A fuzzy appraisal model for affective agents adapted to cultural environments using the Pleasure and Arousal dimensions

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ABSTRACT

Humans use rather vague and imprecise words to express emotions. Therefore, fuzzy logic allows computational affective models to use emotions in the same way that human beings express them. However, people from different cultures and languages assign different meanings to the same emotion word. Unfortunately, there are still no affective computing models that really take these two factors into consideration. In this paper, we propose a fuzzy model of appraisal for multi-agent systems that is adapted to Spanish-speakers. Our methodology has two steps. First, the agent evaluates an event using a set of fuzzy appraisal rules that returns a fuzzy emotion. Then, a defuzzification process returns the Pleasure and Arousal dimensions of the emotion that will be internally represented as a vector in a two-dimensional space. This vector is used to update the agent's mood according to the agent's personality. The agent can express this internal emotional state using a fuzzification process that translates the agent's mood into a fuzzy emotion. This fuzzification process uses the results of an experiment to generate a fuzzy emotion that is adapted to the cultural environment in which the agent is located. This methodology can be easily adapted to other languages.

1. Introduction

Over the last few years, the way in which humans interact with machines has been changing. The emergence of virtual assistants for both mobile phones and home is helping to facilitate how humans communicate with machines. However, human beings are emotional beings and these interactions can be improved by taking into account human emotions. Emotions affect the way in which we interact with others and establish links that will be the basis of future relationships. Thus, a computer system that can express emotions and understand the emotions of its human interlocutor will be able to improve its interactions with humans.

Affective computing [31] is the area of computation related to emotions that is based on theories of the sciences of psychology and cognition. One of the main goals of affective computing is to design computational models of affect to simulate human emotional behavior in a realistic way. Thus, different proposals have been designed from the computational [15, 26, 35] and psychological [43] perspectives. However, in general, most of these proposals are simplifications of psychological theories that were not originally proposed to be incorporated into computational models, thus reducing emotions to simple labels (as in emotion recognition) [17]. When this label-based representation is used, some inherent properties of emotions, such as the intensity or the proximity to other emotions, is lost. In this paper, we propose an internal representation of emotions using a continuous multidimensional space that is more appropriate for use in computational models since it provides a great capacity to represent emotions and mood, and we analyze their variations when receiving both internal and external stimuli.

Considering that humans use expressions like "very happy" or "a little sad", in recent years, some authors have proposed the use of fuzzy logic [49] to model affective processes since fuzzy logic is closer to the way in which human beings express their emotions [21]. On the other hand, another important difficulty when studying emotions is that the internal way of feeling emotions is highly dependent on the person's personality and the cultural environment. Different authors have shown that emotions depend on language and culture [40, 48]; specifically, the same emotion name/label can be interpreted in a different way in different cultures. Moreover, different people show different amounts of spoken affect according to their language and cultural characteristics. That means that any appraisal process used in an affective agent should be adapted to the culture and language in which the agent will be used. Therefore, when

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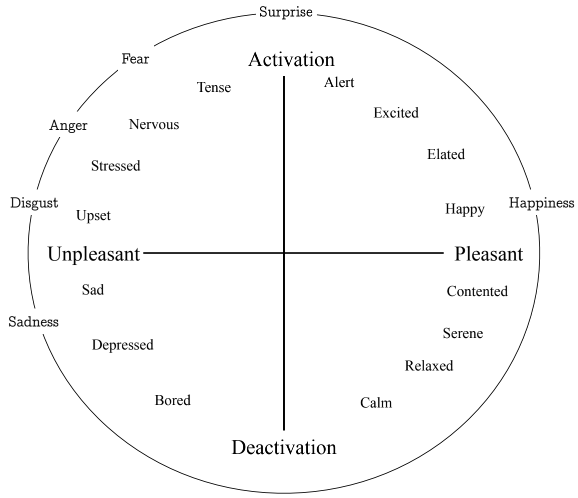

Figure 1: The circumplex model of affect: the outer ring contains the "prototypical emotion episodes" that match the basic emotions of Ekman's theory. Source: [39].

computational models of affect are designed, the cultural environment in which they will be used must be considered. However, even though cultural and language factors are taken into account in other domains such as personal assistants, to our knowledge, there are still no affective computing models that really take cultural and language factors into consideration.

This paper presents a new appraisal model for a multi-agent affective BDI architecture [33] based on fuzzy logic that is adapted to cultural and language factors. Our proposal is composed of two independent processes. First, in the *Event Appraisal* process, an event is evaluated using fuzzy rules, producing a fuzzy emotion as a result. Second, the *Affect Adaptation* process defuzzificates the appraised emotion obtaining its *Pleasure* and *Arousal* dimensions, which are adapted to the cultural and language in which the emotion was elicited. These dimensions are used to update the agent's mood using the elicited emotion, taking into account the agent's personality and the language and culture in which the agent is located.

2. Previous work

Over the years, different theories have been developed to explain what emotions are and how emotions are elicited. Appraisal theories postulate that emotions are the result of an evaluation process that is triggered when an event occurs. From a theoretical perspective, the appraisal process is a response to a stimulus that triggers a series of processes that is in charge of evaluating that stimulus and, as a result, eliciting an emotion. In most cases, the appraisal process is explained using a set of variables known as *appraisal variables*. The number of emotions that can be generated in each appraisal theory depends on the number of appraisal variables used and the number of values that these variables can have. This way of eliciting emotions as the result of the evaluation of a set of variables is very useful when using this model in a computer system. This is why, in recent years, most affective intelligent agent models have incorporated an appraisal process [2, 15, 26].

Different authors use different sets of appraisal variables to define the appraisal process. For example, Frijda [13] posits that the familiarity, expectedness, valence, controllability, agency, certainty, and importance of the detected event should be taken into consideration. The Scherer approach [43] makes a more detailed description of the factors involved in the appraisal processes such as predictability, urgency, power, or suddenness. Scherer also proposes a series of patterns that relate the appraisal variables to different emotions in order to propose an expert system for affective computing [42]. However, Scherer uses twenty-two appraisal variables, which makes this model very complex to use. This is why this model has not been widely used in affective computing. In contrast, the OCC (Ortony, Clore, and Collin) model [30], which uses only eight appraisal variables, is the most commonly used model in affective computing.

