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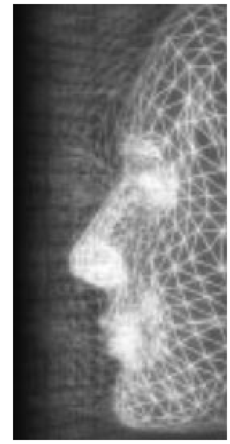
Generation and visualization of emotional states in virtual characters



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This paper presents an affective model that determines the emotional state of a character according to the personality traits and the experienced emotions. We consider an emotional state as the layer between personality and emotion. The proposed affective model offers a mapping between emotions and emotional states. To evidence emotional states of a virtual character, we can attribute them facial expressions based on their associated emotions. Facial expressions for intermediate emotions are generated automatically from expressions for universal emotions. The experiments show coherent emotional states produced by a simulated story. They also present how the corresponding emotions were represented through dynamic and static facial expressions. Finally, the obtained results demonstrate the satisfactory recognition by a group of people unfamiliar with the work described. Copyright © 2008 John Wiley & Sons, Ltd.

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Introduction

The evolution of human–computer interfaces has lead to researchers in artificial intelligence, computer graphics, computer vision, and psychology to produce embodied agents capable of autonomous interaction with humans, or with each other. Realism is achieved providing individuality by means of personality traits. They also influence behaviors and the intensity of the experimented emotions. The relation between personality and emotions can be established using an in-between state which changes more frequently than personality, but prevails longer in time than emotions. This state is named mood, temperament, or emotional state. Kshirsagar and Magnenat-Thalmann[1] considered that mood directly controls emotions, and hence facial expressions. It can be affected by momentary emotions as cumulative effect. We use the term *emotional state* to support the fact that this state is attained as a result of a set of sensed emotions.

The main goal of our research was the design and implementation of an affective model that evidences the emotional state of a character, and its correspondent visualization using facial expressions. It is generated from a set of emotions elicited at successive times and influenced by personality traits. Facial expressions can be considered one of the most important measures and manifestations of the emotional state.

Related Work

This work has been inspired by previous works on generation of emotions, emotional states, and their facial representation. El-Nasr *et al*.[2] used a fuzzy logic model based on event appraisal for simulating emotions in agents. The model included learning algorithms for learning patterns of events, associations among objects, and expectations. However, they did not take into consideration personality. Egges *et al*.[3] presented a generic personality and emotion simulator where mood can have any number of dimensions. The relationship between emotions, personality, and moods was done using matrices that relate them according to their influence on each other. Nevertheless, the values of the matrices appeared to be chosen empirically. Kshirsagar and Magnenat-Thalmann[1] presented a layered approach

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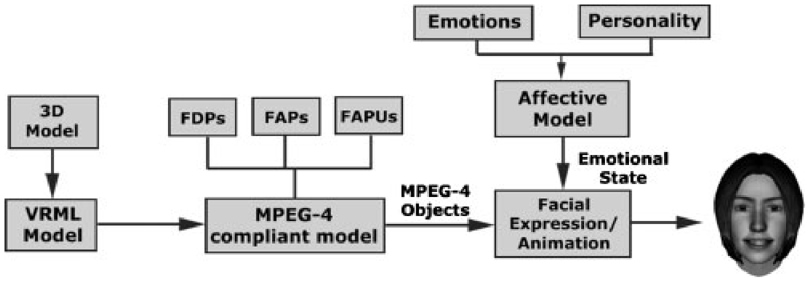

Figure 1. Graphic overview of our system.

for modeling personality, moods, and emotions. For the implementation, they used Bayesian Belief Networks with conditional probability values set by intuition. Su *et al*.[4] constructed a hierarchical fuzzy rule-based system to facilitate the personality and emotion control of the body language of a dynamic story character. Gebhard[5] proposed a layered model of effect named ALMA which integrates emotions, moods, and personality. All these models used the OCC model of emotions and the FFM personality model. For visualization, the work of El-Nasr *et al*. used 2D characters that showed the resultant behaviors or 2D baby faces with the resultant emotions. The work of Kshirsagar and Magnenat-Thalmann and Egges *et al*. used MPEG-4 *facial animation parameters* (FAPs) for a synthetic head, which shows the resultant mood: good, bad, or neutral. Gebhard's work used facial expressions for visualizing the dominant emotion and body postures for visualizing the resultant mood. Raouzaiou *et al*.[6] proposed a method for obtaining intermediate emotions from basic, or universal, emotions (anger, disgust, fear, happiness, sadness, surprise, proposed by Ekman[7]), and for visualization also used MPEG-4.

