifiers, we calculate the mean value of PAD vectors for all positive emotions in OCC emotion model (i.e., a set of 11 emotions, such as love, pride, hope, etc.) as well as for all negative emotions (i.e., a set of other 13 emotions such as fear, anger, shame, etc.). These mean values will be considered as a general mood indicator of the agent. Hence, only the type of emotion (either positive or negative) would be required to be passed to the system. Thus, we have:

$$\sum \overrightarrow{PAD}_{Pos-emos} = 5.81$$

$$Mean(\overrightarrow{PAD}_{Pos}) = \frac{\sum \overrightarrow{PAD}_{Pos-emos}}{\#pos-emos} \implies 5.81/11 = 0.53$$

$$\sum \overrightarrow{PAD}_{Neg-emos} = 7.85$$

$$Mean(\overrightarrow{PAD}_{Neg}) = \frac{\sum \overrightarrow{PAD}_{Neg-emos}}{\#neg-emos} \implies 7.85/13 = 0.61$$

Hence, equation (2) to express the value of β can be rewritten as follows:

$$\beta = \begin{cases} 0.53 & if\_positive\_emotion \\ 0.61 & if\_negative\_emotion \end{cases} \quad (2)$$

Therefore, in our model the value for persistence factor unlike the original model which was picked up as a constant with value 0.7 without any reasoning, will be a simple function of the mood of the agent.

Emotion	P	A	D	Mood octant
Admiration	0.5	0.3	-0.2	+P+A-D Dependent
Anger	-0.51	0.59	0.25	-P+A+D Hostile
Disliking	-0.4	0.2	0.1	-P+A+D Hostile
Disappointment	-0.3	0.1	-0.4	-P+A+D Anxious
Distress	-0.4	-0.2	-0.5	-P-A-D Bored
Fear	-0.64	0.6	-0.43	-P+A+D Anxious
FearsConfirmed	-0.5	-0.3	-0.7	-P-A-D Bored
Gratification	0.6	0.5	0.4	+P+A+D Exuberant
Gratitude	0.4	0.2	-0.3	+P+A-D Dependent
HappyFor	0.4	0.2	0.2	+P+A+D Exuberant
Hate	-0.6	0.6	0.3	-P+A+D Hostile

Table 3.3: Mapping of some OCC emotions into PAD space[36]

Difference between the two emotion response levels   As discussed before, the difference between emotion response level ERL and the aimed at emotion response level ERL_{norm} at any point in time poses the main motor to direct the process of choosing the more effective strategies in emotion regulation. Considering the fact that these two variables have qualitative nature, in order to express them numerically, the agent would need to estimate them. In our model we consider the interval of [0...2] to express the level of the emotional response, in which 0 means completely neutral (unmentioned) and 2 shows an extremely emotional agent. In reality, most people can not accurately measure (estimate) their current emotional response values. This is also the case for the favorite emotional response level where they might not have a specific level in mind rather than simply they seek for instance more excitement. In order to take this fact into account, we add a random number to both of these quantities. This random number reflects a possible inaccuracy in measuring the current ERL or in estimating ERL_{norm}. We set this variable to 5% in either way (i.e., more or less) for both quantities thus, it reflects a total of error range between $[-0.1...0.1]$ in d.

$$d = ERL - ERL_{norm} + Rand \qquad (3)$$

With regards to ERL_{norm}, we assume that it will remain constant during the simulation. This assumption was made for the sake of getting a more robust analysis for d since it enables us to track the values of d more accurately. Although we believe that some other factors such as mood and personality play a role in determining the value of ERL_{norm} but in fact, it would be necessary to include those factors in ERL itself as well in order to robustly measure the difference d. As will be mentioned later, this issue is one of extensions that will be considered in the future work.

Updating emotional components   In order to specify the emotional contribution level of each regulation strategy v_n in the total emotion response level ERL, we use the same approach taken in the original study. Therefore, we have:

$\triangle v_n = -\alpha_n * \frac{d}{d_{max}} \triangle t$ 　　(4)

$v_{n_{new}} = v_n + \triangle v_n$ 　　(5)

How adaptive the modification factors are?   The modification factors are the most critical elements that provide the required dynamism and adaptivity for the system. As elaborated before, a modification factor α_n reflects the willingness to change behavior by adopting emotion regulation strategy n. In other words, it gives a measure for the speed with which different emotional values are changed over time. In our model, once again we adopt the same difference equations for updating $\alpha'_n s$. Here, we use the historical (temporal) knowledge to record the specifications and outcomes of the past situations. Agents can use those recorded events from history knowledge as a mean for guidance in selecting a regulation strategy. As explained in the base model, the historical knowledge approach was applied using the moving average of d in the last two consecutive equal time intervals. Therefore:

$\triangle \alpha_n = \gamma_n * \left(\frac{\alpha_n}{\alpha_n + 1}\right) * \left(\frac{Eval(d_{new})}{Eval(d_{old})} - c_n\right)\triangle t$ 　　(6)

In the above equation, γ_n as the personal flexibility to adjust the emotion regulation behavior is considered constant similar to the base model.

$$\alpha_{n_{new}} = \alpha_n + \triangle\alpha_n \qquad (7)$$

$$Eval(d_{t-(t+p)}) = mean(abs(d_{t-(t+p)})) \qquad (8)$$

But, beside historical knowledge, we believe that domain specific knowledge as a more effective knowledge component needs to be incorporated as well in the adaptation process of the modification factors. Domain specific knowledge is an important knowledge source which reflects the degree of professional knowledge and skills acquired through (either formal or informal) education and training in a specific field/domain by the agent. For instance, the level of fear (panic) a nurse experiences when facing a critical medical situation would be much lower than that of an ordinary person with no experience in the field of medicine. In this example, the relatively calm state of the nurse is related to both historical knowledge (getting used to) and domain specific knowledge (cognitive aspects and skills). In our model, we link the domain specific knowledge to the cost parameter associated with each strategy. As explained before, there is a cost of c_n associated to adjusting the modification factor for element n. We argue that adjusting the modification factor in favor of a regulation strategy for a knowledgeable agent will result in lower cost. This can be analyzed from two perspectives. First, considering situation selection strategy for instance, a knowledgeable agent would spend less efforts in the process of choosing the preferred situation which results in having a lower cost (e.g., shorter time). Second, the probability that the selected situation was better for the agent is higher and thus more beneficial (with less cost) in the sense that such an agent will have a better assessment capabilities in evaluating different available situations and identifying the better one. Hence, we have:

$$\triangle C_n \propto f_{Knowledge_{strategy\_n}}$$

Different fitness functions can be used to express the domain knowledge. It can be argued that since domain knowledge is closely related to a learning process, we can use a learning curve described in [94] with some changes. Such a modified sigmoid function is expressed in equation (9). The graph of this function is depicted in Figure 3.2. Here, the maximum knowledge that can be reached is 1 (i.e., complete knowledge). The exact value of parameter a which is intended to influence the speed (steepness) of the function is left for the experiments. In order to build the equation that expresses the changes in strategy costs $\triangle C_n$ in terms of the domain knowledge function, we consider two components in such an equation. The first component shoes an inverse proportion between the changes in knowledge amount and that of the costs. As elaborated before, a knowledgeable agent will have a lower cost in the regulation process. This is reflected in the first part of equation (11). Coefficient φ is a constant that translates the domain knowledge values into associated costs and prevents the cost values from over or below quantities. The negative sign in φ reflects an inverse proportion with the cost. Furthermore, $\triangle f_{Knowledge_{strategy\_n}}$ shows the change in knowledge levels at two consecutive steps.

The second component on the other hand, has a direct proportion with the cost and reflects an over confidence side effects. We argue that over confidence has an adverse potential role with regards to associated costs. For instance, an over confident nurse might pay less attention to some of his/her critical tasks which might result in forgetting steps or making mistakes in performing them and thus increase the final cost. In this component, the positive sign of coefficient ϕ indicates that such an over confidence will have a direct proportion with the associated cost. From the equation itself, it is obvious that the possible negative impacts of over confidence would appear at times close to the end of the simulation (at top levels of acquired knowledge). In order to determine the values for φ and ϕ, we argue that since the maximum value for the knowledge function is 1, therefore the maximum for $\triangle C_n$ will be $-\varphi$ (the second

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component is always positive). Also by considering the fact that C_n can not be less than 0, thus a suitable value for φ will be $C_{n_{init}}$ (i.e., the initial cost of strategy n). With regards to ϕ, in order to stay in line with our previous assumptions, we consider a maximum over confidence level of 10%. Since a possible over confidence state usually appears at very high level of knowledge, by looking at Figure 3.2, we observe that at almost step $= 80$, the agent reaches its top level of knowledge. Since $ln(80) \simeq 4.4$, therefore $\phi = a/44$. Since in almost all of our experiments we have $a = 10$, therefore $\phi = 0.227 \simeq 0.2$. Here, when step $= 1$, $ln(1) = 0$ which means that a non-knowledgeable agent will have an over confidence level of zero which is completely logical.

$$f_{Knowledge_{strategy\_n}}(t) = \frac{1}{1+a*\exp(-t/a)} \qquad (9)$$

$$C_{n_{new}} = C_n + \triangle C_n \qquad (10)$$

$$\triangle C_n = ((-\varphi * \triangle f_{Knowledge_{strategy\_n}}) + (\phi * \triangle f_{Over\_confidence_{strategy\_n}}))\triangle t \qquad (11)$$

$$\triangle f_{Knowledge_{strategy\_n}} = f_{Knowledge_{strategy\_n}}(t) - f_{Knowledge_{strategy\_n}}(t-1)$$

$$f_{Over\_confidence_{strategy\_n}}(t) = 1/a * \ln(t)$$

$$\triangle f_{Over\_confidence_{strategy\_n}} = \triangle f_{Over\_confidence_{strategy\_n}}(t) - \triangle f_{Over\_confidence_{strategy\_n}}(t-1)$$

3.2.8   Simulation experiments and discussion

In order to assess the behavior of our suggested model under different circumstances and its consistency with Gross theory, as well as to compare its performance against the base model, a number of simulation experiments have been conducted. Various types of cases were addressed such as: the regulation process with or without considering mood states. Modification factors with fixed values versus those associated with historical knowledge. Fixed regulation costs versus those expressed in terms of
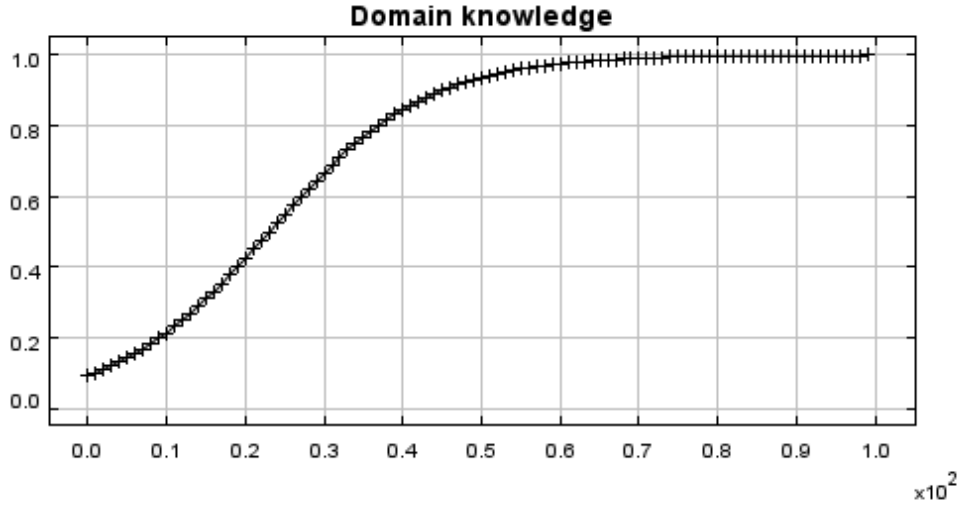
Figure 3.2: Domain knowledge function with $a = 10$: Knowledge levels over time

Table 3.4: Values of parameters used in the simulation

Variable	Fixed value	Variable	Initial value
ERL_{norm}	0.7	ERL	1.85
β	$\begin{cases} 0.53 & pos\_mood \\ 0.61 & neg\_mood \end{cases}$	v_1	1.90
w_1	0.35	v_2	1.85
w_2	0.30	v_3	1.80
w_3	0.20	v_4	1.75
w_4	0.15	$c_1 - c_4$	0.10
$\gamma_1 - \gamma_4$	0.05	$\alpha_1 - \alpha_4$	$\begin{cases} 0.15 & optimal \\ 0.01 & u\_reg \\ 0.50 & o\_reg \\ var & adp\_\alpha \end{cases}$

domain specific knowledge. The different cases were established by taking different settings for some of the system parameters. Table 3.4 gives a summary of the setup and values for the system parameters. Based on Gross process model, those strategies applied at an earlier time in the regulation process will have a bigger influence on the regulation process. This was implemented in our model by assigning a descending weights to later strategies.

Experiment 1 and 2: constant versus variant modification factors In these two experiment, we compare the values of the emotion response level ERL and
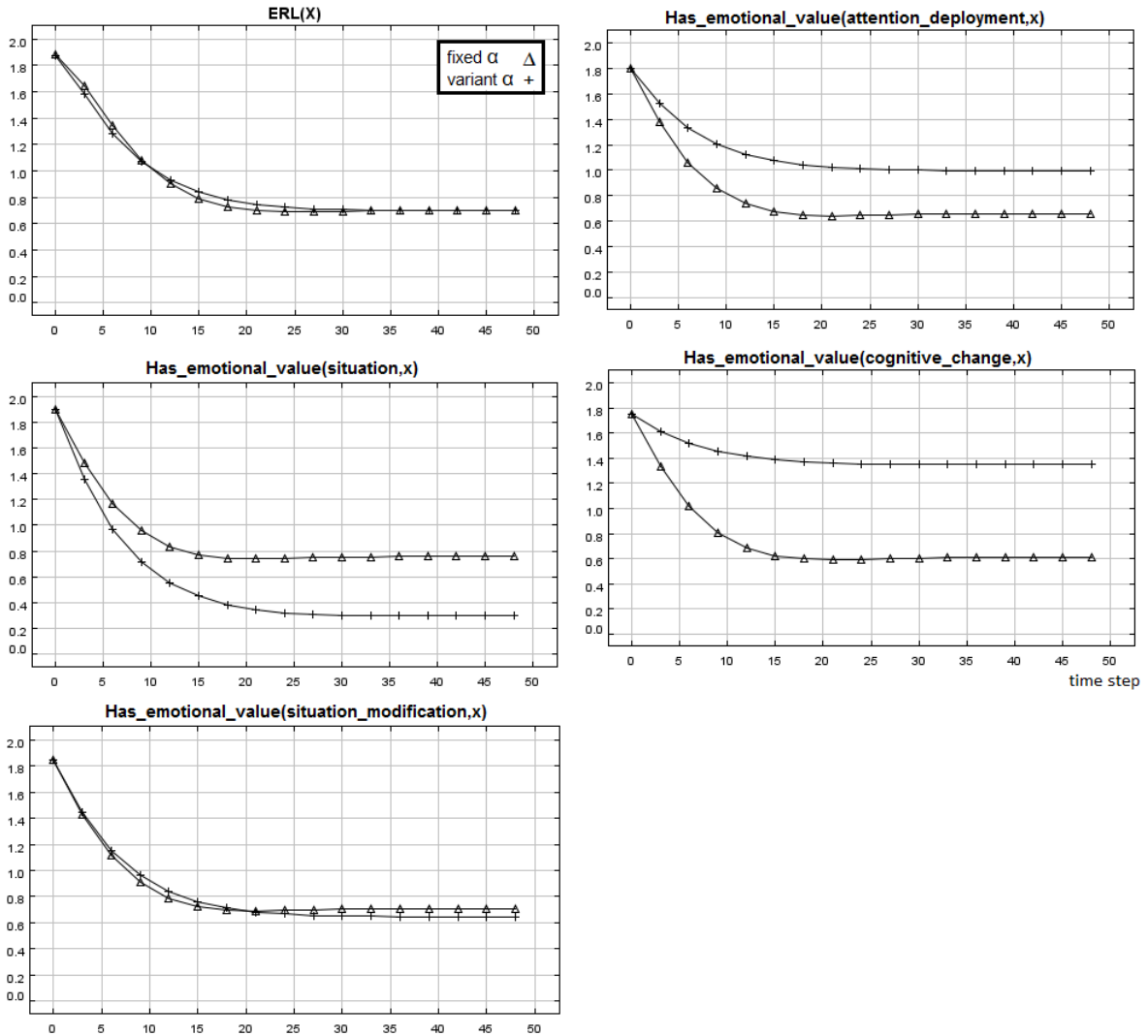
Figure 3.3: Results for experiments 1 and 2: fixed versus variant α_n. The graphs depict ERL and $v_i's$

all emotional components of $v_n's$ in two different scenarios of having a fixed versus variant $\alpha_i's$. The results for both experiments are reflected in Figure 3.3. In the first experiment, all modification factors to be constant and all equal to 0.15. After trying different values for $0 \prec \alpha \prec 1$, we found out that at $\alpha = 0.15$, the regulation seemed optimal (i.e., with regards to the speed and smoothness of ERL and $v_n's$). Based on the results' graphs, we observe that at almost step= 25, ERL manages to reach its target level (i.e., ERL_{norm}). As expected, since all regulation strategies had the same modification factors, the willingness of the agent to change its emotional behavior for the sake of regulating its emotion is divided equally among all strategies. Those strategies which had a slightly lower initial values (e.g., v_4) have ended up slightly lower than those with higher initial values (e.g., v_1), though all with almost same difference. These results are clearly in line with one of Gross rules stating that "Emotion approaches norm monotonically" [13]. The results of this experiment have no noticeable difference with those obtained in the base model.

In the second experiment, we consider different values for the modification factors in order to test a possible preference for those regulation strategies with higherα. Thus, we have: $\alpha_1 = 0.20$, $\alpha_2 = 0.15$, $\alpha_3 = 0.10$, $\alpha_4 = 0.05$ Based on results' graphs, we see that ERL has reached its aimed at level with almost the same speed of experiment 1 but we notice that unlike experiment 1 in which all regulation strategies had the same contribution in the regulation process, those strategies with higher modification factors had a bigger influence on ERL. For instance, we see that situation selection strategy went down from 1.90 (i.e., its initial value) to less that 0.4 at step=50. during the same time, the cognitive change strategy experienced a change of as low as 0.35 (from 1.75 to 1.40). This is clearly related to its low α. Again, these results and graphs are much in line with the second rule of Gross theory since we see clearly that those strategies with higher values of α managed to reach to the target

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levels faster (i.e., with different speed). Here, our results were very much similar to those of the base model.

Experiment 3: The role of mood Figure 3.4 shows the regulation process in the ERL of (a) an agent with a positive mood and (b) another agent with a negative mood. We notice that the agent with a positive mood regulates its emotion more smoothly than that of an agent in a negative mood. At almost time step = 24, good mood agent manages to reach its ERL_{norm}while for negative mood agent this does not occur before step 35 (although it passes through this level with a sharp trend at an earlier time but it does not get stable at that level before time step =35). This confirms our prediction of having a faster and smoother regulation process for a positive thinker agent (i.e., with a good mood). This finding can be linked to the second rule in Gross theory which states that "Emotion approaches norm with specific speed" [13]. Here no comparison with the B-model was possible since the mood attribute was not considered in the original study.