On the other hand, basic emotion theories, like the one proposed by Ekman [10], hold that there is a limited number of emotions (*Happiness*, *Surprise*, *Fear*, *Anger*, *Disgust*, and *Sadness*) and that each detected event elicits an associated emotion. According to this theory, these emotions are universally understood in different cultures and languages.

While Ekman argues that basic emotions are universal and transcultural, constructivist theorists, like Russell, argue that emotions depend on language and culture [40]. Russell's theory [39] is based on the fact that there is not always a direct correspondence between the words representing emotions in two different languages. For example, in the German language, there is an emotion called "*Sehnsucht*" [18], whose meaning is "a strong desire for an alternative life". In languages such as English or Spanish, there is no single word to express this emotion. Russell's theory is more consistent with findings in cognitive neuroscience [32]. These claim that emotions are a combination of a small number of dimensions rather than being directly related to events, as in Ekman's theory and other basic emotion theories [10], which affirm that emotions are related to an independent neuronal system. Russell relates emotions with a pair of values, *Pleasure* and *Arousal*, providing a two-dimensional space for the representation of emotions. In addition, through experimentation, he observed that emotions follow a circular pattern in these two dimensions, which led him to propose his best-known theory: *The Circumplex Model Of Affect* [38] (Fig. 1). Mehrabian proposed the PAD (*Pleasure*, *Arousal*, *Dominance*) model [28], which adds the *Dominance* dimension to represent emotions. This third dimension can help to clarify negative emotions. For example, the emotion of *Fear* is associated with a low level of *Dominance*, while the emotion of *Anger* is associated with a high level of *Dominance*. However, the *Dominance* dimension is not included within many models, and it is used as an appraisal variable instead [25]. Moreover, this dimension does not seem to have a high variability among emotions [18], and some authors have found that human beings have difficulty and show confusion when they try to assign a *Dominance* value to the emotions that they are feeling [22].

Other authors, such as Reisenzein [34], showed the relationship of the intensity of emotions with the variables of *Pleasure* and *Arousal*. In an experiment, Reisenzein observed that the levels of *Pleasure* and *Arousal* are related to the intensity of emotions. Apparently, the intensity of emotions is proportional to the levels of *Pleasure* and *Arousal* so that the higher these levels, the greater the intensity. For example, the intensity of the *Happiness* emotion is highly dependent on the level of *Pleasure*, while the intensity of the *Alert* emotion is more dependent on the level of *Arousal*. He also observed that certain minimum levels of *Pleasure* and *Arousal* are required in order for emotions to show themselves. Therefore, when both variables have low values, the absence of emotions can be considered.

2.1. The relation between emotions, personality, and mood

When modeling the appraisal process, the relation between emotions and other affective characteristics such as personality or mood must be taken into consideration. Although the difference between emotions and mood continues to be a topic of debate [3], in general, it is accepted that an emotion is a rapid response to a given stimulus, while mood has a longer duration (from minutes to days) and a lower intensity than emotions and is not related to any particular stimulus. Instead, mood is produced by a succession of stimuli and other factors such as the context or the person's personality [9]. Empirical evidence suggests that there is a critical impact of emotions on cognition and a high variability of this impact among individuals with different personality factors. Personality can make a person more or less likely to experience certain types of mood [23].

One of the most commonly used models to define personality is the five-factor model (FFM) [27] in which personality is defined using five variables (or traits): *Openness*, *Conscientiousness*, *Extraversion*, *Agreeableness*, and *Neuroticism*. Different works that are based on the FFM relate personality factors with cognitive abilities, behaviors, and social skills. For example, there is evidence [8] that the *Extraversion* factor predisposes one to experience a more positive affect more frequently and with greater intensity, appraising emotions such as joy, enthusiasm, or energy. In contrast, *Neuroticism* predisposes one to experience a negative affect as well as suffering from negative moods such as fear, sadness, depression, or anger.

2.2. Emotions in affective agents

In recent years, different models have been proposed to simulate emotions using intelligent agents [1, 7, 35]. The proposed model for the EMA affective agent [26] is based on the subsequent formalization of the theory presented by Smith and Lazarus [24] that was carried out by Gratch and Marsella [16]. They propose a one-level appraisal process that takes into account past, current, and future events. They define different thresholds for the appraisal variables to elicit emotions [16]. In this model, intensity is defined as the product of different numeric appraisal variables. For example, the product of desirability and likelihood is used to estimate the intensity of the *Joy* emotion. The appraisal process of EMA has been used as a base to define emotion elicitation processes in other affective agent models such as *GenIA[3]* [2].

Another interesting approach is the one proposed by Gebhard in ALMA (A Layered Model of Affect) [15]. This model is based on the OCC appraisal theory [30] and models appraisal using subjective appraisal rules; therefore, each agent can have different appraisal rules. In these rules, the different appraisal variables are bounded by numeric values for eliciting each emotion. The authors also propose a decay rate for emotions, which decreases the intensity of the emotion over time until the emotion disappears.

Generally, humans express emotions and moods through terms such as "very happy" or "a little happy". Therefore, in the last few years, some authors have proposed using fuzzy logic to define affective computational models. For example, the appraisal model for FLAME [11], which is based on the Roseman [37] and OCC theories, uses variables with fuzzy values. In this approach, each emotion is selected based on a series of simple rules. Another interesting approach is the one presented by Jain et al. in EMIA [19]. The authors propose a fuzzy logic emotional model for five of Ekman's basic emotions (all except the *Disgust* emotion) [10]. The EMIA model implements a simplification of the Scherer model using five appraisal variables. The appraisal process is affected by the agent's memory and allows more than one emotion to be elicited in each appraisal cycle. All of the emotions have a fuzzy intensity value, and this intensity is modified over time by an emotion decay process.