Our model possesses some significant properties of its own. One is the simplified affective model, which allows us to obtain an emotional state produced by the emotions elicited by world events and the influence of personality. The other novelty is the visualization of eight emotional states using facial expressions. Mapping emotions to emotional states makes possible to determine the emotional state of a character, and the association of a corresponding facial expression. We implement algorithms that use MPEG-4 FAPs, allowing the generation of facial expressions for intermediate emotions with different levels of intensity. Figure 1 shows a graphic overview of our system.

The paper is organized as follows. First, we describe the affective model where emotions and personality are related through emotional states. Then, we briefly explain its implementation and the process to generate facial expressions. Results of the affective model implementation and facial expressions evaluation are given in Section "Visualization of the Emotional States." Finally, we conclude with future directions of research.

Affective Model

We present a computational model for the generation of emotions and emotional states. It is based on the model proposed by Mehrabian,[8] which relates personality and emotion. It identifies almost independent basic dimensions of temperament used to describe and measure emotional states: pleasure–displeasure, arousal–nonarousal, dominance–submissiveness (PAD). The resultant temperaments, or emotional states, are: Exuberant, Bored, Docile, Hostile, Dependent, Disdainful, Relaxed, and Anxious. The importance of choosing this model is the capability of mapping personality, emotions, and emotional states parameters into the same space. Using the values assigned to each personality trait and the emotional state of the character, our model computes the resultant intensity of each elicited emotion and hence a new emotional state.

Based on the work of Gebhard,[5] an emotional state (**ES**), is defined as $\mathbf{ES} = (P, A, D)$, where $P, A, D \in [-1, 1]$ are its coordinates in the PAD space. ESi is its intensity computed as the norm of the vector, $ESi = \|\mathbf{ES}\|$, which goes from the PAD space origin, (0, 0, 0). Its intensity is related to an emotional degree that can be: slightly, if $ESi \in [0.0, 0.57)$; moderate if $ESi \in [0.57, 1.15)$; and highly, if $ESi \in [1.15, 1.73)$. The idea behind such generalization is to provide three linguistic variables to determine the intensity of an emotional state.

Personality is considered as the set of traits that characterizes an entity.[4] We have used the five factor model (FFM)[9] also known as the OCEAN model. It defines what could be considered by many psychologists,

ES	Emotions
Exuberant	Gratification, joy, love, pride
Bored	Disappoint., sadness, pity, remorse
Dependent	Admiration, gratitude, hope, liking
Disdainful	Disliking, reproach
Relaxed	Relief, satisfaction
Anxious	Fear, resentment, shame
Docile	Gloating
Hostile	Anger, hate

Table 1. Mapping emotional states (ES)—emotions in PAD space[5,17]

the five basic dimensions of the personality space: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. From this point of view, any personality can be obtained as a combination of these factors. The traits of the FFM model are used to compute a *default emotional state* **DES**, using Equation (1) proposed by Mehrabian:

$$\begin{aligned} P &= (0.21 \times E) + (0.59 \times A) + (0.19 \times N) \\ A &= (0.15 \times O) + (0.30 \times A) - (0.57 \times N) \\ D &= (0.25 \times O) + (0.17 \times C) + (0.60 \times E) - (0.32 \times A) \end{aligned} \tag{1}$$

The **DES** is considered the *normal* state of the character according to the personality. The intensity of **DES** is calculated as the norm of the vector that goes from the origin of the PAD space. Emotions are elicited with certain intensity due to different events that occur in the world that surrounds the character. An emotion E_i is also considered a point in the PAD space, where $E_i = (P_{E_i}, A_{E_i}, D_{E_i})$. Each emotion has its corresponding mapping in the PAD space, presented in Table 1. They have a weight Ew_i, which is the intensity of the emotion and it is associated to the event that generates it.