Experiment 4: Over and under regulation In this experiment, in order to assess the performance of over and under regulation processes, we set the modification factors for all elements α_n to very high and very low levels. In particular, we set $\alpha_n = 0.4$ which means that the agent subject has a relatively high flexibility in all regulation strategies. We expect to see an over-regulation scenario (i.e., a too high adjustment of behavior). Figure 3.5, part (a) shows the behavior of the ERL. In this case, ERL starts to decrease rapidly right after the beginning of the experiment and it goes below the aimed at level of 0.7. It can be seen from the graph that at step = 9, it reaches its minimum of 0.45 (i.e., 0.25 below the target value). After this point, the ERL starts to rise until it reaches its target value of 0.7 at almost step=22 and stays around the target value for the rest of the simulation. This confirms that a high level of flexibility in emotion regulation results in over-regulation. A similar
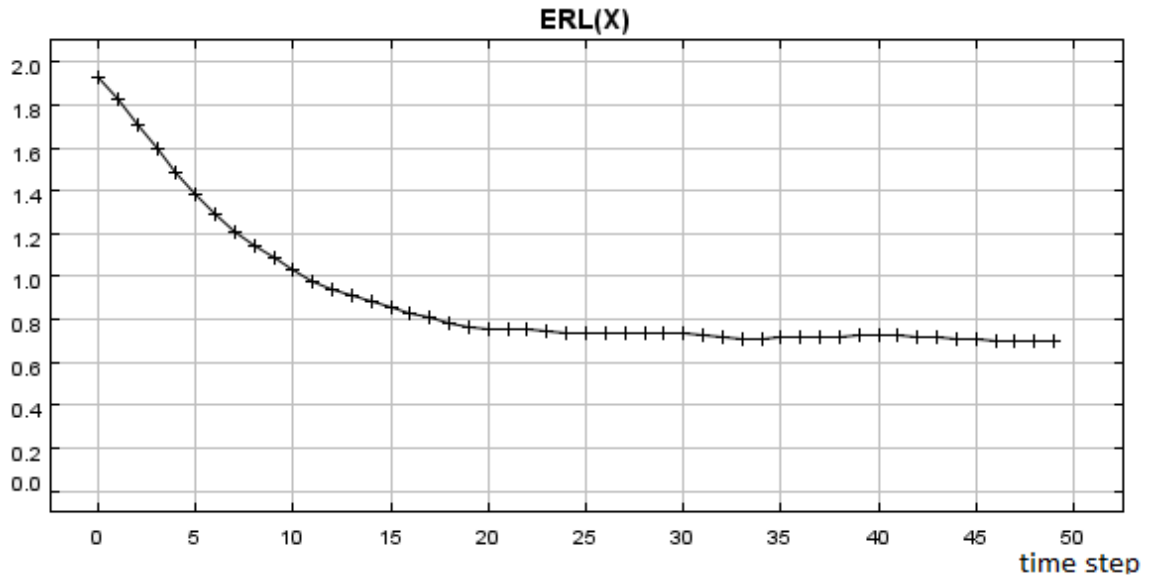
(a) Agent in a good mood
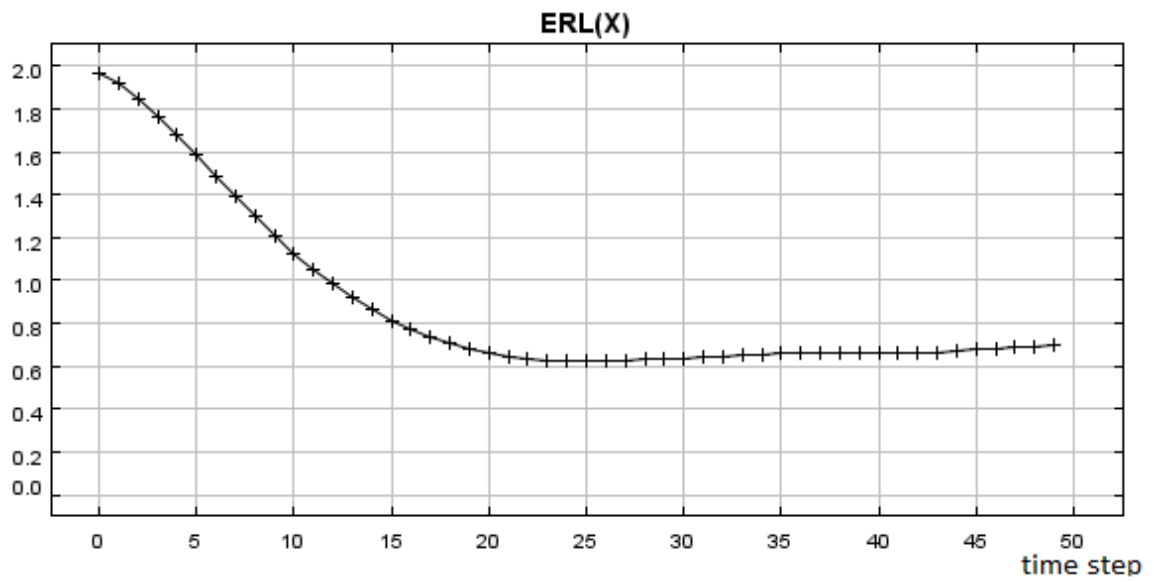
(b) Agent in a bad mood

Figure 3.4: The role of mood state in the regulation process

experiment was performed using a very low value for the modification factors. Here we set all $\alpha_n = 0.01$. the graph for the ERL is depicted in Figure 3.5, part (b). This time we expect to see an under_regulation scenario. Here, the ERL decreases very quickly resulting in under-regulation state. We observe that at step=40, it has reached 1.5 (i.e., a decrease of only 0.4 from the initial value). This trend stays till the end of the simulation and at step=100, the emotion response level touches 1.0. Therefore, it did not manage to meet with its target level.

We need to add that, all above experiments were in line with the third rule of Gross which states that "Early strategies are more effective" [13]. This was obvious through the fact that changes made to the modification factor of those strategies applied at an earlier time (such as situation selection) resulted in a more significant change in the ERL of the agent.

In all of the above experiments (except the mood case), our results did not show a significant difference with those obtained from the base model. In fact, in some cases, base model's results even showed a smoother trend in ERL and v_n graphs. This did not pose a surprise for us since the difference between our values for the persistence factor β and that of their approach is not significant. In addition, the smoother trend of ERL and $v'_k s$ in the original model is clearly related to their assumption of having an absolutely accurate prediction and measuring of the emotional values. Yet our model which is more dynamic and sensitive to the changes in the internal states of the agent (as elaborated in section 5.1) managed to show a very similar performance to the base model.

Experiment 5: Cost function In this experiment which poses the back bone of our work, we include the different knowledge components in the process of emotion regulation. In previous experiments, the cost was considered to remain fixed during the simulation and also was presumed equal among all regulation strategies. In this
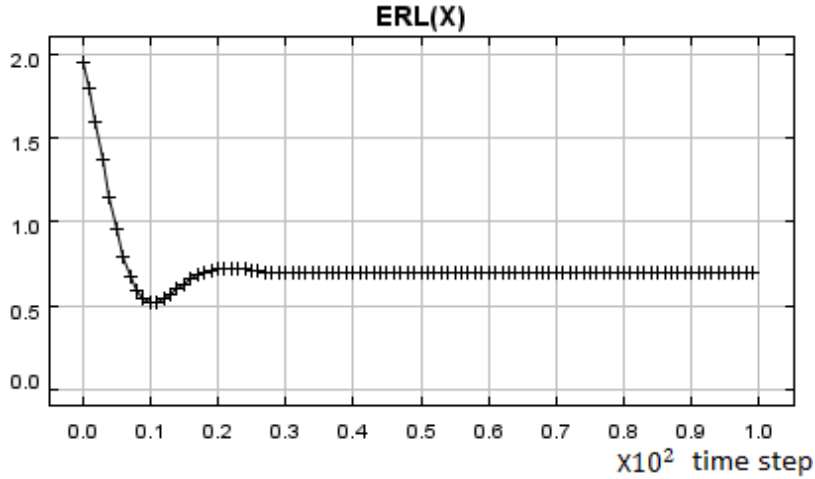
(a) over_regulation scenario
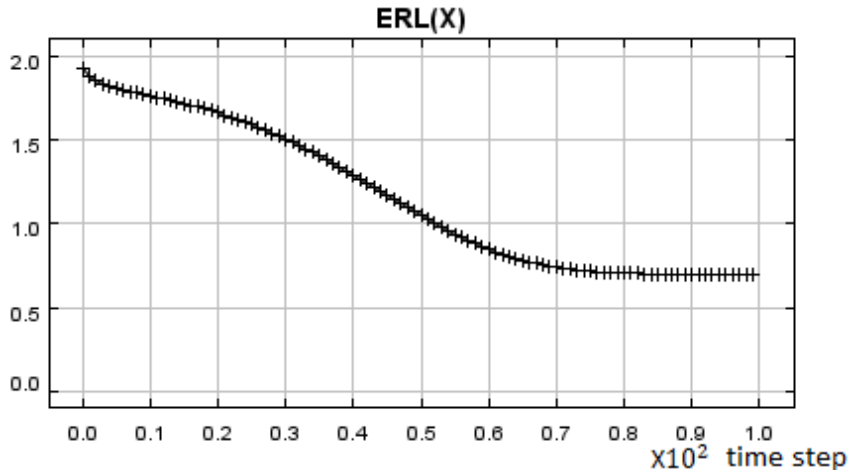
(b) under_ regulation scenario

Figure 3.5: Extremely high versus extremely low values for the modification factor α_n

experiment, we link the cost of the strategies to the domain specific knowledge of the agent about each strategy. (See equations 9-11 in section 5). In fact, this knowledge component will work beside the historical knowledge which was considered in the base model. Here, we choose $a = 10$, therefore ϕ will be 0.2, while the level of the knowledge at the beginning of the simulation will be 0.1. This value makes sense since everybody has at least a low level of knowledge even before getting specialized or trained in a field. Furthermore, the initial values for allα_n in both models was set to 0.05, while the initial cost for all strategies was set to 0.2. In addition, the changes in costs for all strategies in the base model beside all strategies except situation selection in our

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Figure 3.6: The performance of the regulation process with costs lined to the domain knowledge of the agent

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model were set to use historical knowledge only, while the cost changes for situation selection strategy was linked to both historical and domain specific knowledge. The results are reflected in Figure 3.6. We observe clearly that the ERL in our model managed to reach to its target level much faster than the base model, particularly at step=30 while the ERL for the base model did not meet with its target value before step =60. Also, the graph of situation selection strategy shows that its level was much below other strategies and thus had a more significant contribution in the rapid regulation process in ERL. Here, only one strategy (i.e., attentional deployment-aspect) from the set of those use only historical knowledge was shown since the other two have more or less a similar performance. With regards to the situation selection graph, we notice several jitters around and after step =65. In fact, these are much have to do with the bigger component of over confidence as elaborated in the model design before. These findings are very much consistent with the fourth rule in Gross model which states that "High strategy flexibility leads to large adjustments" [13]

3.2.9 Conclusion and future work

In this paper, a computational model for emotion regulation strategies based on Gross theory developed by Bosse and colleagues was considered. According to Gross [45], humans use strategies to influence the level of emotional response to a given type of emotion. Based on this approach, emotion can be regulated at five points in the emotion generative process: (a) selection of the situation, (b) modification of the situation, (c) deployment of attention, (d) change of cognition, and (e) modulation of experiential, behavioral, or physiological responses. In Gross process model for emotion regulation, the hypothesis and inferential rules are described informally.

Bosse and colleagues have built a computational model based on the above process model. Although they argue that their computational model is consistent with Gross theory and has successfully managed to match with the inferential rules within that

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theory, we believe that it has several shortcomings. These shortcomings inspired us to have a follow-up on their model and enhance it in different dimensions.

In brief, we argue that the persistence factor can not be constant and hence, in our model it was defined as a function of mood and personality. The findings from our experiments were consistent with the tenet that a person in a bad mood tends to internally impede the modulation in his/her emotional state through maintaining a bigger portion of the previous emotion response ERL in the new emotion response ERL_{new} and thus to have a slower emotion regulation process. While an agent with a positive mood will exhibit more cooperative behavior and thus has a relatively faster regulation process. Furthermore, we believe that people are generally unable of measuring (predicting) their precise emotional levels and often they can only identify their emotion type with an estimation of its intensity. Hence, using fixed values for the emotion response levels seems unrealistic. In our model, this fact was taken into consideration by declaring a random number in a certain range in order to regulate the measurements of the emotional response levels. The major achievement of our model comes from injecting a component of domain specific knowledge into cost calculations associated with the regulation strategies. In the original study only a component of historical knowledge was considered, while we believe that other knowledge categories, especially domain specific knowledge plays an important role in the associated costs. Domain specific knowledge includes all those knowledge and skills obtained though either formal or informal education and training. By including this component, we managed to build a more realistic and dynamic model while it is still completely consistent with Gross theory.

One direction for future work would be to address other constant parameters of the system (such as ERL_{norm}) and make them dynamic. Furthermore we will consider a direct personality component in all relevant parameters (such as the persistence factor β). In addition, the suggested model can be more comprehensive with the

addition of event items. Moreover, other knowledge categories such as normative and situational can be considered in computing regulation costs. Finally, we would consider validations for the suggested model with actual data from case studies.

3.3 A Fuzzy Logic Computational Model for Emotion Regulation Based on Gross Theory

Abstract. Emotion regulation looks into methods and strategies that humans use in order to control and balance their possible extreme levels of emotions. One important challenge in building a computational model of emotions is the mainly non-quantitative nature of this problem. In this paper, we investigate a Fuzzy logic approach as a possible framework for providing the required qualitative and quantitative description of such models. In our proposed fuzzy computational model which was constructed based on Gross theory for emotion regulation, beside the fuzzy structure, it includes a learning module that enhances the model adaptivity to environmental changes through learning some relevant aspects such as patterns of events' sequences. The results of the simulation experiments were compared against a formerly presented non-fuzzy implementation. We observed that the agents in our proposed model managed to cope better with changes in the environment and exhibited smoother regulation behavior. Moreover, our model showed further consistency with the inferential rules of Gross theory.

3.3.1 Introduction

According to recent research findings, emotions pose a vital component in the human cognitive activities [42]. They have deep impacts on the memory functions, decision making and judgments [32]. In addition, Some neurological studies such as [27] showed that those suffering from complications in expressing/balancing their emotions, often perform poorly in making decisions. This leads to serious difficulties in establishing effective relationships with other members of their communities, which consequently

endanger their social roles. Furthermore, some psychologists were able to track these negative impacts in several forms of depression and even psychopathology[42].

Emotion regulation strategies address the potential risk of having inappropriate level of emotions. Gross in [45] states that "Emotion regulation includes all the conscious and non-conscious strategies we use to increase, maintain, or decrease one or more components of an emotional response." In other words, they are aimed at making "changes in emotion latency, rise time, magnitude, duration and offset of responses in behavioral, experiential or physiological domains" [42].

This article proposes a fuzzy logic computational model for emotion regulation strategies based on Gross theory. In the next section, we review some of the recent computational models of emotions and briefly discuss Gross emotion regulation strategies. Section 3 introduces our fuzzy approach for emotion regulation problem and highlights its benefits and distinctions from a non-fuzzy model. Next, a description about the conducted simulation experiments is given, followed by discussion and conclusion sections.

3.3.2 Emotions

3.3.2.1 Computational models of emotion

Affective computing in general and computational models of emotion in particular, have recently managed to attract many researchers from a wide spectrum of science fields. These models have several applications in Psychology, Biology and Neuroscience at which such models are used to test and improve formalization of the underlying hypothesis. With regards to robotics and computer gaming fields, many applications for these models can be named. Additionally, these models can make significant improvements to HCI applications, such as increasing the believability of virtual agents by exhibiting a maximal degree of human-like behavior.

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CoMERG is the abbreviation for Cognitive Model for Emotion Regulation based on Gross. It was developed by *Bosse et al.* [13]. This model includes some differential equations combined with inferential rules, and it aimed at simulating the dynamics of Gross emotion regulation process model. An enhanced version of CoMERG was suggested in [112], which focuses on improving the realism and agent's adaptation capabilities to the environmental changes. The results from our proposed fuzzy model were bench-marked against the results obtained from this non-fuzzy implementation.

FLAME [30] is another OCC based appraisal model, which uses the principles of fuzzy logic to describe the process model of emotion. FLAME consists of several learning algorithms used for agent's adaptation purposes. Some of the concepts and formulas of FLAME were adopted in parts of our proposed emotion regulation model.

3.3.2.2 Emotion regulation strategies

Gross identifies two categories of strategies that can be used in the regulation process. They are antecedent-focused and response-focused strategies. Antecedent-focused are those strategies that can be used for the regulation process before an emotional response has fully activated. Response-focused, on the other hand, are those strategies that can be used for the regulation process once certain emotional responses have already appeared as a result of an event or internal state.

The first antecedent-focused regulation strategy in Gross theory is *situation selection*. This strategy is aimed at selecting a situation among available options that best meets with the desired level of a certain emotional response of the person. *Situation modification* is the second strategy in this category and it does not try to change the world but rather to alter some controllable aspects of the situation. In *attention deployment* strategy, we try to focus on positive and distract ourselves from negative aspects of the current situation. In *cognitive change*, the person tries to look at undesired events from a different perspective in order to change the negative cognitive

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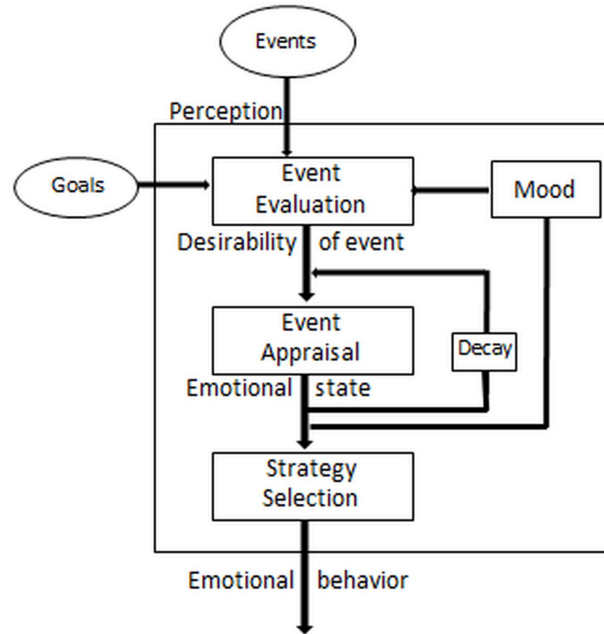
Figure 3.7: Emotion regulation process

meaning of them. As of the response-focused category, *response modulation* is an important strategy that can be applied after the manifestation of the emotion.

For brevity, we do not elaborate more on Gross theory, and interested readers are referred to [42, 45].

3.3.3   Proposed computational model

In order to build a computational model for emotion regulation based on Gross informal process model, we propose a regulation architecture described in Figure 3.7. As it can be seen from the diagram, we consider three major components involved in the regulation process. The first module, *Event Evaluation* is the component that perceives external events and calculates the desirability of each event based on the goals and the internal emotional state of the agent.

The output from Event evaluation unit, i.e., the event's desirability value will be passed to the *Emotion Elicitation* unit at which the triggered emotions along with their intensities will be specified using a set of inferential rules and quantifying for-

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mulas. These inferential rules are, in fact, mapping functions from event desirability measures and expectations to certain emotion types. Furthermore, these emotional states will influence the mood of the agent. In addition, emotional responses will experience some decay over time. Finally, a hyper emotional response will undergo a regulation process based on Gross process model. A possible regulation process takes place at the *Strategy Selection* unit.

The detailed explanation for the mechanisms of all these processes follows in the next section.

3.3.3.1 The detailed model

Event desirability measure The function of the Event evaluation unit can be explained in two steps. In the first step, we determine the set of goals affected by the external event along with the degree of impact on each goal. In the second step, the desirability of the event is calculated based on the degree of influence computed in the previous step and the importance of the involved goals.

Triggered emotions and their intensities Once, the desirability measure of an event is specified, it will be forwarded to the *Emotion Elicitation* unit at which the changes in the emotional states of the agent is determined. Here, event expectations will be included in the calculations. These expectations are derived from the learning module which is explained later in this article. We adopt the emotion generation rules proposed by OCC model [83] and formulated by Price et al. [90] in order to measure the emotional state changes as well as computing the intensities of elicited emotions. These rules are based on the relationships between emotions, events' desirability and expectations. Table 3.5 reflects partially some of these rules along with the corresponding generated emotions. Table 3.6 contains some of Price's equations used to compute the intensities of the generated emotions.

Table 3.5: Events desirability and corresponding emotions

Emotion generation rule	Emotion
Occurrence of an unconfirmed undesirable event	Fear
Occurrence of a dis-confirmed undesirable event	Relief
Occurrence of a desirable event	Joy
Action performed by the agent and disapproved by standards	Shame
Action performed by the agent and is approved by standards	Pride
Compound emotion; sadness + reproach	Anger

Table 3.6: Intensity computing rules [90]

Emotion	Degree of intensity
Fear	$= (2 * expectation^2) - desirability$
Joy	$= (1.7 * expectation^{0.5}) + (-0.7 * desirability)$
Relief	$= Fear * desirability$
Sadness	$= (2 * expectation^2) - desirability$
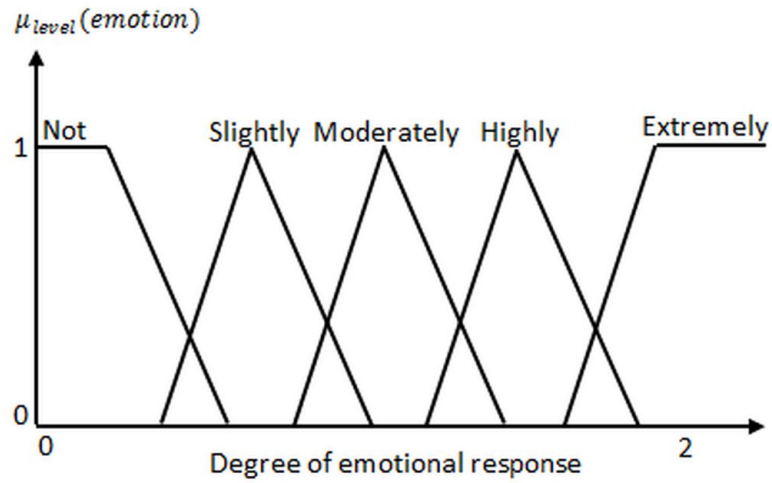
Figure 3.8: Emotional response for any emotion expressed using five fuzzy sets

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Regulation process People usually have a basic idea about their current emotional status as well as the target level of emotions that they are looking for or would be able to tolerate in a certain situation with regards to the related circumstances. These "quantities" are usually being expressed in a fuzzy way without full certainties which makes it hard to quantify them accurately. This fact inspired us to build a computational model for this problem based on a fuzzy logic approach. Hence, using fuzzy logic principles and the fuzzy partial membership concept, expressions such as *slightly angry, very happy* or *extremely sad* can be easily converted into their equivalent fuzzy sets. (see Figure 3.8)

In a regulation process, the agent in a certain situation, will have an estimation of its target emotional response level with regards to the circumstances of that situation. For example, in a situation of regulating extremely angry emotional state, if the agent can tolerate being up to slightly angry state, then the required amount of regulation would be:

$d = ExtremlyAngry - SlightlyAngry$

In fact, the target level of *SlightlyAngry* will work as a threshold that once it is reached, it can be considered as the end of the regulation process.

Strategy selection in the regulation process Humans often target a relatively high level for positive emotions such as pride and joy whereas, they aim lower levels for negative emotions such as anxiety and fear. Emotion regulation process is, in fact, nothing rather than a trial to direct the current emotional response level, ERL towards it's aimed at level, ERL_T. Therefore, the regulation process is an optimization problem as follows:

$d = ERL - ERL_T$

therefore we have,

$\arg\min_{s} d(s), \quad s \in STRATEGY\ set$

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The target here is to find and apply a regulation strategy that would minimize d at each time step. On the other hand, changes in ERL come from two sources. The first is through the regulation process and the second is the normal decay factor over time, hence:

$$\triangle ERL = f_{reg}(s) + f_{decay}(t)$$

In order to calculate $f_{reg}(s)$, we would need to declare a set of variables corresponding to Gross regulation strategies. Hence, we assume that each strategy k has an emotional value of v_k. Each emotional component v_k contributes to the emotion response level ERL based on its corresponding weight of w_k. Therefore:

$$f_{reg}(s) = f(v) = \sum_{n \in s} v_n . w_n$$

With regards to f_{decay}, we argue that there exist a regular time-driven decay for any emotional state even with the absence of conscious regulation strategies. It can be stated that this normal decay is some type of unconscious regulation process.