Other affective characteristics, such as personality or mood, have also been used in affective computing to define the emotion appraisal process. Personality is usually used to create behaviors in multi-agent systems [6, 46]. For example, in [5], the authors propose that personality and mood have an effect on the appraisal variables and thus on the elicited emotions. This model proposes that personality affects the ranges of the fuzzy appraisal variables. Similarly, in [6], a model that uses fuzzy appraisal variables is proposed based on the *Integrative Model* [36]. That model is designed to adapt the cognitive and affective capacities of an agent to internal and external factors among which gender or personality are considered. To this end, each appraisal variable is defined with a membership function that is adapted according to these internal and external factors. The modification of the membership function of each appraisal variable is done both by modifying the type of function (e.g., pyramidal, trapezoidal) and by modifying the parameters of the membership function. However, at the moment, this model is only a proof of concept.

2.3. Discussion

When affective agents are modeled to simulate emotional behavior, the most important task is to choose the right emotion when an event is triggered. This is because the generated emotion will affect the cognitive processes of the agent, such as reasoning or the selection of behavior. The selected emotion will also have an impact on affective characteristics such as mood or empathy. Therefore, generating an incorrect emotion when an event occurs can cause erroneous behaviors that decrease the realism of the emotional behavior simulation. To model this process, several variables must be taken into account, such as the agent's concerns or the desirability of the event and other factors such as personality or mood. Several affective models use numerical variables, but this is problematic because it is somewhat different from how human beings express their emotions; humans find it very difficult to quantify emotions with numerical values.

In our model, we have decided to use fuzzy logic as a more natural way of eliciting emotions in the appraisal process. Models that use fuzzy logic are more suitable for simulating the human appraisal process due to the "fuzzy" way of expressing emotions by human beings. The use of fuzzy logic helps the understanding of the emotional states of the human beings that are interacting with the agents. In recent years, some proposals for emotion elicitation processes have been defined using fuzzy logic. For example, FLAME [11] proposes a small set of rules but involves the user too much in its implementation. In addition, even though the FLAME model allows emotions with intensity to be generated, the simplicity of the rules makes it a very basic model. For example, the *Joy* emotion is elicited if a desirable event occurs without taking into account the rest of the appraisal variables. Therefore, the rules are too simple, assigning the selected emotion by using only one appraisal variable. In addition, the appraisal variables are evaluated in a binary way: desirable or undesirable. Therefore, there are only a few combinations of values available to generate different emotions. Thus, this model has a very limited catalog of emotions, which, as stated above, hinders the user experience. Other fuzzy models, such as the model presented in EMIA [19], proposes a fuzzy logic approach for the appraisal process. That model reduces Scherer's model to five appraisal variables. However, the final model has two hundred rules to define an appraisal process that generates only five emotions. Therefore, even though the FLAME model is very basic due to the small number of rules, the EMIA model is too complex given its enormous number of rules. In addition, the EMIA model does not consider mood or personality in the appraisal process.

When simulating human affective behavior, the effect that different external and internal factors (e.g., personality or mood) have on cognitive processes must be taken into account. These factors have a direct consequence when evaluating an event, biasing the appraisal processes and consequently influencing emotions or mood. Some current proposals, such as the one presented in [5], use personality and mood to influence emotion selection in the appraisal process. However, in this model, the intensity of emotion is not contemplated. Therefore, this model becomes much simpler to design and implement. This can have a negative effect on the behavior of the agent since the catalog of emotional responses decreases. Other proposals such as the one proposed in [6] take into account the importance of these internal and external factors, but that model has only been tested with the gender factor. Furthermore, although it is accepted that factors such as personality have an effect on emotions, which predisposes the individual to certain types of emotion, there is not enough evidence to determine what the effect of personality is on an appraisal variable.

As we have stated above, there is a large number of appraisal theories that try to explain how emotions are generated. Each theory has a series of advantages and disadvantages. For example, the patterns that Scherer [42] proposes in his computing model of affect are interesting when determining which variables affect each emotion. However, Scherer uses a large number of variables, which makes this model very complex for development in an affective agent. Furthermore, in this model, the intensity of the emotions is not considered. This may affect the behavior of the agent since the catalog of actions of the agent will be very limited because the intensity of the emotion cannot be taken into account to decide the action to be executed. A small catalog of emotions can affect the interactions with human users because, if an agent shows the same emotions very often, the agent loses credibility and the users tend to become bored. Therefore, the more we expand the catalog of emotions of an agent, the greater the number of different emotional behaviors that can be simulated.

The internal representation of emotions must also be taken into account when defining an emotional model for an affective agent. Most of the emotional models proposed to date reduce the representation of emotions to simple labels [12]. However, dimensional representations seem to be more appropriate for developing computational models since they allow emotions to be stored using variables instead of simple labels and variables can hold a wider range of values. The Circumplex Model of Affect [38] (Fig. 1) has already been used in affective computing [41]. Nevertheless, the schema proposed by Russell is only a reinforcement for his theory. In this scheme, he uses a simplified spacial location for each emotion, but this is unnatural, and, consequently, an agent using this simplified representation of emotions could show erratic behavior that is very different from the real behavior of a human being. Therefore, performing a direct use of this model in a computational system could lead to unreal emotional behaviors.

In the next section, we introduce our new fuzzy appraisal model based on representing emotions in a *Pleasure-Arousal* space. Section 3.1 describes how a fuzzy rule-based system selects one or more emotions by evaluating the appraisal variables. Section 3.2.1 presents the *Pleasure-Arousal* space where agents can internally represent the appraised emotions using a defuzzification function. This internal representation of emotions allows the agent to update its mood as presented in Section 3.2.2. Finally, when the agent needs to communicate or express its internal emotional state, a fuzzification process (presented in Section 3.2.3) translates the internal emotional state represented in the *Pleasure-Arousal* space into a fuzzy emotion. The fuzzification process uses the results of an experiment to generate a fuzzy emotion that is adapted to the language and cultural environment of the human interlocutor of the agent. The article ends with conclusions and future works.