Using all the emotions in an instant t, we obtain a new point in PAD called *emotional center* (**EC**). This is the center of mass of all these emotions, see Equation (2). Its intensity ECi, is computed as the norm of this vector. **EC** is considered as the point where all emotions E_i are centralized and induces the displacement of the emotional state **ES**.

$$\mathbf{EC} = \frac{\sum_{i=1}^{n}(P_{E_i}, A_{E_i}, D_{E_i}) \times Ew_i}{\sum_{i=1}^{n} Ew_i} \tag{2}$$

Having the values of the **DES**, and the emotional center of the elicited emotions **EC**, we compute the

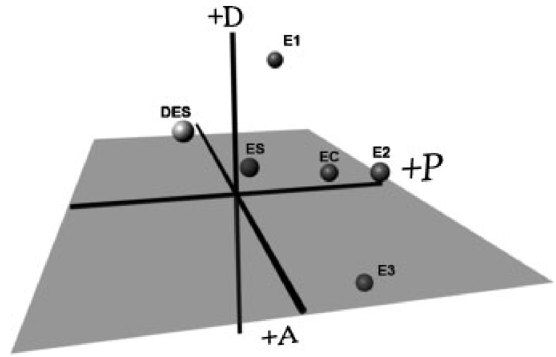

Figure 2. Personality, emotions, and emotional state in the PAD space.

actual emotional state at the instant t, $\mathbf{ES}(t)$, according to Equation (3). Then, personality represented by **DES**, displaces the emotional center **EC** using the center of mass of both of them. We have used this approach instead of vectorial calculation used by Gebhard. Thus, we propose a different and simplified method for computing the influence of personality in the emotions set. Figure 2 show graphically the location of each element in the PAD space.

$$\mathbf{ES}(t) = \frac{\mathbf{DES} \times \mathrm{DESi} + \mathbf{EC} \times ECi}{\mathrm{DESi} + ECi} \tag{3}$$

In a more realistic model, when the character experiments new emotions, these will not be affected by the **DES** but by the actual emotional state. Then, the emotional state at the instant $t+1$ will depend on the emotions experimented at the instant t, $\mathbf{ES}(t)$, and this will affect the future emotions generating a *new emotional state*.

Finally, an important aspect that has to be considered is *decay*. It allows the character to return to the **DES** after certain period of time. We have defined a decay function presented in Equation (4) that computes the center of mass between **DES** and $\mathbf{ES}(t)$. The motivation for this formulation is to obtain a new point in the PAD space that represents the emotional state and responds to the influence of the **DES** and the actual emotional state. The result is that vector $\mathbf{ES}(t)$ is moved toward **DES** in the PAD space. Figure 3 shows schematically the model explained before.

$$\mathbf{ESdec} = \frac{(\mathbf{DES} \times \mathrm{DESi}) + (\mathbf{ES}(t) \times ESi(t))}{\mathrm{DESi} + ESi(t)} \tag{4}$$

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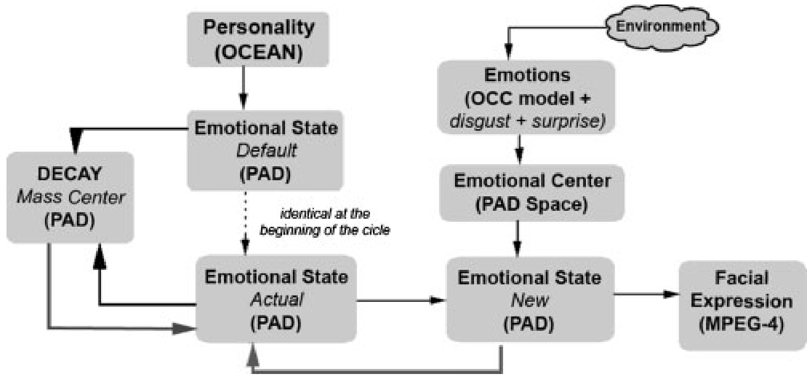

Figure 3. Schema of the affective model.

Visualization of the Emotional States

In this phase, the objective is the visualization of the generated emotional states. As there is not a visual representation for them, we associate emotions and their facial expressions with emotional states. This association is presented in Table 1.