Therefore, we would have:

$$ERL_{new} = (1 - D) * ERL + 1/a * \sum_{n} (w_n * v_n)$$

The above equation shows the new emotion response level at the end of each time step after applying some regulation strategies on the previous ERL along with the implication of the decay factor.

Here, the emotional contribution for each strategy v_n in the total ERL can be formulated as below:

$$\triangle v_n = -\beta_n * d * \triangle t, \qquad v = v_n + \triangle v_n$$

β_n is an adaptation factor which indicates the flexibility of the agent toward applying strategy n in a certain condition. This factor in fact, is related to several psychological, physiological, social, etc., aspects of the agent such as the personality traits and mood of the agent. Considering the fact that the emphasis in our model is to study the fuzzy nature of emotions, we refrain from performing a so-

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phisticated analysis to calculate the exact values for β_n's and instead, we pass some pre-determined values for them to the model.

Impact of events In order to make the model more realistic, we consider a dynamic environment in which different events occur in the system during the regulation process. The agent will evaluate each event and assign a desirability degree to it. The evaluation process is based on the the impact of the event on the set of goals of the agent as well as the importance of each goal. The fuzzy modeling for this evaluation process is as follows:

We use fuzzy sets to express the degree of impact that an event can have on an agent's goal. Hence, the fuzzy variable *Impact* can be one of the following fuzzy sets:

$Impact = \{HighlyNegative, SlightlyNegative,$

$\qquad\qquad NoImpact, SlightlyPositive, HighlyPositive\}$

Furthermore, the importance of each goal is measured with *Importance* fuzzy variable which can take values from three other fuzzy sets as below:

$Importance = \{ExtremlyImportant,$

$\qquad\qquad SlightlyImportant, NotImportant\}$

In addition, *Level* is the fuzzy variable used to measure the intensity for a certain emotion. For example, if the current emotion is sadness, *Level* will take a value from the following fuzzy sets: (see Figure 3.8)

$Level = \{NotSad, SlightlySad, ModeraetlySad,$

$\qquad\qquad HighlySad, ExtremelySad\}$

Desirability, is the fuzzy variable that we use to express the desirability level of the perceived event. Similarly, it can take any of the following values:

$Desirability = \{HighlyUndesired, SlightlyUndesired,$

$\qquad\qquad Neutral, SlightlyDesired, HighlyDesired\}$

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Therefore, using fuzzy rules, the problem of determining the desirability of an event based on its impact on the agent's goals and goals' importance can be formalized as below:

$IF \quad Impact(G_1, E) \ is \ A_1$

$\qquad AND \ Impact(G_2, E) \ is \ A_2$

$\qquad ...$

$\qquad AND \ Impact(G_k, E) \ is \ A_k$

$THEN \quad Impact(G_1, E) \ is \ C$

where k is the number of relevant goals. A_i, B_i and C are fuzzy sets as elaborated above. This rule reads as follows: if event E affects goal G_1 to the extent of A_1 and affects goal G_2 to the extent A_2, etc., and that the importance of goal G_1 is B_1 and for goal G_2 is B_2, etc., then event E will have a desirability equal to C.

In order to quantify C, we use the approach taken in [30] based on Mamdani model [67] which applies centroid defuzzification of the fuzzy rules. Hence, using the $sup\,min$ composition rule between the fuzzy variables of *Impact*, *Importance* and *Desirability,* we would be able to compute the matching degree between the input and the antecedent of each fuzzy rule. For example, consider the following set of n rules:

$IF \ x \ is \ A_i \ THEN \ y \ is \ C_i$

$...$

$IF \ x \ is \ A_n \ THEN \ y \ is \ C_n$

Here, x and y are input and output variables respectively. A_i and C_i are fuzzy sets and i is the ith rule. If the input x is a fuzzy set A', represented by a membership function $\mu_A(x)$ (e.g. degree of desirability), a special case of A' is a singleton, which represents a crisp (non-fuzzy) value. Considering the definition of the $sup\,min$ composition between a fuzzy set $C \in F(X)$ and a fuzzy relation $R \in F(X \times Y)$ which is defined as:

$$C \, o \, R(y) = \sup_{x \in X} \min \{C(x), R(x, y)\} \quad \text{for all } y \in Y$$

We can calculate the matching degree w_i between the input $\mu_A(x)$ and the rule antecedent $\mu_{A_i}(x)$ using the equation below:

$$\sup_{x \in X} \min \{\mu_A(x), \mu_{A_i}(x)\}$$

which can be rewritten as:

$$\sup_{x}(\mu_A(x) \wedge \mu_{A_i}(x))$$

The $\wedge$ operator calculates the minimum of the membership functions and then we apply the sup operator to get the maximum over all $x's$. The matching degree influences the inference result of each rule as follows:

$$\mu_{C_i'}(y) = w_i \wedge \mu_{C_i}(y)$$

Here, C_i' is the value of variable y inferred by the ith fuzzy rule. The inference results of all fuzzy rules in the Mamdani model are then combined using the max operator $\vee$ as follows:

$$\mu_{comb}(y) = \mu_{C_1'}(y) \vee \mu_{C_2'}(y) \vee ... \vee \mu_{C_k'}(y)$$

We use the following formula based on the center of area (COA) defuzzication rule in order to defuzzify the above combined fuzzy conclusion:

$$y_{final} = \frac{\int \mu_{comb}(y) y \, dy}{\int \mu_{comb}(y) \, dy}$$

The result of above defuzzication process, y_{final} will return a number that is the measure of the input event's desirability. This value along with the event expectation measure will be used to determine the corresponding emotion intensity of the event based on the rules of table 3.6.

In order to enable the agent to make a good estimation for event expectation measure, we let it learn patterns of events. Next section describes briefly the function of the learning component in our model.

3.3.3.2 Learning patterns of events (events expectation)

Mechanisms for expectations obtained through learning can have a major influence on emotional dynamics [62]. In our model, the agent is capable of learning patterns of events and thus can expect the next event through a probabilistic approach.

Learning about what events to expect, given a set of already occurred events, poses a crucial information for the agent. As discussed before, the type of triggered emotions and their intensities rely strongly on the event's expectations through the event appraisals process.

Considering the dynamic nature of the interactions between the agent and its environment, we use a probabilistic approach in order to enable the agent to identify possible patterns for event sequences. These patterns are formed based on the frequency with which an event v_1 is observed to happen while a set of previous events v_2, v_3, etc., has already occurred. In our model, we consider patterns of three consecutive events.

A table data structure is used to count the number of iterations for each event pattern. The conditional probability of $p(e_3 \mid e_1, e_2)$ indicates the probability for event e_3 to happen, assuming that events e_1 and e_2 have just taken place. The first time that a pattern is observed, a corresponding entry for the event's pattern will be created, and the count is set to 1. This flag will be incremented for each future observation. These count flags can be used to compute the conditional probability for a new event Z to occur, given that events X and Y have already occurred. Therefore, The expected probability for event Z is:

$$P(Z \mid X, Y) = \frac{C[X,Y,Z]}{\sum_i C[X,Y,i]}$$

In case that the number of observations is low, only one previous event can be considered in the conditioned probability, hence:

$$P(Z \mid Y) = \frac{\sum_i C[i,Y,Z]}{\sum_j \sum_i C[i,Y,j]}$$

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Table 3.7: List of agent's goals

Goal	Importance
G1	HighlyImportant
G2	SlightlyImportant
G3	HighlyImportant

However, if the priori for event Y occurring right before event Z was never been observed, then we can use unconditional prior based on the mean probability for all events to calculate the probability of event Z as follows:

$$P(Z) = \frac{\sum_{i,j} C[i,j,Z]}{\sum_{i,j,k} C[i,j,k]}$$

These probabilities will enable the agent to determine how likely an event is to happen, given the set of previous events.

3.3.4 Simulation experiments and discussion

In order to evaluate and compare the performance of our proposed model with a non-fuzzy approach, as well as its consistency with Gross theory, a set of simulation experiments were conducted. In these experiments, emotional values are measured in a range of [0 - 2], initial ERL and ERL_T are parameters passed to the system and *agent* is an individual who tries to regulate his/her extreme emotional response.

Here, we elaborate on two of those experiments. In the first experiment, a learning agent tries to regulate its hyper fear emotional response. In the second scenario, we monitor the regulation behavior of another agent which is incapable of learning while all other parameters of the system are kept similar to experiment1. Furthermore, the environment of the agent is dynamic with several events occurring during the simulation. Tables 3.7 and 5.4 list the set of agent's goals and the events that occur in the system respectively. Figure 3.10 reflects the computed desirability of these events.

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Table 3.8: List of events' occurrence time along with their impact on each goal

t	Impact on G1	Impact on G2	Impact on G3
20	HighlyPositive	NoImpact	HighlyPositive
30	HighlyNegative	SlightlyPositive	SlightlyPositive
45	HighlyPositive	SlightlyNegative	SlightlyNegative
50	HighlyNegative	HighlyPositive	HighlyNegative
80	HighlyPositive	HighlyPositive	NoImpact
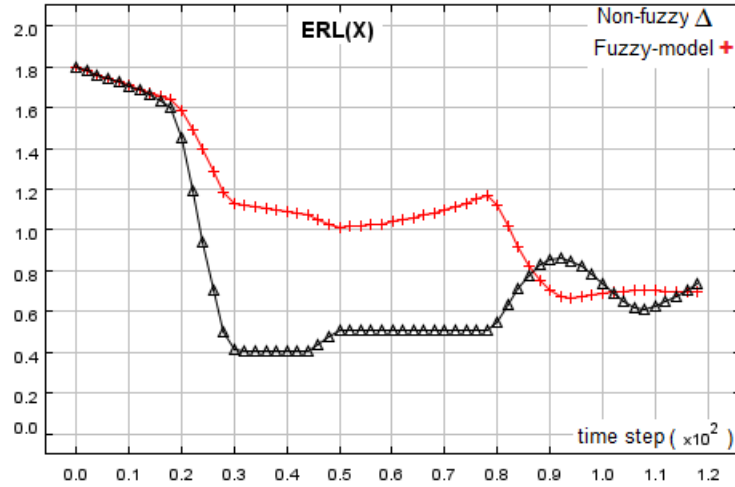
Figure 3.9: Trend of ERL for a fuzzy-based learning agent

3.3.4.1 Experiment 1: learning agent

In this scenario, the agent is capable of identifying possible patterns of events that occur in the system and consequently, event expectation is an important factor in calculating the intensity of elicited emotions as elaborated before. Hence, we expect to see a smoother impact for the events on the regulation process. Figure 3.9 shows the ERL regulation trend for our proposed model against the non-fuzzy implementation adopted in [112]. Based on this graph, we observe that until time-step=20, both models had a very similar behavior since there was no active event in the system and both started the regulation with a similar adaptation factor of $\beta = 0.05$.

Once a positive event occurred at step=20, the ERL in both approaches experienced a sharp decline in favor of the regulation toward its target level, (i.e., ERL_T).

However, in the non-fuzzy model, due to regulation optimism emerged as a result of the strong positive event, the ERL experienced a huge sudden drop of the ERL much below its aimed at level, while in our approach, the change in ERL was less and controlled due to the role of event expectations, which prevents excessive optimism.

At step=30, the occurrence of a slightly negative event caused the regulation in our proposed model to slow down and stabilize with a mild down trend, while it stopped completely in the non-fuzzy model. At step=45, a mild positive event managed to slightly speed up the regulation trend for both systems. This situation did not last for long due to the occurrence of a strong negative event at step=50.

Here, we observe a moderate up trend for ERL in our model which takes it to around 1.2 in 30 time-steps. This is up by 0.2 from its minimum value reached right before step=50. This increase seems realistic considering the high intensity of the event. On the other hand, this event caused the regulation process to stop completely once again in the non-fuzzy model. This is due to the lack of adaptivity to environmental changes in that approach as elaborated before.

The occurrence of a very strong positive event at step=80, manages the regulation process in our model to make ERL touches its aimed at value at step$\cong$90, and stays at that level until the end of the simulation. It can be seen that, this strong positive event caused the non-fuzzy model to experience another raid of excessive optimism, and although it made the ERL touches its aimed at level at step$\cong$ 120, but it suffered from sharp jitters between steps 80 to 120. This experiment shows that our model is more in line with one of the important Gross rules stating that "Emotion approaches norm monotonically" [45].

3.3.4.2 Experiment 2: agent without learning capability

In order to be able to make a precise analysis of the role of agent's learning in the regulation process, the second experiment was purposefully designed with identical
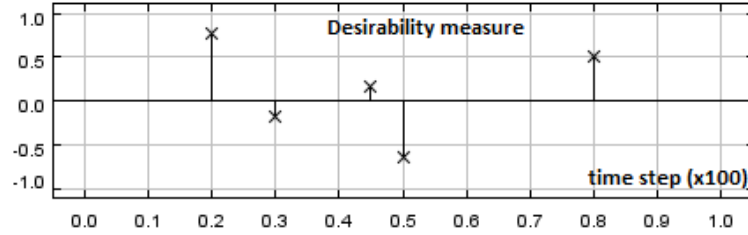
Figure 3.10: Desirability measure for occurred event

conditions to experiment 1. Here, we expect to see less smooth and more fragile regulation as a result of the absence of events' expectation and consequently larger implication for event's desirability measure. It is clear that the non-fuzzy model will exhibit the same behavior as of experiment1, since learning is not part of the corresponding model.

Figure 3.11 depicts the behavior of the regulation process in this experiment. We first observe that the strong positive event occurred at step=20 and caused the ERL to drop to almost 1.1 in the previous experiment, made the ERL to experience a sharper drop to around 0.9 due to event's element of surprise for the agent. Furthermore, it can be seen that unlike learning agents, even mild negative events can reverse the regulation process for this type of agents. This scenario was the case for the slightly negative event that took place at step=30. Moreover, it can be seen that the influence of strong negative events similar to that occurred at step=50, caused the slightly in-favor of regulation trend which started at step=45, to be reversed dramatically to an opposite trend which took the ERL to high levels above 1.4, eliminating considerable amounts of the regulation gains obtained up to that point. Finally, we observe that the system could not reach and stabilize close to its aimed at value before step $\cong$ 105.

The results from these experiments are consistent with our expectations of having a relatively fast and smooth regulation for a learning agent and conversely, a relatively slow and fragile regulation for a non-learning agent.

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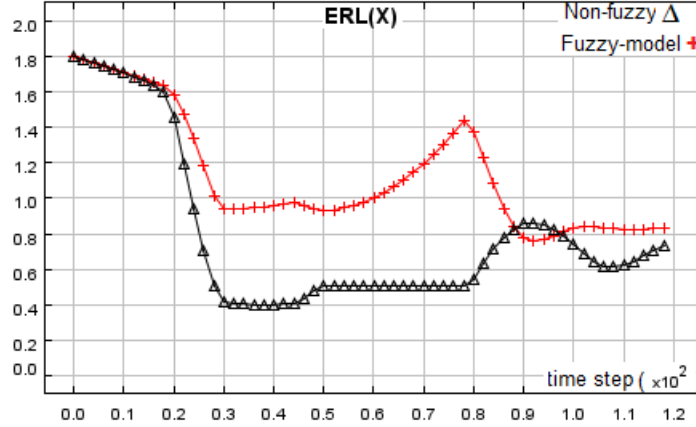
Figure 3.11: Trend of ERL for a non-learning agent

3.3.5   Conclusion

In this paper, we proposed a fuzzy computational model for Gross emotion regulation theory. In this model, events and events' expectations play an important role in determining the elicited emotions and their intensities via desirability measures of the events. We used several fuzzy sets to represent event's desirability, agent's goals importance and the degree of impact that events have on the goals of the agent. Fuzzy inferential rules and a defuzzification technique were used to perform the necessary computations and derive the final results.

We compared the results of our model to those obtained from a previously presented non-fuzzy implementation for this problem. Consistently with our expectations, our proposed model managed to outperform the performance of the non-fuzzy model by providing a more realistic and smoother regulation process. Furthermore, the new model exhibited more adaptivity to the environmental changes and also showed more consistency with Gross theory.

Acknowledgments

3.4   Conclusion

The problem of emotion regulation is an open problem under the field of emotion modeling. A computational model for emotion regulation is intended to reflect the mechanisms of transitions between different emotional states. In particular, the focus is on balancing hyper emotional responses resultant from negative situations (e.g., events). Two research works with regards to modeling the mechanisms and dynamics of emotion regulation were presented in this chapter. The first research work reflects a set of augmentations that were investigated and applied to an existing computational model for emotion regulation. For instance the impact of the mood as well as different levels of knowledge on the process of emotion regulation was studied and modeled. In the second presented research work, a fuzzy approach for modeling emotions was investigated and then utilized in building a computational model for emotion regulation.

Chapter 4

Emotion Contagion

4.1 Introduction

Possible analogies between models for transmission of some social constructs such as thoughts and behaviors with models for infectious diseases spread were always a matter of interest and study for researchers within the fields of sociology and other humanistic sciences. They believe that the similarities between the two phenomena are sufficient to come up with models for social interactions inspired by transmission models for infectious diseases [46]. In a great deal of scientific research in sociology and cognitive science, it is strongly believed that thoughts, attitudes and behaviors can spread through populations in a similar mechanism to that of infectious diseases especially among peer groups of close relatives, friends, co-workers, etc. [126].

Emotion contagion, the tendency for an individual's emotions to consciously or unconsciously influence the emotions of others, is a subset of a larger group known as social contagion. Throughout several studies conducted within the fields of sociology, economics, healthcare, etc., it was shown that a great deal of social behaviors and beliefs are directly influenced by the actions and beliefs of the others. For instance, thisphenomenon can be seen in purchasing decisions, rule breaking, fear and greed

affective states in financial markets and addiction. As a matter of fact, "the process of emotion contagion is a primary mechanism through which individual emotions create a collective emotion" [126].

This chapter includes a computational model that was proposed to address the problem of modeling thephenomenon of emotion contagion and was published as a research paper under the following reference:

- A. Soleimani and Z. Kobti, "Toward a Computational Model for Collective Emotion Regulation Based on Emotion Contagion Phenomenon", Proceedings of the 27th Canadian Conference on Artificial Intelligence, May 2014, Montreal, QC [116]:

  In this article, a computational model is proposed that models the underlying appraisal processes of emotion contagion as well as the dynamics of changes in the population of emotional versus neutral agents. By using a fuzzy appraisal approach, the proposed mode was able to integrate the traditional appraisal approach with the dynamics of emotion contagion.

4.2 Toward a Computational Model for Collective Emotion Regulation Based on Emotion Contagion Phenomenon

Abstract. This paper proposes a novel computational model for emotion regulation process which integrates the traditional appraisal approach with the dynamics of emotion contagion. The proposed model uses a fuzzy appraisal approach to analyze the influence of applying different regulation strategies as directed pro-regulation interventions to the system. Furthermore, the dynamics of changes in the population of emotional and neutral agents were modeled. The proposed model provides an effective framework to monitor and intervene as affect regulator in catastrophic situations such as natural disasters and epidemic diseases.

4.2.1 Introduction

Affective Computing (AC) [88] represents the wide-spanned efforts made by AI researchers interested in modeling emotions. An AC system through using a set of rich methods and techniques derived from AI reflects an effective and efficient framework for testing and refining emotion models often proposed within humanistic sciences.

E*motion regulation* [42] on the other hand is involved in studying and applying techniques aimed at regulating hyper emotions. According to Gross [42], it includes all of the "conscious and non-conscious strategies we use to increase, maintain, or decrease one or more components of an emotional response".

This article looks at the problem of modeling the process of emotion regulation from the perspective of emotion contagion as a special type of social contagion. With

respect to the possible applications for the proposed model, it would appear that an extended version of this model would have the potentials to be used within the field of rescue and disaster management where modeling crowd emotional behavior in catastrophic and time stressed situations such as the resulted panic from earthquakes or epidemic diseases is crucial. In such scenarios, the patterns and rates of emotion contagion in different types of social networks within the stricken community as well as the enforcement of interventions aimed at regulating hyper negatives emotions are of high importance.

4.2.2   Related studies

4.2.2.1   Computational models of emotion

Different approaches such as appraisal (e.g., [83]), dimensional (e.g., [36]), adaptation (e.g., [73],), etc. can be taken in the process of building a computational model for emotions. Among them, appraisal models are the most widely used approaches to model emotions [72]. At the core of the appraisal theory, a set of dimensions or appraisal variables exist that guides the appraisal processes.

4.2.2.2   Social contagion

In a great deal of scientific research in sociology, the tenet that beliefs, attitudes and behaviors can spread through populations in a similar mechanism to that of infectious diseases is emphasized [126]. Accordingly, the term contagion in psychology is "the spread of a behavior pattern, attitude, or emotion from person to person or group to group through suggestion, propaganda, rumor, or imitation"[46]. Affective behaviors and especially emotions are important examples for social contagion processes. It was shown that emotions spread quickly among the members of social networks with similar dynamics that of infectious diseases . *Hatfield et al.* [46] call this phenomenon as "emotional contagion".

4.2.3 Our approach

In order to model emotion contagion phenomenon, the first step would be to split the population of the individuals within the target society into two sub populations of "emotional" and not-emotional or "neutral" agents. The classification is performed based on the measured emotion response level, ERL of each agent for a given emotion such as *fear*. The ERL is measured in a numeric scale of $[0..1]$ with and imaginary threshold as the cutting edge between the two classes of the population. It needs to be emphasized here that the level of the threshold is completely customizable and that it was not designated specifically for a certain emotion type; serving the generality of the proposed approach.

