Event-Driven Fuzzy Paradigm for Emotion Generation Dynamics

Ahmad Soleimani and Ziad Kobti

***Abstract*—This paper proposes using a fuzzy appraisal approach to model the dynamics for the emotion generation process in an individual as a result of events that take place in the environment of the individual. The proposed computational model uses guidelines from OCC emotion theory to formulate a system of fuzzy inferential rules that is capable of tracking the emotional states of the agent. Events are thoroughly analyzed and appraised against the set of goals of the agent and consequently elicited emotions along with their intensities are determined. Results from experiments showed that OCC theory is a suitable and easy to implement framework to be used as a core component in computational models of emotion.**

***Index Terms*—emotion generation, fuzzy computational models of emotion, emotional intelligence**

I. Introduction

Affect in general and emotion in specific is a non-detachable element of our daily lives. Every day we get into situations that make us feel happy, upset, proud, etc. Emotion is part of our personality which is in fact the uncovered motor for a large part of our actions and decisions [15]. Beside the traditional theories of emotions by philosophers such as Aristotle, Descartes, and psychologists such as Freud and Darwin and their hypothesis about emotion that can be rooted back into the early stages of human civilization era, a recent fresh wave of interest in studying this phenomenon by researchers from a wide spectrum of different science fields can be seen. This interdisciplinary research tendency can be attributed to the contemporary research findings that confirm the deep influence of emotion on human attention, behavior, decision making and other cognitive tasks [14].

Research work in emotions by IT specialists can be tracked back to few decades ago where Computer researchers started to develop and propose computational models of emotions which were derived and built based on emotion theories from psychology and other humanistic sciences. For example, in the work of Scherer [17], a computational model of emotion was implemented as an expert system. The model suggested by Ortony *et al.* [13] was highly influential in this regard and has inspired a number of other computational models that appeared later such as [5], [11], [3]. Emotion research by Computer scientists was extended and fostered more in a systematic way after the eruption of the new field of *Affective Computing* (AC). Despite the relatively young age of affective computing, it has managed to turn into a well-established research area with its own professional conferences and journals. According to its founder, R. Picard [14], affective computing is "computing that relates to, arises from, or deliberately influences emotions" [14].

An AC system strives to make computer artifacts more emotionally intelligent, that is, be able to recognize (e.g., from person's facial expressions or vocal tones), respond to (e.g., adapting the interface) and represent (e.g., in service robots) affective states. A core component of an AC systems is a computational model that reflects the dynamics of the changes in the emotional behavior of the subject.

In the process of developing a computational model of emotion, different approaches such as appraisal (e.g., [13]), dimensional (e.g., [5]), adaptation and coping (e.g., [11]), etc., can be used. The proposed model is an OCC [13] inspired model that uses a fuzzy approach to evaluate the competent events that take place in the environment of the agent and by using guidelines from the OCC theory, it suggests the corresponding emotions that the agent will experience as a result of these events and calculates their intensities.

Fuzzy logic principles were used by ElNasr *et al.* [3] to build a fuzzy computational model of emotion, FLAME. in FLAME, fuzzy sets are used to express the qualitative nature of emotions. It consists of several learning algorithms to be used for agent's adaptation to some aspects of the users and its environment. Some of these aspects are event expectations, patterns of user actions, rewards, etc. In [9], a fuzzy system was used to map some physiological readings into a point on a core affective space of arousal and valence. This point then is mapped again using another fuzzy system into a set of five emotions.

According to the OCC model, emotions are individual's internal reaction to a stimulus originated by an event, object or other individual(s). In particular, an agent will be either pleased or displeased with an event; approves or disapproves the action of other agent(s); and likes or dislikes an object. A total of of 22 different emotional states were identified and considered in OCC. Figure 2 depicts a diagram for OCC event-competent emotions.

With respect to the possible applications for the proposed model, two directions can be considered. The first would be to track and identify the emotional state of the subject as a result of the occurrence of a series of events. This emotional state poses the input to the emotionally intelligent interfaces such as those used in HCI, robotics and computer gaming at which identifying the affective state of the human user is an essential element in establishing a successful affective rapport between the machine and their human users in theses systems[14]. The other direction would be to use such a model in Neuro-therapeutics and social behavioral therapies for the purpose of regulating hyper negative emotional responses and psychological complications.