Emotions can be categorized as universal (basic) emotions and intermediate emotions. Universal emotions were defined by Ekman *et al.*[10]: *joy*, *sadness*, *anger*, *disgust*, *fear*, and *surprise*. Intermediate emotions are those emotions that can be represented as the mixture of two universal emotions, or as a category of one of them. The considered emotions were the 24 proposed in the OCC model, except *happy-for* and *fear-confirmed*. In their place, *disgust* and *surprise* were added.[1]

In order to generate them, we implement an algorithm that uses the standard MPEG-4. It provides a facial object that represents a human face, as well as facial data: FDPs, FAPs, and FAPUs. *Facial definition parameters* (FDPs) are defined by the locations of feature points and are used to customize a given face model to a particular face. FAPs are those associated with the FDPs. Their values are the normalized displacement of particular feature points from their neutral position.[11] The algorithm also uses the theory proposed by Whissell. She proposes a model where each emotion has activation and evaluation values, used to locate the emotions in a coordinate system.[12] Because all these values are positive numbers, and according to Russell,[13] emotions are distributed forming a circle, we need to know to which quadrant the emotion belongs.

To know this, first we centered the Whissell's values of activation, $a \in (0, 6)$, and evaluation, $e \in (0, 6)$, in the origin of the coordinate system. This is done by subtracting the mean of all values of activation and evaluation, $\bar{a} = 4.3$ and $\bar{e} = 3.7$, from a and e, respectively. Then, given an intermediate emotion, we found its angle with respect the X-axis using Equation (5).

$$\omega = \arctan \frac{a - \bar{a}}{e - \bar{e}} \tag{5}$$

Each emotion E_i is associated with a set of activated FAPs, P_i. Each P_i has a range of variation (set of values) $X_{i,j}$ for each FAP, such as $P_i = \{X_{i,j}\}$, where j is the number of the FAP ($j = \{1, \ldots, 64\}$). $X_{i,j}$ has the form [minValue, maxValue]. The ranges $X_{i,j}$ for universal emotions were obtained from a 3D database which provides images and 3D models with faces showing expressions of joy, sadness, fear, disgust, anger, surprise, and neutral.[14] Figure 4 shows the obtained universal emotions.

Knowing the intermediate emotion we want to obtain, we find which universal emotions are in its neighborhood (according to the angular measure), and combine them to generate its FAPs.

If the angular distance of one of the universal emotions with respect to the intermediate emotion exceeds 45°, then it is not considered. In this case, the intermediate emotion is a category of the universal emotion that does not exceed the 45°. For instance, *gratitude* is considered a category of *joy*. The FAP's ranges of the intermediate emotion are obtained multiplying the FAP values of the universal emotion by the result of the division between the activation values of the intermediate and universal emotion.

If the differences between the angles of both universal emotions and the angle of the intermediate emotion are

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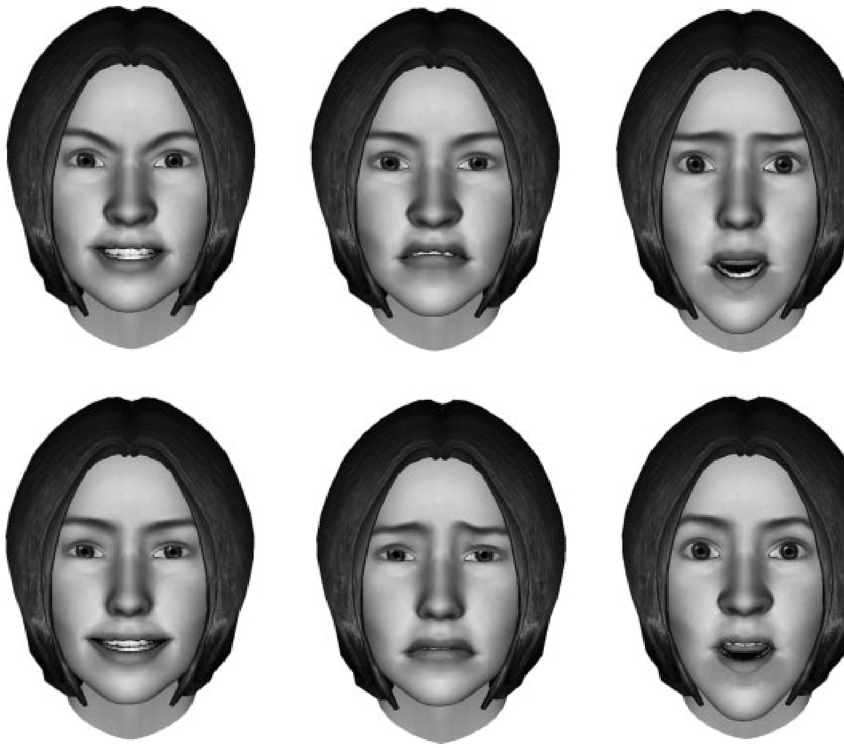

