A Multidimensional Culturally Adapted Representation of Emotions for Affective Computational Simulation and Recognition

Joaquin Taverner, Emilio Vivancos, and Vicente Botti

Abstract—One of the main challenges in affective computing is the development of models to represent the information that is inherent to emotions. It is necessary to consider that the terms used by humans to name emotions depend on the culture and language used. This article presents an experiment-based method to represent and adapt emotion terms to different cultural environments. We propose using circular boxplots to analyze the distribution of emotions in the Pleasure-Arousal space. From the results of this analysis, we define a new cross-cultural representation model of emotions in which each emotion term is assigned to an area in the Pleasure-Arousal space. An emotion is represented by a vector in which the direction indicates the type, and the module indicates the intensity of the emotion. We propose two methods based on fuzzy logic to represent and express emotions: the emotion representation process in which the term associated with the recognized emotion is defuzzified and projected as a vector in the Pleasure-Arousal space; and the emotion expression process in which a fuzzification of the vector is produced, generating a fuzzy emotion term that is adapted to the culture and language in which the emotion will be used.

Index Terms—Affective computing, individual and cultural differences, modeling human emotion

1 Introduction

Emotions play an important role in our behavior as humans. Emotions are present in our day-to-day relationships with other human beings and when we face any situation or event. Systems that are capable of recognizing, processing, or simulating emotions can improve the interaction between humans and machines by making this interaction more natural and realistic.

Over the years, different models have been proposed to recognize emotions in human beings. With the improvement of machine learning, there is currently a large number of models that recognize emotions using images, voice, text, or electroencephalograms. However, most of these models focus on improving the accuracy of the recognition without paying much attention to the way of representing that knowledge for its possible use in systems such as affective agents. An affective agent is a system that is capable of simulating human affective behaviour. Currently, there are several approaches for affective agents in which different models of representation of emotions are used [1], [2], [3], [4], [5]. Frequently, proposals made from affective computing represent emotions using simple labels (e.g., *Happy* or *Sad*). However, a representation of emotions that uses a continuous multidimensional space seems to be more appropriate for use in computational models since it allows storing more information about emotions, such as the intensity of emotions or the proximity between emotions [6]. This representation also provides a greater capacity to analyze the variations that occur in emotions and mood over time, thereby improving the simulation of human emotional behavior.

Different models of representation of emotions have been proposed from psychology. One of the best known is *The Circumplex Model of Affect* proposed by J. A. Russell [7] (Fig. 1). This model relates emotions with their *Pleasure* and *Arousal* values. In addition, according to several studies, emotions greatly depend on language and culture [8], [9], [10]. In other words, the same emotion label can be interpreted in a different way depending on the culture and the language. Nevertheless, even though cultural and language factors are taken into account in other domains such as recommendation systems, to our knowledge, there are still no proposals in the affective computing area that really consider cultural and language factors to represent and express emotions in a computational system.

On the other hand, there is a recent tendency to use emotional models based on fuzzy logic [11], [12]. This is due to the fact that this type of knowledge representation is closer to the way in which human beings express their emotions using terms such as *very happy* or *a little happy* [13]. Therefore, a model that represents human emotions should be able to deal with this type of fuzzy terminology.

This paper proposes an experiment-based method that represents emotions in a *Pleasure-Arousal* dimensional space adapted to the language and culture where the emotions will be expressed. This model uses fuzzy logic to better simulate the way in which humans express emotions. The rest of this paper is organized as follow. In Section 2, we discuss the most important proposals for emotion representation in

• *The authors are with the Valencian Research Institute for Artificial Intelligence (VRAIN), Universitat Politècnica de València, 46022 Valencia, Spain. E-mail: {joataap, vivancos, vbotti}@dsic.upv.es.*

Manuscript received 8 July 2020; revised 6 Oct. 2020; accepted 9 Oct. 2020. Date of publication 13 Oct. 2020; date of current version 28 Feb. 2023. (Corresponding author: Joaquin Taverner.) Recommended for acceptance by C. de Melo. Digital Object Identifier no. 10.1109/TAFFC.2020.3030586

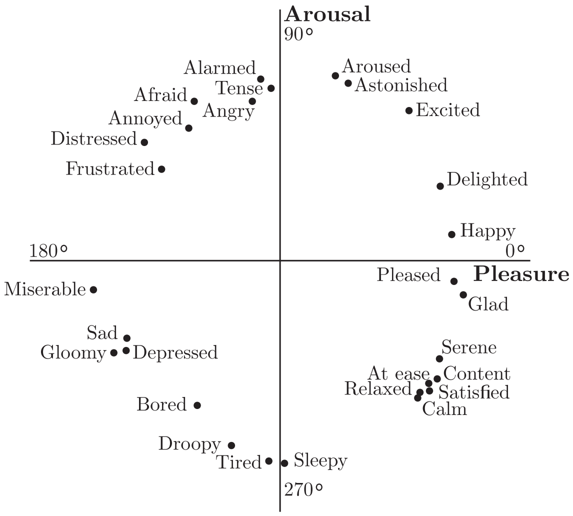


Fig. 1. The circumplex model of affect.

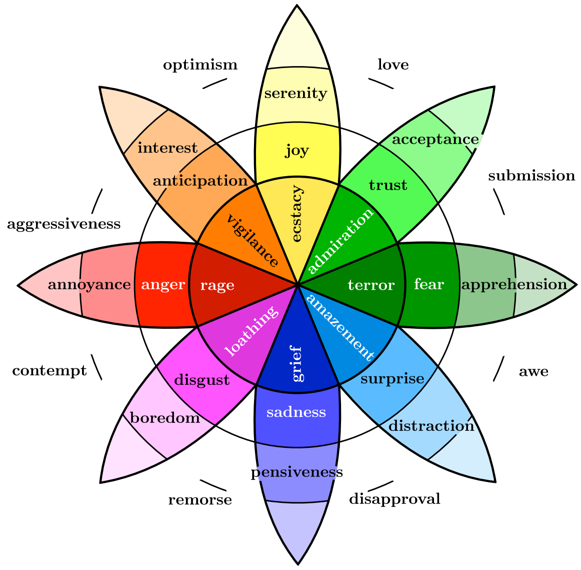


Fig. 2. Wheel of emotions proposed by Plutchik [14].

affective computing. Section 3 introduces an experiment-based method to adapt the emotion representation to the cultural environment in which emotions are used. The fuzzy culturally adapted model of affect obtained from the experiment is presented in Section 4. Finally, the main conclusions and some future works are presented in Section 5.

2 Related Works

The term emotion is a psychological construct whose definition has long been the subject of debate. Over the years, different theories have been proposed to explain emotional behavior. Some theories, such as basic emotion theories, propose that there is a limited number of emotions and that these emotions are understood universally. One of the best known theories in this area is the Basic Emotion Theory proposed by Ekman [15]. Ekman's theory is based on six basic emotions: *Happiness*, *Surprise*, *Fear*, *Anger*, *Disgust*, and *Sadness*. Plutchik defined his theory using eight basic emotions [14] in which different feelings can be derived from the combination of two adjacent emotions (Fig. 2). According to these theories, one event is universally related to a single emotion.

In contrast, the constructivist theories contradict the basic emotions theories stating that emotion labels/words do not have a universal meaning. According to constructivism, the labels that we use to refer to emotions depend on the culture and the language used. Therefore, there is no direct correspondence for all of the emotion labels among different languages [16]. For example, in the German language, there is an emotion called *Schadenfreude*, whose meaning could be translated into English as "pleasure from the suffering of others" but this translation does not quite capture the complete meaning of the emotion as it is shown in [17].

One of the most cited constructivist theorists is J. A. Russell. In his *Core-Affect* theory [8] language and culture have an important weight when cataloging different emotions. He also proposed that emotions are related to the dimensions of *Pleasure* (sometimes called *Valence*) and *Arousal* (sometimes called *Activation*) [18]. He observed through experimentation that emotions follow a circular pattern within a continuous space based on these two dimensions. He called this pattern *The Circumplex Model Of Affect* [7] (Fig. 1), which shows the relationship between emotions and the values of *Pleasure* and *Arousal*.

On the other hand, Reisenzein [19] observed that the intensity of emotions is proportionally related to the values of *Pleasure* and *Arousal*: the greater the value of these dimensions, the greater the intensity of the emotion. For example, the intensity of the *Happy* emotion is more related to the level of *Pleasure*, while the intensity of the *Alert* emotion is more related to the level of *Arousal*. In addition, he also observed that low levels of *Pleasure* and *Arousal* mean that the intensity of emotions is so low that it can be assumed that there is no emotion.