In brief, this article proposes a fuzzy event-driven compu-

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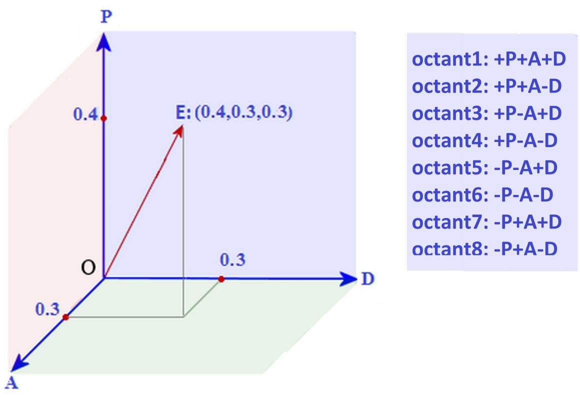

Figure 1. PAD vector and mood octant [20]

tational model that is capable of predicting the OCC event-competent emotions of the subject. Furthermore, it suggests a mechanism for emotion control at which external stimuli can be applied as a mean for emotion control and regulation. It would appear that this objective is of high importance considering its promising utilization in behavioral therapies at which the events could be some auxiliary elements such as audio/video clips similar to those used in [2].

II. Computational models of emotions

Computational models of emotions could have several applications in the fields of Psychology, Biology and Neuroscience at which such models can be used to test and improve the formalization of the background theories[22]. Furthermore, many application for such models can be named in the fields of robotics and computer gaming industry. Also, these models can be used to improve the performance of HCI applications in order to develop intelligent virtual agents that exhibit a maximal degree of human-like behavior [1].

A. Appraisal theory

Appraisal theory non-arguably is the mostly accepted and used approach in the recent computational models of emotion [21]. In appraisal theory, the link between emotion and cognition is highly emphasized. The essence of this theory is the fact that emotions are generated based on an appraisal or assessment process performed continuously by the individual on the situations and events that take place in the environment. Based on this theory which was formally proposed by Smith and Lazarus [19], the way that different individuals perceive their environment is the major factor that determines the set of elicited emotions.

According to appraisal theory, in order to appraise the different situations that arise in the relationship between an individual and the environment, a set of relevant variables or dimensions needs to be considered. Scherer [18] and Frijda [4] argue that these appraisal variables should be able to address some criteria such as those listed below in order to be effectively used in the process of emotion generation.

- Relevance (importance) of the situation and to implications on individual's own goals. (beneficial or harmful)
- Self/other responsibility of the situation (agency)
- Degree of expectancy by the individual. (probability)
- Potentials for coping and adjusting to the new situation.

Table I
Mapping of event-competent OCC emotions into PAD space[5]

Emotion	P	A	D	Mood octant
Joy	0.4	0.2	0.1	+P+A+D Exuberant
HappyFor	0.4	0.2	0.2	+P+A+D Exuberant
Relief	0.2	-0.3	0.4	+P-A+D Relaxed
Pity	-0.4	-0.2	-0.5	-P-A-D Bored
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
Sentiment	-0.2	-0.3	-0.2	-P-A-D Board
Disappointment	-0.3	0.1	-0.4	-P+A+D Anxious
Hope	0.2	0.2	-0.1	+P+A-D Dependant
Gloating	0.3	-0.3	-0.1	+P-A-D Docile
Satisfaction	0.3	-0.2	0.4	+P-A+D Relaxed

B. Examples of appraisal computational models

a) EMA: Emotion and Adaptation (EMA) [10] adopts the approach of Lazarus[6] to build a detailed computational model of emotion. The core of EMA is its causal interpretation which reflects the representation of the agent-environment relationship. It considers the belief, desires and intentions of the agent as well as past events, current and possible future world states. The causal interpretation is built based on two types of cognitive processes. One type is slow and deliberative whereas the other is fast and reactive. Furthermore, EMA includes a detailed sub-model for coping techniques which enables the emotionally intelligent agents to regulate their negative emotions. EMA considers four categories of coping strategies based on coping process being targeted on either attention, belief, desire or intentional aspects of the agent.

b) ALMA : A Layered Model of Affect (ALMA) [5] is an OCC [13] 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 an individual. ALMA adopts the approach of Mehrabian [12] in which he describes the mood with the three traits of pleasure (P), arousal (A) and dominance (D). 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 components build the so called PAD space in which each point represents a mood state called mood octant (see Figure 1). Furthermore, in order to initialize the mood states, ALMA uses a mapping between OCC emotions to the PAD components of the mood octant. Table I depicts partial mapping between OCC emotions and the PAD space. In our model, we exploit this approach to calculate the overall mood state of the agent. As will be dissected in next section, overall mood is widely used in our emotion intensity calculations.