Figure 4. Universal emotions. Upper row: anger, disgust, fear. Lower row: joy, sadness, surprise.

less than 45°, then we have to combine the FAPs of both universal emotions according to the following rules:

(I) If FAP j is involved in the set of activated FAPs of universal emotions 1 and 2, P_1, P_2, with the same sign, then the range of variation of the intermediate emotion, $X_{n,j}$, is computed as a weighted translation of $X_{1,j}$ and $X_{2,j}$. These translations represent sub-ranges of FAPs of the universal emotions, affected by the activation value of the intermediate emotion.

Then, we have to compute the center $c_{1,j}$, $c_{2,j}$ and the length $s_{1,j}$, $s_{2,j}$ of the translated ranges of the universal emotions. Hereafter, we multiply these values by two constants that indicates the angular measure universal emotions should move to get to the intermediate emotion.

Finally, we compute the length and center of the intermediate emotion according to Raouzaiou *et al*.[6] These values are used to compute the new range of variation for each FAP of the intermediate emotion using the length and center of the intermediate emotion.

(II) If FAP j is involved in both P_1, P_2 but with contradictory sign, then $X_{i,j}$ is computed as the intersection of the ranges for each common FAP in both emotions. Usually, the FAPs are canceled because a range where they intersect is never found.

(III) If FAP j is involved only in one of P_1 or P_2, then the range of variation $X_{n,j}$ will be averaged with the corresponding of the neutral face position.

As a result, we obtain a set of FAPs with a range of variation that indicates all the possible intensities of the emotion. The final intensity of the represented emotion is provided by the affective model. This is a value between 0.0 (neutral expression) and 1.0 (full expression of the emotion), and could be reflected as the proportion in which an emotion has been felt. Figure 5 shows some facial expressions obtained for intermediate emotions with the highest intensity.

Experiments

Evaluation was divided into two: evaluation of the affective model and evaluation of the generated facial expressions. The later was also subdivided in two groups: subjective and objective evaluation. The used method and the obtained results are discussed in the following subsections.

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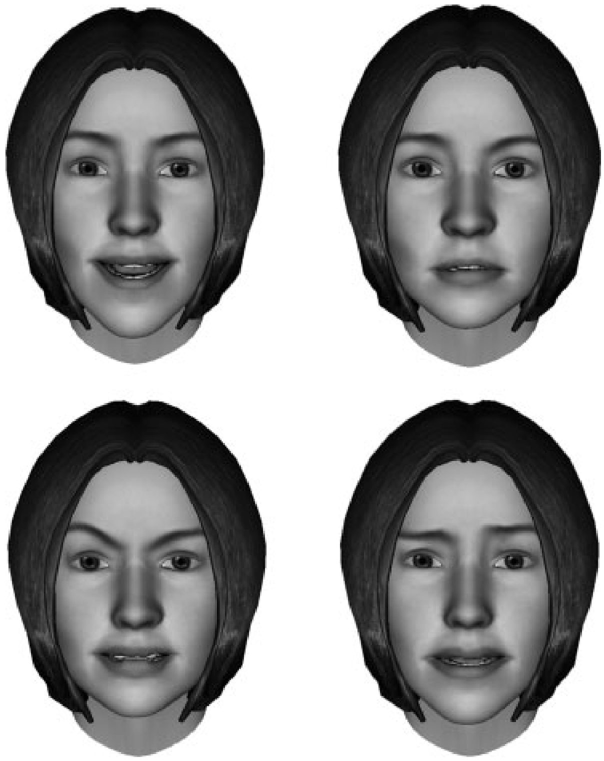

Figure 5. Intermediate emotions. Upper row: love, disappointment. Lower row: hate, pity.

Personality 1	Personality 2
O = 0.15	O = 0.45
C = 0.77	C = 0.37
E = 0.01	E = 0.91
A = 0.16	A = 0.96
N = 0.95	N = 0.05

Table 2. Personality traits according to FFM

Group 1	Sadness = 0.8, pity = 0.9
Group 2	Satisfaction = 0.9, joy = 0.8
Group 3	Sadness = 0.7, disappointment = 0.5
Group 4	Hate = 0.9
Group 5	Surprise = 0.9, remorse = 0.7
Group 6	Admiration = 0.6, relief = 0.8
Group 7	Gratitude = 0.9, joy = 0.9

Table 3. Elicited set of emotions

Affective Model

We verified that transitions between emotional states were correctly performed and consistent with the assigned personality traits. Two types of personality were defined according to Table 2.