3. A model for emotion elicitation in affective agents

The appraisal process is one of the most important processes in an affective agent because suitable agent behavior depends on the emotion selected. A good definition of this process is even more important when the agent is designed to interact with humans since erratic or erroneous behavior of the agent can make the human become frustrated. In addition, processes such as the selection of the action to be executed or the updating of the agent's mood will depend on the emotion elicited.

As we have discussed above, there are different psychological theories to explain emotional processes. Appraisal theories provide an explanation of how an emotion is generated when an event is perceived. Alternatively, other theories, such as Russell's theory [38], offer the possibility of relating emotions with dimensional variables. We propose a fuzzy model of emotions that adapts the advantages of the appraisal models for selecting an emotion when an event occurs and the advantages of representing the emotion in a multidimensional space. As a novelty, by using this multidimensional representation, our model can adapt emotions to the agent's affective characteristics and to the culture and the language in which the agent will be located.

Our model is composed of two processes. First, in the *Event Appraisal* process, an event is evaluated by our fuzzy appraisal algorithm and produces an emotion which we will refer to as *Appraised Emotion*. This fuzzy process allows us to generate emotions and their intensity, capturing the kind of uncertainty that humans beings use when expressing their emotions. Second, in the *Affect Adaptation* process, the mood is updated based on the *Appraised Emotion*, the agent's personality, and the culture and language in which the agent is located. The following section describes both processes in detail.

3.1. The Event Appraisal process

The *Event Appraisal* process defines a fuzzy appraisal process to select an emotion when the agent perceives an event. The selected emotion corresponds with one of the six basic emotions proposed by Ekman [10]: *happiness*, *disgust*, *sadness*, *anger*, *fear*, and *surprise*. Moreover, based on the emotions proposed by Russell in [40], two emotions, *calm* and *boredom*, have also been incorporated to represent the lack of interactions between the agent and the user and also the lack of relevance of the event.

We have designed a fuzzy rule-based system [22] that, depending on the value of the appraisal variables, returns the elicited emotion and its intensity. The fuzzy values used to define the rules are based on the computational model proposed by Scherer [42], but we solve the main weakness of this model: Our model needs a smaller number of appraisal variables and it also calculates the intensity of the elicited emotion. Moreover, in our model, the values of each appraisal variable are associated with the intensity of the emotions as proposed by OCC[1]. According to this theory, two of the most relevant appraisal variables attributed to emotions produced by events, such as happiness or sadness, are desirability and likelihood. Therefore, in our model, we associate these two variables with Scherer's model to obtain the label and the intensity of the emotions using fuzzy variables. The appraisal variables selected for our model are the following:

- **Expectedness**, which represents the agent's level of expectation associated with the event.
- **Likelihood**, which represents the estimated probability of occurrence of the event.
- **Desirability**, which represents how desirable or undesirable the event is for the agent; it can be positive or negative.
- **Causal attribution**, which represents who is responsible for the event.
- **Controllability**, which represents the number of possible plans that the agent has to deal with for that event.

The use of fuzzy logic in the appraisal process facilitates the definition of fuzzy rules to generate emotions since fuzzy logic is closer to the way in which human beings express their emotions. Therefore, our fuzzy logic-based approach produces better and more reliable results than other non-fuzzy appraisal processes.

In our appraisal model, each event is associated with a tuple:

$$event \leftarrow \langle e, l, d, a, c \rangle \tag{1}$$

where e, l, d, a, and c represent the fuzzy values for the appraisal variables *Expectedness*, *Likelihood*, *Desirability*, *Causal_attribution*, and *Controllability*, respectively. The possible values for these variables are:

$$\begin{aligned} &e, l, c \in \{Low, Medium, High\} \\ &d \in \{High\_desirable, Desirable, Low\_desirable, Low\_undesirable, Undesirable, High\_undesirable\} \\ &a \in \{Self, Other\} \end{aligned} \tag{2}$$

On the other hand, an emotion is defined by a tuple:

$$emotion = \langle type, int \rangle \tag{3}$$

where $type$ is the label representing the emotion type, and *int* represents the fuzzy intensity of the emotion:

$$\begin{aligned} &type \in \{Happiness, Disgust, Sadness, Anger, Fear, Surprise, Calm, Boredom\} \\ &int \in \{Strong, Medium, Light, Neutral\} \end{aligned} \tag{4}$$

[1] The relationship between the appraisal variables of both the OCC and the Scherer model can be found in [42]

The *Neutral* value is the default value for emotions that have not been elicited in the appraisal process. In addition, we have introduced a new appraisal variable named *Time Without Events* (TWE). This variable is not part of the event; it is an internal variable of the agent that measures the time that has passed since the last event. We have proposed this appraisal variable to elicit the *calm* and *boredom* emotions. The possible values for this variable, represented by t, are:

$$t \in \{Low, Medium, High\} \tag{5}$$

We use a fuzzy rule-based system to calculate the elicited emotion and its intensity. The general structure of a fuzzy rule [29] is:

$$r_i : \text{IF } e \text{ is } x_e^i \text{ and } l \text{ is } x_l^i \text{ and } d \text{ is } x_d^i \text{ and } a \text{ is } x_a^i \text{ and } c \text{ is } x_c^i \text{ and } t \text{ is } x_t^i \text{ THEN } type \text{ is } y_{type}^i \text{ and } int \text{ is } y_{int}^i \tag{6}$$

where r_i is the ith fuzzy production rule, x_e^i represents the fuzzy value for the *Expectedness* appraisal variable in the ith rule, x_l^i is the fuzzy value for *Likelihood*, x_d^i is the fuzzy value for *Desirability*, x_a^i is the fuzzy value for *Causal attribution*, x_c^i is the fuzzy value for *Controllability*, x_t^i is the ith fuzzy value for *Time Without Events*, and y_{type}^i and y_{int}^i are the output values for the emotion type and the intensity calculated by the ith rule (see Table 1).