III. Our approach

The essense of the proposed model is to provide a computational method for the elicitation dynamics of the 12 event-competent emotions introduced in OCC [13] (see Figure 2). The elicitation rules of these emotions along with the

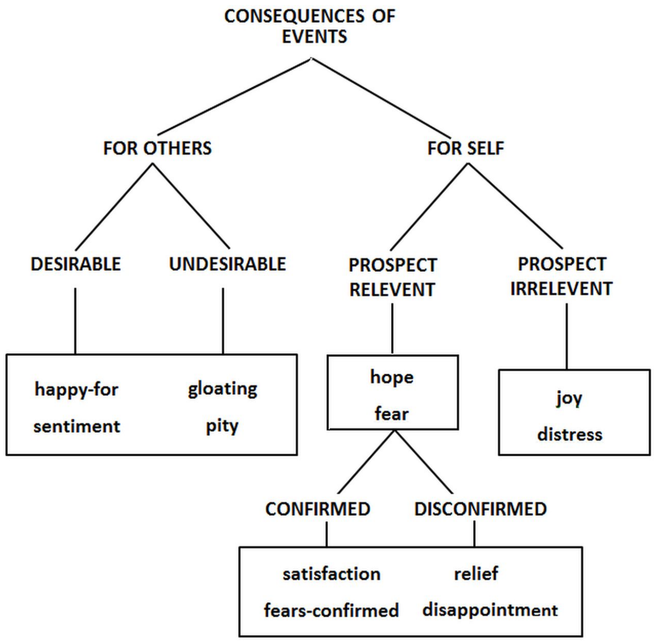

Figure 2. OCC event-competent emotions. Adopted partially from [13]

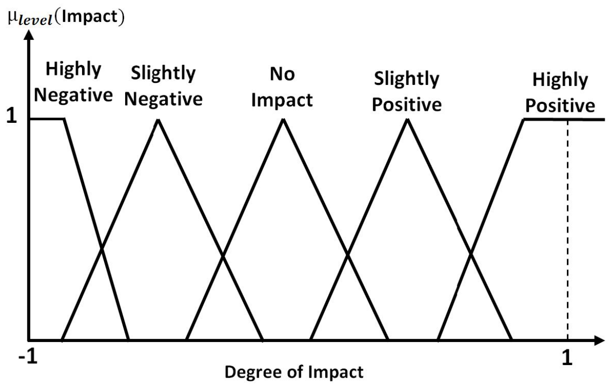

Figure 3. Event's fuzzy degree of impact on individual's goals

calculations of the intensity for each elicited emotion has been performed using guidelines from the background theory and an appraisal process of te relevant variables.

According to Figure 2, the first variable assessed by the agent is the orientation of the event that take place in the system; meaning that if the utility of the event is oriented toward the agent itself or some other agent(s). This evaluation process yields in an initial classification of the potential emotions into *for self* or *for others* categories. Another classification process takes place for *self* emotions based on the prospect appraisal variable that indicates if the event has already taken place (prospect=False) or would possibly take place in the future (prospect=true). A prospect emotion transforms into a post-prospect emotion such as relief or disappointment using some temporal dynamics.

A. *Event's desirability*

The desirability of an occurred or prospect event poses the most influential factor in the specification of the emotion type that will be triggered along with its intensity. We adopt a fuzzy approach to determine the desirability level of an event. Accordingly, a fuzzy scale for the desirability would consist five fuzzy sets as follows:

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

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. We use two other fuzzy variables to express this impact. variable *Impact* that indicates the event's degree of influence on one or more goals of the agent 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 would have its own importance level, the problem of measuring the desirability of an event would turn into solving a system of fuzzy rules [3].