On the other hand, among the disease spread models, the SIS (Susceptible-Infected-Susceptible) [3] is a well- known and widely used model. Accordingly, in the proposed model, a corresponding approach to SIS was introduced and called NEN (Neutral-Emotional-Neutral) to model the emotional transitions (see Fig. 4.1). Accordingly, the transitioning process in each direction involves one operation that is associated with event appraisal processes and another operation originated in the emotion contagion process (see Fig. 4.1).

4.2.3.1 Problem formulation

Emotions and events As discussed earlier, two out of the four transition operations introduced in the proposed NEN model are associated with a deliberative appraisal process of emotion triggering events that take place in the environment of the agent. The full description and formulation of the appraisal processes is provided in [118].

Emotional contagion In this section, we focus on formulating the problem of emotion contagion. Accordingly, the change in the emotional response levels of each
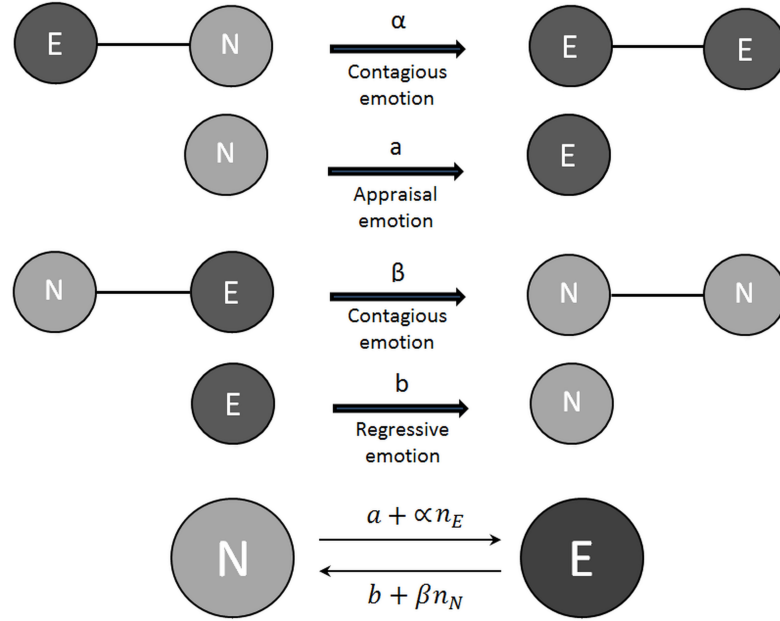
Figure 4.1: The NEN model of emotion regulation dynamics. There are four processes by which an emotional state can change. (i) An emotional agent transmits its emotion to a neutral agent with rate α. (ii) A neutral agent becomes emotional as a result of an emotion-triggering event at rate a. (iii) An emotional agent becomes neutral as a result of being exposed to other neutral agents with rate β. (iv) An emotional agent spontaneously becomes neutral as a result of a reversed event at rate b. n_E and n_N represents the population of emotional and neutral agents respectively.

agent is linked to the "transmissioned quantities" of emotion as a result of interactions between agents. Generally, the changes in the emotional response level of the agents as a result of emotional contagion can be formalized as follows:

$$ERL_{new} = \mu * ERL + (1 - \mu) * E_c$$

where E_c indicates the emotional value that was transmitted through the corresponding contagion process. A persistence factor, μ was introduced to reflect the portion of the current emotional level that will be carried directly to the next time step and consequently will contribute in forming the new emotional response level at the next time step. Hence, $\mu * ERL$ in the above equation reflects the portion of the old ERL that persists in ERL_{new}.

According to *Sutcliff et al.* [123], in social networks, each individual has a intimate support group of five people who are close family members and friends. Furthermore,

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each individual deals and interacts with about 150 people who know him and he knows them within the community. In addition, we still consider a less influential affective impact for the rest of the population who are out of these two groups. Accordingly, in the proposed model, three different weights corresponding to the three social networks introduced above were considered. An initial heuristic about these three weights was made based on choosing the first three perfect square numbers, i.e., $1^2, 2^2, 3^2$.

for simplicity, we approximate the above values which leads to $w_1 = 5\%$, $w_2 = 30\%$, $w_3 = 65\%$, therefore,

$E_c = \sum_i E_{ci} w_i$, where $i \in \{1, 2, 3\}$ represents the social network type.

E_{ci} in the above sum is the average of emotional response levels for all agents within the competent social network. With respect to the changes in the population of neutral and emotional agents, the following general equations can be obtained,

$\frac{dN}{dt} = -aN - \alpha NE + bE + \beta E$

$\frac{dE}{dt} = aN + \alpha NE - bE - \beta E$

where, α reflects the rate of transitioning from neutral agents to emotional agents. Similarly, β is the contagion rate of emotional agents transitioning to neutral ones. Furthermore, a and b are the rates of transitions originated in appraisal processes of occurred events.

In order to find a good approximation for α, it is required that the major factors and parameters that influence this rate to be identified. Here, we introduce a virtual affective channel, CH_{affect} between a pair of agents at which one agent plays the role of affect sender, A_S, and the other agent plays the role of affect receiver, A_R. We argue that α has a close relationship with the strength of the affective channel between the two agents. On the other hand, the strength of this channel has to do with the emotion response level, ERL at both sides of the communication. Hence,

$\alpha \propto STRENGTH(CH_{affect})$ and $STRENGTH(CH_{affect}) \propto |ERL_S - ERL_R|$
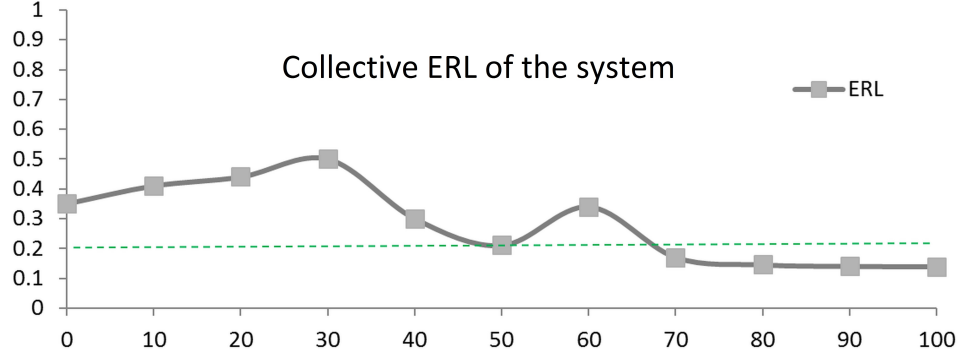
Figure 4.2: Collective ERL for all agents of both emotional and neutral margins

As an important implication for the proposed approach, it can be inferred that a guided emotion regulation process will be turned into an optimization problem at which the target is to the maximize the population of the neutral agents. By looking at the population equations, such a goal would be achievable by maximizing the rates of b and β through regulation interventions in terms of injected events that are desirable for the neutral agents and preferably undesirable for the emotional agents.

4.2.4 Simulation experiment and discussion

At this point, we explore one of the simulation experiments that was conducted in order to test the performance of the proposed model. Here, the process of emotion regulation under the influence of emotion contagion as well as interventions in terms of the application of regulation strategies as external events was modeled. Some of experiment conditions were as follows: the population of the agents is chosen to be 1000 distributed equally and randomly between the two groups of emotional and neutral agents, i.e., $P_{E_0} = P_{N_0} = 500$. The cutting edge (threshold) for the two groups is at $ERL = 0.2$. Emotion under study was $sadness. E = \{e_1, e_2, e_3, e_4, e_5\}$ is the set of possible events (regulation strategies).

According to Fig. 4.2, the collective ERL of all agents within both margins started at $ERL = 0.35$. For the first 30 time steps, at the absence of any external regulation

interventions, the changes in the ERL is uniquely driven by the spontaneous emotion contagion between the agents. Because of the higher average of the collective ERL for emotional agents (i.e., higher α than β), the collective ERL of the system moved in an anti-regulation direction and at step=30 it touched 0.50. In other words, at this point we ended up with a sadder population. This influence is well reflected in the graph that depicts the population changes of the two groups. Accordingly, in Fig. 4.3, a huge increase in the population of sad agents during the first 30 time steps can be seen clearly (i.e., $P_E \cong 800, P_N \cong 200$). At step=30, a regulation intervention took place through the injection of e_3 to the system which reflects a very strong in favor of regulation event. The enforcement of this regulation strategy managed to take the collective ERL to a record low amount even below the threshold. Accordingly, the population of sad agents dropped dramatically to around 300 at step=50.

At step=50, the occurrence of e_1 as an anti-regulation event caused the regulation process to flip its direction towards a higher amounts for the collective ERL. This situation did not last long as a result of applying e_2 at step=60. Considering the strong undesirability for this event for the emotional agents, it created a strong wave of spontaneous regulation processes supported by a rapid emotion contagion in favor of regulation that took the ERL to record low of $ERL = 0.145$ at step=80 and further to $ERL = 0.139$ at the end of the simulation. In accordance with such regulation-favored direction, the population of the emotional agents dropped to record low of $P_N = 92$ and later to $P_N = 82$ at the end of the experiment (step=100). Furthermore, it can be seen that the system showed signs of emotional equilibrium starting at step=80 where no significant changes in the collective ERL of the system as well as the population of both groups of agents could be seen.
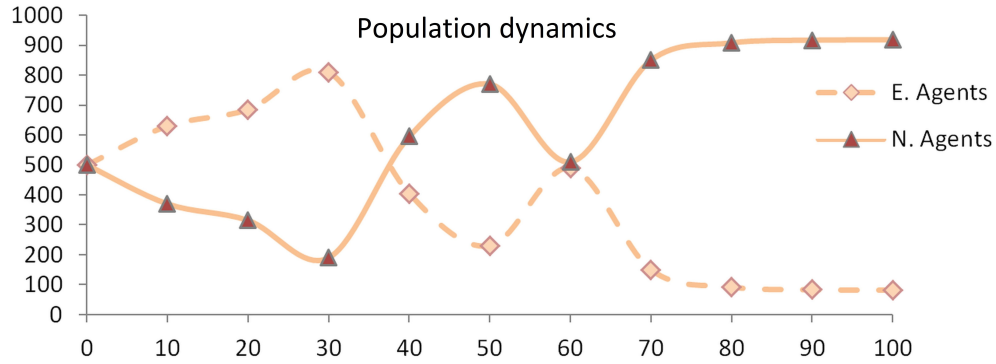
Figure 4.3: Dynamics of agent population changes as a result of spontaneous emotion contagion and regulation interventions

4.2.5 Conclusion and future directions

In this article the process of emotion regulation often aimed at regulating negative hyper emotions from the perspective of emotion contagion was studied and modeled. The proposed model can be expanded in several directions. One direction would be to extend the scope of events as well as the types of social networks between individuals. Furthermore, the dynamism of the system can be increased by considering agent movements which probably make them form clusters of those who have common emotional tendencies.

Chapter 5

Fuzzy Computational Model for Emotion Regulation Based on Affect Control Theory

5.1   Introduction

Due to the broad potential use of computational models of emotion and other affective processes in the fields of robotics, agent modeling, and other AI systems in general as well as in HCI applications, studying the mechanisms underlying affective behaviors and emotional processes has recently managed to receive an increasing amount of interest by numerous researchers from within Computer Science and in particular AI sub-fields. As a result of this affect studying campaign by AI specialists, several computational models that are intended to interpret the mechanisms of human affective behavior and to identify and generate emotions similar to those of humans were developed (e.g., [83, 36, 73]) and implemented in emotionally intelligent autonomous agents (e.g., social robots, virtual characters, etc.) in order to make them more realistic and believable by their users.

The proposed model falls within such trials at which the author try to present a computational model that accounts for the dynamics of the changes in the emotional states of the agents driven by the external events that take place in the environment of the agent. The dynamic of emotional changes is at the heart of the emotion regulation processes. The main concept in emotion regulation is to deliberately regulate hyper negative emotions by means of applying some self-originated regulation strategies or through external interventions.

Our proposed model studies the regulation impact of external stimuli and proposes a detailed computational model for emotional changes dynamics. Accordingly, the emotional response level of the agent under study can be tracked and directed in favor of the proposed regulation process. The model evaluates the affective influence of the events that occur in the system using the three dimensional appraisal space of Affect Control Theory (ACT) [47]. The appraisal processes are established using a fuzzy automata framework [58] at which a transition vector is built from the three dimensions of the ACT (i.e., evaluation, potency, and activity) in order to represent the transitions between different emotional states (see Fig. 6.1).

To the best knowledge of the author, in very few previous models, a fuzzy automata approach was used for the purpose of emotion modeling. For instance, the work proposed by Chakraborty et al. [23] uses a set of audio and video stimulus as external events to influence the emotional states of the agent and hence, to enable the agent to transition between different states of the fuzzy automata. Only those transitions with the shortest path and minimal cost between the initial and target emotions are selected. Although the way that the agent transitions between different emotional states is similar to that of the proposed model, but the two differs dramatically considering the deep analytical assessment that is performed on the input of the fuzzy transition function rather than raw data from questionnaires used in their model.

Some concepts used in the proposed model with respect to fuzzy analysis were influenced by the work of ElNasr and colleagues [30]. Their fuzzy computational model of emotion, FLAME, establishes a fuzzy system of rules to come up with a process model for emotion generation. FLAME uses a number of learning techniques to enhance the adaptation capabilities of the agent towards the changes that occur in the environment of the agent.

With regards to possible applications for the proposed model, two trajectories can be considered. The focus in the first trajectory is to detect and track the affective state of the agent to be used as the input to emotionally intelligent applications in the fields of HCI, robotics, computer gaming, etc. In such applications, detecting the emotional state of the user and modeling the dynamics of changes in the user's affective state are crucial in order to build a successful affective relationship with the machine [88]. The other direction would be to use the findings of this research work in the field of emotion regulation [43]. Accordingly, some kind of deliberately enforced events will be used as coping strategies by specialist like psychotherapists in order to regulate hyper negative emotions.

5.2 Emotion Modeling

5.2.1 Theoretical frame work

In this section, some major theoretical foundations used in a great deal of recent computational models of emotions are briefly reviewed.

5.2.1.1 Appraisal theory

The core tenet in appraisal theory is the fact that a certain emotion is experienced due to a set of appraisal processes at which the agent continuously evaluates its relationship with other entities in the world; particularly the events that take place in the

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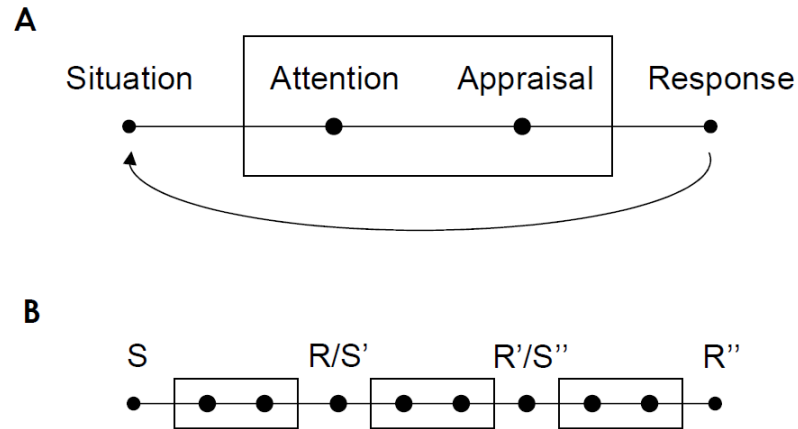
Figure 5.1: appraisal processes. A- recursive property of situation-response relation. B- temporal representation of figure A. here, three cycles are drawn back-to-back [42]

environment of the agent. This widely used theory in cognitive computational modeling of emotions was formally proposed by Smith and Lazarus [110]. According to appraisal theories, the way the agent perceives its relationship with the environment, especially how affect-relevant events are evaluated along with their implications on the set of the agent's goals are crucial factors that trigger different emotions in the agent and set the intensity of the emotional states.

Furthermore, it is believed that an emotional response creates a new situation in the environment which entails another appraisal process and consequently a chain of situation-response cycles will be created. This approach is described in Fig. 5.1 [42].

What's meant by appraisal processes in this approach are a set of evaluation and assessment operations at which the relationship between the agent and its environment is analyzed and measured in certain ways using some appraisal variables. Some of these appraisal variables are listed below: [103]

- The preference of the new situation

- The impact of the situation on the set of goals of the agent

- Changeability of the situation's circumstances

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- Available coping potentials with the new situation

Appraisal theory was adopted in several psychological hypothesis for emotion modeling such as [83, 33, 43]. The computationally tractable attribute of the OCC model proposed by Ortony *et al.* [83] was taken by numerous researchers within the field of affective computing [88] as the basis for developing a number of computational models for emotional processes. According to OCC, all emotions can be classified as reactive responses to either an object, an event or an action of some agent.

5.2.1.2 Dimensional Theory

According to dimensional approaches to emotion modeling, emotions are merely affective states expressed in terms of a multidimensional space. One of the famous theories under this category is the theory of core affect proposed by Russell [99]. In this theory, two dimensions of pleasure and arousal are considered to be sufficient to represent and measure the different affective states that an individual might experience due to changes in the agent-environment relationship. According to this theory, core affects are relatively long term states that indicate unlabeled affective tendencies often associated with the mood states of the agent and are not directly related to specific stimuli; whereas emotions such as joy or distress are transient states often caused explicitly by an event or other types of stimuli. (see Fig. 5.2)

Affect control theory (ACT) on the other hand is another important theory in this category that has managed recently to attract a great deal of research work in emotion modeling. This theory which was initially introduced by Osgood [84] is founded on the tenet that meanings of concepts can be measured and expressed along the perceptual dimensions of evaluation, potency, and activity [57].

With respect to the first dimension of ACT, evaluation, it differentiates between good and nice sentiments from those bad and awful. Potency is associated with the situation's aspect of strength and control in contrast to weakness and ineffectiveness.

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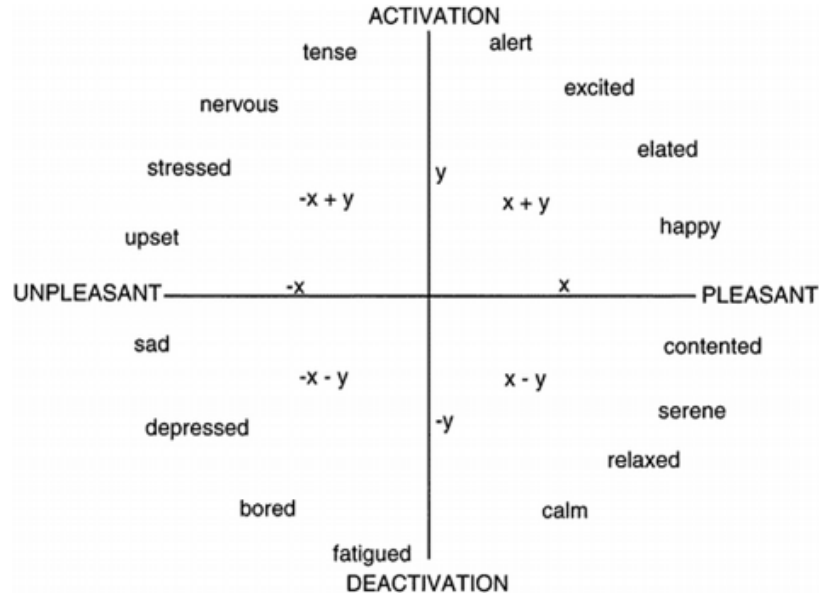
Figure 5.2: The two dimensional space for core affects[99]
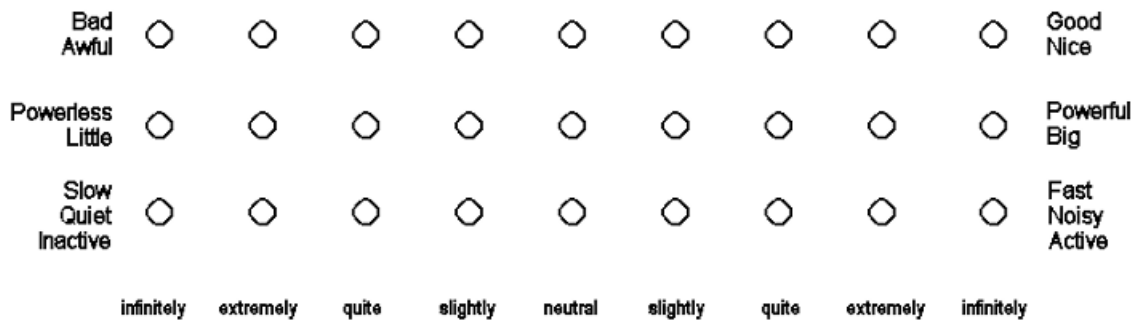
Figure 5.3: Rating scales for measuring the three dimensions of affect control theory, EPA [47]

Activity dimension on the other hand is an indicator of arousal and preferences. By virtue of this dimension, excited and bored affective states as well as active and passive actions can be differentiated from each other (see Fig. 5.3).

By means of these three appraisal quantities, a three dimensional affective space can be built where the affective meaning of all concepts including emotions, individuals, situations, objects, etc. can be described [47].

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5.2.1.3 Emotion Regulation and Adaptation

In emotion regulation, the main focus is on studying the mechanisms of adaptation in elicited emotions. Different regulation and coping strategies are considered by researchers within this field. According to Gross [43], two categories of regulation strategies exist; antecedent-focused and response-focused. These two categories are discriminated from each other based on the timing at which a certain strategy can be employed during an emotional episode. Accordingly, antecedent-focused strategies are those that can serve the regulation process before an emotional state has been fully activated. In other words, they target those emotional tendencies that are most likely to elicit a certain emotional response in a later time. Response-focused, on the other side, are those strategies applied to regulate a fully triggered emotional response as a result of some stimuli or an internal state. Fig. 5.4 depicts the big picture for Gross emotion regulation strategies.