Mehrabian proposed adding a third dimension, known as *Dominance*, to the *Pleasure-Arousal* space. This created a new model known as the PAD model [20], which is one of the most widely used models when designing affective agents that simulate emotional behavior. The *Dominance* dimension increases the space of representation allowing some emotions to be disambiguated. However, many models propose that this third dimension must be considered as an appraisal variable rather than as a representation variable [21].

Jackson *et al.* [22] analysed around 2500 languages to determine the level of similarity of 24 emotion labels across different cultures. They studied six dimensions associated with emotions (*Pleasure*, *Arousal*, *Dominance*, *Certainty*, *Approach-avoidance*, and *Sociality*) and detected that *Pleasure* and *Arousal* are the two most important dimensions to determine emotion semantics across different languages. In fact they concluded that *Pleasure* and *Arousal* are "common psychophysiological dimensions shared by all humans". Other studies showing that the behavior of emotions in the *Pleasure-Arousal* space depends on culture and language have been conducted over the years [8], [23]. Based on these findings, different psychology researchers have adapted some psychological models to different cultures and languages [24].

2.1 Emotions in Affective Computing

Currently, most of the proposals made in the affective computing area, both in the field of recognition and simulation, use Ekman's emotional model to define emotions [2], [25]. However, there are other models that use a dimensional representation of emotions [12], [26], [27]. For instance, the World Wide Web Consortium (W3C) recommends a markup language that allows both dimensional and label-based representations of emotions (EmotionML [28]).

Generally, the proposals performed in the field of affective behavior simulation are focused on the use of intelligent multi-agent systems [29], [30]. Most of these proposals take advantage of a dimensional representation to model different affective processes, such as the mood decay rate or the displacement of the mood when receiving an emotion, which would be impossible to simulate using a label-based representation. For example, the model proposed by Gebhard in ALMA (A Layered Model of Affect) [2] uses the PAD model to represent the mood in an affective intelligent agent. On the other hand, *GenIA*^{3} (a general purpose architecture for affective agentes) [1] is a BDI architecture created to simulate affective behavior in multi-agent systems. *GenIA*^{3} offers a set of tools to represent affective traits like personality, emotions, and mood. This architecture also uses a dimensional representation for mood and emotions. However, these models assume that a basic emotion can be universally represented by a simple point in the dimensional space. The work proposed in this paper extends the *GenIA*^{3} architecture through a new emotional representation model to adapt *GenIA*^{3} affective agents to different cultures and languages.

In recent years, there seems to be a tendency to define affective models using fuzzy logic. Through fuzzy logic, it is possible to approximate the artificial representation of emotions to the way in which humans express them. For example, Jain *et al.* propose EMIA [31] which uses fuzzy rules to handle uncertainty in its appraisal process for five of Ekman's basic emotions. Another interesting proposal is the one presented in [32] in which a methodology to translate emotional labels from Spanish to English through fuzzy logic is proposed. The author designed an experiment in which 8 Spanish-speakers answered a questionnaire to obtain the values of *Pleasure*, *Arousal*, and *Dominance* associated with 30 Spanish emotional labels/words. From the results of the experiment, the fuzzy membership functions for each emotion were obtained. Then a comparison with the functions obtained with English-speakers in a previous experiment was performed to translate the emotional labels/words.

As the *Circumplex Model of Affect* shows, emotions follow a circular pattern in the *Pleasure-Arousal* space. This property suggests that emotions could be represented by the use of vectors in a polar coordinate system. For example, in [33], a vector based representation model of emotions using *Pleasure* and *Arousal* dimensions is proposed. The authors modify the representation space by displacing the origin of coordinates to the negative extreme of the *Arousal* dimension. However, when displacing the origin of coordinates, both the direction and the modulus of the vector are modified, which can lead to difficulties when calculating the intensity or type of the emotion. In addition, the concept of negative *Arousal* (usually referred to as *Sleepiness* or *Deactivation*) becomes blurred, producing a decontextualization of emotions that depend on this dimension, such as *Boredom* or *Calm*. These disadvantages can be solved by the use of circular statistics.

When using circular representation spaces, such as the *Circumplex Model of Affect*, traditional statistics that are focused on linear data may not be adequate since the representation space is finite and constrained between 0 and 2π. In a circular representation space based on *Pleasure* and *Arousal*, the dispersion can be estimated by the circular standard deviation σ expressed as follows [34]:

$$\sigma = \sqrt{-2 \ \ln \overline{R}}, \tag{1}$$

where

$$\overline{R} = \sqrt{\overline{P}^2 + \overline{A}^2}, \tag{2}$$

where $\overline{P}$ and $\overline{A}$ represent the mean values for the *Pleasure* and *Arousal* dimensions. The distribution of the data in a circular area delimited by 2π also makes it difficult to use the probability distributions that are commonly used in linear statistics. Instead, the von Mises distribution [35] could be used to estimate the normal (Gaussian) distribution for circular data. For example, in [36], a probabilistic model based on a mixture of von Mises distributions for the recognition of emotions in faces is proposed. The authors use a representation space that is based on the dimensions of *Pleasure* and *Arousal*. The face images were projected to coordinates in the representation space to determine the type of emotion using the von Mises distribution.

2.2 Discussion

Despite the great amount of effort made to recognize and simulate emotions, there is still much to be done until we are able to understand and correctly simulate affective processes. Nowadays, there is no consensus about what is the best way to represent emotions. This is because emotions are complex concepts and their generation depends on multiple personal, contextual, and cultural factors. However, in order to make better use of the current systems for emotion recognition and affect simulation, it is necessary to design a computational model of affect that represents this knowledge as flexibly and accurately as possible. A common representation using a continuous dimensional space for both recognized and simulated emotions can improve the understanding and simulation of affective processes such as emotion elicitation, emotional contagion, or empathy.

However, in affective computing, the use of emotions is usually simplified by using categorical approaches that reduce emotions to simple labels (e.g., using the six basic emotions of Ekman). With this type of representation, part of the information inherent to the emotion, such as intensity or proximity to another emotion, is lost. Therefore, representations of emotional knowledge based on a multidimensional continuous space are more appropriate for use in affective computing. In a multidimensional space, emotions can move through continuous variables representing a greater amount of information (e.g., the intensity of the emotion) than if only labels were used.

When a dimensional representation is used, different alternatives for representing the emotions within the space arise. The most commonly used model consists of representing each basic emotion as a point in the representation space as is done in *The Circumplex Model of Affect* (Fig. 1). The main problem that appears when using this model is the way basic emotions are represented using a simple point in the space. This representation is far from the way in which emotions are associated with *Pleasure* and *Arousal* by humans, as we prove in our experiment. The second problem when using this scheme is the ambiguity that appears in the spaces between adjacent emotions, because the area around each point is not clearly defined. In addition, it is very difficult to determine categorically and without error that a point in space corresponds to a certain emotion. Moreover, this model does not represent important information such as the intensity of the emotion. Therefore, a more appropriate method for representing the emotions consists of defining each emotion as an area in the emotion space, instead of a simple point as proposed by other approaches. An area-based method better represents the complexity and similarities among multiple emotions.

Some findings suggest that languages around the world primarily differentiate emotions on the basis of *Pleasure* and *Arousal* [22]. Therefore, when defining a computational model of affect, the culture and the language in which it is going to be used must be considered since different cultures may attribute different *Pleasure* and *Arousal* values for the same emotion label [10], [37]. For example, in the experiment presented in [8], the authors note, among other results, that the Polish participants related the calm emotion with a significantly higher level of arousal than the Greeks. Extrapolating an emotional model from one language to another without adapting it to the culture and language may produce inconsistencies, which can lead to erratic agent behavior and emotion expression. Moreover, the way in which emotions are expressed when the system interacts with humans must also be taken into account. Fuzzy logic allows affective agents to express their emotions in a similar way to humans.

3 An Experiment-Based Method to Adapt Affective Models to Culture and Language

Labels that are used to represent emotions do not have the same meaning in different languages and cultures, but a model that is based on the *Pleasure* and *Arousal* dimensions can represent the universal meaning of the emotions [22]. Nevertheless, the scheme proposed by Russell is a basic scheme that is used to support the circular representation of emotions. Therefore, the direct use of this scheme in a computational model can easily be criticized since it was not defined for that purpose. In addition, this scheme was generated from experiments with English-speakers. Therefore, following the foundations of constructivist theories, this representation of basic emotions may not be valid in other cultures or languages. It is necessary to design processes to adapt this emotional model to the culture and language of the environment in which the model will be used and also to discover the areas of the multidimensional space where emotions have a higher probability of occurrence. We present an experiment-based method to find the regions representing each emotion, that can be used for different languages and cultures.