With regards to the composition of the fuzzy rules in the resulted fuzzy system, we consider a combination of the sup_min composition technique proposed by Mamdani [8] and the weighted average method for defuzzification [16]. Using the composition approach explained in [3], we can apply 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:

$$IF\ \ x\ is\ A_1\ THEN\ y\ is\ C_1$$
$$\ldots$$
$$IF\ \ x\ is\ A_n\ THEN\ y\ is\ C_n$$

where x and y are the input and output variables respectively, A_i and C_i are fuzzy sets and i is the i^{th} rule. Based on the definition of the $sup\,min$ composition between a fuzzy set $C \in \mathcal{F}(X)$ and a fuzzy relation $R \in \mathcal{F}(X \times Y)$, we have:

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

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 centroid of each symmetric membership function. The result of above defuzzification process, y_{final}, is the event's desirability level which will be equivalent to the intensity of the generated self emotion. Hence, $Desirability_f(e) = y_{final}$

B. *Event's prospect*

Event's prospect is directly linked to the possibility of occurrence for an event based on the perception of 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 [7]. We strive to find a simple but acceptable estimation for this measure and hence we adopt the approach taken in [3]. 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

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approach. The event's patterns are constructed based on the frequency with which an event, e.g., e_1 is observed to occur right before previous events of e_2, e_3, etc. Hence,

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

Where C denotes the count of each event sequence. Here, we have considered a length of three for the sequence of the event patterns. For brevity we refrain from providing detailed description of this approach and interested readers are referred to the above mentioned reference.

IV. Problem formulation

As elaborated before, in the OCC model, event competent emotions are classified into two groups of *self-related* and *other-related*. This classification was made by considering the consequences of occurred event to be directed toward either the subject agent or some other agent. The diagram of Figure 2 shows that the first group includes the set of $\{joy, distress, hope, fear, satisfaction, disappointment, fearsconfirmed, relief\}$ emotions and the second group consists of $\{happyfor, resentment, gloating, pity\}$ emotions. In the next section we dissect in details about the methods used to perform the calculations for each emotion. At this point, we affirm the fact that at the end of the occurrence of each relevant event, it would be necessary to consider an impact on the overall (global) emotional state of the agent. In emotion literature, this impact is often referred as mood changes of the individual which is called mood-impact-factor in our proposed model.

A. Mood-impact-factor

According to [5], there exist a relationship between different emotions and the previously described PAD components of the agent's mood. Therefore, in order to calculate the global mood state of the agent we propose the following equation:

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

Where α is a signed adaptation coefficient which its exact value is left for the experiment, but knowing that it would 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.

B. Emotion calculations

At this point, we use guidelines from the OCC emotion theory in order to come up with a set of computational equations to be used for specifying the potential emotions that the agent might experience as a result of the occurrence of event e. In the following rules, subscript $_p$ stands for *potential* and subscript $_t$ stands for *threshold*. 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/undesirable feeling would yield into an explicit emotion [13].

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

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

1) Self-related:

a) Emotion Joy:

$$\begin{array}{l} IF\ Desirability(p, e, t) > 0 \\ THEN\ JOY_p(p, e, t) = Desirability(p, e, t) \\ IF\ JOY_p(p, e, t) > JOY_t(p, t) \\ THEN\ Intensity(p, e, t) = JOY_p(p, e, t,) - JOY_t(p, t) \\ ELSE\ Intensity(p, e, t) = 0 \end{array}$$

b) Emotion Distress:

$$\begin{array}{l} IF\ Desirability(p, e, t) < 0 \\ THEN\ DISTRESS_p(p, e, t) = -Desirability(p, e, t) \\ IF\ DISTRESS_p(p, e, t) > DISTRESS_t(p, t) \\ THEN\ Intensity(p, e, t) = DISTRESS_p(p, e, t) - DISTRESS_t(p, t) \\ ELSE\ Intensity(p, e, t) = 0 \end{array}$$

c) Emotion Hope:

$$\begin{array}{l} IF\ Prospect(p, e, t)\ AND\ Desirability(p, e, t) > 0 \\ THEN\ HOPE_p(p, e, t) = Desirability(p, e, t) * Likeihood(p, e, t) \\ IF\ HOPE_p(p, e, t) > HOPE_t(p, t) \\ THEN\ Intensity(p, e, t) = HOPE_p(p, e, t) - HOPE_t(p, e) \\ ELSE\ Intensity(p, e, t) = 0 \end{array}$$

d) Emotion Fear:

$$\begin{array}{l} IF\ Prospect(p, e, t)\ AND\ Desirability(p, e, t) < 0 \\ THEN\ FEAR_p(p, e, t) = -(Desirability(p, e, t)) * Likeihood(p, e, t) \\ IF\ FEAR_p(p, e, t) > FEAR_t(p, t) \\ THEN\ Intensity(p, e, t) = FEAR_p(p, e, t) - FEAR_t(p, t) \\ ELSE\ Intensity(p, e, t) = 0 \end{array}$$