For example, a fuzzy rule appraising the Fear emotion with High intensity is defined as:

$$\begin{aligned} r_{13} : &\text{ IF } e \text{ is Low and } l \text{ is High and } d \text{ is High\_Undesirable and } a \text{ is Other and } c \text{ is Low and } t \text{ is Low} \\ &\text{ THEN } type \text{ is Fear and } int \text{ is High} \end{aligned} \tag{7}$$

Table 1 summarizes the parameters of the 24 fuzzy rules that are proposed to define the appraisal process. Each row corresponds to a fuzzy rule, while each column contains the possible fuzzy values for each appraisal variable that is associated with each emotion. As we stated above, the definition of the appraisal variable values is based on the model proposed by Scherer [42] and the OCC model [30].

We have defined three fuzzy values for the intensity of each emotion. This intensity depends on the fuzzy values of the set of appraisal variables [26]. This fuzzy process not only derives emotions and their intensity from the set of appraisal variables, it also unifies the selection of the type and the intensity of the emotion in the same rule. Therefore, it is not necessary to define a new process to derive the intensity as in other models [11, 26].

3.2. The Affect Adaptation process

Two important factors that must be taken into consideration when modeling affective agents are mood and personality. Mood can be seen as the result of the various emotional events that are produced during a period of time. On the other hand, personality influences the type and intensity of the mood of a person [23]. For example, a person with high levels of neuroticism will be more likely to experience negative moods more frequently and with more intensity. In our model for affective agents, mood is represented in a two-dimensional space in terms of *Pleasure* and *Arousal*. The *Affect Adaptation* process updates the mood by modifying the values of *Pleasure* and *Arousal* according to the current emotion, the agent's personality, and the language and culture in which the agent is located. We describe the different phases of this process in the following sections.

3.2.1. Representing emotions in a Pleasure-Arousal space

As we have shown in the previous sections, the result of the *Event Appraisal* process is the *Appraised Emotion*, which is composed of an emotion type and a fuzzy intensity. In the *Affect Adaptation* process, we use the *Pleasure* and *Arousal* dimensions of the *Appraised Emotion* to adapt the agent's mood. Therefore, to calculate how the mood will be modified by the *Appraised Emotion*, we need to represent this emotion in the same two-dimensional space that is used for representing the agent's mood. To avoid the loss of information, our multidimensional model must be able to represent both the emotion type and the emotion intensity.

Our proposal represents a fuzzy emotion in a two-dimensional space that is adapted to the culture and language in which the agent will be used. This model is based on the results of the experiment presented in [47]. In this experiment, one-hundred European Spanish-speakers, 40 females and 60 males ranging in age between 18 and 60 years old, were asked to assign fuzzy values of *Pleasure* and *Arousal* to ten terms/words expressing emotions in their mother tongue. The emotions selected for this experiment were: *Happiness*, *Excitement*, *Surprise*, *Fear*, *Disgust*, *Anger*, *Sadness*,

Table 1
Fuzzy model for estimating the emotion and its intensity. Where HD = High desirable, D = Desirable, LD = Low Desirable, LU = Low Undesirable, U = Undesirable, and HU = High Undesirable.

Emotion	***Intensity***	**Expectedness**	**Likelihood**	**Desirability**	**Causal attribution**	**Controllability**	**TWE**
	High	Medium	High	HD			
Happiness	Medium	Medium/Low	High/Medium	D			
	Low	Medium/Low	High/Medium	LD			
	High	Low	High	HU	Other	High/Medium	
Disgust	Medium	Low	High	U	Other	High/Medium	
	Low	Low	High	LU	Other	High/Medium	
	High		High	HU/U		Low	
Sadness	Medium		High/Medium	U		Low	
	Low		High/Medium/low	LU		Low	
	High	Medium	High	HU		Medium	
Anger	Medium	Medium	High/Medium	U		Medium	
	Low	Medium	High/Medium/Low	LU		Medium	
	High	Low	High	HU	Other	Low	
Fear	Medium	Low	High/Medium	U	Other	Low	
	Low	Low	High/Medium/Low	LU	Other	Low	
	High	Low	Low		Other		
Surprise	Medium	Low	Medium		Other		
	Low	Low	High		Other		
	High					Medium	Low
Calm	Medium					Medium/Low	Medium
	Low					Medium/Low	High
	High					Low	Low
Boredom	Medium					Low	Medium
	Low					Low	High

Boredom, *Calm*, and *Sleepiness*. When the *Pleasure* and *Arousal* dimensions have low levels, the intensity of the emotion is so low that it can be considered that there is no emotion. Therefore, we discarded those responses whose values of *Pleasure* and *Arousal* were close to zero. We obtained the mean of the *Pleasure* and *Arousal* for each emotion, and then we calculated the mean and the standard deviation of the angle of each emotion in this two-dimensional space. This angle represents the meaning that each participant associates to each emotion. The results of the experiment are summarized in Table 2.

Our model also divides the *Pleasure-Arousal* space into four degrees of intensity: *Strong*, *Medium*, *Light*, and *Neutral* (Fig. 2). We have added the fuzzy value *Neutral* to refer to those emotions that are not intense enough to be considered as elicited. When we superimpose the results of the experiment on the model proposed for the intensity of emotions, we obtain different areas that relate the *Pleasure* and *Arousal* dimensions to each emotion label and its intensity adapted to the Spanish language. Fig. 3 shows the emotion model proposed in this paper, where the area assigned to each emotion, using one standard deviation, is represented in a different color. This model can be easily adapted to other languages and cultural environments using the results of similar experiments to assign different areas to each emotion. An agent with more than one *Pleasure-Arousal* space can easily adapt its emotion expression depending on the language and culture of its interlocutor without modifying the rest of its affective components.