5.3 Events and Affect Control Theory

The first step towards studying the dynamics of emotional behavior as well as the process of emotion regulation is to come up with an appropriate mean for measuring emotions. In the proposed computation model, a fuzzy-based approach [134] was taken for this purpose. According to this fuzzy scale, emotional responses are represented by fuzzy states within their relevant emotional channels. Each emotional channel is an imaginary bipolar affective axis at which a pair of opposite emotional sentiments appear at the extremes of each side (e.g., HighlySad to HighlyHappy or HighlyAshamed to HighlyProud). A total of five fuzzy sets reflecting different response levels within each emotional channel is used to measure the emotional state of the agent at any point of the time. These fuzzy sets are: *Highly, Slightly, None, Slightly and Highly* (see Fig. 5.5). Accordingly, the two symmetrical states of *Highly* at the two opposite
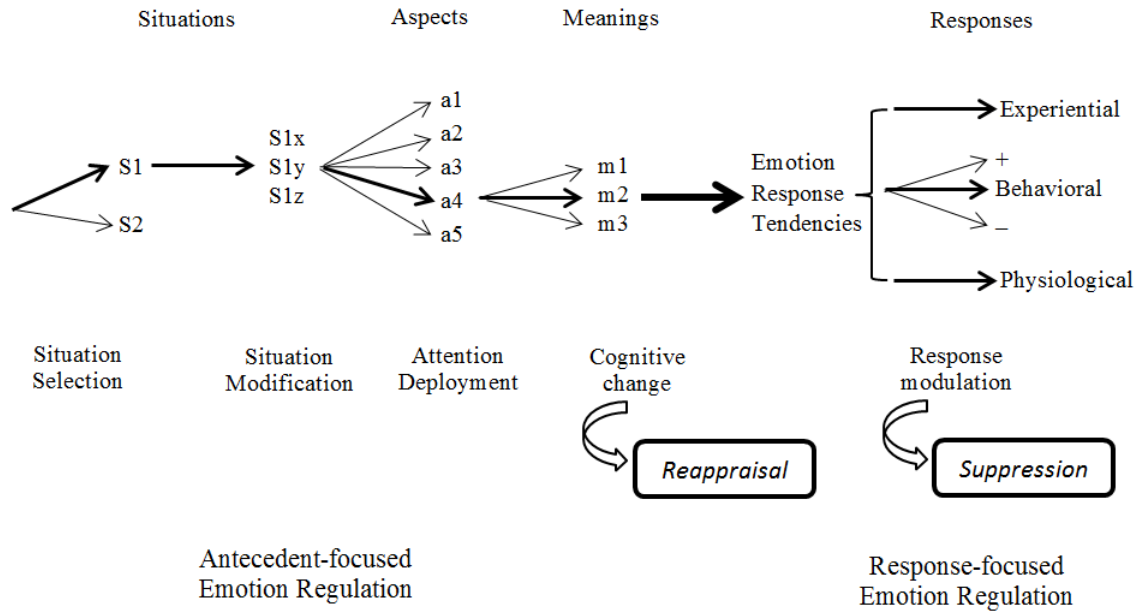
Figure 5.4: A process model for emotion regulation. According to this model, emotion may be regulated at five points in an emotional experience: (a) selection of the situation, (b) modification of the situation, (c) deployment of attention, (d) cognition change, and (e) modulation of experiential, behavioral, or physiological responses. [45]

sides of the affective axis represent the two extremes of the emotional channel under study. It is worth noting that since most discrete emotions can be expressed using one of these bipolar channels, this approach represents a sufficiently generic model.

Based on this scale, in order to measure the intensity of experienced emotions, a fuzzy variable, *Level,* is introduced. For instance, if the emotional channel under study is distress-joy, *Level* will take a value from the following fuzzy sets:

$$Level = \{HighlyDistressed, SlightlyDistressed, Neutral,$$

$$SlightlyJoyfull, HighlyJoyfull\}$$

Considering the fact that the ultimate goal for emotional models is to interpret and simulate human emotion dynamics, we believe that the above mentioned fuzzy scale represents an appropriate approximation to measure emotional responses; since this type of expressive grammar often replicates the one used by individuals to convey

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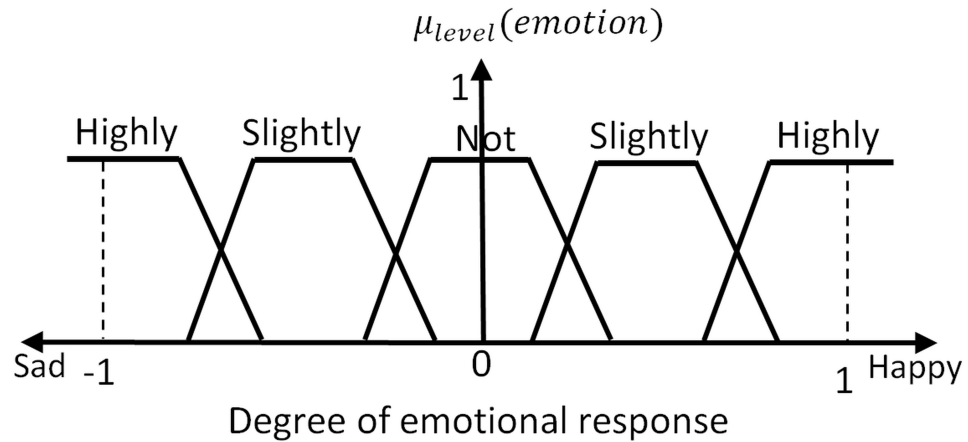
Figure 5.5: Response level for sad-happy emotional channel instance expressed using five fuzzy sets

their emotions; and hence, it constitutes the initial input to these systems as well as the output generated by the emotional models to be used in the verification and validation steps. Additionally, this representation is consistent with emotion theories and the way that psychologists use to express emotion intensities (e.g., [33, 110]).

With respect to the type of the fuzzy membership function, it was concluded that a trapezoidal function rather than an often used triangular one is a better fit to the problem of modeling emotions. A trapezoidal function representation helps to enhance the flexibility of the system by hiding the imprecision often associated with the input data, whereas the fuzziness of the system remains at an acceptable level and is limited to the boundaries of each fuzzy set only. (see Fig. 5.5).

From a numerical perspective, These fuzzy sets are corresponding to a numerical range (e.g., [0..1]) typically used to measure the intensity of an emotional response in non-fuzzy computational models of emotions (e.g., [13, 52, 127]).

5.3.1 Events as EPA Vectors

As discussed earlier, according to affect control theory [47], a three dimensional space exists that is sufficient to describe the affective aspects of most objects, behaviors and other entities. This concept was used in the proposed model to analyze the affective

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influence of relevant events that take place in the environment of the agent. The aspect of relevance is associated with the degree of impact that the occurred events have on the goals of the agent. These events are assessed and measured using a set of appraisal variables and then projected onto a three dimensional space of *Evaluation*, *Potency* and *Activity*.

In particular, the first dimension of this ternary space tries to identify the valence (i.e., overall positiveness or negativeness) of the occurred event along with the intensity of the elicited emotion; Potency looks at the degree of control or dominance that the agent posses over the event or its outcomes. In other words, it represents the agent's degree of adaptation with the occurred event; Activity, on the other hand is concerned with the degree of involvement or attendance that the agent manifests towards the occurred event. The numerical scale for of these three dimensions is within the interval of $[-1, 1]$. For instance, an event with a EPA vector of $\overrightarrow{EPA} = (-0.74, 0.65, -0.41)$, represents a highly undesirable event that is substantially involving for the agent whereas the degree of control over the outcomes of the event is generally weak with possibly very few applicable coping strategies.

5.3.1.1 Appraisal Variables

At this point, a set of appraisal variables that are the most influential in the process of evaluating events is listed. As a matter of fact, a large number of such appraisal variables play a role in the evaluation process that the agent performs to assess the impact of the occurred events on its goals. But, in order to keep the complexity of the system at an acceptable level, it would be necessary to maintain a relatively short list of these appraisal variables by extracting only those features that are the most influential in these assessment processes. The following appraisal variables were partially adopted from EMotion and Adaptation model (EMA) [73] but augmented from an affect control theory perspective.

Relevance   This appraisal variable represents the first step taken by the agent to assess the situation. It indicates if the occurred event deserves the attention of the agent for further evaluation. In fact, it is at this step that the agent decides to either ignore the event or consider it for further assessment. This filtering process is often being implemented using a non-zero or above threshold utility concept.

Desirability   This appraisal criterion determines if the relevant occurred event is being perceived as either positive or negative. The degree or level of positiveness (negativeness) is evaluated next and the value of this appraisal variable reflects the degree of desirability (undesirability) of the event.

Likelihood   The possibility that similar outcomes will be generated from multiple occurrences of the same event at different times is measured using this appraisal variable.

Unexpectedness   This variable reflects the degree of unexpectedness of the occurred event from the perspective of the evaluating agent.

Urgency   Urgency reflects how fast the event needs to be attended by the agent

Controllability   This variable is one of the indicators that is associated with the event's adaptation. It identifies the degree of control that the agent has on the new situation arose in the environment after the occurrence of the event.

Changeability   Another adaptation variable that indicates whether the event or its outcomes will change by itself through time.

Causal-attribution   The main role for this appraisal variable is to identify the causal factors of the occurred event and hence to attribute credit or blame to the actor.

Table 5.1: List of appraisal variables used in the proposed model

variable	implication
Relevance	to attend to the event or drop attention - events filtering tool
Desirability	valence of the event and its intensity
Likelihood	similarity of event's impacts
Control ability	the extent to which the event is under control or reversible
Changability	possible self-changing attribute of the event
Unexpectedness	was the occurrence of the event anticipated at all?
Urgency	how urgent the event needs to be attended
Adaptability	which coping strategies are applicable
Causal attribution	assigning credit/blame to actor, emotion channel

Table 5.2: Association of the appraisal variables to the dimensions of affect control theory

App.Variable	E	P	A
Relevance	x		
Desirability	x		
Likelihood			x
Controllability		x	
Changability		x	
Unexpectedness			x
Urgency			x
Adaptability		x	
Causal attribution	x		

Furthermore, it determines the type of the bipolar emotional channel associated with the occurred event (e.g., fear-hope or distress-joy).

Table 5.1 summaries the appraisal variables used in the proposed model along with the implication of each.

5.3.1.2 Implications of the appraisal variables

In this section, each appraisal variable and based on its nature and functionality is linked to one of the three dimensions of affect control theory. Table 5.2 summarizes these implications

5.3.2 Modeling Events Using ACT Dimensions

As discussed earlier in this article, objects can be described using a three dimensional space. Each of these dimensions can be characterized by a set of contrasts. Evaluation looks at the overall positiveness or negativeness, Potency indicates strength versus weakness, and Activity reflects liveliness versus quietness.

In the proposed model, this concept was adopted and has been applied to the entity of events. Accordingly, events that take place in the environment of the agent are analyzed with respect to these three aspects of the EPA space. The objective of this analysis is to decompose each event and project it into its components of evaluation, potency and activity. The values for these components are processed further according to some methodologies to determine their affective influence and consequently their impact on the dynamics of emotion elicitation and regulation.

5.3.2.1 Evaluation

The purpose of analyzing occurred events under this dimension is to first identify the overall valence of the event to be in favor or against the goals of the agent; and second to come up with an approximation for the affective intensity of the event.

According to Table 5.2, the dimension of evaluation is associated with three appraisal variables of Relevance, Desirability and Causal-attribution. Relevance, reflects a filtering sub-system that differentiate worth attending events from non relevant ones. The function of this sub-system is simple. It uses the influential relationship between the occurred event with the set of goals of the agent to determine its importance. Typically, a threshold mechanism is used as a cutting edge between relevant and non-relevant events. An event that was identified as a relevant one in this phase will be passed to the next phase where its desirability level is measured. The third appraisal variable of this dimension, i.e., causal attribution, identifies the type of the emotional channel that is associated with the occurred event. In case that an event involves

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more than one emotional channel (e.g., fear and sadness), the affective impact of the event on each emotional channel will be assessed separately as of having two different events.

Measuring the desirability level of the events on the other hand, is of crucial importance in the overall process of evaluating the affective impact of events; since it analyzes the relationship between the event and the set of goals of the agent in details. As discussed earlier, a fuzzy approach was adopted and found a good fit to model this problem considering its fuzzy-consistent nature. Accordingly, the evaluation process for the occurred event is being performed based on the the impact of the event on the set of goals of the agent as well as the importance of each goal. The fuzzy modeling for this evaluation process is as follows:

Fuzzy variable *Impact* was introduced for the purpose of measuring the impact that the occurred event has on each agent's goal. Accordingly, this variable can take one of the following fuzzy sets:

$$Impact = \{HighlyNegative, SlightlyNegative,$$
$$NoImpact, SlightlyPositive, HighlyPositive\}$$

In addition, goals can have different levels of importance from the perspective of the agent, hence, another fuzzy variable, *Importance,* was declared which can take values from the three following fuzzy sets:

$$Importance = \{ExtremlyImportant, SlightlyImportant, NotImportant\}$$

Furthermore, *Level* is a third fuzzy variable that is used to determine the intensity level of the elicited emotion. As discussed earlier in this article, the affective state of the agent at any point of time is depicted using a bipolar emotional channel at which a pair of opposite emotions appear at the two extremes of the emotional axis. For instance, if the current emotional channel is sad to happy, *Level* will take a value from the following fuzzy sets: (see Figure 5.5)

$$Level = \{HighlySad, SlightlySad, None, SlightlyHappy, HighlyHappy\}$$

Accordingly, *Desirability,* would be the fuzzy variable that indicates the overall desirability level of the occurred event and would take one of the following values:

$Desirability = \{HighlyUndesired, SlightlyUndesired,$

$Neutral, SlightlyDesired, HighlyDesired\}$

Considering the fact that an event e can influence more than one goal, a system of fuzzy rules needs to be built to reflect these multiple interactions. Accordingly, the problem of determining the desirability level of an event can be formalized as below [30]:

$IF \qquad Impact(G_1, e)\ is\ A_1$

$\qquad AND\ Impact(G_2, e)\ is\ A_2$

$\qquad ...$

$\qquad AND\ Impact(G_k, e)\ is\ A_k$

$\qquad AND\ Importance(G_1)\ is\ B_1$

$\qquad AND\ Importance(G_2)\ is\ B_2$

$\qquad ...$

$\qquad AND\ Importance(G_k)\ is\ B_k$

$THEN \quad Desirability(e)\ is\ C$

where, k is the number of relevant goals. A_i, B_i and C are fuzzy sets as elaborated above. This rule reads as follows: if event e affects goal G_1 to the extent of A_1 and affects goal G_2 to the extent A_2, etc., and that the importance of goal G_1 is B_1 and for goal G_2 is B_2, etc., then event e will have a desirability level of C.

In order to quantify C, we use the approach taken in [30] based on Mamdani model [67] which applies centroid defuzzification of the fuzzy rules. Hence, using the *sup min* composition rule between the fuzzy variables of *Impact*, *Importance* and *Desirability,* we would be able to compute the matching degree between the input and the antecedent of each fuzzy rule. For example, consider the following set of n rules:

$$IF \ x \ is \ A_i \ THEN \ y \ is \ C_i$$

...

$$IF \ x \ is \ A_n \ THEN \ y \ is \ C_n$$

Where, x and y are input and output variables respectively. A_i and C_i are fuzzy sets and i is the ith rule. If the input x is a fuzzy set A', represented by a membership function $\mu_{A'}(x)$ (e.g. degree of desirability), a special case of A' is a singleton, which represents a crisp (non-fuzzy) value. Considering the definition of the $sup \ min$ composition between a fuzzy set $C \in F(X)$ and a fuzzy relation $R \in F(X \times Y)$ which is defined as:

$$C \ o \ R(y) = \sup_{x \in X} \min \{C(x), R(x,y)\} \quad \text{for all } y \in Y$$

We can calculate the matching degree w_i between the input $\mu_{A'}(x)$ and the rule antecedent $\mu_{A_i}(x)$ using the equation below:

$$\sup_{x \in X} \min \{\mu_{A'}(x), \mu_{A_i}(x)\}$$

which can be rewritten as:

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

The $\wedge$ operator calculates the minimum of the membership functions and then we apply the sup operator to get the maximum over all $x's$. The matching degree influences the inference result of each rule as follows:

$$\mu_{C_i'}(y) = w_i \wedge \mu_{C_i}(y)$$

Here, C_i' is the value of variable y inferred by the ith fuzzy rule. The inference results of all fuzzy rules in the Mamdani model are then combined using the max operator $\vee$ as follows:

$$\mu_{comb}(y) = \mu_{C_1'}(y) \vee \mu_{C_2'}(y) \vee ... \vee \mu_{C_k'}(y)$$

We use the following formula based on the center of area (COA) defuzzification rule in order to defuzzify the above combined fuzzy conclusion:

$$y_{final} = \frac{\int \mu_{comb}(y) y \, dy}{\int \mu_{comb}(y) \, dy}$$

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The result of above defuzzification process, y_{final} will return a numerical value which indicates the desirability level of the event.

5.3.2.2 Activity

This dimension of ACT is concerned with determining the level of the agent's activeness and involvement with respect to the occurred event. In other words, it indicates the preference and the level of attention that the agent assigns to the new situation arose as a result of the occurrence of the current event. Activity is a highly sophisticated and not comprehensively explored construct that is the outcome of a complicated interplay between many known and unknown factors [64].

In order to come up with an acceptable approximation for this dimension in the proposed model, some of the major role playing factors associated with this dimension were considered. According to Table 5.2, the dimension of activity is linked with three appraisal variables. These variables are *Likelihood*, *Unexpectedness* and *Urgency*.

Likelihood measures the similarity in the outcomes and consequences of multiple occurrences of the same event taken place at different times. Unexpectedness, reflects the degree of unexpectedness with respect to the occurrence of the current event from the perspective of the agent. Urgency, sets the priority level for responding to the occurred event. It shows how fast the event needs to be attended by the agent.

The value of urgency is set based on a quick reactive assessment performed solely by the agent and it reflects the agent's preference for attending different events according to their importance degree. For instance, a top urgent level will be assigned to escaping from a looming life-threatening danger where it reflects a situation that involves a direct threat to an extremely important goal (i.e., staying alive). The relationship between urgency and activity can be expressed as simple as the following two fuzzy rules:

If urgency is high then activity is high

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If urgency is low then activity is low

With respect to unexpectedness, according to [62], it was shown that an unexpected event will create a much higher level of arousal in the agent than an expected same event. Hence, the relationship can be reduced to the following pair of fuzzy rules:

If unexpectedness is high then activity is high

If unexpectedness is low then activity is low

Likelihood, on the other hand is an assessment mean that measures the similarity between the effects of the same event at different occurrences. In other words it reflects the expectation to have the same outcomes for the event as of previous experiences. According to ACT, this similarity can be measured by declaring a deflection factor, D, that determines the differences between two occurrences of the same event [47]. Therefore,

$$D = |[Historical\_Outcomes] - [Generated\_Outcomes]|$$

In order to reduce the complexity caused by absolute value calculations, we consider using square root instead, hence,

$$D = (O_h - O_g)^2$$

where O_h is a dual component vector that is represented by historical data for the evaluation and potency dimensions obtained from a previous occurrence of the same event under assessment; whereas O_g represents the generated evaluation-potency vector for the most recent occurrence of the event. Accordingly, the subjective likelihood, L, of an event is defined as follows:

$$L = c - D$$

where c is an arbitrary constant.

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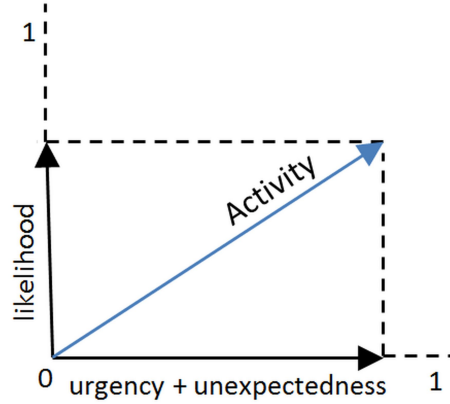
Figure 5.6: Overall activity level for an event calculated from its appraisal components of *urgency, unexpectedness* and *likelihood*

The above equation shows that the less the deflection the higher the likelihood between the two occurrences of the same event. By expanding the terms of the deflection equation, we obtain:

$$D = O_h^2 - 2O_hO_g + O_g^2$$

Since the two dimensions of evaluation and potency were assumed to be independent from each other with no correlations, the above equation can be rewritten as follows:

$$D = (E_h^2 - 2E_hE_g + E_g^2) + (P_h^2 - 2P_hP_g + P_g^2)$$

Considering the fact that all of the terms in the above equation are known, D is computable and accordingly a value for L can be obtained.

Finally, in order to come up with an overall quantity for the dimension of activity from its three components (i.e., urgency, unexpectedness, and Likelihood), two further steps would be required. First, the fuzzy values for urgency and unexpectedness will be composed in a similar way to the approach taken in calculating the desirability level (see section 5.3.2.1). Second, the former defuzzified value of expectedness and urgency is numerically combined with the amount of likelihood obtained from the previous processing step. The result from this combination divided by $\sqrt{2}$ forms the final quantified value for activity dimension. (see Fig. 5.6)

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5.3.2.3 Potency

The third dimension in EPA space, *potency* is associated with the agent's perception about the strength of its attitude with respect to the occurred event. In other words, it is the sentiment of being either dominant or submissive towards the event or its outcomes. This is closely related to the level of control that the agent has on the new situation arose from the occurrence of the event as well as the set of available and applicable coping strategies.