As discussed earlier, *Prospect* in the above equations is a binary logical variable that reflects the occurrence prospect of a future event e. Hence, it merely indicates if person p believes that such event might occur (TRUE) or will not occur (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.

e) Emotion Relief:

$$\begin{array}{l} IF\ FEAR_p(p, e, t) > 0\ AND\ NOT(Occurred(p, e, t_2))\ AND\ t_2 \geq t \\ THEN\ RELIEF_p(p, e, t_2) = FEAR_P(p, e, t)) \\ IF\ RELIFE_p(p, e, t_2) > RELIFE_t(p, t_2) \\ THEN\ Intensity(p, e, t_2) = RELIFE_p(p, e, t_2) - RELIFE_t(p, t_2) \\ AND\ reset\ FEAR_P(p, e, t_2) = Desirability(p, e, t_2) * Likeihood(p, e, t_2) \\ ELSE\ Intensity(p, e, t_2) = 0 \end{array}$$

In the above rules it is simply assumed that once a prospect negative event was dis-confirmed, 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 recomputing the value of $Fear_p$ since at least one of its parameters (i.e., Likelihood) was changed.

f) Emotion Disappointment:

$$\begin{array}{l} IF\ HOPE_p(p, e, t) > 0\ AND\ NOT(Occurred(p, e, t_2))\ AND\ t_2 \geq t \\ THEN\ DISAPPOINTMENT_p(p, e, t_2) = HOPE_P(p, e, t)) \\ IF\ DISAPPOINTMENT_p(p, e, t_2) > DISAPPOINTMENT_t(p, t_2) \\ THEN\ Intensity(p, e, t_2) = DISAPPOINTMENT_p(p, e, t_2) - DISAPPOINTMENT_t(p, t_2) \\ AND\ reset\ HOPE_p(p, e, t_2) = Desirability(p, e, t_2) * Likeihood(p, e, t_2) \\ ELSE\ Intensity(p, e, t_2) = 0 \end{array}$$

In the above rules, we 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.

g) Emotion FearsConfirmed:

$$\begin{array}{l} IF\ FEAR_p(p, e, t) > 0\ AND\ (Occurred(p, e, t_2))\ AND\ t_2 \geq t \\ THEN\ FEARSCONFIRMED_p(p, e, t_2) = -(Desirabiklity(p, e, t_2)) \\ IF\ FEARSCONFIRMED_p(p, e, t_2) > FEARSCONFIRMED_t(p, t_2) \\ THEN\ Intensity(p, e, t_2) = FEARSCONFIRMED_p(p, e, t_2) - FEARSCONFIRMED_t(p, t_2) \\ ELSE\ Intensity(p, e, t_2) = 0 \end{array}$$

h) Emotion Satisfaction:

$$\begin{array}{l} IF\ HOPE_{pot}(p, e, t) > 0\ AND\ (Occurred(p, e, t_2))\ AND\ t_2 \geq t \\ THEN\ SATISFACTION_p(p, e, t_2) = Desirability(p, e, t_2) \\ IF\ SATISFACTION_p(p, e, t_2) > SATISFACTION_t(p, t_2) \\ THEN\ Intensity(p, e, t_2) = SATISFACTION_p(p, e, t_2) - SATISFACTION_t(p, t_2) \\ ELSE\ Intensity(p, e, t_2) = 0 \end{array}$$

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.

2) Others-related:

a) Emotion HappyFor:

$IF\ Desirability(p_2, e, t) > 0\ AND\ Friend(p_1, p_2)$
$THEN\ IF\ Desirability(p_1, e, t) > 0$
$THEN\ HAPPYFOR_p(p_1, e, t) = (Desirability(p_2, e, t) + Desirability(p_1, e, t))/2$
$ELSE\ THEN\ HAPPYFOR_p(p_1, e, t) = |Desirability(p_2, e, t) - Desirability(p_1, e, t)|$
$IF\ HAPPYFOR_p(p_1, e, t) > HAPPYFOR_t(p_1, t)$
$THEN\ Intensity(p_1, e, t) = HAPPYFOR_p(p_1, e, t,) - HAPPYFOR_t(p_1, t)$
$ELSE\ Intensity(p_1, e, t) = 0$

b) Emotion Pity:

$IF\ Desirability(p_2, e, t) < 0\ AND\ Friend(p_1, p_2)$
$THEN\ IF\ Desirability(p_1, e, t) < 0$
$THEN\ PITY_p(p_1, e, t) = |(Desirability(p_2, e, t) + Desirability(p_1, e, t))|/2$
$ELSE\ THEN\ PITY_p(p_1, e, t) = |Desirability(p_2, e, t) - Desirability(p_1, e, t)|$
$IF\ PITY_p(p_1, e, t) > PITY_t(p_1, t)$
$THEN\ Intensity(p_1, e, t) = PITY_p(p_1, e, t,) - PITY_t(p_1, t)$
$ELSE\ Intensity(p_1, e, t) = 0$

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. The other scenario would be when the two agents have opposite desirability 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., $Desirability(p_1, e, t) = 0$).

c) Emotion Gloating:

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

d) Emotion Resentment:

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

For the above two emotions, since the other agent is an opponent to the subject agent, a utility for the object agent will be a loss for the subject agent and vice versa. Thus, in emotion gloating for instance, an event e that is perceived by agent $p_1$as a negative event for agent $p_2$would make agent $p_1$experience gloating emotion. The intensity of this emotion is related to the desirability of e for agent p_1. If e is negative for $p_1$as well, the overall gloating intensity will be equal to the difference of the two desirability measures.

C. Algorithm 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.

Table II
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

Table III
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			

V. 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, we consider only one of these experiments. In this experiment, p_1 is the subject 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 II. Table III 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; meaning that an emotional response starts 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. 4.

According to Table III, 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

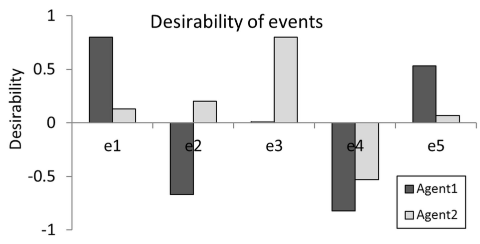

Figure 4. Calculated event's desirability for both agents

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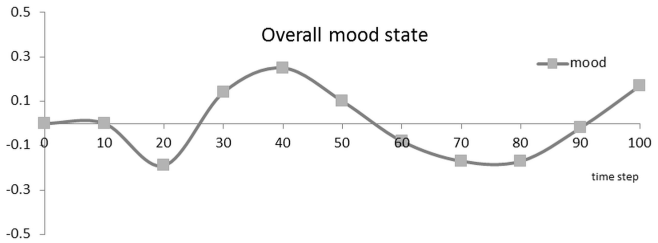

Figure 5. Global mood level changes as a result of occurred events

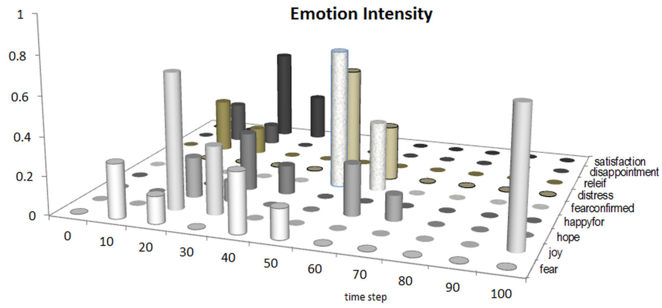

Figure 6. Intensity of all emotions for agent p_1 during the simulation

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 emotion relief. At step=40, the occurrence of e_3 which is 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, prospect 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 prospect 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 prospect 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 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. 6 shows the big picture of all 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. The agent ended the simulation with another wave of joy emotion as a result of the re-occurrence of e_1.

VI. Conclusion

In this article we proposed a fuzzy approach for anticipating the emotions that will be elicited in an individual as a result of the relevant events that take place in the environment of the agent. Emotion generation rules were formulated based on some guidelines from the OCC emotion model. According to the OCC model, emotions can be triggered as a result of consequences of events, actions of agents or reactions to objects. We proposed a computational model for OCC event-driven emotions that uses fuzzy approach to appraise the occurred events against the goals of the agent and calculate the degree of desirability for each event accordingly. With respect to the prospect based emotions, 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 the time as well as the overall mood state of the agent during the simulation time. 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.

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