We start from the main hypothesis that Russell's model might not be valid for representing emotions in a context with a language and a culture that is different from the context in which Russell carried out his experiment. We propose a methodology that consists of two experiments. The first experiment finds the labels that best represent the meaning of the *Pleasure* and *Arousal* dimensions in the target language. In our experiment the target language is European Spanish. The second experiment finds the intervals of *Pleasure* and *Arousal* that are associated to each emotion in the target language.

For our experiment, we have selected the ten emotions used by Russell in [8]: *Fear*, *Anger*, *Disgust*, *Sadness*, *Boredom*, *Sleepiness*, *Calm*, *Happiness*, *Excitement*, and *Surprise*. The most common literal translations of these emotions into Spanish are *"Miedo"*, *"Enfado"*, *"Asco"*, *"Tristeza"*,*"Aburrimiento"*, *"Somnolencia"*, *"Calma"*, *"Felicidad"*, *"Emoción"*, and *"Sorpresa"*. However, these are not the only possible translations, and, depending on the selected word, we could be expressing different emotional meanings. Therefore, making a literal translation of emotions could lead to significant differences in the interpretation of the levels of *Pleasure* and *Arousal* of these emotions.

3.1 Method

3.1.1 Experiment 1: Naming the Pleasure and Arousal dimensions

Starting from the hypothesis that the literal translation of the labels associated with the *Pleasure* and *Arousal* affective categories may introduce a bias, the main objective of this first experiment is to find the words that best represent the meaning of theses affective categories in the target language. Generally, these dimensions are defined using four affective categories: *Pleasure* and its opposite *Misery*, and *Arousal* and its opposite *Sleepiness*. However, despite the fact that emotional terms are often equated in translation dictionaries, a literal translation may not accurately reflect the meaning of the original emotional term since the terms used to define emotions vary in meaning depending on the culture and the language [9], [10]. To translate these words we have used the following methodology:

- We consulted the translations provided by the four most widely used bilingual dictionaries: The Cambridge [38], Collins [39], Oxford [40] and WordReference [41] English-Spanish Dictionaries. We selected 30 Spanish words for the four affective categories: 8 words for *Pleasure*, 10 words for *Misery*, 5 words for *Arousal*, and 7 words for *Sleepiness*.
- Fifty people participated in this first experiment: 20 females and 30 males ranging in age between 18 and 60 years old and with different study levels (from secondary school to the doctoral level). The instructions were given to each participant at the beginning of the experiment. Each participant was asked to read each group of words and identify the general affective category represented by the group. Each participant was given an unlimited time to select the word that best represents the concept of the group and to remove those words that clearly do not express the meaning of the affective category of the group.

3.1.2 Experiment 2: Assigning Areas to Each Emotion

Based on the hypothesis that the *Pleasure* and *Arousal* levels of an emotion can vary depending on the culture and language, this second experiment was designed to define the levels corresponding to each emotion in the target language. We decided not to consider other dimensions because recent studies, like [22], have shown that the *Pleasure* and *Arousal* dimensions predict the structure in emotion across language families. Moreover, some authors have found that human beings have difficulty and display confusion when they try to assign a *Dominance* value to the emotions that they are feeling and that this dimension does not show much difference between emotions [22].

One hundred people participated in this second experiment: 40 females and 60 males ranging in age between 18 and 60 years old with different study levels (from secondary school to the doctoral level). To avoid bias, the participants performed the experiment individually and without a time limit. We designed a questionnaire using the four affective categories translated into Spanish in the first experiment. It was composed of 10 prompts, one for each emotion. At the beginning of the experiment, the instructions were given to each participant individually. For each prompt, the participants were asked to assign a level of *Pleasure* and a level of *Arousal* to the 10 selected emotions. The structure of the prompts was designed to collect the *Pleasure* and *Arousal* variables individually. To assign these two levels, each prompt was composed of two 7-item Likert scales. The scale for *Pleasure* was defined from *very miserable* to *very pleased* and the scale for *Arousal* was defined from *very sleepy* to *very aroused*. Note that the value 4 corresponds to a neutral value on these scales.

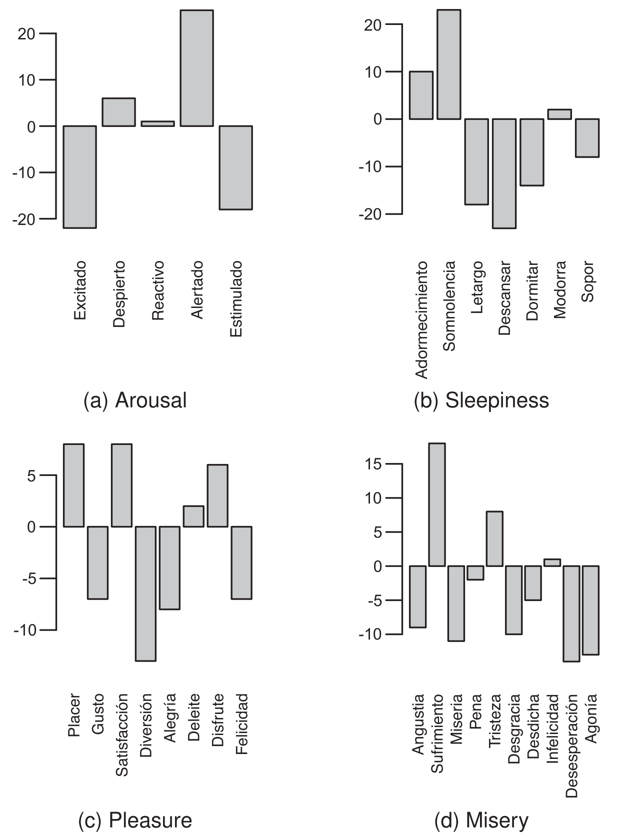


Fig. 3. Degree of acceptance of the candidate words for each affective category.

3.2 Analysis and Results

In the first experiment, we define the *degree of acceptance* of one word w for the affective category c ($accept_c(w)$) as the difference between the number of times the word w has been selected as being representative of the affective category c and the number of times the word has been removed. The *degree of acceptance* for all of the candidate words are represented in Fig. 3. For instance, Fig. 3a shows that the word *Alertado* has a *degree of acceptance* for the *Arousal* category $accept_{arousal}(alertado) = 25$, while *Excitado* has $accept_{arousal}(excitado) = -22$. The negative *degree of acceptance* means that the participants mostly rejected that word to represent the affective category of the group. The results confirm the hypothesis of the first experiment, and the need to carry out studies of this type when translating affective concepts to other languages and cultures. For example, according to the selected dictionaries, the closest translation into Spanish of the affective concept *Misery* is *Miseria*. However, as Fig. 3d shows, this word only has an $accept_{misery}(miseria) = -11$. Therefore, it was not selected to represent this affective category since a great number of people discarded it. For the concept of misery, the participants selected words such as *Suffering*, *Sadness*, and *Unhappiness* (in Spanish *Sufrimiento*, *Tristeza*, and *Infelicidad*). This is probably due to the fact that the concept of misery in Spanish is related more to economic poverty than to suffering. We can also see that the best translation for *Arousal* is *Alerta*. For *Sleepiness*, the words selected as most representative were *Somnolencia* and *Adormecimiento*. Finally, for *Pleasure*, there is a tie between *Placer* $accept_{pleasure}(placer) = 8$ and *Satisfacción* $accept_{pleasure}(satisfaccion) = 8$. The results of the first experiment show that there are some affective categories in which there are more than one word with a positive *degree of acceptance*. For example, in the case of *Pleasure*, it is very clear that both *Placer* and *Satisfacción* are relevant to the understanding of this abstract concept. Therefore, by selecting one of the two, we could be biasing the translation of *Pleasure* since each person can have an individual conceptualization that could be influenced by their geographical location, age, or cultural environment. The conclusion we drew from these results was that, in order to avoid a possible bias that could produce misunderstandings, we needed to contextualize each affective category by using more than one word. To determine the appropriate number of words for each affective category, we used the results of the experiment. For the affective categories *Arousal*, *Sleepiness*, and *Misery*, we selected those words with a positive *degree of acceptance*, obtaining three words for each affective category. However, by applying the same criteria for *Pleasure*, four possible words were obtained. Therefore, in order to define all of the affective categories homogeneously to avoid misunderstandings, for *Pleasure*, we decided to select the three words with the highest *degree of acceptance*.