The appraisal process of an occurred event starts with the dimensions of evaluation and activity which constructs the main drive for the emotions dynamics. Potency, on the other hand represents a post appraisal process of the occurred event and it acts as a regulation mechanism based on the available coping strategies and the notion of emotion regulation [43].

According to the dimensional theories of emotion such as [76, 36], each unique emotion has a basic potency value, $Potency_0$. These values are reflected in Table 5.3. A more important component of potency is the value obtained from the above mentioned post appraisal processes at which the set of coping strategies along with their applicability levels are determined. Therefore, the equation for calculating the level of potency can be written as follows:

$Potency = Potency_0 + \sum_n(w_n * v_n)$

In the above equation, potency level is associated with the emotional impact, v_n, of each applicable regulation strategy. According to Gross model of emotion regulation [43], regulation strategies applied at different points of time during the regulation process have different impacts on the overall process of regulation. This fact was considered in the proposed computational model by accompanying each v_n with its weight, w_n. By normalization, the sum of all weights w_n is taken to be 1. Hence, the weighted sum of $\sum w_n v_n$ calculates the aggregate affective impact of all applicable coping strategies for the occurred event. For brevity, we refrain from dissecting this

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Table 5.3: Basic potency values for individual emotions [36]

Emotion under study	Potency initial value
Admiration	0.5
Anger	-0.51
Disliking	-0.4
Disappointment	-0.3
Distress	-0.4
Fear	-0.64
FearsConfirmed	-0.5
Gratification	0.6
Gratitude	0.4
HappyFor	0.4
Hate	-0.6
Hope	0.2
Joy	0.4
Liking	0.4
Love	0.3
Pity	-0.4
Pride	0.4
Relief	0.2
Remorse	-0.3
Reproach	-0.3
Resentment	-0.2
Satisfaction	0.3
Shame	-0.3

method further and interested readers are referred to [112] for a model of quantifying $v_n s$ and computing the related weighted sum.

5.3.3 Mood

Mood is another construct that plays an important role in the emotional dynamics of individuals. Mood can be considered as an intermediate affective state that persists for a relatively long period of time [76]. Such mid-term lifetime for mood states contrasts transient and short term emotional states triggered often in response to some external stimuli (e.g., events) as well as the long-term and sometimes lifelong affective states of personality traits [35].

Considering the deep impact of the mood on the overall affective states of individuals such as the way that people perceive external events at which the tendency of perception would be biased in a way that makes it in line with the mood state; and offsetting threshold levels for triggering different emotions (e.g., a person with negative mood may become sad with minor negatively perceived events), it would be essential to incorporate this construct in the computational model for emotions.

However, knowing the fact that mood has a sophisticated nature which is the outcome of a complex interplay between numerous internal and external factors, and also the fact that it is deeply linked to the different personality traits of different people, makes it extremely difficult to come up with a general model for mood that can accurately determine the mood states of all individuals. Hence, the endeavor in the proposed model is to consider a simple but relatively precise approximation for the mood states.

Accordingly, mood was looked at as a two component construct at which the first is the outcome of internal appraisal processes directly associated with the preferences and personality traits of every individual. These appraisal variables are concerned with the set of background goals such as staying alive, being healthy, being wealthy and in short, general well-being and pleasure from the perspective of the agent itself. For simplicity, this component was given a constant value in the system. Further research on this component would enhance the performance of the proposed model.

The second component on the other hand, is a computationally tractable quantity that is derived from a special aggregation of the recently experienced emotions. Accordingly, each elicited emotional state and based on a certain mechanism will contribute (positively or negatively) to the value of the general mood. Hence,

$MOOD = f(internal\_processes) + f(Emotion)$

$MOOD = c + f(Emotion)$

The initial mood value is set using the affect grid concept proposed by Russell [99]. Accordingly, at any point in time, changes in the mood state of the agent can be tracked using the following equation:

$Mood_{t+1} = Mood_t + f(Emotion_e)$

Based on the above equation, at the absence of any affect relevant events, the mood of the agent will not change. This fact asserts the relatively long life term for mood states. In addition, moods are measured in the range of [-1 ..1] at which -1 indicates extremely negative mood (i.e., highly pessimistic) whereas +1 reflects extremely positive mood (i.e., highly optimistic).

5.4   Proposed Computational Model

The ultimate goal for the proposed model is to come up with a general computational model for emotion dynamics at which the transitions in the emotional states of an affective agent as a result of the changes in the agent-environment relationship represented by the occurrence of relevant events can be tracked. These dynamics are later used in the process of emotion regulation where events could be generated purposefully in order to intervene in the affective state of the agent and possibly regulate those disturbing negative emotions.

The following equation which constructs the starting point for the proposed computational model, clearly separates between the internal factors represented by mood, and the external affective stimuli represented by occurred events.

$ERL = Mood + f(event)$

Where ERL stands for Emotion Response Level and $f(event)$ is the EPA (Evaluation, Potency and Activity) appraisal vector for the occurred event derived according to the affect control theory principles. It can be implied from the above equation that a portion of the emotion response level of the agent at any point in time will be

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preserved in the next response level through the construct of mood. As mentioned earlier, $Mood$ is an aggregate quantity that gets updated according to the following equation

$$Mood_{t+1} = Mood_t + \triangle Mood$$

$$Mood_{t+1} = Mood_t + f(emotion_e)$$

$f(emotion_e)$ on the other hand reflects the affective impact on the current emotional state of the agent caused by event e. In order to quantify this affective impact, we use the following rule adopted from EMotion and Adaptation model (EMA) [73]:

$$f(emotion_e) = Desirability_e * Likelihood_e$$

The way the above two quantities (i.e., $Desirability$ and $Likelihood$) are obtained was discussed in sections 5.3.2.1 and 5.3.2.2 respectively.

With regards to $f(event)$, each occurred event is appraised according to the three dimensions of evaluation, potency, and activity of affect control theory (i.e., the $\overrightarrow{EPA}$) as discussed in the previous section. Here, an important challenge is to express the components of the $\overrightarrow{EPA}$ in terms of emotion dynamics and particularly to translate them into explicit transitions between different emotional states. After investigating several possible approaches, we found that fuzzy automata approach is an efficient framework for this purpose.

5.4.1   Fuzzy Automata

In order to study the dynamics of changes in the emotion response levels of an affective agent within the proposed fuzzy bipolar emotional channels, a general frame work that defines the methodology for transitions between different fuzzy sets will be required. For this purpose, a fuzzy state machine was considered at which the states reflect the fuzzy emotional response levels; and the transitioning edges indicate the fuzzy membership values for transitions between each pair of source and destination states.

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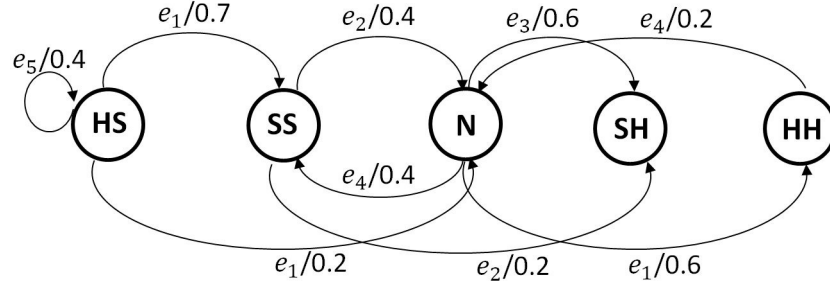
Figure 5.7: Fuzzy automata for the five fuzzy states for the emotional channel of sad-happy. Here, the fuzzy states are HighlySad, SlightlySad, Neutral, SlightlyHappy and HighlyHappy. The stimuli are the set of five events, $e_1 - e_5$. The number beside each event indicates the fuzzy membership value for the related transition

Accordingly, the emotional state of the agent transitions into a set of new states as a result of the occurrence of relevant events that take place in the system. Hence, each transition is induced according to the corresponding EPA 3-tuple vector that represents the affective impact of the occurred event based on affect control theory.

The related fuzzy finite state machine can be defined using a 5-tuple [58] as below:

$A = \{Q, q_0, \Sigma_e, \delta, q_f\}$

where:

Q is non-empty finite set of states

q_0 is the initial state

Σ_e is a finite input obtained based on ACT

$\delta : Q \times \Sigma_e \to F(Q)$ is the fuzzy transition function

q_f is the fuzzy subset of final states

In the above definition, each state in Q is a fuzzy set that indicates the emotional response level of the agent at a given point in time. Furthermore, Σ_e is the $\overrightarrow{EPA}$ of the event under study (see Fig. 6.1).

5.4.2 Fuzzy Transitioning Function

As discussed earlier, transitions over different states in the proposed fuzzy emotional automata is based on an appraisal process of the EPA components for the occurred

event. Since a fuzzy transition function between a pair of states is a transformation of the fuzzy membership function of the starting state into the fuzzy membership function of the ending state, it would be convenient to represent such transition functions using relational matrices. However, since there are no established methods that link explicitly the changes in EPA values to the emotional response levels, some guidelines from the theory and results obtained from relevant studies and computational models would be needed.

Based on Russell's concept of *core affect* [99] and *affective grid* [98], there exist explicit correlations between the two dimensions of the core affect (i.e., the *valence* and *activity*). Studying these two dimensions [99] shows that they are very similar to the two components of desirability and activity in the EPA space of affect control theory. This fact makes it possible to have a single compound transition matrix for these two dimensions. By joining the values of evaluation and activity of the occurred event, the core affective bias of the event will be determined.

A general rule in building the relational matrix of evaluation-activity (EA) that reflects the fuzzy membership values for the transitions between different emotional states within a bipolar affective channel (e.g., stress to joy) is the fact that higher levels of desirability will result into farther reachable states. Algorithm Fuzzy-Transition in section 5.4.3.4 describes the method used to fill in the entries of the EA fuzzy transition matrix.

On the other hand, since the third dimension in affect control theory, potency, is not correlated to the other two dimensions, another transition matrix would be required to study the impact of this dimension on the affective state of the agent. As a matter of fact, potency is closely associated with the concept of coping strategies and in particular to the controllability, changeability and adaptability attributes of the occurred event. Therefore, the corresponding transition matrix for the dimension

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of potency can be linked to the theory of emotion regulation strategies proposed by Gross [42] and its corresponding computational model proposed by Bosse et al. [13].

In particular, the following inferential rules from Gross theory were extensively used in the calculations of the fuzzy membership values for the potency transition function.

- "Early regulation strategies are more effective" [43], which implies that the impact of potency deteriorates as the agent gets farther from the initial state, and

- "High strategy flexibility leads to large adjustments" [43], which implies that higher values for the potency at the starting state will result in higher fuzzy membership values in the transition function to the target state.

Furthermore, the following rule was a major guideline that assisted us to extensively limit the number of potential transitions by ruling out a great deal of impractical transitions in the fuzzy automata,

- "Emotion approach norm monotonically" [13]

The last principle is very beneficial in the sense that it reduces dramatically the size of the search space in the process of finding the shortest transition sequence between a pair of initial and target states. (see Algorithm Best-Transition in section 5.4.3.3)

In summary, the EPA components of each relevant event will be translated into two state transition relational matrices of R_{EA} and R_P. The fuzzy membership value for each state transition will be determined by the composition of the current state's fuzzy membership and the two relational matrices of R_{EA} and R_P. The destination state of a transition would be the fuzzy state that holds the highest fuzzy membership in the obtained matrix. (see Algorithm Track-State in the next section)

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5.4.3 Automata Algorithms

5.4.3.1 Algorithm Track-State: to track the emotional state of the agent as a result of the occurrence of a series of events

Input: $q_0, E = \{e_1, e_2, ..., e_k\}, Q = \{q_E, q_H, q_M, q_S, q_N\}$

    Output: q_f

    Begin

      Defuzzify state $q_i = q_0$ using weighted average method

      For each event $e_i \in E$

        Begin

          Calculate the $\overrightarrow{EPA}$ for event e_i

          Obtain R_{EA} and R_P for e_i

          Calculate $\widetilde{\mu}(q_i) = \mu(q_i) \circ R_{EA} \circ R_P$

          Reset $i := k$ such that $\mu_k(q_i) = \underset{s \in Q}{Max}(\widetilde{\mu}_S(q_i))$

        End For;

         Print $q_f = q_k$

    End.

5.4.3.2 Algorithm Build-Automata: to construct the full automata

Input: E, Q

    Output: A

    Begin

    For each $q \in QA$

      Begin

    Defuzzify state q using weighted average method

    For each event $e \in E$ applicable at q

      Begin

        Calculate the $\overrightarrow{EPA}$ for event e_i

        Obtain R_{EA} and R_P for e_i

        Calculate $\widetilde{\mu}(q) = \mu(q) \circ R_{EA} \circ R_P$

        For all $s \in Q$ such that $\widetilde{\mu}_S(q) \neq 0$

          Add a transition link between q and s

          Label $\mu_s(s) = \widetilde{\mu}_S(q)$ for that transition link

        End For;

        $Q = Q - q$

      End For;

Print $q_f = q_k$

End.

5.4.3.3 Algorithm Shortest Path-Transition: to find the shortest transition sequence between a given pair of initial and final states

Input: A, q_0, q_f

Output: sequence of transitions

Begin

Defuzzify state $q = q_0$ using weighted average method

While $q \neq q_f$

Begin

For each transition $qq' \in A$

Calculate $dist(q) = Euclidean(q'q_f)$

End For;

Choose p such that $dist(p) \preceq distEuclidean(q_i') \ \forall i$

If $dist(p) \prec dist(q)$ **Then**

Begin

add transition qp to the sequence s

$Q = Q - q, \ q = p$

End If

End While;

Print s

End.

5.4.3.4 Algorithm Fuzzy-Transition: to fill the entries of the EA (evaluation-arousal) fuzzy transition matrix (Sad-Happy)

Input: $e, Q = \{q_{HS}, q_{SS}, q_N, q_{SH}, q_{HH}\}$

Output: $Fuzzy - Transition - matrix, FTM[][]$

Begin

Obtain the values of E (evaluation) and A (Arousal) for event e

For each starting state $s_i \in Q$

Begin

Determine all states $S' \subset Q$ reachable from s

For each ending state $s_j' \in S'$

```
    Begin
      If j > i Then
        FTM[i][j] = E + (E * A) − E_J * (j − i − 1)
        If FTM[i][j] < 0.05 Then
            FTM[i][j] = 0
        If FTM[i][j] > 1.0 Then
            FTM[i][j] = 1
        Else
          FTM[i][j] = 1 − [E + (E * A) − E_J * (j − i)]
        If FTM[i][j] < 0 Then
            FTM[i][j] = 0
        End If;
      End For;
    End For;
  End.
```

5.5 Experiments and Discussion

In order to evaluate the performance of the proposed model and to verify its functionality, several simulation experiments were conducted. Here, two of these experiments are discussed. In both of these experiments, a set of three goals of $G = \{G_1, G_2, G_3\}$ as the agent's goals beside a set of five possible events of $E = \{e_1, e_2, e_3, e_4, e_5\}$ were considered. According to Table 5.4, it is assumed that the goals preference and the impact of an occurred event on each goal are all given to the system. In addition, column U is a flag that reflects the urgency of the event to be attended by the agent at which 'u' indicates a highly urgent event whereas 'r' represents a regular event with low urgency.

The first step towards building a model for this problem would be to determine the $\overrightarrow{EPA}$ for all events of E by calculating the three components of evaluation, potency and activity for each event. As discussed in section 5.3.2.1, with respect to the dimension of evaluation, a system of fuzzy rules that links the fuzzy variable of *Desirability* to other fuzzy variables of *Importance* and *Impact* will be built. The chart in Fig. 5.8 represents the EPA vectors calculated for all events of E.

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Table 5.4: List of agent's goals and events along with their impact on each goal

Goal	U	G1	G2	G3
Importance		HighlyImportant	SlightlyImportant	HighlyImportant
Event		*Impact*(G1)	*Impact*(G2)	*Impact*(G3)
e_1	r	HighlyPositive	NoImpact	HighlyPositive
e_2	u	HighlyNegative	SlightlyPositive	SlightlyNegative
e_3	r	HighlyPositive	SlightlyNegative	SlightlyNegative
e_4	u	HighlyNegative	HighlyPositive	HighlyNegative
e_5	r	HighlyPositive	HighlyPositive	NoImpact

Experiment 1

The goal of this experiment is to study the affective impact and to track the changes in the emotional response level of an agent as a result of the occurrence of some stochastic events. The emotion under study in this experiment is *distress*. The initial emotional state of the agent is neutral or not stressed. The transition stimuli is the event sequence of $< e_2, e_1, e_4, e_5 >$ that take place at time steps $< 20, 50, 60, 80 >$ respectively. In order to study the impact of applying above sequence of events on the level of distress of the agent, it would be necessary to establish the EA and P relational matrices for all occurred events according to the methodology and algorithms discussed in section 6.3. Next, it would be required to apply the related EA and P relational matrices of each participating event to the emotional fuzzy state of the agent. This task is accomplished by using algorithm Track-State described in section 5.4.2.

Accordingly, as a result of applying the above mentioned sequence of events on the given initial state of neutral, the final state of the agent was concluded to be SJ or SlightlyJoyful.

As an instance for the intermediate transitions of the above scenario, the first state transition is dissected here. In this transition, the source state is $q_0 = N$ (i.e., Neutral) and the destination state is an unknown state of q that needs to be determined. Therefore,

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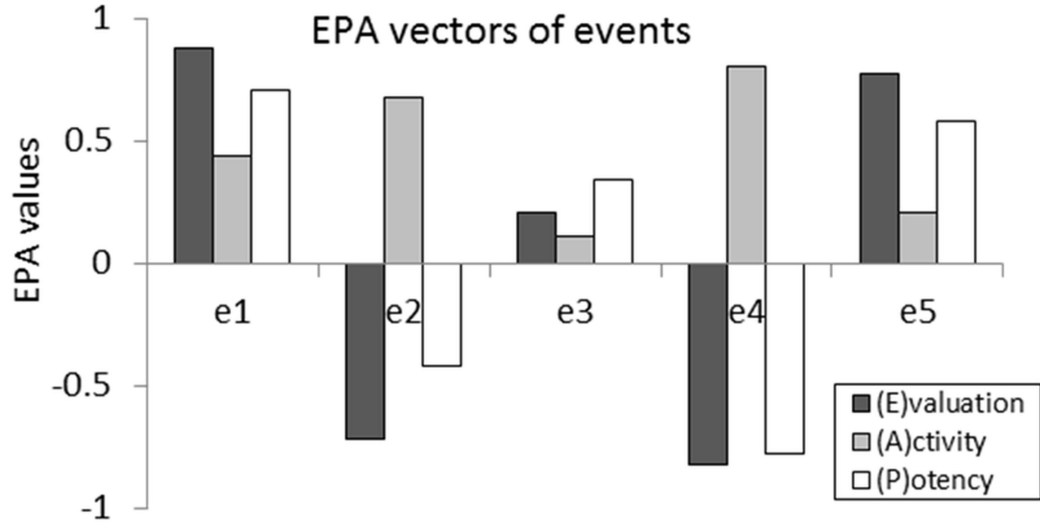
Figure 5.8: EPA components calculated for all events of the automaton

using the defuzzification rule of weighted average method, we will have, $\mu(q_0) = \mu(N) = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \end{bmatrix}$ the transition process and the relations of R_{EA} and R_P for stimulus e_2 arrived at state $q_0 = N$ are as follows:

$\mu(q) = \mu(q_0) \circ R_{EA} \circ R_P$

where R_{EA} and R_P were calculated for stimulus e_2

$$\mu(q) = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \end{bmatrix} \circ \begin{array}{c} \\ HD \\ SD \\ N \\ SJ \\ HJ \end{array} \begin{array}{ccccc} HD & SD & N & SJ & HJ \\ \begin{bmatrix} 0.97 & 0.58 & 0 & 0 & 0 \\ 0.94 & 0.74 & 0.06 & 0 & 0 \\ 0.61 & 0.92 & 0.40 & 0 & 0 \\ 0.32 & 0.88 & 0.64 & 0.10 & 0 \\ 0.08 & 0.64 & 0.89 & 0.71 & 0.14 \end{bmatrix} \end{array}$$

$$\circ \begin{array}{c} HD \\ SD \\ N \\ SJ \\ HJ \end{array} \begin{array}{ccccc} HD & SD & N & SJ & HJ \\ \begin{bmatrix} 0.90 & 0.56 & 0.05 & 0 & 0 \\ 0.81 & 0.68 & 0.16 & 0 & 0 \\ 0.31 & 0.94 & 0.21 & 0 & 0 \\ 0.08 & 0.65 & 0.91 & 0.30 & 0 \\ 0.02 & 0.24 & 0.69 & 0.81 & 0.24 \end{bmatrix} \end{array} = \begin{bmatrix} 0.81 & 0.68 & 0.21 & 0 & 0 \end{bmatrix}$$

As it can be seen, the resulted $\mu(q)$ shows that the destination state of the above transition would be $q = HD$ (i.e., *HighlyDistressed*). At this state, the process of

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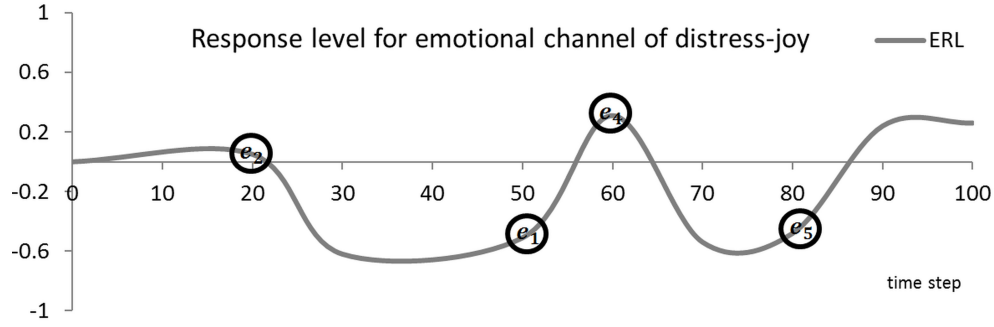Figure 5.9: Emotion response level changes as a result of occurred events

transitioning into new states continues as a result of the arriving events of e_1, e_4, e_5 which eventually takes the agent to the final state of $q_f = SJ$. Here, the sequence of all transitions is: N, HD, SJ, HD, SJ. Furthermore, Fig. 5.9 depicts the changes in the emotional response level in a defuzzified metric.