We have designed a defuzzification function that translates the fuzzy appraised emotion into its *Pleasure* and

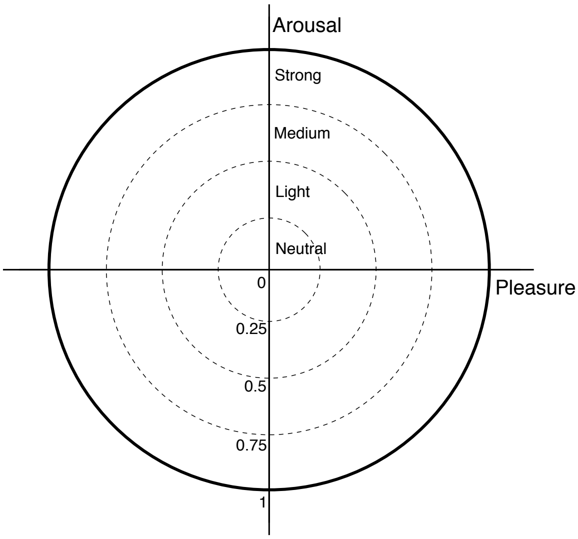

Figure 2: The proposed fuzzy model for the intensity of the emotions in the *Pleasure-Arousal* space.

Table 2
Results of the experiment expressed in degrees.

Emotion	Pleasure	Arousal	Mean angle	Standard deviation
Happiness	0.90	0.42	25.09	19.02
Excitement	0.76	0.64	39.97	10.32
Surprise	0.31	0.95	71.63	26.38
Fear	-0.58	0.81	125.51	15.61
Anger	-0.74	0.66	138.55	16.90
Disgust	-0.99	-0.04	182.58	43.65
Sadness	-0.96	-0.27	196.02	22.48
Boredom	-0.41	-0.91	245.34	21.41
Sleepiness	-0.11	-0.99	263.59	15.56
Calm	0.74	-0.67	318.12	35.89

Arousal equivalent values. The defuzzification function determines the direction of the *Appraised Emotion* vector $\vec{e}$ in this culturally located, two-dimensional space using the mean angles obtained in the experiment for each emotion (see Table 2). For example, if the *Appraised Emotion* is *Anger*, the direction of the corresponding vector $\vec{e}$ will be 138.5 degrees, which corresponds to the mean angle obtained in the experiment for the *Anger* emotion . The defuzzification function also calculates the vector modulus, which indicates the intensity of the emotion, as the mean value for each intensity. For example, if the intensity of the *Appraised Emotion* is *Strong*, the modulus of the emotion vector $\vec{e}$ will be 0.875, which corresponds to the midpoint of the *Strong* intensity that goes from 0.75 to 0.1. The result of this defuzzification function is the vector $\vec{e}$, which represents the *Appraised Emotion*. Considering that the horizontal axis in this two-dimensional space represents *Pleasure* and the vertical axis represents *Arousal*, if α is the angle of the vector $\vec{e}$, then the *Pleasure* and *Arousal* values of the *Appraised Emotion* can be calculated by a simple trigonometry formula as follows:

$$(Pleasure, Arousal) = \left(\left|\vec{e}\right| \cdot \cos\alpha, \left|\vec{e}\right| \cdot \sin\alpha\right) \tag{8}$$

For instance, let us suppose an agent a receives an event. The fuzzy appraisal process evaluates the values of the appraisal variables associated to that event and obtains the emotion e defined by the type *Anger* and the intensity

Strong by using the fuzzy rule-based system. The direction of the vector $\vec{e}$ corresponding to the *Anger* emotion is $\alpha = 138.5$ (as shown in Table 2), and its modulus is $|\vec{e}| = 0.875$. The agent can calculate the *Pleasure* and *Arousal* values associated with the emotion vector $\vec{e}$ using Formula 8: $(Pleasure, Arousal) = (-0.66, 0.58)$.

We have shown how our model internally represents an emotion by a vector in which the modulus represents the intensity of the emotion and the direction represents the type of emotion. The result is a circular representation of the emotions with some similarities with the scheme proposed by Russell (Fig. 1). However, as we stated above, Russell's scheme should not be used directly since it is only a scheme that was used to reinforce the idea that emotions follow a circular pattern; the area assigned to each emotion is more restricted, and the emotion intensity is not considered.

3.2.2. Updating the mood

Once the agent obtains the *Pleasure* and *Arousal* values of the appraised emotion, the agent can use these values to update its mood according to the agent's personality. In this phase, the vector of the agent's mood, which is also represented in the *Pleasure-Arousal* space, is "attracted" by the emotion vector to a greater or lesser extent depending on the agent's personality. We have defined two functions, called *Mood_Resistance* and *Emotion_Influence*, to model this behaviour. The *Mood_Resistance* function determines how a mood m resists being changed by the appraised emotion. The *Emotion_Influence* function determines the influence or force of the emotion e to modify the agent's mood. Both functions depend on the agent's personality. For example, an agent with a personality that is prone to negative affect will have a *Mood_Resistance* for the negative moods that is higher than the *Mood_Resistance* for the positive moods. That means that the agent will be more prone to suffer a negative mood with greater intensity than an agent with a personality that is prone to positive affect [45].

The current mood of an agent at instant t, $\vec{m}_t$, will be updated as a combination of the previous mood vector (mood at instant $t-1$), $\vec{m}_{t-1}$, weighted by the $Mood\_Resistance(m)$ and the emotion vector $\vec{e}$ weighted by the $Emotion\_Influence(e)$ function:

$$\vec{m}_t = \vec{m}_{t-1} \cdot Mood\_Resistance(m_{t-1}) + \vec{e} \cdot Emotion\_Influence(e) \tag{9}$$

where $Mood\_Resistance(m_{t-1})$ and $Emotion\_Influence(e)$ represent how the personality of the agent affects its mood, These two functions are calculated using the following formulas:

$$Mood\_Resistance(m) = \frac{\sum_{p\in P} \beta_p \cdot \theta_{m,p}}{\sum_{p\in P} \theta_{m,p}} \tag{10}$$

$$Emotion\_Influence(e) = \frac{\sum_{p\in P} \beta_p \cdot \theta_{e,p}}{\sum_{p\in P} \theta_{e,p}} \tag{11}$$