We used the second experiment to define the levels of *Pleasure*, *Misery*, *Arousal*, and *Sleepiness* associated to each emotion label. Then, we performed a circular statistical analysis of the results of the second experiment to determine the best circular representation of the selected emotions based on their *Pleasure*

TABLE 1
Results of the Second Experiment

Emotion e in Spanish (English)	Mean $\overline{P}_e$	Mean $\overline{A}_e$	Mean $\overline{\alpha}_e$	Sd σ_e
Felicidad (Happiness)	0.90	0.42	0.44	0.33
Emoción (Excitement)	0.76	0.64	0.70	0.18
Miedo (Fear)	-0.58	0.81	2.19	0.27
Enfado (Anger)	-0.74	0.66	2.42	0.29
Tristeza (Sadness)	-0.96	-0.27	3.42	0.39
Aburrimiento (Boredom)	-0.41	-0.91	4.28	0.38
Somnolencia (Sleepiness)	-0.11	-0.99	4.60	0.27
Calma (Calm)	0.74	-0.67	5.55	0.63
Asco (Disgust)	-0.99	-0.04	3.19	0.76
Sorpresa (Surprise)	0.31	0.95	1.25	0.46

$\overline{\alpha}_e$ and σ_e expressed in radians.

and *Arousal* components. Henceforth, we will refer only to the dimensions of *Pleasure* and *Arousal*, considering that *Misery* is negative *Pleasure* and *Sleepiness* is negative *Arousal*. First of all, we discarded all of the answers of the participants that represent unexpressed emotion. These emotions are characterized by zero values in the *Pleasure* and *Arousal* dimensions, which correspond to the 4th item in the Likert scales. We made this decision taking into account that, with low levels of *Pleasure* and *Arousal*, the intensity of the emotions is so low that it can be considered that there is no emotion [19]. Second, for all of the answers of each participant for each selected emotion, we calculated the angle α between the *Pleasure* axis and the line defined by the (*Pleasure*, *Arousal*) point and the origin of the coordinate system. This angle α represents the "meaning" that each participant associates to each emotion in this two-dimensional space. Third, we carried out a circular statistical analysis to eliminate possible outliers. To do this, we estimated the circular dispersion of the data associated to each emotion by the participants.

Table 1 summarizes the results of the second experiment: the mean values associated with the *Pleasure* and *Arousal* variables for the emotion e ($\overline{P}_e$ and $\overline{A}_e$), and the mean angle $\overline{\alpha}_e$ and circular standard deviation σ_e calculated using the Formula (1). To analyze the distribution of emotions in this polar representation, we use circular boxplots [42]. The circular boxplots in Fig. 4 show the circular distribution in the *Pleasure-Arousal* space that we obtained for the 10 emotions. As can be observed, *Sadness* is related to low levels of *Pleasure* and mean levels of *Arousal* (Fig. 4d), while *Excitement* is related to high levels of *Pleasure* and *Arousal* (Fig. 4i). These graphs also show the great differences between the dispersion levels of the emotions. For example, the dispersion of the *Excitement* emotion (Fig. 4i) is clearly lower than that of the *Calm* emotion (Fig. 4g). This confirms that, by representing the emotion with a simple point, as proposed in previous approaches, it is performed a simplification that does not correspond to the area that humans assign to emotions in their minds. It also confirms the hypothesis of the second experiment, and the need to perform these types of experiments when modeling emotions in different cultural contexts.

When analyzing the results obtained for *Disgust* (Fig. 4c), we found that it occupies a large part of the dimensional space. The most likely explanation for this behavior is that

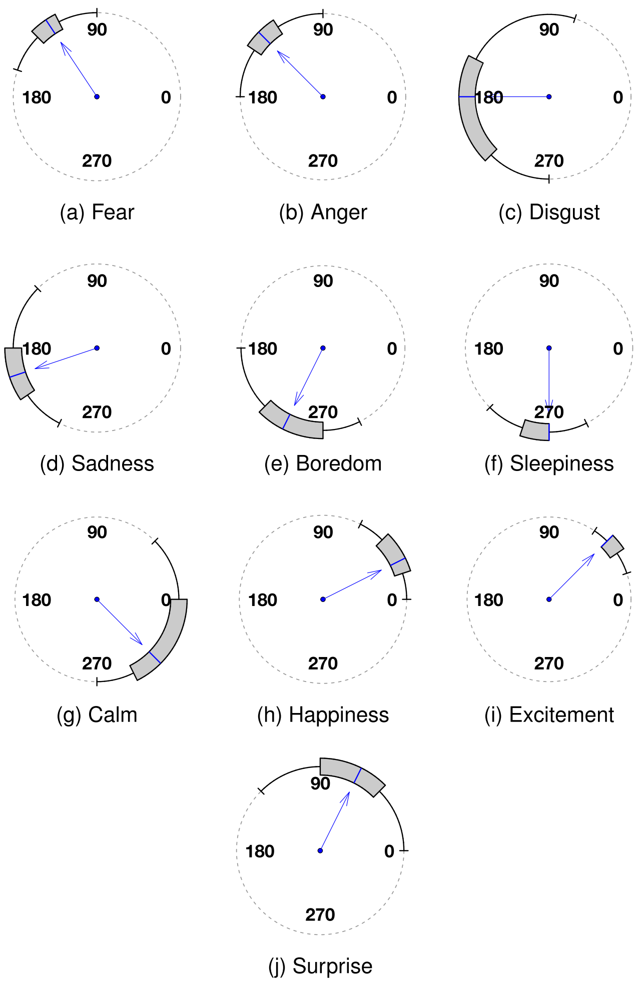


Fig. 4. Circular boxplot graphic for the ten selected emotions in Spanish (see Table 1) where the horizontal axis represents *Pleasure* and the vertical axis represents *Arousal*.

in Spanish, the *Disgust* emotion does not seem to have a clear definition in the dimension of *Arousal* even though it is clear that the *Pleasure* value is negative. This behavior is better observed in Fig. 5, where the dispersion of the *Arousal* values for the *Disgust* emotion is very high (but always with a negative *Pleasure* value).

From these results, we estimated the circular normal distribution of each emotion. Fig. 6 shows the overlap of the von Mises models obtained for each emotion. As can be observed,

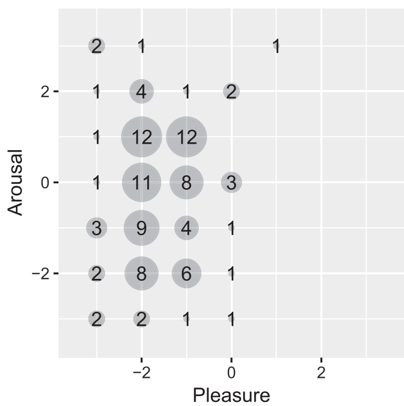


Fig. 5. Dispersion of the *Disgust* emotion.

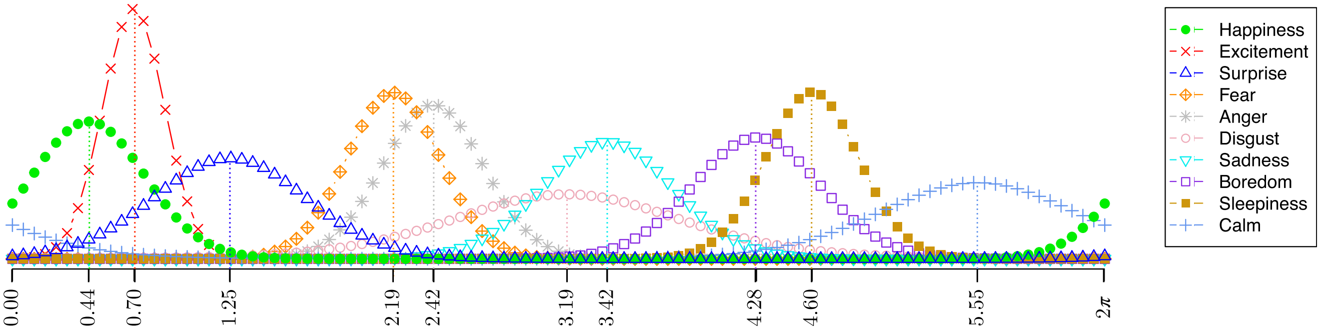


Fig. 6. Von Mises curves of the ten Spanish emotions (see Table 1). The axis represents the angles α_e in degrees. Note that the order of the means of the emotions on the plot corresponds to the order of the legend.