Initially, the agent was in neutral status with no explicit emotion along the distress-joy emotional channel. At time step=20, a strong negative event, e_2 took place and caused the ERL to slip sharply towards hyper distress region. The resulted *HighlyDistressed* state was slightly improved later due to the temporal changes of the mood. At step=50, the occurrence of the strong positive event of e_1 managed to take the ERL to the joy zone where it reached +0.30 at step=60. This situation did not last long due to the occurrence of the very strong negative event of e_4 which quickly returned the affective state of the agent to the highly distressed region at which it showed a sharp drop in ERL by almost 0.8 unit (from $ERL = 0.3$ to $ERL = -0.5$). However, at step=80, the occurrence of the strong positive event of e_5 managed to move the ERL to *SlightelyJoyful* state which represents the final state of the simulation. The emotional behavior of the agent represented by the changes in the ERL of the agent came in line with the theoretical basis of the proposed model and our expectations.

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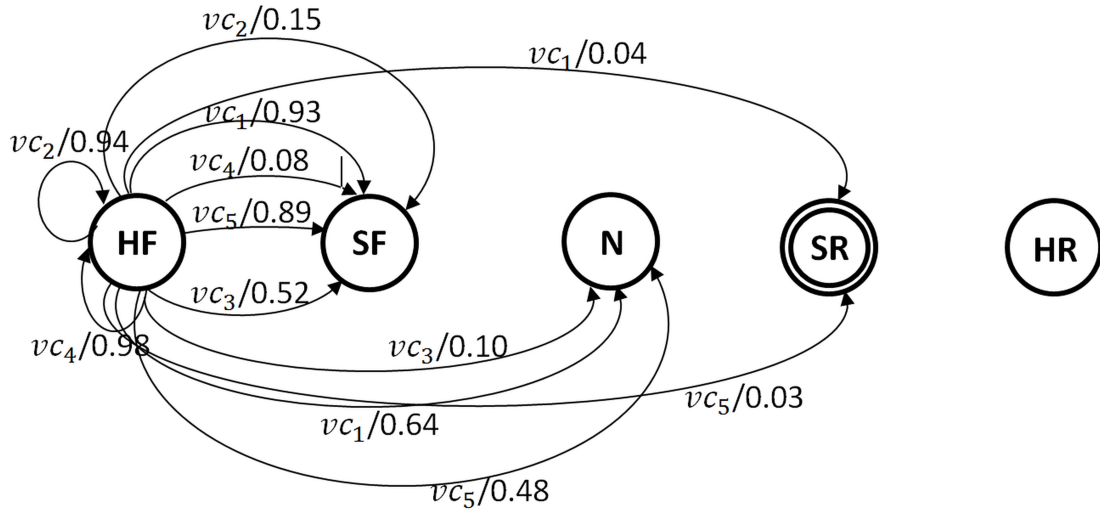
Figure 5.10: Partial fuzzy transition automaton for experiment 2. Only transitions initiated from state HF are shown here

Experiment 2

In the second experiment, the emotional channel under study is fear-relief. The scenario depicts a situation at which a psychotherapist is involved in regulating a hyper fear emotion of a patient. The initially diagnosed affective state of the agent was *HighlyFear*. The aimed at emotional level was set to *SlightlyReleif* since due to the special circumstances, it was concluded that the desirable state of *HighlyRelief* is unreachable. The stimuli to the related state machine that models the above problem is a set of 5 video-clips of $VC = \{VC_1, VC_2, VC_3, VC_4, VC_5\}$. With regards to the affective influence of these video clips, for simplicity it is assumed that there exist a one-to-one symmetry correspondence between the set of VC and the set of events $E = \{e_1, e_2, e_3, e_4, e_5\}$ used in experiment1. Accordingly, each video-clip, VC_i, is corresponding to event e_i in terms of its impact on the set of goals of the agent. The ultimate goal for the psychotherapist is to find the best pattern for a subset of VC that would take the patient to the target emotional state in the shortest time possible. Furthermore, it is assumed that each stimulus reaches its peak impact after

Figure 5.11: The shortest reliable transition sequence from HF to SR states

20 time-steps and that each stimulus (i.e., video-clip) can be applied up to one time only in order to be effective.
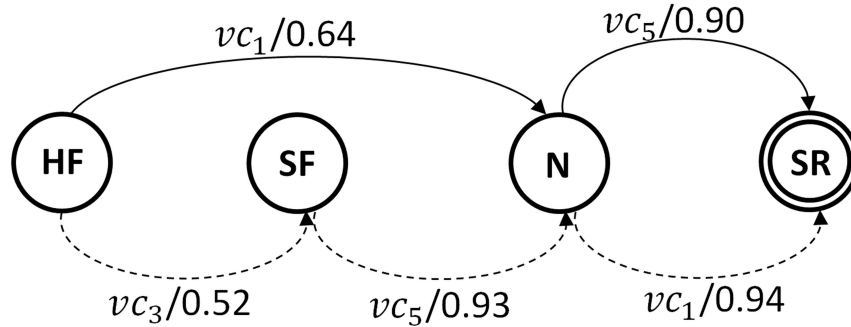
Unlike experiment 1, it would be necessary here to build the entire fuzzy automaton as the first step. Algorithm Build-Automata (see section 5.4.3.2) was used for this purpose in order to establish the links between the different states of the emotional channel under study as well as the fuzzy membership values for the transitioning edges between different states. Fig. 5.10 is a partial representation of this automaton. For brevity, we refrain from displaying the full automaton since according to our calculations, it includes around 75 distinct transitions with non-zero membership.

The next step is to apply Algorithm Shortest Path-Transition (see section 5.4.3.3) in order to find a sequence of VC_i's that enables the agent to regulate its emotional state from *HighlyFear* to *SlightlyRelief* in a shortest path possible. The result obtained from algorithm Shortest Path-Transition indicates that $s = \{HF, N, SR\}$ using video-clips $\{vc_1, vc_5\}$ is the shortest reliable transition sequence from HF to SR (solid transitions in Fig. 5.11).

Additionally, the second shortest reliable sequence is $\{HF, SF, N, SR\}$ that involves the set of video-clips $\{vc_3, vc_5, vc_1\}$ (dashed transitions in Fig. 5.11). Here, the determinacy factor for the first sequence is higher than the second one (i.e., 0.58 compared to 0.45). besides, the time period required for the regulation process is shorter also (i.e., 40 steps compared to 60 steps). As a result, the psychotherapist

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will present vc_1 followed by vc_5 to the patient in order to realize the goal of the regulation process.

5.6   Conclusion

In the proposed model, the principles of affect control theory (ACT) were used to appraise the affective influence of the occurred events on the emotional response level of an individual agent. Each relevant event was analyzed using a set of appraisal variables and then projected on the ACT's three dimensional space of evaluation, potency and activity (EPA). These three quantities were combined to establish a fuzzy state machine that models the dynamics of changes in the affective state of the agent under study. The affective state of the agent was considered within a bipolar emotional axis at which two opposite emotions appear at the two extremes of the axis. For instance, the fuzzy automaton for the emotional channel of sad to happy included the five fuzzy states of *highlysad, slightlysad, neutral, slightlyhappy and highlyhappy*. Additionally, relational matrices were used to represent the outcome of the $\overrightarrow{EPA}$ vector for each occurred event and consequently to determine the destination state of each transition.

The proposed computational model was able to construct the full automaton of transitions over different states of an emotional channel; to track the target emotional response level of the agent as a result of the occurrence of an event; and finally to identify the shortest reliable transition path between a pair of initial and target emotional levels.

One important feature of the proposed model is its high flexibility in accommodating possible changes in the cognitive analysis of events. Accordingly, if a more efficient interpretation for the role of each event is adopted, the model can easily adapt itself to the amendments.

Limitations of the proposed emotion model   One apparent limitation of the current model has to do with the term of bipolar emotional channel at which an agent can transition between different emotional levels within the range of two opposite emotions only. Several scenarios can be thought of where the transition might go beyond that limit and includes other emotions outside of the channel. According to the current approach, such transitions need to be modeled separately using a chain of transitions. A mechanism for simultaneous modeling of all transitions might yield to more realistic results.

Future directions   The author believes that the proposed model has the potential for further development and research and is a candidate for numerous applications across a broad spectrum of fields such as robotics, HCI, psychotherapy and healthcare.

Chapter 6

Verification and Partial Validation of the Proposed Emotion Model: Event-Emotion Matrix in a Healthcare System

6.1 Introduction

The verification and validation processes for naturally qualitative systems are often sophisticated and are associated with major challenges. Despite the fact that there have been many computational models of emotion proposed in the last decade, surprisingly very limited research work can be identified that has addressed the matter of validating these models (e.g., [69] and [40]).

It can be argued that emotional models can be validated in different ways according to the application of the model. For instance, does the emotion model improve the performance of a certain application that it was used for? e.g., in HCI, how does the model improve the user satisfaction and believability in their affective rapport

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experience between the user and the machine? Similarly, the learning effectiveness of a tutoring system can be assessed according to the approach and methodology taken in modeling the emotional constructs and processes of that system.

Here, the goal is to verify and validate the general computational model of emotions that was proposed in the previous chapter. The proposed computational model studied the relationship between affect relevant events that take place in the environment of a human agent and the set of emotions that were elicited in the agent in response to the occurred events. The model used a hybrid appraisal and dimensional approach in order to deeply analyze emotion triggering events and to project their affective impacts onto the three dimensions of evaluation, potency and activity introduced in the Affect Control Theory (ACT) [84].

For the purpose of verification and validation, it would be necessary to implement the proposed general model in a certain context using the properties of the chosen scenario. Hence, in this chapter and using the principles of Affect Control Theory [84], we investigated building an event-emotion matrix that links every relevant event to its corresponding emotional state in a healthcare system (e.g., hospital) at which the aim is to study the affective behavior of two active agents (i.e., patient agent and nurse agent) in response to the occurrence of different events.

Considering the important non-deterministic factor in emotional dynamics, a fuzzy state machine framework was used to best reflect the transitioning processes between different emotional states. Where applicable, some model generated results were validated using corresponding data obtained from two related case studies (i.e., [8, 79]).

In our proposed work, we focus on an appraisal process at which the consistency between model's predictions is assessed according to what a human individual would have emotionally behaved in a realistic situation. In particular, we assess the accuracy of the proposed model by analyzing the similarity between the predictions made by

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the model and what affective states would have been experienced by an individual in a particular situation. Furthermore, the intensity of each elicited emotion as well as the temporal dynamics of the changes in the emotional response levels as a result of the occurrence of relevant events are other essential components that shape our performance analysis and validation process.

In order to verify the performance of the proposed model, the results obtained from the proposed model were contrasted against their counterparts from a detailed test-case that uses a blend of realistic and simulation generated data which reflects the affective behavior of patient and nurse agents in a healthcare unit. The predictions of the proposed model were partially validated using a set of data and statistics obtained from two relevant case studies.

6.2   Computational Models of Emotion

The interest in studying emotion as an important part of the personality as well as a major role player in forming human's personal and social behaviors is still increasing among research communities spanned over a large spectrum of scientific fields. A large portion of recent scientific emotion research is originated in the fields of computer science and information technology in general. In particular, a concrete systematic research endeavor aimed at effectively modeling emotional processes and studying the dynamics of changes in different affective states can be found under the umbrella of *Affective Computing* [88] and *Human-Computer-Interaction* (HCI).

Despite the relatively young age of the affective computing research area, it has managed to make huge achievements in several areas especially, emotion detection (e.g., [19]), emotion modeling (e.g., [36]), and emotion exhibition in artificial agents (e.g., [10]).

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A key element in an affective computing based system is the mechanism taken in modeling different processes involved in an emotional experience using computational methods. Different approaches such as dimensional (e.g., [36]), core-affect (e.g., [99]), fuzzy (e.g., [30]), etc., were considered by researchers for this purpose. Undoubtedly, appraisal models (e.g., [83]) are among the most widely used approaches for emotion modeling [72].

The basic idea in appraisal theories (e.g., [110, 61, 83] is the close relationship between experienced emotions and the changes in the situations of the environment. Accordingly, an individual continuously monitors and appraises the changes in the environment such as the occurrence of relevant events and the way that these events influence the set of goals of the individual. The appraisal processes are typically performed by means of a set of appraisal variables such as the preference, desirability and the coping potentials associated with the new situation. The affective behavior of these appraisal processes are manifested in terms of the elicitation of certain emotions.

Dimensional approaches on the other hand emphasize the tenet that different emotional states can be expressed in terms of few dimensions. For instance, the theory of core affect proposed by Russell [99] argues that two dimensions of pleasure and arousal are sufficient to measure and represent all affective states that an individual might experience due to the situational changes in the environment. Therefore, one of the major differences between appraisal and dimensional models is the fact that in appraisal theories, the distinction between different emotions such as joy, pride, anger, etc., is emphasized, whereas in dimensional theories, the focus is mostly on affect tendencies that direct the mind to experience a certain emotion at a certain time without caring a lot about emotion labels.

Affect Control Theory

Affect control theory (ACT) is a dimensional theory for emotion modeling which has managed recently to attract a great deal of research work. This theory, initially introduced by Osgood [84], is based on the belief that the meanings of concepts can be measured and expressed in terms of the perceptual dimensions of evaluation, potency, and activity.

The first dimension in ACT evaluates the valence of the situation to be either a positive or negative. The second dimension deals with the level of attention that is triggered in the agent as a result of the situation. Potency, reflects the degree of power and activeness or passiveness that the agent feels about the situation.

6.3   Proposed Computational Model at a Glance

The proposed computational model is aimed at achieving two major goals: the first is to establish an event-emotion matrix that links affect relevant events to the corresponding elicited emotions; and the second is to come up with an emotion dynamics mechanism that is capable of tracking the changes in the emotional states of an individual.

In order to achieve the first goal, a special approach based on a hybrid of dimensional and appraisal methods was utilized. Accordingly, occurred events were assessed and measured using a set of appraisal variables and then were projected onto the three dimensions of the ACT, i.e., *Evaluation*, *Potency* and *Activity*.

The first dimension of this ternary space, evaluation, determines the overall positiveness or negativeness of the occurred event along with its valence intensity; Potency is linked to the degree of adaptation and coping strategies associated with the occurred event; Activity, on the other hand measures the degree of activeness or passiveness that the agent experience as a result of the occurrence of the event. In a numerical
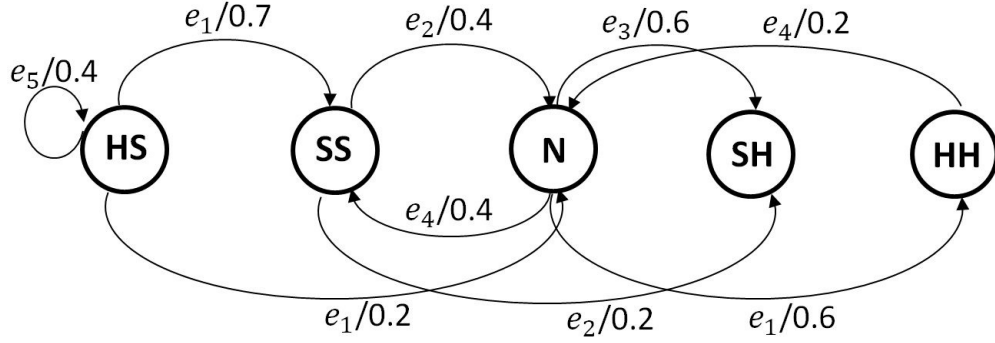
Figure 6.1: Fuzzy automaton for the five fuzzy states of the sad-happy emotional channel . Here, the fuzzy states are HighlySad, SlightlySad, Neutral, SlightlyHappy and HighlyHappy. The stimuli are the set of five events, $e_1 - e_5$. The number beside each event indicates the fuzzy membership value for the associated inter-state transition

scale, all of these three dimensions are measured using an interval of $[-1, 1]$. For instance, an event with an EPA vector of $\overrightarrow{EPA} = (-0.78, -0.68, -0.45)$, represents a highly undesirable event that creates a hyper tension in the agent with a considerably low degree of control over the outcomes of the event.

Considering the fact that this article is mostly intended to verify and validate the proposed model for event-emotion matrix, for brevity, we refrain from dissecting the entire model here and only a short summary about this model is provided. Interested readers are referred to [114] for a detailed description of the full model.

In order to quantify the dimension of evaluation, a fuzzy system that describes events in terms of their impact on the set of goals of the agent was created. Accordingly, the desirability of an event is being determined based on the impact of the event on the set of goals of the agent as well as the importance of each goal.

Potency as the second dimension of ACT is the sentiment of being either dominant or submissive towards the event or its outcomes. This is closely related to the level of control that the agent has on the new situation that arose from the occurrence of the event as well as the set of available and applicable coping strategies. Potency in fact represents a post appraisal process of the occurred event and it acts as a

regulation mechanism based on the available coping strategies and the notion of emotion regulation [43].

With respect to finding an acceptable approximation for the third dimension of ACT, activity, it was concluded that activity is mostly associated with the three appraisal variables of *Likelihood*, *Unexpectedness* and *Urgency*. Likelihood measures the similarity in the outcomes and consequences of multiple occurrences of the same event taken place at different times. Unexpectedness is inversely proportional to the possibility of the occurrence of the current event from the perspective of the agent. Urgency, sets the priority level for responding to the occurred event. It shows how fast the event needs to be attended by the agent. A system made of related fuzzy rules was built to describe the interactions between this dimension with the aforementioned appraisal variables. Solving this fuzzy system yields to a quantity that is a measure for activity dimension.

In order to achieve the second goal of this research work, i.e., modeling emotion dynamics, a fuzzy state-machine framework was considered at which the fuzzy states are the emotional states within the related emotional channel and the fuzzy transitioning functions are the EPA vectors for each event that were obtained through the first stage of event's assessments. For example, Fig.6.1 depicts a partial automaton for sad-happy bipolar emotional channel. For instance, the occurrence of event e_2 at the state of SS (*SlightlySad*) can either take the agent to state N (*Neutral*) with a fuzzy membership value of 0.4 or directly to the state of SH (*SlightlyHappy*) with a fuzzy membership value of 0.2.

6.4   Experiments and Discussion

In order to evaluate the performance of the proposed computational model and to verify its functionality, several simulation experiments were conducted. Here, one of
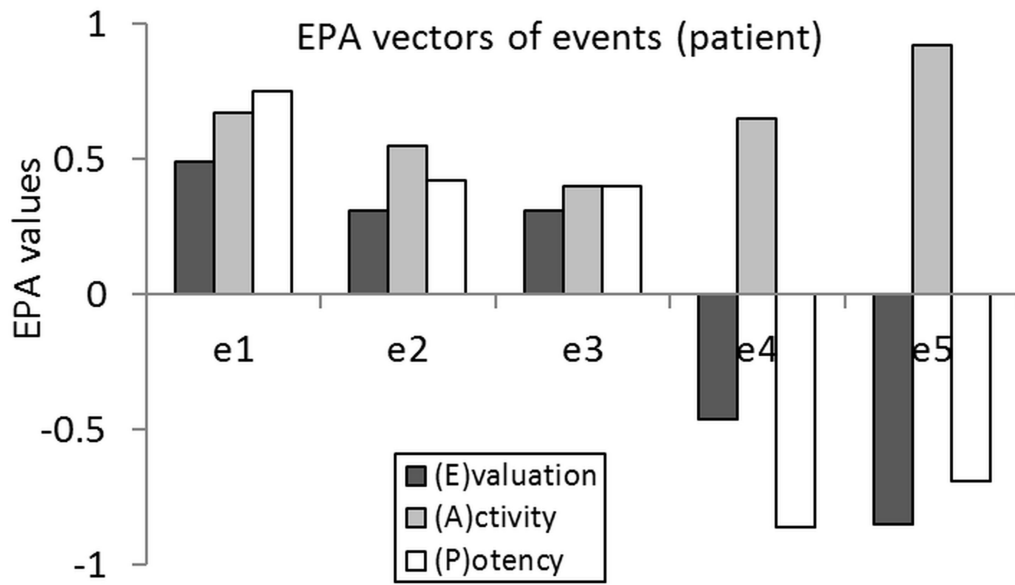
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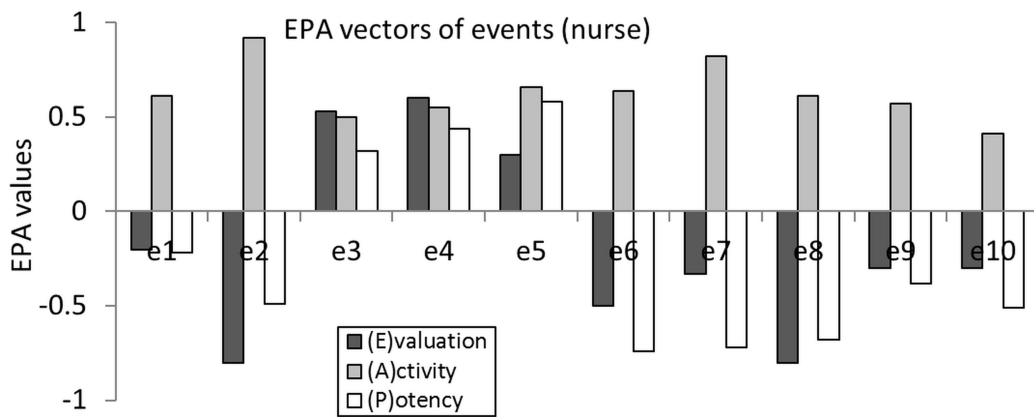Figure 6.2: EPA values of all events for the patient agent

Figure 6.3: EPA values of all events for the nurse agent

Table 6.1: List of goals for both agents

Goals	
(Agent type: Patient)	(Agent type: Nurse)
Prolonged life	Being professional
Shorten hospital stay	Being humanistic
General well being	Calmness and minimum stress
Healthy as possible	Job affairs
Less pain (pain free)	

Table 6.2: List of relevant events for a patient agent

Events (Agent type: patient)
Discovery of relevant cure
Visit of a family member
Treatment/care with respect and kindness
Death of a roommate/friend
Wrong procedure in treatment/drugs

these experiments is discussed. The environment for this experiments is a healthcare unit (e.g., hospital). The purpose for thsi experiment is to study the affective behavior of the two types of agents that exist in the system and to track the changes in their emotional status as different events take place in the environment. The first class of agents is the patients and the second class of agents is nurses. A set of five goals were considered for patient agents, whereas the goals for nurse agents were kept at 4. Table6.1 reflects the set of goals for each type of agents. Furthermore, $E_p = \{e_1, e_2, e_3, e_4, e_5\}$ reflects the set of five events that are affectingly relevant for patient agents (Table 6.2) whereas $E_n = \{e_1, e_2, ..., e_9, e_{10}\}$, is a set of 10 events that has an affective impact on nurse agents (Table 6.3).