where P represents the set of personality traits of an agent. For example, for the five-factor model (FFM), these traits are *Openness* (O), *Conscientiousness* (C), *Extraversion* (E), *Agreeableness* (A), and *Neuroticism* (N); therefore, P is defined by the set $P = \langle O, C, E, A, N\rangle$. β_p is the value of a personality trait $p \in P$. $\theta_{e,p}$ is a weight that relates the personality trait p with the emotion e. There will be one weight $\theta_{e,p}$ for each pair of emotion type and personality trait (e, p), but many of these weights could be zero. Each weight $\theta_{e,p}$ determines how the personality trait p influences the emotion type e. Therefore, the set of weights $\theta_{e,p}$ can be viewed as the set of correlations between emotions and personality traits: the greater the correlation between the personality trait p and the emotion type e, the greater the value of $\theta_{e,p}$. For example, considering that the trait of *Extraversion* E is related to positive emotions and *Neuroticism* N does not have a very high relation with emotions of this type, for the *Happiness* emotion, the value of the weight $\theta_{Happiness,E}$ will be greater than the value of the weight $\theta_{Happiness,N}$. Different $\theta_{e,p}$ values can be chosen by the agent programmer to generate agents with different emotional behaviors and personalities.

To better understand this method, let us reconsider the previous example where after evaluating an event at instant $t-1$, an agent $a1$, has elicited the *Appraised Emotion* represented by vector $\vec{e}$ in Fig. 3. Let us consider that the mood for agent $a1$ at instant $t-1$ is defined by the vector $\vec{m}_{t-1,a1}$. The *Pleasure* and *Arousal* components for the mood vector $\vec{m}_{t-1,a1}$ are $(-0.30, -0.20)$. Let us also consider a second agent, $a2$, who has appraised the same emotion as agent $a1$ ($\vec{e}$) and has the same mood. To simplify, we will represent the mood of both agents by $\vec{m}_{t-1}$ ($\vec{m}_{t-1} = \vec{m}_{t-1,a1} = \vec{m}_{t-1,a2}$). The *Affect Adaptation* process will update the agents mood at instant t taking into account the effect of the *Appraised*

Table 3
Example of $\theta_{e,p}$ values.

Emotion	E	N
Anger	$\theta_{Anger,E} = 0.5$	$\theta_{Anger,N} = 0.8$
Sadness	$\theta_{Sadness,E} = 0.6$	$\theta_{Sadness,N} = 0.7$

Emotion, the mood of the agents at instant $t-1$, and the personality of the agents. To simplify this example, the agent's personality is defined using only two traits: *Extraversion* (E), which is related to positive affect; and *Neuroticism* (N), which is related to negative affect. Therefore, the personality in this example is defined by the tuple:

$$P = \langle E, N \rangle \tag{12}$$

On the other hand, for this example, we consider the values for $\theta_{e,p}$ shown in Table 3. These values are based on the results obtained from the experiments presented in [14], making them consistent with theories that associate *Extraversion* with positive emotions and *Neuroticism* with negative emotions [44]. Taking into account these values, if we define the personality of agent $a1$ by a level of *Extraversion* of 0.9 and a level of *Neuroticism* of 0.1 ($P_{a1} = (0.9, 0.1)$) and the personality of agent $a2$ by a level of *Extraversion* of 0.1 and a level of *Neuroticism* of 0.9 ($P_{a2} = (0.1, 0.9)$), then the values of *Pleasure* and *Arousal* for the new mood of agents $a1$ and $a2$ at instant t calculated by Formula 9 are $\overrightarrow{m}_{t,a1} = (-0.4, 0.1)$ and $\overrightarrow{m}_{t,a2} = (-0.6, 0.3)$. These values are represented in Fig. 3 by the vectors $\overrightarrow{m}_{t,a1}$ and $\overrightarrow{m}_{t,a2}$.

Comparing the resulting moods of both agents, it can be observed that, in the case of agent $a1$, which has a high level of extraversion, the mood has been less affected by a negative emotion than in the case of agent $a2$, which has a higher level of neuroticism. These results are consistent with theories that claim that personalities with low *Extraversion* and high *Neuroticism* are more prone to negative moods [4, 8].

As we have shown in our proposal, the mood is adapted to the current emotion according to the agent's personality. Therefore, our model facilitates the development of emotional multi-agent systems since it allows different moods to be easily obtained for each agent based on the agent's personality. Different moods will produce different agent behaviors, which will improve the agent's capability to simulate human behaviors [45]. For example, an agent with a negative personality will be more prone to negative moods than an agent with a positive personality. Therefore, from psychological and neurological perspectives, this proposal is more consistent with the different theories that argue that emotions and personality have an effect on mood [23] and it also explains why people are more or less likely to have certain types of mood.

3.2.3. The Fuzzification Process

In our model, the pair $(Pleasure, Arousal)$ is internally used by an agent to represent the appraised emotion and its mood in the two-dimensional space. When the agent needs to express its mood, it has to perform a fuzzification process to determine the emotion type and intensity corresponding to the mood vector defined by the pair $(Pleasure, Arousal)$. The intensity of the emotion is easily calculated using the modulus of the emotion vector and the fuzzy model represented in Fig. 2. On the other hand, the process to calculate the emotion type corresponding to an emotion vector can be viewed as a classification problem where there is a set C of ten classes that correspond to the ten emotions.

$$C \in \{Happiness, Excitement, Surprise, Fear, Anger, Disgust, Sadness, Boredom, Sleepiness, Calm\} \tag{13}$$