TABLE 2
Distribution of Emotions in European Spanish and British English

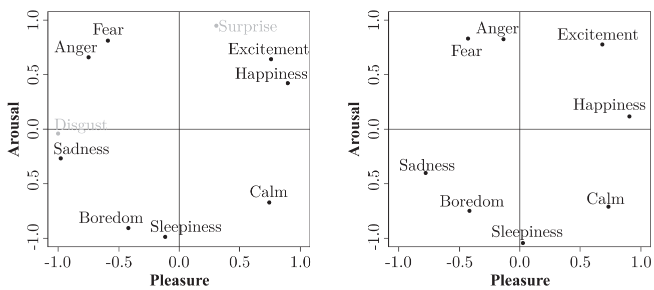
Emotions in Spanish			Emotions in English			Statistical comparison	
Label/word	Mean $\overline{\alpha}_e$	Sd σ_e	Label/word	Mean $\overline{\alpha}_e$	Sd σ_e	t-value	p-value
Felicidad	0.44	0.33	Happiness	0.14	0.58	3.78	0.0002*
Emoción	0.70	0.18	Excitement	0.84	0.34	-3.27	0.0013*
Miedo	2.19	0.27	Fear	1.27	0.58	12.54	0.0000*
Enfado	2.42	0.30	Anger	1.73	0.76	7.63	0.0000*
Tristeza	3.42	0.40	Sadness	3.62	0.77	-1.98	0.0488*
Aburrimiento	4.28	0.39	Boredom	4.20	0.69	0.91	0.3638
Somnolencia	4.60	0.27	Sleepiness	4.75	0.33	-2.60	0.0102*
Calma	5.55	0.63	Calm	5.52	0.34	0.30	0.7612

*(Data for British English obtained from [7]). * indicates* $p - value < 0.05$.

there are some emotions that overlap each other. For example, the *Fear* and *Anger* emotions have similar mean angles ($\overline{\alpha}_{fear} = 2.19$ and $\overline{\alpha}_{anger} = 2.42$), and the same relation can be observed for *Boredom* and *Sleepiness*, or *Excitement* and *Happiness*. In addition, as expected, it can be observed that the *Disgust* emotion has a very large standard deviation and is overlapped by several emotions. This representation allows us to estimate the probability of selecting an emotion according to the angle α between the *Pleasure* axis and the line defined by the (*Pleasure*, *Arousal*) point and the origin of the coordinate system. Therefore, instead of defining emotions as areas, we define regions of probability in which emotions can occur with a certain degree of uncertainty. By introducing this uncertainty, the model becomes more versatile, allowing the same point in space to belong to more than one emotion with different probabilities. In addition, with this model, we avoid one of the main problems of a point-based representation because we cannot categorically affirm that a point belongs to one and only one emotion.

We have performed a similar circular statistical analysis of the results obtained by Russell with English speakers [7] (using Formulas (1) and (2)). To demonstrate the need to adapt the emotional models to the language in which it will be used, we have compared these results with those obtained in our experiment with Spanish speakers. In order to determine if the samples are different, we performed a t-Student statistical analysis starting from the null hypothesis H_0: the samples are equal. The results are shown in Table 2. As can be observed, the p-value for the emotions *Happiness*, *Excitement*, *Fear*, *Anger*, *Sadness*, and *Sleepiness* is less than 0.05. Therefore, we can reject the null hypothesis H_0 and accept that the samples are significantly different. However, for the *Boredom* and *Calm* emotions, the p-value is greater than 0.05. Therefore, the samples are not significantly different. Fig. 7a shows the mean position of the 10 selected emotions in Spanish according to their level of *Pleasure* and *Arousal*. When we compare the results of our second experiment with those obtained by Russell (Fig. 7b), some differences can be easily detected. For example, our experiment shows that the *Happiness* emotion is related to higher levels of *Arousal* for European Spanish-speakers than the levels obtained by Russell for British English-speakers. These differences can also be seen in other emotions such as *Anger*, which is more related to lower levels of *Pleasure* in Spanish than in English.

We can conclude that, for six of the eight selected emotions, the differences between languages are significant. Therefore, these results confirm the need for experiments of this type



(a) Results of our experiment. (b) Results obtained by Russell.

Fig. 7. Results obtained in our experiment (with emotions expressed in Spanish (see Table 1)) and Russell's (with emotions expressed in English) [7]. Note that the emotions not represented in the Russell's experiment are shown in gray.

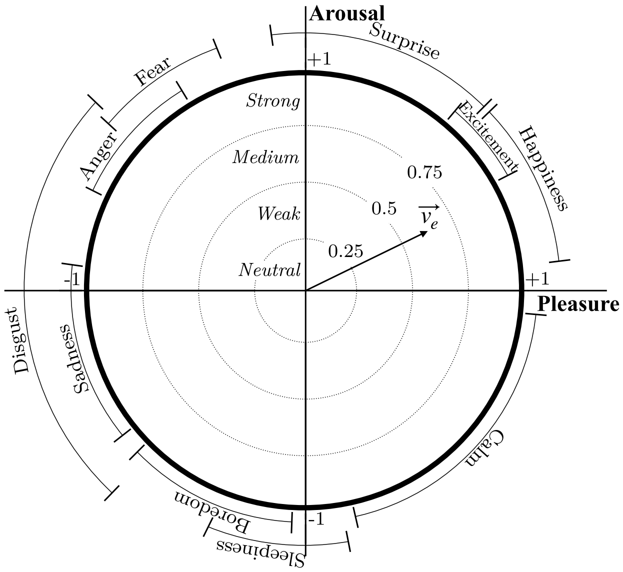


Fig. 8. Levels of *Pleasure* and *Arousal* associated to Spanish emotions (see Table 1) using one standard deviation.

when working with emotions in different cultures and languages since there are significant differences in the affective meaning of the words that are used to define emotions.

4 A Fuzzy Culturally Adapted Model of Affect

We have defined a fuzzy model to represent emotions in the *Pleasure-Arousal* space using the results of the second experiment. Our model uses a circular representation in which an emotion is represented by a vector that is defined by a pair of values of *Pleasure* and *Arousal*. This vector represents both the type and intensity of the emotion. Taking into account the relationship between the variables of *Pleasure* and *Arousal* and the intensity of emotions proposed by Reisenzein [19], we have divided the *Pleasure-Arousal* space into four fuzzy values of intensity: *Strong*, *Medium*, *Weak*, and *Neutral*. We have introduced the concept of the *Neutral* intensity to represent those emotions whose intensity is too low to be considered as elicited.

Therefore, given a point in space defined by its *Pleasure* and *Arousal* value, we obtain the intensity of the emotion represented by that point using the modulus of the vector that forms the point with the origin of the coordinate system. Then, we transform this point into a fuzzy value following the model of intensity represented in Fig. 8, where the direction of the vector indicates the emotion type. We have used the results obtained in the second experiment to define the areas where the 10 basic emotions have the greatest probability of being located. Fig. 8 shows the representation of these probability areas in the circular two-dimensional space. This figure has been obtained from the von Mises model shown in Fig. 6 using a single standard deviation. The outer arcs in Fig. 8 represent the regions assigned to each emotion. This figure clearly represents the distribution of the basic emotions in the *Pleasure-Arousal* space for Spanish-speakers.

As mentioned in Section 3.2, when we described the model obtained from the results of the second experiment, the distribution of the basic emotions in the *Pleasure-Arousal* space produces overlaps and intersections between emotions. This is easily observed in Fig. 8: The *Excitement* emotion intersects with the *Happiness* and *Surprise* emotions. Similarly, the *Boredom* emotion intersects with the *Sleepiness* and *Disgust* emotions. The *Anger*, *Fear*, and *Disgust* emotions have also an intersection. Finally, there is an overlap between the *Sadness* and *Disgust* emotions. This overlap is largely due to the fact that the *Disgust* emotion has a high dispersion. The resulting model clearly shows the relationship between emotions and the angle of the vector that we use to identify the emotion.

Next section presents our model which consists of two processes to represent and express emotions: the *Emotion Representation Process*, a defuzzification process which represents fuzzy emotions in the *Pleasure-Arousal* space; and the *Emotion Expression Process*, a fuzzification process which expresses emotions using fuzzy terms in the same way as human beings express the emotion in their own language.