Table 6.4 and Table 6.5 indicate the impact of each applicable event on the set of goals as well as the importance of each goal for the patient and nurse agents respectively. The entries in these tables were represented using a fuzzy scale. SN stands for *SlightlyNegative, HN* stands for *HighlyNegative, SP* stands for *SlightlyPositive, HP* stands for *HighlyPositive, and* finallyNI stands for *NoImpact or neutral.*

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Table 6.3: List of relevant events for a nurse agent

Events
(Agent type: nurse)
Misbehavior/abuse of a patient agent
Wrong prescription / service
Appreciation from a patient
Appreciation from supervisor
Unpleasant coworker/supervisor left work unit
Problems getting along with a coworker/supervisor
Benefits were reduced
Received negative performance evaluation
Complain from a patient
Assigned to undesirable task

Table 6.4: Impact of events on goals for patient agent

Goal	G_1	G_2	G_3	G_4	G_5
Importance	HI	SI	HI	HI	HI
Event	$\text{Imp}(G_1)$	$\text{Imp}(G_2)$	$\text{Imp}(G_3)$	$\text{Imp}(G_4)$	$\text{Imp}(G_5)$
e_1	HP	SP	SP	SP	SP
e_2	NI	NI	HP	SP	NI
e_3	NI	NI	HP	NI	SP
e_4	SN	NI	HN	SN	SN
e_5	HN	HN	SN	HN	HN

The first step in modeling the emotional behavior of patient and nurse agents would be to determine the affective impact of each applicable event. Such a step entails determining the $\overrightarrow{EPA}$ for all events of E by calculating the three components of evaluation, potency and activity for each event. As discussed in section 3, with respect to the dimension of evaluation, a system of fuzzy rules that links the fuzzy variable of *Desirability* to other fuzzy variables of *Importance* and *Impact* will be created. Once defuzzified, the solution of the aforementioned fuzzy system would be the value for *Evaluation* dimension. Accordingly, similar approaches would be taken to calculate the values of *Potency* and *Activity*. The charts in Fig.6.2 and Fig.6.3 represents the EPA vectors calculated for all events of E_p and E_n respectively.

Case1: Patient Agent The goal of this experiment is to study the affective impact and to track the changes in the emotional response level of the patient agent as a result of the occurrence of some stochastic events from E_p. The bipolar emotional channel under study is *distress*-joy. The initial emotional state of the agent was considered Neutral (N) or not stressed. The simulation period was considered to be 100 time units. The affective stimuli of the system for the entire duration of the simulation is the event sequence of $< e_2, e_4, e_1, e_5, e_3 >$ which that take place at time steps of $< 0, 20, 40, 60, 70 >$. In order to study the impact of applying the above sequence of events on the Emotional Response Level (ERL) of the patient agent within the emotional channel of distress-joy and the way that the emotional level of the agent transitions between different sates, it would be necessary to generate the EA and P relational matrices for all occurred events. Next, it would be required to apply the related EA and P relational matrices of each participating event to the current emotional fuzzy state of the agent.

according to the above given values, by applying the EPA vectors of the above mentioned sequence of events, the ultimate emotional state of the patient agent would be SD or SlightlyDistressed. That can be noticed by looking at the ERL of the agent under study reflected in Fig. 6.4. In particular, the occurrence of the desirable event of e_2 (i.e., visit of a family member) at the beginning of the simulation (step=0) managed to improve the ERL of the patient from the initial state of N (Neutral) to SJ (SligtlyJoyful) which was fully achieved at step=10. For the time steps between 10 and 20, it can be seen that ERL had experienced a smooth uptrend which can be attributed to the positive mood of the agent during and after the visit of the family member. At step=20, the occurrence of the highly undesirable event of e_4 (i.e, the death of a roommate patient) caused a fast deterioration in the ERL of the agent which reached to approximately -0.3 at step=30. After that, the agent started to

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Table 6.5: Impact of events on goals for nurse agent

Goal	G_1	G_2	G_3	G_4
Importance	HI	HI	SI	HI
Event	Imp(G_1)	Imp(G_2)	Imp(G_3)	Imp(G_4)
e_1	SN	NI	HN	NI
e_2	HN	HN	HN	HN
e_3	SP	HP	SP	SP
e_4	HP	NI	NI	HP
e_5	SP	NI	HP	SP
e_6	HN	NI	NH	SN
e_7	NI	NI	SN	HN
e_8	HN	SN	HN	HN
e_9	SN	NI	HN	SN
e_{10}	SN	SN	HN	NI

adapt itself to the new situation and that was interpreted into slow recovery in the ERL level for the period of step=30 and step=40.

The changes in the ERL of the agent continued as more events took place in the system. The last event, e_3 that took place at step=70, helped the agent to recover gradually from the severe negative impact of e_5 occurred at an earlier time. At step=80, and at the absence of any significant event, the agent reached a kind of static state where the simulation ended at the state SD. The affective behavior of the patient agent during the simulation time was compared against the trivial behavior of an instantaneous stimulus-response agent. The ERL for the stimulus-response agent was implemented using the mathematical step function.

As it can be noticed in Fig. 6.4, the changes in the ERL of the model generated results were much smoother that those of the reactive agent where it suffered from very sharp immediate positive and negative changes in its emotional state. Hence, it can be argued that the affective performance of the model's agent was more realistic and more favored for a human agent.

Table 6.6: Positive event emotions correspondence: adopted partially from [8]

JOB EVENTS	Pleasure		Happiness		Pride		Relief	
	N	%	N	%	N	%	N	%
Goal Achievement	(22)	24	(12)	13			(24)	26
Receiving Recognition	(9)	14	(19)	28	(25)	37		
Act of Colleagues	(8)	16	(15)	30			(6)	12
Acts of Customers			(6)	38				
Interactions with Customers	(15)	100						
Goal Progress			(13)	100				
Organizational Reputation			(12)	100				
Disconfirmation of Negative Expectations							(11)	100

Case2: Nurse Agent   Similar to case1, the aim of case2 experiment is to study the emotional dynamics of a nurse agent within the same experiment conditions and setup of case1. A major distinction between this study versus the previous one is the fact that the model generated results were compared with the results obtained from two realistic case studies. The first study, referred as study1 in this article investigates the relationship between events and the affective states of a worker agent in a workspace. Study1 included 101 participants at which they briefly described organizational events or situations that caused them to recently experience the specified emotions at work. Participants were hotel employees from functional and administrative departments of ten international hotels in Australia and the Asia/Pacific region. The full description of the study can be found in[8]. Table 6.6 reflects the event-emotion matrix for positive events that was concluded at the end of study1.

On the other hand, the purpose of the second study referred as study2 in this article, was to investigate the causes and consequences of emotions at work by identifying several job-related events likely to produce affective states and then to study the impact of the latter on work attitudes. The hypothesis argued in this study was: "experiencing certain work events leads to affective reactions, which in turn influence work attitudes". The hypothesis was supported by results obtained from an empirical

study which included 203 questionnaires performed on a sample of French managers. More details about study2 can be found in [79]. Besides, Table 6.7 reflects the statistics and results obtained from study2 that were used for the validation purpose of the proposed model.

Here, it is worth mentioning that in both of the case studies, more than one emotion fell under the wider emotion of joy considered in the experiment. For instance, emotions pleasure, happiness and relief from study1 were all considered to be related to emotion joy; and hence the value of emotion joy for such scenarios was computed as the average (mean) of all those related values. Same concept was applied to negative emotions such as unhappiness and sadness which fell under the wider title of emotion distress.

The performance of the ERL for the nurse agent according to the proposed model as well as the two case studies are all reflected in the chart of Fig.6.5. A subset of E_p that includes the sequence of events $< e_3, e_{10}, e_6, e_8, e_5, e_4, e_7 >$ which took place at time steps $< 0, 10, 30, 40, 50, 70, 80 >$ was considered. Initially, the occurrence of the positive event of e_3 (i.e., appreciation from a patient agent) managed to significantly improve the ERL of the nurse agent and to take it to above SlightlyJoyful from the initial state of Neutral. Being assigned to a trouble-some patient at step=10, caused the ERL of the nurse to drop quickly to its initial value of Neutral. During the time steps of 20 - 30, and at the absence of any affective relevant event, the agent started to cop with the new situation and that can be seen through the smooth gradual increase in the ERL. A highly undesirable event of e_6 that occurred at step=30 caused the ERL of the agent to drop to the Distressed zone. The changes in the ERL of the nurse agent continued as more events took place in the system. The ultimate emotional state of the nurse at the end of the simulation was SD or SlightlyDistressed.

Fig. 6.5 shows that the affective behavior of the nurse agent according to the proposed model was either between the ERL curves of the two studies or was moving

Table 6.7: Event emotion matrix: adopted partially from [79]

| JOB EVENTS	Pleasure	Comfort	Anxiety	Anger
Successfully completed a project or task	0.333			
Received praise from your supervisor	0.260			
Received praise from a coworker	0.278			
Unpleasant coworker left work unit		0.191		-0.185
Assigned undesirable work or project	-0.283	-0.244		
Problems getting along with a supervisor	-0.173	-0.249		0.256
Problems getting along with a coworker			0.146	0.249
Denied a promotion	-0.249	-0.179	0.145	0.279
Received negative performance evaluation	-0.187			
Denied a raise	-0.203			0.156
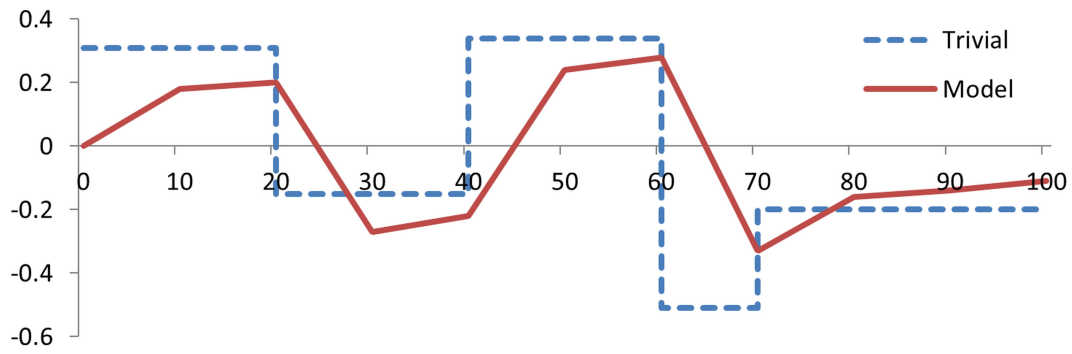
Figure 6.4: ERL for patient agent in distress-joy channel

slightly above or below them. Therefore, it can be argued that the performance of the model-generated ERL was almost completely inline with that obtained from the case studies yielding in a limited validation of the proposed model.
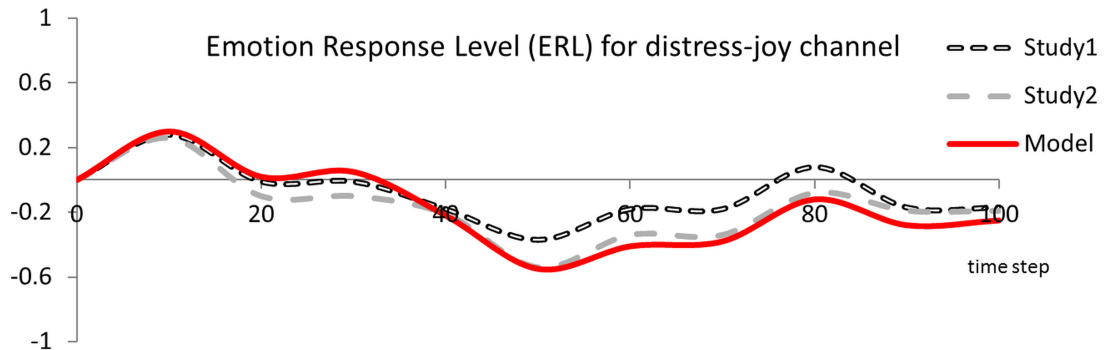

Figure 6.5: ERL for nurse agent in distress-joy channel

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With respect to the few distinctions in the ERL values between the proposed model and the case studies such as at and around step=60, where the model generated ERL moved slightly away from its counterparts, that phenomena can be attributed to the missing element of domain knowledge and specialty training typically possessed by a professional agent (i.e., a nurse) which is considered as a future extension through using a possible cultural algorithmic approach. That missing element has caused the agent to exhibit a slightly exaggerated reaction to certain negative events.

As an instance for the intermediate state transitions for the above scenario, we dissect with some details the fuzzy transition that takes place at step=30. At this step, the source state is $q_{t=20} \cong N$ (i.e., Neutral) and the destination state is an unknown state of $q_{t=30}$ that was resulted due to the occurrence of event e_6 and needs to be determined. Therefore, using the defuzzification rule of weighted average method, we will have,

$$\mu(q_{t=20}) \cong \mu(N) = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$ the transition process and the relations of

R_{EA} and R_P for stimulus e_6 arrived at state $q_{t=20} = N$ are as follows:

$$\mu(q_{t=30}) = \mu(q_{t=20}) \circ R_{EA} \circ R_P$$

where R_{EA} and R_P are the relational matrices calculated for stimulus e_6 as indicated below. Hence,

$\mu(q_{t=30}) =$

$$\begin{bmatrix} 0 & 0 & 1 & 0 & 0 \end{bmatrix} \circ \begin{matrix} & HD & SD & N & SJ & HJ \\ HD & \begin{bmatrix} 0.87 & 0.68 & 0 & 0 & 0 \\ SD & 0.92 & 0.81 & 0.06 & 0 & 0 \\ N & 0.61 & 0.92 & 0.40 & 0 & 0 \\ SJ & 0.22 & 0.88 & 0.64 & 0.10 & 0 \\ HJ & 0.03 & 0.64 & 0.89 & 0.71 & 0.10 \end{bmatrix} \end{matrix} \circ \begin{matrix} HD & \begin{bmatrix} 0.90 & 0.86 & 0.15 & 0.04 & 0 \\ SD & 0.61 & 0.88 & 0.26 & 0.02 & 0 \\ N & 0.31 & 0.94 & 0.21 & 0 & 0 \\ SJ & 0.08 & 0.65 & 0.91 & 0.30 & 0 \\ HJ & 0.05 & 0.24 & 0.69 & 0.81 & 0.24 \end{bmatrix} \end{matrix} =$$

$$\begin{bmatrix} 0.61 & 0.88 & 0.26 & 0.04 & 0 \end{bmatrix}$$

As it can be seen, the resulted $\mu(q_{t=30})$ shows that the destination state for the above transition would be $q = SD$ (i.e., $SlightlyDistressed$). At this state, the process of transitioning into new states continues as a result of the arrival of e_8, e_5, e_4, e_5 which

eventually takes the agent to the final state of $q_f = SD$. Here, the sequence of all transitions would be: N, SJ, N, SD, HD, HD, SD

6.5 Conclusion and Future Directions

It can be argued that emotion modeling is the art of transforming traditional informal theories of emotion into models built using computational architecture at which the emotional processes are fully detailed, concrete and trackable. As a result of addressing the details and uncovering hidden assumptions in such computational models, the scope of the original theories will be extended which promotes these computational models to possible frameworks for theory construction.

In this chapter, a previously proposed computational model for predicting the generated emotions in a human agent as a result of the occurrence of affect relevant events was considered. The proposed model benefited from a hybrid architecture of appraisal and dimensional processes based on affect control theory. Furthermore, it utilized a fuzzy automata framework for the purpose of modeling emotion dynamics and in particular the transitions between different states within the same emotional channel.

The performance of the proposed model was evaluated using a test-case from healthcare. Accordingly, the affective behavior of patient and nurse agents within a healthcare unit (e.g, a hospital) was deeply analyzed and found to be compliant with the results obtained from two relative case studies. One important limitation of this study is the fact that the factor of knowledge and training of the nurse agent was not included in the event-emotion relationship. This matter would be considered as a future extension for the current model at which the authors would study the influence of applying different sets of knowledge such as domain knowledge and historical knowledge on the affective behavior of professional agents.

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An important possible extension has to do with the concept of affective interventions and reverse engineering of events. The idea here is to generate and purposefully enforce a set of pro-regulation events in order to neutralize or reverse a hyper negative affective state that was reached at as a result of the occurrence of some adverse events. It would appear that such an extension could be promising within the field of psychopathology and in particular the treatment of event-related traumas.

Chapter 7

Conclusions

Emotion modeling research work within the field of IT constitutes a sub field that lays at the edge of Affective Computing and HCI (Human Computer interaction).

Computational models of emotions are generally intended to incorporate an affective component into computer applications. This research area uses the techniques and methods from a variety of other major research areas in computer science such as machine learning, uncertain reasoning, robotics, NLP, Multi-agent systems, and Game theory in order to promote the mechanisms of interaction between machines and their human users. By injecting a component of affect into the interfaces of interactive web applications (e.g., avatar guides) or to the physical machines (e.g., humanoid service robots), the nature of communication in terms of quality, believability and enjoyment will be enhanced.

The necessity for enriching current computer applications especially in the fields of robotics and HCI with an affect component was accelerated due to the findings from different studies which showed the important role that emotions play in human cognitive tasks and in particular in the process of decision making. Hence, the ultimate goal for my research work was to add a comprehensive component of affect

(emotion) to the artificial agents that enable them to reason about and mimic the emotional behavior of humans to a high extent.

Prospect applications for emotion models span to a wide spectrum of science and engineering fields such as psychology, physiology, sociology, computer gaming, HCI and healthcare. At least two major broad lines can be considered with respect to the function of an emotional model for such applications. The first would be to track and identify the emotional level of a human agent at any time to be used as the input to emotionally intelligent applications. In such applications, identifying the affective state of the user is a key item in establishing a successful affective relationship with the machine. The other direction would be to use these computational models in the process of emotion regulation, where internal or external interventions are applied as coping strategies utilized by specialists such as social behavioral therapists in order to regulate hyper emotional states and their negative consequences.

Some particular applications that may benefit from the proposed model can be named as follows:

- In e-learning applications, the model can be used to customize the presentation style of an avatar tutor in a way that best considers the affective states of the learners (i.e., bored, frustrated, or interested).

- In psychological health services and psychopathology, the proposed model can be beneficial for the purpose of reverse engineering the events and situations that have created undesirable emotional state for the client.

- In service robots, the proposed model can be utilized in order to make these robotic system capable of exhibiting higher levels of flexibility especially under uncertain or complex environments. That would be beneficial in terms of augmented realism and higher levels of believability for the autonomous systems.

- In social monitoring, the proposed emotion model can be used to monitor the behavior norms of crowd and to identify possible negative intentions that might lead to preventable offensive actions, especially at high risk communities or sensitive locations.

- In gaming industry and some HCI applications, the proposed model can be used to increase the liveliness of the interactions or communications between the computer agent and the human agent.

With respect to the temporal structure of the research works that led to the formation of this dissertation, it is worth noting that considering the scope of the problem and the major complications associated with this kind of research areas with qualitative nature, I adopted an incremental approach toward building a comprehensive computational model for emotions that fits the needs for computer applications.

Accordingly, in the initial models, several attributes were either ignored or considered to be given to the system. For instance, in the first emotion regulation model, some important parameters such as the mood state and knowledge level of the agents were ignored from the emotional computations. In a following study, the proposed model was enhanced by adding full computational components for the mood and the domain knowledge of the agent. As another example for the incremental attribute of this dissertation, it is the fact that initial computational models for emotion generation or regulation were designed using a pure modeling approach such as appraisal or dimensional for the sake of less complexity whereas later versions included a blend of modeling techniques which led to higher levels of accuracy and performance.

Current and upcoming research plans:

- Augmentation of existing as well as developing new affect-enabled applications within active social networks such as Facebook and Twitter.

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- Developing simple affective mobile applications for different purposes from entertainment to alarming systems and general wellbeing.

- Enhancement of the proposed emotion models by investigating the usage of other types of algorithmic approaches (currently being investigated: cultural algorithms and the concept of shared belief between a population of agents).

- Utilizing the techniques used in data mining and big data management to create a multi-purpose affective API.

As final words, I hope that my research work will contribute in enhancing the interaction between machines and humans. Furthermore, I hope that it will help us to acquire a better understanding and appreciation for the valuable emotions that we possess as part of our humanistic personality; and ultimately to utilize them for a higher physical and mental health by applying the principles of emotion regulation in order to prevent their potential adverse impacts.

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APPENDICES

Appendix A

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Appendix B

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Appendix C

Appendix D

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