Using the Gaussian models obtained from the experiment for Spanish-speakers (Table 2), we can estimate the probability of each emotion. We have defined the $t(\overrightarrow{v})$ function as a Bayesian classifier that returns the emotion type with the maximum likelihood for an angle α of the emotion vector $\overrightarrow{v}$:

$$t(\overrightarrow{v}) = \arg\max_{c} \widehat{P}(C = c \mid \alpha) \tag{14}$$

where $c \in C$, and $\widehat{P}(C = c \mid \alpha)$ represents the estimated conditional probability of the class of emotion c for the angle α. This probability is estimated by the normal distributions obtained in the experiment as:

$$\widehat{P}(C = c \mid \alpha) \sim f(\alpha \mid \mu_c, \sigma_c) \tag{15}$$

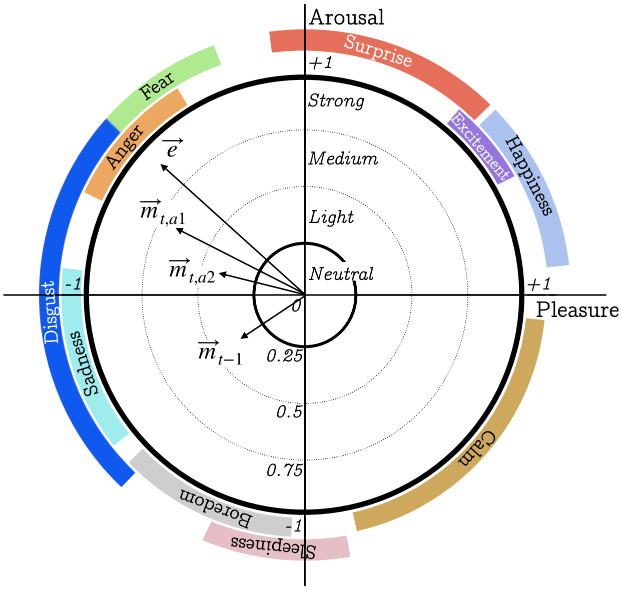

Figure 3: Example of the estimation of the mood considering two different personalities.

where μ_c and σ_c represent the mean and the standard deviation of the class of emotion c. $\widehat{P}(C = c \mid \alpha)$ is estimated using the probability density function of a Gaussian distribution $f(\alpha \mid \mu_c, \sigma_c)$ [20]:

$$f(\alpha \mid \mu_c, \sigma_c) = \frac{1}{\sigma_c \cdot \sqrt{2\pi}} \cdot e^{-\frac{(\alpha-\mu_c)^2}{2\cdot\sigma_c^2}} \tag{16}$$

Continuing with the previous example, if agent a wants to express the emotion $\vec{e} = (-0.66, 0, 58)$ (see Figure 3), the agent will calculate the most probable labels for the type and the intensity of the emotion through the *Fuzzification Process*. First, the modulus of the vector is calculated (in this example, $\left|\vec{e}\right| = 0.875$) to obtain the fuzzy intensity. In this case, since the module is in the range of the *Strong* intensity ($0.75 \leq \left|\vec{e}\right| \leq 1$), the label of the emotion intensity is *Strong*. Then, the label of the emotion type is obtained using Formula 14 and the Gaussian models obtained from the experiment in the same cultural environment in which the agent is located. In this case, the maximum argument for the function $t(\vec{e})$ is $\widehat{P}(C = Anger \mid \alpha = 138.5)$. Therefore, the most likely label for that emotion is *Anger*.

Traditionally, in affective computing, most of the proposed appraisal models calculate the intensity and the emotion type of emotions independently by using numerical variables. Our model unifies the appraisal of the type and intensity of the emotion in the same rule. Dimensional models, such as the one proposed in this paper, also allow the affective behavior of the agent to be described in a more precise way. This dimensional representation defines regions where emotions can occur and therefore represents the proximity between two emotions and the intensity of the emotions. This representation allows the simulation of processes such as the decay rate of the mood over time and opens the doors to the simulation of new processes such as empathy or emotional contagion.

4. Conclusions and future work

In this paper, we have proposed a new fuzzy appraisal model using the *Pleasure* and *Arousal* dimensions, which is adapted by a defuzzification process to the culture and language in which the agent is located. Our model uses fuzzy logic to better reproduce the way in which humans express emotions. We propose two processes to simulate affective behavior. When an event is perceived, the *Event Appraisal* process evaluates five fuzzy appraisal variables to obtain the fuzzy *Appraised Emotion*. Then, the *Affect Adaptation* process defuzzificates the *Appraised Emotion* and adapts the mood using this defuzzificated *Appraised Emotion*, the agent's personality, and the cultural environment. This *Affect Adaptation* process allows different agents to have different moods when they perceive the same event, which will allow agents to show different behaviors depending on the personality of each agent.

The proposed appraisal model has two important advantages. It can be easily adapted to trigger more than one emotion in each appraisal cycle, and it is capable of eliciting ten different types of emotions with different intensities despite having an objectively small number of fuzzy rules. Our model uses the *Pleasure* and *Arousal* dimensions internally to define emotions and mood instead of simple labels. With these dimensions, emotions and mood can be defined as vectors in which the modulus represents the intensity of the emotion, while the type of emotion is represented by the direction of this vector. Through this dimensional representation, the variables representing affective characteristics of agents (emotion and mood) can be easily adapted to obtain different emotions and moods. Therefore, our model improves the representation of emotions because it allows emotions and mood to be modified, adapted, and stored using a dimensional representation. In this work, we have also defined a fuzzy model of intensity that depends on the modulus of the emotion's vector. This model allows the agent to express emotions in the same way as humans.

One important novelty of our proposal is that our model allows the agent to express its emotional state using the same interpretation of the fuzzy emotional terms used in the language and culture of its human interlocutor. This has been achieved by defining the two-dimensional *Pleasure-Arousal* space using the results of an experiment with participants of the same cultural environment in which the agent is located. Moreover, one agent can easily adapt the expression of its emotions to other cultural environments using different *Pleasure-Arousal* spaces that can be easily incorporated to its affective component.

We are currently integrating our emotional model in the affective agent architecture *GenIA^3* in order to allow the development of different behaviors depending on the agent's personality and mood. We are interested in defining a new *Pleasure-Arousal* space that is adapted to other language and/or cultural environments. This will allow agents to adapt their emotion expression to interlocutors of different cultural environments. We are also interested in analyzing the effect of adding the *Dominance* dimension to the *Pleasure-Arousal* space. We think that this additional dimension could disambiguate the overlaps that occur between some emotions in the two-dimensional model.

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