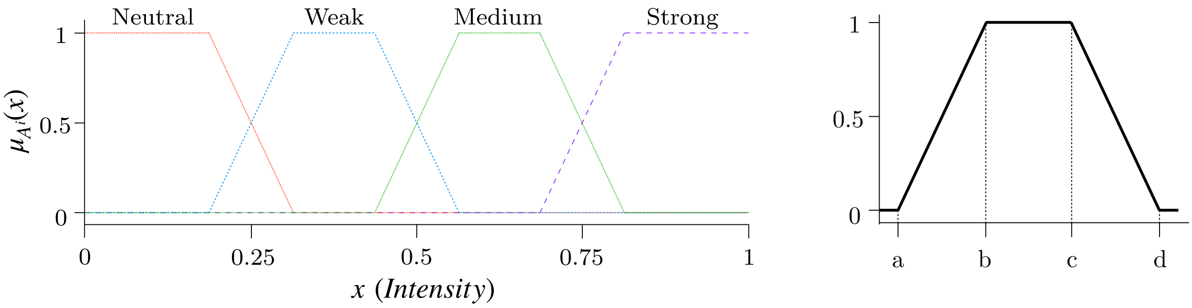
4.1 The Emotion Representation Process

The *Emotion Representation Process* is a defuzzification process, in which the emotions recognized or elicited by an affective agent are internally represented in the *Pleasure-Arousal* two-dimensional space. Human beings express emotions using a fuzzy terminology. Therefore, the model must be able to represent fuzzy emotion values in the *Pleasure-Arousal* continuous space. A fuzzy emotion that is recognized by the agent is internally represented using the mean values of *Pleasure* and *Arousal* obtained in the second experiment. In the same way, the intensity is represented in this multidimensional space by using the mean value of each intensity value from the model represented in Fig. 8. Let us illustrate this process with a simple example. If the emotion perceived by the emotion recognition process of an affective agent is *Happiness* with a *Medium* intensity, the agent will internally represent this emotion using a vector $\vec{v_e}$ with a direction $\alpha_e = 0.44$ radians (≈ 25.2 degrees) (see Table 1) and a modulus $|\vec{v_e}| = 0.625$, which correspond to the *Medium* intensity (the midpoint between 0.5 and 0.75 according to Fig. 8). From this vector $\vec{v_e}$ representing the emotion e, the agent will obtain the *Pleasure* P_e and *Arousal* A_e values using the following equation:

$$(P_e, A_e) = (|\vec{v_e}| \cdot \cos\alpha_e, |\vec{v_e}| \cdot \sin\alpha_e). \tag{3}$$

Therefore, by using this formula, the values of *Pleasure* and *Arousal* associated with the "*Happiness* emotion with *Medium* intensity" in the Spanish language are 0.57 and 0.27, respectively. An example of the resulting representation of the vector $\vec{v_e}$ in our model is shown in Fig. 8.

Note that this representation of the emotion is based on the values of *Pleasure* and *Arousal*. Therefore, this representation has a universal semantics [22]. The agent uses this representation of the emotion for all its affective processes. When the agent needs to express an emotion, which is internally represented in the *Pleasure-Arousal* space, the agent will use the process presented in the next section.



(a) The proposed fuzzy model for the intensity of the emotions in the *Pleasure-Arousal* space. See Table 3 for the linguistic values in Spanish.

(b) Parameters of the trapezoidal membership function.

Fig. 9. Fuzzy model for the intensity.

4.2 The Emotion Expression Process

Any emotion that is internally represented by a vector $\vec{v}_e$ is transformed into a fuzzy expression (emotion label and fuzzy intensity) by the *Emotion Expression Process*. This process allows the agent to express its emotions using a fuzzy expression adapted to the cultural environment in which the agent is located. In this process, a fuzzification of the vector $\vec{v}_e$ is performed transforming the intensity and the type of the emotion into fuzzy values. This process is composed of two fuzzification subprocesses: One for the intensity and the other for the emotion type.

We define the linguistic variable x for the fuzzification process of the intensity of the emotion as a quintuplet [43]:

$$x = \langle L_x, T(L_x), U_x, G_x, M_x \rangle, \tag{4}$$

where L_x represents the name of the linguistic variable $L_x = intensity$, and $T(L_x)$ represents the set of fuzzy terms (linguistic values for the intensity) that the variable x can take:

$$T(intensity) = \{Strong, Medium, Weak, Neutral\}. \tag{5}$$

U_x (universe of discourse) represents the range of crisp values that the variable can take in the range $U_x = [0,1]$, G_x is the syntactic rule that generates the terms in $T(intensity)$, and M_x is a semantic rule that associate each linguistic term in $T(intensity)$ with its meaning.

We define a Type-1 fuzzy logic set $\tilde{A} \in M_x$ using a trapezoidal membership function defined by the equation [44], [45]:

$$\mu_{A^i}(u) = max\left(min\left(\frac{u-a}{b-a}, 1, \frac{d-u}{d-c}\right), 0\right), \tag{6}$$

where $i \in T(intensity)$, A^i represents the ith fuzzy set belonging to $\tilde{A}$, u takes the value of the modulus of the vector of the emotion such that $u \in U_x$, and a, b, c, and d are the parameters of the membership function (see Fig. 9b) that is described in Table 3 [45]. Fig. 9a shows the resulting fuzzy model.

On the other hand, we define the linguistic variable y for the fuzzification process of the emotion type ($L_y = type$):

$$T(type) = \{Happiness, Excitement, Surprise, Fear, Anger, Disgust, Sadness, Boredom, Sleepiness, Calm\}. \tag{7}$$

The universe of discourse is defined in the range $U_y = [0, 2\pi]$. We use the results obtained in the second experiment (Fig. 6) to define a Type-1 fuzzy logic set $\tilde{B} \in M_y$. The proposed membership function for an emotion t is derived from the normalization of the von Mises distribution and is defined as:

$$\mu_{B^j}(t) = \frac{m_j(t) - \min_{x\in[0,2\pi]} m_j(x)}{\max_{x\in[0,2\pi]} m_j(x) - \min_{x\in[0,2\pi]} m_j(x)}, \tag{8}$$

where $j \in T(type)$, B^j represents the jth fuzzy set belonging to $\tilde{B}$, t takes the value of the angle of the vector of the emotion expressed in radians such that $t \in U_y$, and $m_j(\theta)$ represents the jth von Mises function defined as:

$$m_j(\theta) = \frac{\exp\left(\kappa_j \cos\left(\overline{\alpha_j} - \theta\right)\right)}{2\pi I_0(\kappa_j)}, \tag{9}$$

where $\overline{\alpha_j}$ is the mean for the jth fuzzy set B^j (see Table 1), κ_j represents the jth concentration parameter of the von Mises distribution estimated as the inverse of the variance $(1/\sigma_j)$ [35], and $I_0(\kappa_j)$ is the modified Bessel function of order zero used to normalize the function [36]. Fig. 10 shows the resulting fuzzy model.

As a result of this process, an affective agent can express an emotion, which is internally represented in the *Pleasure-Arousal* space by a vector $\vec{v}_e$, by using the same fuzzy expression (emotion label and intensity) that humans use in their language.

Let us again consider our example of an affective agent that has an emotion represented internally by the vector $\vec{v}_e$ (Fig. 8). The *Pleasure* and *Arousal* coordinates of vector $\vec{v}_e$ are 0.57 and 0.27, respectively. Therefore, the direction of the vector is 0.44 radians and the modulus is 0.625. When the affective agent needs to express this emotion in a specific language, it uses the fuzzification process describe above. This fuzzification process for the intensity produces the results shown in Table 4. Therefore, the selected fuzzy value

TABLE 3
Parameter Ranges for the Intensity Membership Function

Intensity level in Spanish (English)	Parameters			
	a	b	c	d
Neutral (Neutral)	0	0	0.2	0.3
Bajo (Weak)	0.2	0.3	0.45	0.55
Medio (Medium)	0.45	0.55	0.7	0.8
Alto (Strong)	0.7	0.8	1	1

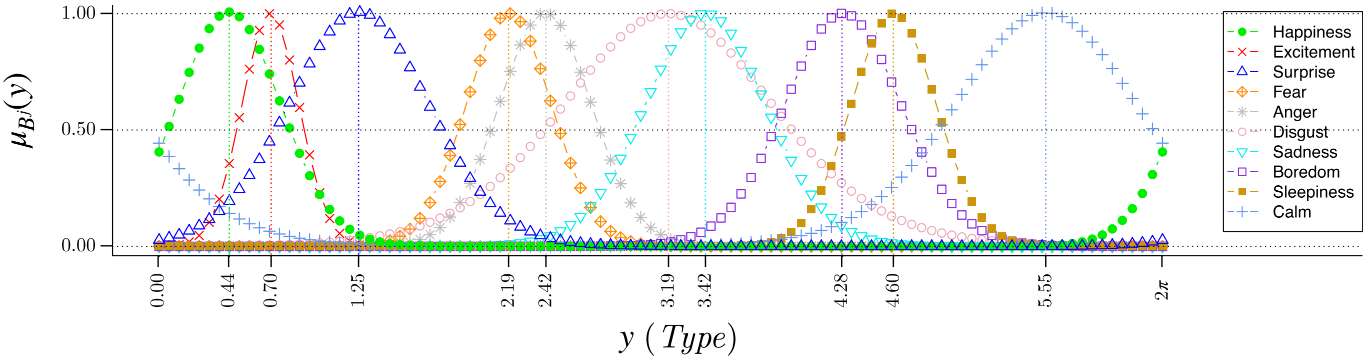


Fig. 10. Proposed fuzzy model for the type of the Spanish emotions (see Table 1) in the *Pleasure-Arousal* space. Note that the order of the means of the emotions on the plot corresponds to the order of the legend.

