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

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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.

Introduction

According to recent research findings, emotions pose a vital component in the human cognitive activities [Gross, 2006]. They have deep impacts on the memory functions, decision making and judgments [Forgas, 1995]. In addition, Some neurological studies such as [Damasio, 1994] 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 [Gross, 2006].

Emotion regulation strategies address the potential risk of having inappropriate level of emotions. Gross in [Gross, 2001] 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" [Gross, 2006].

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.

Emotions

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.

CoMERG is the abbreviation for Cognitive Model for Emotion Regulation based on Gross. It was developed by *Bosse et al.* [Bosse, Pontier, and Treur, 2010]. 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 [Soleimani and Kobti, 2012], 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 [El Nasr, 2000] 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

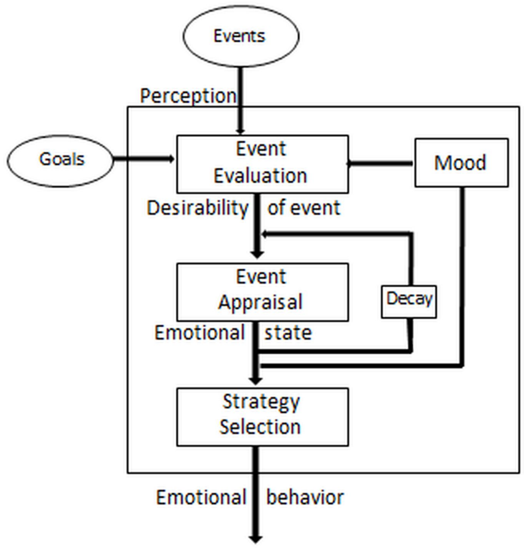

Figure 1: Emotion regulation process

in parts of our proposed emotion regulation model.

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 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 [Gross, 2006; 2001].

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 1. 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.

Table 1: 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

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 formulas. 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.

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 [Ortony, 1988] and formulated by Price et al. [Price and Barrell, 1985] 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 1 reflects partially some of these rules along with the corresponding generated emotions. Table 2 contains some of Price's equations used to compute the intensities of the generated emotions.

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 cir-

Table 2: Intensity computing rules [Price and Barrell, 1985]

Emotion	*Degree of intensity*
Fear	$= (2 * expectation^2) - desirability$
Joy	$= (1.7 * expectation^{0.5}) + (-0.7 * desirability)$
Relief	$= Fear * desirability$
Sadness	$= (2 * expectation^2) - desirability$

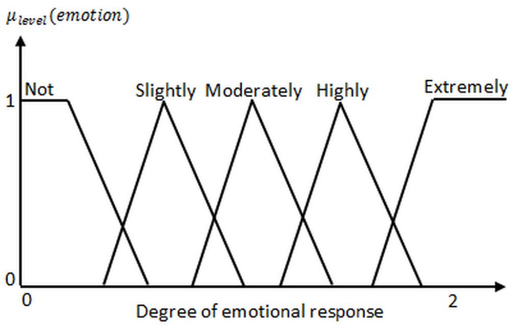

Figure 2: Emotional response for any emotion expressed using five fuzzy sets

cumstances. 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 2)

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,

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

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 sophisticated 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:

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

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

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

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 2)

$$Level = \{NotSad,\ SlightlySad, ModeraetlySad,\ HighlySad,\ ExtremelySad\}$$

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:

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

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:

$$\begin{array}{ll} IF & Impact(G_1, E)\ is\ A_1 \\ & AND\ Impact(G_2, E)\ is\ A_2 \\ & ... \\ & AND\ Impact(G_k, E)\ is\ A_k \\ THEN & Impact(G_1, E)\ is\ C \end{array}$$

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 [El Nasr, 2000] based on Mamdani model [Mamdani and Assilian, 1975] 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 i^{th} 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 2.

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.

Learning patterns of events (events expectation)

Mechanisms for expectations obtained through learning can have a major influence on emotional dynamics [LeDoux, 1996]. 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:

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

Table 3: List of agent's goals

Goal	Importance
G1	HighlyImportant
G2	SlightlyImportant
G3	HighlyImportant

Table 4: 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

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.

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 and 4 list the set of agent's goals and the events that occur in the system respectively. Figure 4 reflects the computed desirability of these events.

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 shows the ERL regulation trend for our proposed model against the non-fuzzy implementation adopted in [Soleimani and Kobti, 2012]. 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 $\beta = 0.05$.

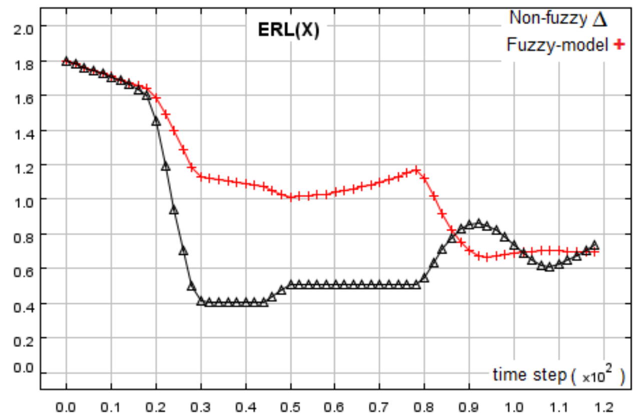

Figure 3: Trend of ERL for a fuzzy-based learning agent

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≅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≅ 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" [Gross, 2001].

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 experi-

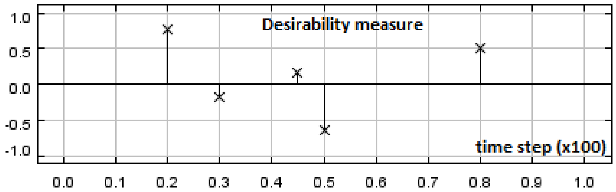

Figure 4: Desirability measure for occurred event

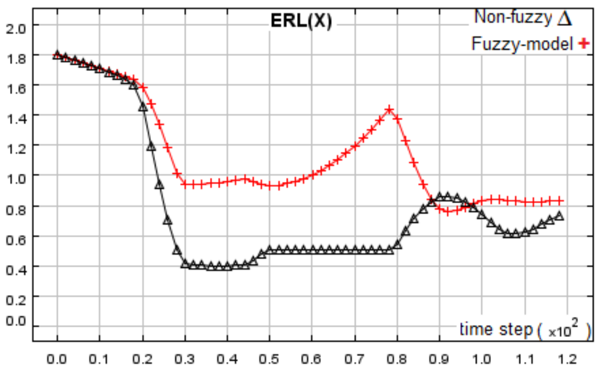

Figure 5: Trend of ERL for a non-learning agent

ment was purposefully designed with identical 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 5 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.

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

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