Emotions were elicited every 5 seconds and with a decay time of 12 seconds, according to a story which emotions are shown in Table 3. We established a fixed set of emotions in order to control the experiment and compare among successive iterations of the model.

The resultant emotional states are shown in Table 4 with its degree and intensity, according to defined personality and the group of generated emotions. Column A indicates the emotional state generated by the group of emotions. Column B indicates the resultant emotional state due to personality.

Personality 1 (*P1*) gives as **DES** *Slightly Relaxed*. Personality 2 (*P2*) gives as **DES** *Moderate Exuberant*. With *P1* negative emotions (groups 1, 3, 4) lead the character to the *Bored* and *Hostile* emotional states with low and moderate intensities. Positive emotions (groups 2, 6, 7) lead the character to her **DES**, and to the states *Disdainful* and *Dependent* with low intensity. We could observe that this type of personality makes the character to experiment negative emotions in a stronger way than positive emotions, which are not fully experienced. With

Personality 1	A	B	Personality 2	A	B
Default **ES**	Relaxed (slightly, 0.56)	Relaxed (slightly, 0.56)	Default **ES**	Exuberant (moderate, 0.93)	Exuberant (moderate, 0.93)
Group 1	Bored (moderate, 0.67)	Bored (slightly, 0.39)	Group 1	Bored (moderate, 0.67)	Exuberant (slightly, 0.29)
DECAY		Docile (slightly, 0.38)	DECAY		Exuberant (moderate, 0.93)
Group 2	Relaxed (slightly, 0.43)	Relaxed (slightly, 0.28)	Group 2	Relaxed (slightly, 0.43)	Exuberant (moderate, 0.76)
Group 3	Bored (moderate, 0.67)	Bored (slightly, 0.44)	Group 3	Bored (moderate, 0.67)	Dependent (moderate, 0.15)
DECAY		Bored (slightly, 0.34)	DECAY		Exuberant (slightly, 0.65)
Group 4	Hostile (moderate, 0.9)	Hostile (moderate, 0.6)	Group 4	Hostile (moderate, 0.9)	Hostile (slightly, 0.53)
Group 5	Bored (slightly, 0.18)	Hostile (slightly, 0.45)	Group 5	Bored (slightly, 0.18)	Hostile (slightly, 0.36)
DECAY		Hostile (slightly, 0.2)	DECAY		Exuberant (moderate, 0.65)
Group 6	Relaxed (slightly, 0.33)	Disdainful (slightly, 0.23)	Group 6	Relaxed (slightly, 0.33)	Exuberant (slightly, 0.43)
Group 7	Dependent (slightly, 0.45)	Dependent (slightly, 0.26)	Group 7	Dependent (slightly, 0.45)	Exuberant (slightly, 0.4)
DECAY		Relaxed (slightly, 0.28)	DECAY		Exuberant (moderate, 0.93)

Table 4. Resultant emotional states

P2, the first group of negative emotions (group 1) sets the character in a *Slightly Exuberant*. This is contrary to the former case in which the character was set to a *Bored* state. The following emotions lead the character to a *Hostile* state, which does not disappear until the third decay.

To obtain emotional states with high intensities is necessary to experiment consecutive and very intense emotions. In our experiment, changes between states are slow due to the center of mass mechanism. It allows representing psychological healthy characters. Otherwise, we could be representing pathologies which are not matter of this work.

Nr.	Emotion	Nr.	Emotion
1	Joy	9	Love
2	Sadness	10	Disappointment
3	Disgust	11	Satisfaction
4	Anger	12	Pity
5	Surprise	13	Admiration
6	Fear	14	Reproach
7	Gloating	15	Gratitude
8	Hate	N	Neutral

Table 5. Evaluated emotions

Subjective Evaluation by Observers

In this experiment, we evaluated the realistic generation of facial expressions. This was achieved through the subjective evaluation of 16 facial expressions, of universal and intermediate emotions, in a synthetic female face. Evaluated emotions are presented in Table 5.