TABLE 4
$\mu_{A^i}(u)$ Values for the Example ($u = 0.625$)

	Neutral	Weak	Medium	Strong
$\mu_{A^i}(0.625)$	0	0	1	0

for the intensity is *Medium*. On the other hand, the fuzzification process for the emotion type produces the results of Table 5. If the agent wants to express only one emotion, the agent will select the emotion term/label with the maximum μ_{Bj}, which in our example is *Happiness*. Therefore, the *Emotion Expression Process* will generate the fuzzy emotion *Happiness* with *Medium* intensity as a result of the fuzzification of the emotion represented in the multidimensional space by the vector $\vec{v}_e$.

This model can be easily adapted to other languages and cultures. Our model allows a multicultural affective agent to represent and express an emotion using the same interpretation of the fuzzy emotional terms used in the language and culture of its human interlocutor. This can be achieved by defining a specific dimensional *Pleasure-Arousal* space for each cultural environment in which the agent is located. All these two-dimensional spaces can be easily incorporated to the affective component of the multicultural affective agent (Fig. 11).

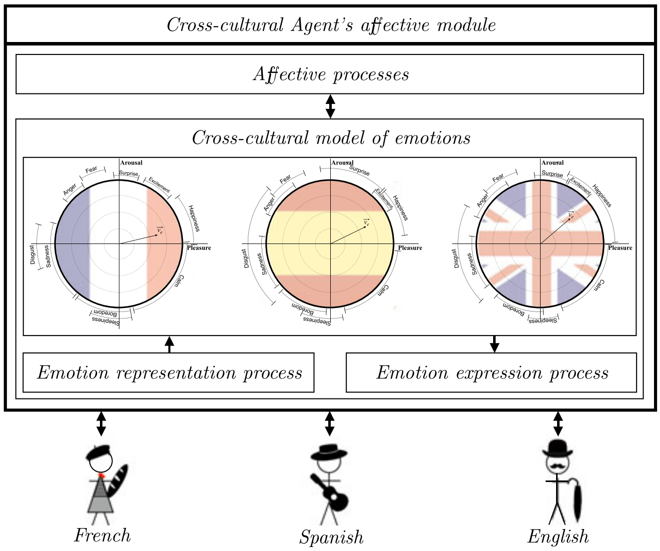


Fig. 11. Example of a multicultural affective agent module.

5 Conclusion and Future Work

In this paper, we have proposed an experiment-based method to adapt the emotion representation to the culture and the language in which the emotion will be used. The results of the first experiment have corroborated the importance of adapting the translation of the emotional models taking into account the different meanings that humans give to emotion labels in different cultures. As observed in the translation of the *Misery* emotion, the literal translation does not have the same contextual meaning for European Spanish-speakers and British English-speakers. The results of the second experiment have allowed us to assign different areas in the *Pleasure-Arousal* space to the different basic emotions. When comparing the results obtained in our experiment with those obtained for British English-speakers, it can be observed that the emotion labels have different values for *Pleasure* and *Arousal* depending on the language. This confirms the need for performing this adaptation with experiments when emotional models are used in other cultures and languages.

From the results obtained in the experiments, we have defined a fuzzy model that represents emotions using a *Pleasure-Arousal* continuous space instead of simple labels. With this cross-cultural dimensional representation, an emotion can be defined as a vector in which the modulus represents the intensity of the emotion, while the type of emotion depends on the direction of this vector. Our model improves

TABLE 5
$\mu_{Bj}(t)$ Values for the Example ($t = 0.44$)

	Happiness	Surprise	Fear	Anger	Disgust	Sadness	Boredom	Sleepiness	Calm
$\mu_{Bj}(0.44)$	1	0.35	0.21	≈ 0	≈ 0	≈ 0	≈ 0	≈ 0	≈ 0

For the Spanish labels see Table 1.

the typical representation of emotions based on labels because it allows emotions and their intensity to be easily represented and modified using a dimensional representation.

We have also defined a fuzzification process that determines an emotion label in a specific language from a pair of *Pleasure* and *Arousal* values. Thus, using our model, an agent can express emotions using the same fuzzy terminology as humans.

We are currently incorporating this model into the affective agent architecture *GenIA*^{3} to improve the simulation of the different affective processes. In addition, we want to analyze whether this emotion representation can be improved by introducing a third dimension (*Dominance*) to better identify emotions such as *Fear* or *Anger* and to analyze the influence of this dimension on social behavior [46].

ACKNOWLEDGMENTS

This work was supported in part by the Spanish Government project TIN2017-89156-R, Generalitat Valenciana, and European Social Fund by the FPI Grant ACIF/2017/085, in part GVA-CEICE project PROMETEO/2018/002, and TAILOR, a project funded by EU Horizon 2020 research and innovation programme under GA No 952215.

REFERENCES

[1] B. Alfonso, E. Vivancos, and V. Botti, "Toward formal modeling of affective agents in a BDI architecture," *ACM Trans. Internet Technol.*, vol. 17, no. 1, 2017, Art. no. 5.

[2] P. Gebhard, "ALMA: A layered model of affect," in *Proc. 4th Int. Joint Conf. Auton. Agents Multiagent Syst.*, 2005, pp. 29–36.

[3] S. C. Marsella and J. Gratch, "EMA: A process model of appraisal dynamics," *Cogn. Syst. Res.*, vol. 10, no. 1, pp. 70–90, 2009.

[4] B. Meuleman and K. R. Scherer, "Nonlinear appraisal modeling: An application of machine learning to the study of emotion production," *IEEE Trans. Affect. Comput.*, vol. 4, no. 4, pp. 398–411, Fourth Quarter 2013.

[5] R. Reisenzein *et al.*, "Computational modeling of emotion: Toward improving the inter- and intradisciplinary exchange," *IEEE Trans. Affect. Comput.*, vol. 4, no. 3, pp. 246–266, Third Quarter 2013.

[6] P. H. Bucci, X. L. Cang, H. Mah, L. Rodgers, and K. E. MacLean, "Real emotions don't stand still: Toward ecologically viable representation of affective interaction," in *Proc. 8th Int. Conf. Affect. Comput. Intell. Interaction*, 2019, pp. 1–7.

[7] J. A. Russell, "A circumplex model of affect," *J. Pers. Soc. Psychol.*, vol. 39, no. 6, pp. 1161–1178, 1980.

[8] J. A. Russell, M. Lewicka, and T. Niit, "A cross-cultural study of a circumplex model of affect," *J. Pers. Soc. Psychol.*, vol. 57, no. 5, pp. 848–856, 1989.

[9] M. Boiger, E. Ceulemans, J. De Leersnyder, Y. Uchida, V. Norasakkunkit, and B. Mesquita, "Beyond essentialism: Cultural differences in emotions revisited," *Emotion*, vol. 18, no. 8, 2018, Art. no. 1142.

[10] D. T. Cordaro, R. Sun, D. Keltner, S. Kamble, N. Huddar, and G. McNeil, "Universals and cultural variations in 22 emotional expressions across five cultures," *Emotion*, vol. 18, no. 1, 2018, Art. no. 75.

[11] J. W. Matiko, S. P. Beeby, and J. Tudor, "Fuzzy logic based emotion classification," in *Proc. IEEE Int. Conf. Acoust. Speech Signal Process.*, 2014, pp. 4389–4393.

[12] K. Bakhtiyari and H. Husain, "Fuzzy model of dominance emotions in affective computing," *Neural Comput. Appl.*, vol. 25, no. 6, pp. 1467–1477, 2014.

[13] A. Kazemzadeh, S. Lee, and S. Narayanan, "Fuzzy logic models for the meaning of emotion words," *IEEE Comput. Intell.*, vol. 8, no. 2, pp. 34–49, May 2013.

[14] R. Plutchik, "The nature of emotions," *Amer. Scientist*, vol. 89, pp. 344–350, 2001.

[15] P. Ekman, "An argument for basic emotions," *Cogn. Emotion*, vol. 6, no. 3–4, pp. 169–200, 1992.

[16] K. Hoemann, F. Xu, and L. F. Barrett, "Emotion words, emotion concepts, and emotional development in children: A constructionist hypothesis," *Developmental Psychol.*, vol. 55, no. 9, 2019, Art. no. 1830.

[17] C. W. Leach, R. Spears, and A. S. Manstead, "Parsing (malicious) pleasures: Schadenfreude and gloating at others' adversity," *Frontiers Psychol.*, vol. 6, 2015, Art. no. 201.

[18] J. A. Russell, "Core affect and the psychological construction of emotion," *Psychol. Rev.*, vol. 110, no. 1, 2003, Art. no. 145.

[19] R. Reisenzein, "Pleasure-arousal theory and the intensity of emotions," *J. Pers. Soc. Psychol.*, vol. 67, no. 3, 1994, Art. no. 525.

[20] A. Mehrabian, "Pleasure-arousal-dominance: A general framework for describing and measuring individual differences in temperament," *Curr. Psychol.*, vol. 14, no. 4, pp. 261–292, 1996.

[21] S. Marsella *et al.*, "Computational models of emotion," *A Blueprint Affect. Comput.*, vol. 11, no. 1, pp. 21–46, 2010.

[22] J. C. Jackson *et al.*, "Emotion semantics show both cultural variation and universal structure," *Science*, vol. 366, no. 6472, pp. 1517–1522, 2019.

[23] M. S. M. Yik, J. A. Russell, C.-K. Ahn, J. M. F. Dols, and N. Suzuki, "Relating the five-factor model of personality to a circumplex model of affect: A five-language study," in *The Five-Factor Model of Personality Across Cultures*. Berlin, Germany: Springer, 2002, pp. 79–104.

[24] S. Detandt, C. Leys, and A. Bazan, "A french translation of the pleasure arousal dominance (PAD) semantic differential scale for the measure of affect and drive," *Psychologica Belgica*, vol. 57, no. 1, 2017, Art. no. 17.

[25] G. Zhao, Y. Ge, B. Shen, X. Wei, and H. Wang, "Emotion analysis for personality inference from EEG signals," *IEEE Trans. Affect. Comput.*, vol. 9, no. 3, pp. 362–371, Jul.-Sep. 2018.

[26] J. Mar ín-Morales *et al.*, "Affective computing in virtual reality: Emotion recognition from brain and heartbeat dynamics using wearable sensors," *Sci. Reports*, vol. 8, no. 1, 2018, Art. no. 13657.

[27] J. Taverner, B. Alfonso, E. Vivancos, and V. Botti, "Modeling personality in the affective agent architecture GenIA3," in *Proc. Int. Conf. Agents Artif. Intell.*, 2018, pp. 236–243.

[28] M. Schröder, P. Baggia, F. Burkhardt, C. Pelachaud, C. Peter, and E. Zovato, "EmotionML–an upcoming standard for representing emotions and related states," in *Proc. Int. Conf. Affect. Comput. Intell. Interaction*, 2011, pp. 316–325.

[29] J. A. Rincon, A. Costa, P. Novais, V. Julián, and C. Carrascosa, "A dynamic emotional model for agent societies," in *Proc. Int. Conf. Practical Appl. Agents Multi-Agent Syst.*, 2016, pp. 169–182.

[30] M. A. Salichs and M. Malfaz, "A new approach to modeling emotions and their use on a decision-making system for artificial agents," *IEEE Trans. Affect. Comput.*, vol. 3, no. 1, pp. 56–68, First Quarter 2012.

[31] S. Jain and K. Asawa, "EMIA: Emotion model for intelligent agent," *J. Intell. Syst.*, vol. 24, no. 4, pp. 449–465, 2015.

[32] A. Kazemzadeh, "Using interval type-2 fuzzy logic to translate emotion words from Spanish to English," in *Proc. Int. Conf. Fuzzy Syst.*, 2010, pp. 1–8.

[33] L. Ivonin *et al.*, "A new representation of emotion in affective computing," in *Proc. Int. Conf. Affect. Comput. Intell. Interaction*, 2012, pp. 337–343.

[34] A. Pewsey, M. Neuhäuser, and G. D. Ruxton, *Circular Statistics in R*. London, U.K: Oxford Univ. Press, 2013.

[35] J. T. Horwood and A. B. Poore, "Gauss von mises distribution for improved uncertainty realism in space situational awareness," *SIAM/ASA J. Uncertainty Quantification*, vol. 2, no. 1, pp. 276–304, 2014.

[36] A. Hakim, S. Marsland, and H. W. Guesgen, "Statistical modelling of complex emotions using mixture of von mises distributions," in *Proc. Humaine Assoc. Conf. Affect. Comput. Intell. Interaction*, 2013, pp. 517–522.

[37] N. Lim, "Cultural differences in emotion: Differences in emotional arousal level between the east and the west," *Integrative Medicine Res.*, vol. 5, no. 2, pp. 105–109, 2016.

[38] U. P. Cambridge Ed., *Cambridge English–Spanish Dictionary*, 2019. [Online]. Available: https://dictionary.cambridge.org/dictionary/english-spanish

[39] P. HarperCollins Ed., *Collins English-Spanish Dictionary*, 2019. [Online]. Available: https://www.collinsdictionary.com/dictionary/english-spanish

[40] U. P. Oxford Ed., *Oxford Dictionary English-Spanish*, 2019. [Online]. Available: https://es.oxforddictionaries.com/english-spanish

[41] WordReference.com, Ed., *Wordreference Dictionary English-Spanish*, 2019. [Online]. Available: https://www.wordreference.com/es/
[42] D. Buttarazzi, G. Pandolfo, and G. C. Porzio, "A boxplot for circular data," *Biometrics*, vol. 74, no. 4, pp. 1492–1501, 2018.
[43] L. A. Zadeh, "The concept of a linguistic variable and its application to approximate reasoning," in *Learning Systems and Intelligent Robots*. Berlin, Germany: Springer, 1974, pp. 1–10.
[44] G. Klir and B. Yuan, *Fuzzy sets and fuzzy logic*, vol. 4, Englewood Cliffs, NJ, USA: Prentice Hall, 1995.
[45] A. Ayesh and W. Blewitt, "Models for computational emotions from psychological theories using type-II fuzzy logic," *Cogn. Comput.*, vol. 7, no. 3, pp. 309–332, 2015.
[46] T. D. Kemper, *Elementary Forms of Social Relations: Status, Power and Reference Groups*. Evanston, IL, USA: Routledge, 2016.

Joaquin Taverner received the degree in computer science and the MS degree in artificial intelligence, pattern recognition, and digital image from Universitat Politècnica de València - UPV (Spain). He is currently working toward the PhD degree in computer science at the Universitat Politècnica de València. As a researcher his interest includes multi-agent systems and affective computing.

Emilio Vivancos received the PhD degree in computer science (artificial intelligence) from the Universitat Politècnica de València - UPV (Spain), in 2004. He is an associate professor with the School of Informatics at the UPV, member of the Valencian Research Institute for Artificial Intelligence (VRAIN) at the UPV, and member of the Spanish Association for Artificial Intelligence (AEPIA). His main research interests include multi-agent systems and affective computing.

Vicente Botti is full professor of Computer Sciences with Universitat Politècnica de València-UPV (Spain) and head of the Valencian Research Institute for Artificial Intelligence (VRAIN). His main research interests include Knowledge Based Systems, Artificial Intelligence (AI), Multi-Agent Systems, Agreement Technologies, Social Simulation, Affective Agents, and Softcomputing. He has more than 366 international refereed publications: 100 in SCI-JCR journals, 2 research books, 235 international conferences, 29 chapters in international research books, 74 research projects (8 EU projects), having been the PI in 40. He is Emeritus member, Treasurer, and Founding Partner of the board of the EURAMAS; member of the management board of the Spanish Association for AI (AEPIA), vice-rector for the Development of ICT Technologies at the UPV; director of the Departament de Sistemes Informàtics i Computació at UPV, deputy director of the Facultat d'Informàtica and of the Escola Universitaria d'Enginyeria Informàtica at UPV; leader of UPV[X], UPValenciaX, and the MOOC UPV Projects in edX. He received the 2005 Research Award of the AEPIA, 2017 fellow of the European Association for AI, and the 2018 Spanish National Computer Science Award.