The evaluation was done through a paper survey. We chose a group of 75 students of 2nd year of Computer Science at Universitat de les Illes Balears, between 18 and 42 years old with a mean of 22 years old, with no previous knowledge about emotion recognition. Images and videos were projected in a screen of $1.20 \times 1.20\,\mathrm{m}^2$. The evaluation time was 40 minutes. The items evaluated were:

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Emotion	In	N	J	Sa	D	A	Su	F
N	—	**80**	9	1	2	0	0	0
1	J	1	**93**	0	1	0	2	0
2	Sa	0	0	**87**	8	2	0	0
3	D	1	0	2	**60**	28	2	0
4	A	0	0	3	3	**84**	2	0
5	Su	0	1	0	2	5	**70**	15
6	F	2	0	3	6	1	**52**	33
7	J/Su	24	**66**	4	0	0	2	0
8	A	0	0	2	18	**68**	0	1
9	J/Su	2	**59**	0	0	0	27	1
10	Sa	18	1	**38**	17	0	11	7
11	J	4	**84**	1	0	2	2	0
12	Sa/F	1	0	24	21	1	1	**43**
13	J/Su	4	**86**	0	1	0	5	0
14	D/A	4	1	0	**54**	33	1	0
15	J	5	**83**	0	2	1	1	1

Table 6. Percentage of recognition of universal emotions. The bold font in some values is used to highlight the higher values obtained

(I) *Recognition of universal emotions in images corresponding to 16 facial expressions.* With this experiment, we verify that the algorithm used for generation of intermediate emotions worked. This was proved when one of the universal emotions used in the generation was recognized. Table 6 shows the results obtained in the recognition of universal emotions in each of the evaluated expressions.

From these results, we could see that intermediate emotions were recognized in 93% of the cases. We could also infer that the facial expression for *fear* must be improved because it was identified as *surprise* in most of the cases.

(II) *Recognition of emotional states grouped by dimension Dominance (D) in images corresponding to 16 facial expressions.* From previous works, we concluded that it was difficult for people to identify the eight emotional states in an image of a facial expression. As former researches[15] support the theory that is possible to work only with dimensions of Arousal (A) and Pleasure (P) from the PAD space, we reduced the eight emotional states to four. We grouped them by the dimension Dominance (D), obtaining the following groups: Exuberant–Dependent (ED), Relaxed–Docile (RD), Bored–Disdainful (BD), and Anxious–Hostile (AH).

Table 7 shows the obtained results when associating each facial expression with a *combined* emotional state. The first column has the emotion associated to the evaluated expression with high intensity. The second column has the emotional state associated to the emotion. The following columns presents the recognition rate (%) of each emotional state, without considering the intensity.

We observed that 73% of the emotions were correctly associated, confirming the theory that emotional states grouped by Dominance can be recognized in facial expressions. *Surprise*, which has no correspondence in PAD space was identified in the state Anxious–Hostile in 55% of the cases. Although this result is not conclusive, it gives an idea about the location of the emotion *surprise* in the PAD space, according to the facial expression given in this experiment.

(III) *Recognition of the emotional states grouped by dimension Dominance (D) in videos.* The evaluation of animated facial expressions for universal emotions going from the neutral state to the highest intensity and their association with an emotional state allowed the validation of the results obtained in (II). Results are shown in Table 8.

Table 8 shows that the recognition rate is high in most of the cases. Emotions of *anger*, *sadness*, *joy*, and *fear* were correctly recognized, and the results are similar to the ones obtained in (I). *Surprise*, with no emotional state associated, was associated with the state Exuberant–Dependent. Nonetheless, it was associated with the state

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Emotion	In	ED	RD	BD	AH
Neutral	RD	12	**77**	5	4
Joy	ED	**86**	3	4	2
Sadness	BD	0	2	**86**	10
Disgust	BD	0	2	46	**48**
Anger	AH	6	0	17	**75**
Surprise	—	23	5	5	**55**
Fear	AH	7	0	19	**71**
Gloating	RD	**56**	23	6	2
Hate	AH	1	0	30	**68**
Love	ED	**92**	6	0	0
Disappointment	BD	2	24	**50**	18
Satisfaction	RD	**82**	8	5	2
Pity	BD	0	1	**62**	34
Admiration	ED	**79**	11	6	0
Reproach	BD	0	2	**56**	38
Gratitude	ED	**82**	7	5	3

Table 7. Percentage of recognition of the combined emotional states

Emotion	Emotional state recognized
Anger	AH (85%)
Sadness	BD (93%)
Disgust	BD (61%)
Surprise	ED (53%)
Joy	ED (88%)
Fear	AH (57%)

Table 8. Results of animated facial expressions

Anxious–Hostile when evaluating static images of the emotion surprise. This result leads to the conclusion that, despite *surprise* can have a very identifiable facial expression, it is not easily related to an emotional state because it can be generated by events of different types. Finally, *Disgust* which was evaluated in the Anxious–Hostile state, was associated with the Bored–Disdainful state in this case.

(IV) *Evaluation of the visual features of the synthetic face.* Results of closed questions about visual features of the synthetic face showed that it was considered credible and people felt comfortable watching it. They also evaluated it as cold and rigid. However, percentage rates were under 60%, which indicates that we have to work on the realism of the face. From open questions, we inferred that mouth and eyebrows, as well as their movement were considered very realistic. Hair was the less realistic feature. Eyes are a very important feature, and although the used textures and size were credible, the lack of movement minimize the expressivity of the emotion.

Objective Evaluation by Automatic Recognizer

The images used in Experiment 1, plus the expressions for: *gratification*, *hope*, *liking*, *pride*, *relief*, *remorse*, *resentment*, and *shame* were validated using an automatic recognizer developed by Cerezo *et al*.[16] The method studies the variation of a certain number of face parameters (distances and angles between some feature points of the face) with respect to the neutral expression. The characteristic points are based on the points defined on the MPEG-4 standard. The objective is to assign a score to each emotion, according to the state acquired by each one of the parameters in the image. The emotion (or emotions in case of draw) chosen will be the one that obtains a greater score. The reason to use this method was the recognition reliability percentage which is 90.93% in average. The emotions recognized by the method are: *joy* (J), *sadness* (Sa), *disgust* (D), *anger* (An), *fear* (F), *aversion* (Av), *surprise* (Su), and the neutral face (N). Table 9 shows the obtained results.

The results show that universal emotions were recognized, except *fear* which was confused with *surprise*, and *disgust* was evaluated as *sadness*.

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Expression	IN	Automatic recognizer
Joy	J	J
Disgust	D	Sa
Anger	An	An/Av
Fear	F	Su
Surprise	Su	Su
Sadness	Sa	Sa
Admiration	J/Su	Su
Disappointment	Sa	Sa
Gloating	J/Su	Su
Gratification	J	J/N
Gratitude	J	J
Hate	An	Av/An
Hope	J	Av
Liking	J/Su	J
Love	J/Su	Su/F
Pity	Sa/F	Av
Pride	J	J
Relief	J	N
Remorse	Sa	Sa
Reproach	D/An	Sa/Av
Resentment	D/An	Av/An
Satisfaction	J	J
Shame	Sa/F	Sa/Av

Table 9. Results of the objective evaluation

In conclusion, the automatic recognizer evaluated 82% out of the total number of expressions, which can be considered satisfactory. Failed emotions were: *hope*, *pity*, and *reproach*, which were considered as *aversion*. *Relief* was identified as the neutral face, but it makes sense considering that this emotion is taken as *calm*.

Conclusions and Future Work

Our work has three main contributions: an affective model for generation of emotional states; an algorithm for the generation and visualization of facial expressions; and the evaluation of the affective model.

The proposed affective model allowed the relation of personality, emotional state, and emotions in the same space. As a result, we obtained an emotional state with an associated emotion whose intensity was given by the emotional state.

The visualization of emotional states was done through facial expressions for emotions. The expressions for intermediate emotions were acquired from the automatic combination of the expressions for universal emotions. Using linear interpolation, we could generate animations for a dynamic visualization of the expressions.

From the results of subjective and objective evaluation of the generated facial expressions, we concluded that the obtained emotional states were coherent to the elicited emotions that produce them. Also, recognition of emotions in images of facial expressions is not an easy task. Subjectivity and diversity in psychological theories leads to have neither unanimity nor universality in the description of a facial expression for an intermediate emotion. In addition, lack of context, voice, or movements make harder the recognition of emotions in images than in animations. That is why the recognition rate of emotions in videos was higher than in images.

One point of further investigation are evaluation methods. We will focus on different techniques that allow us a more complete validation of the generated facial expressions. Also, we need to implement our system in a real application where human–computer interaction could be possible. In order to achieve this, speech, head, and eye movement must be added to our expressions.

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