# An Internal Model for Characters in Virtual Environments: Emotion, Mood and Personality

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## 1 Introduction

Emotions influence the interactions between people because they are present on everything we experience daily. They affect our mental state, facial and body expressions, decision making and social interactions. During the last years there has been a significant increase in research on computational models of emotional processes, stemming from the fields of emotion research in psychology, cognitive science, philosophy, artificial intelligence and computational science. This interest has been driven both by their potential for basic research on human emotion and cognition and by the perspective of an ever growing range of applications. One of such applications is the realistic modeling of characters in Virtual Environments, which are subsequently able to exhibit a varied range of non-monotonous, human-like behaviors.

The interaction with computers should be as natural as possible, and we, as users, tend to expect that computers react and behave as human beings would, so it is of utmost importance that computer applications are able to interpret and simulate emotions in a natural way. One of the tools provided by computational science that allows us to model the approximate reasoning mechanisms that humans use is fuzzy logic. However, few research works have been carried out on the use of fuzzy logic to model and simulate emotions. The most important models turn out to be too theoretical and fail to put forward a way to combine emotions with mood and personality traits to obtain an even more complex and realistic emotional simulation.

The internal model of emotions for virtual characters proposed in this chapter takes as its main reference the theoretical basis of fuzzy logic applied to emotions of existing computational models, being the combination with mood the most advanced step that these models have developed. The main objective of the work described in this chapter is to simulate emotions as a reaction to events that occur in the environment, enhancing the behavior of characters through the additional use of both mood and personality traits.

To achieve these goals, an overview of the main psychological theories of emotions are provided in section 2. Subsequently, an overview of the state of the art in computational models of emotion is presented in section 3, examining the most relevant and influential models in the field. These two sections do not intend to be a comprehensive study of the field, for which the reader can refer to (Marsella et al., 2010). In addition, in section 4, the foundations of fuzzy logic are shown and how it is applied to the generation of emotions of virtual characters. In section 5 we present our model for virtual characters, providing details on how emotions, mood and personality have been modeled and integrated. After that, section 6 provides details of our implementation of this model, which empirically validates it and which has served as a basis to establish the experimental values of some of the constants used in the model. Finally, some conclusions obtained from our work are presented.

# 2 Psychological Models of Emotion, Mood and Personality

In this section we provide an overview of the psychological basis that ground the computational models presented in the following section for emotions, mood and personality, describing their purpose and classifications.

## 2.1 Emotions

Although classic philosophers like Plato or Descartes considered that emotions were not part of human intelligence but an obstacle for human thinking, modern psychologists acknowledge emotions as a positive component of human cognition (Ekman, 1992). Modern research defends that emotions have a great impact on cognition, memory and beliefs (Forgas, 1995), to the point of considering that not having emotional response capabilities implies that it is more difficult to make good decisions (Damasio and Sutherland, 2008).

The main goal of a psychological theory of emotion is to describe the processes related to the creation of emotions within an individual, even if these processes occur in a social context and not within the individual (Frijda et al., 2000). Despite extensive research on emotions from a psychological point of view, it is not possible to establish a theory of emotion that is considered "correct" and, therefore, widely accepted by the scientific community (Reisenzein et al., 2013). For example, Kenneth Strongman, in his more than fourteen years of experience in the field of psychology, concludes that there are more than 150 different emotion theories (Strongman, 2003). In the same way, theories can be described in different ways and, although they may not seem similar, they do not necessarily contradict each other.

It is usually considered that there are four major trends in the psychology of emotion, corresponding to a classification of the most famous and influential theories used to model emotions: somatic, discrete, dimensional and cognitive. *Somatic theories* consider emotions as experiences similar to sensations. *Discrete theories* suppose that emotions are something innate in all human beings and therefore have their own processing mechanisms hard-coded in the human brain. *Dimensional theories* argue that emotions are mainly psychological labels that are assigned to mental and physical states, and identify them with a position in a bidimensional or tridimensional space. *Cognitive theories* assume that there are physiological, subjective and cognitive components involved in the simulation of emotions, and that mental representations are required to explain the importance of cognition in emotions.

*Appraisal theory* (Marsella et al., 2010) is a cognitive theory that is one of the most prominent theories used for emotion modelling. Appraisal theory states that emotions arise from the interaction between things we consider important and events that happen in our environment, so they can not be easily explained by focusing only on the individual or his environment. Therefore, it is not only our relation with the environment or the relative importance of things, but also the interaction between both factors, what produces our emotional responses. Within the field of appraisal theory there are even more specific theories. The most important ones, and the basis of many computational models of emotion, are the theories of Frijda (Frijda, 1986), OCC (Ortony et al., 1990) and Lazarus (Lazarus, 1991).

Frijda's theory was defined in 1986 when Nico H. Frijda wrote his famous book *"The emotions"* (Frijda, 1986), where he describes the development of his psychological theory of emotion. His book had two main goals: one was to find a definition of emotion that could be widely accepted, and the other was to understand the origin and function of emotions, as well as the conditions that are necessary for them to appear.

A short time later, Ortony, Clore and Collins (Ortony et al., 1990) developed a joint theory (usually called OCC model) that is currently widely used to build computational models of emotion (Hudlicka, 2011). Their main objective was to describe the cognitive architecture of emotions so that they could be easily defined, and then it was possible to establish relationships between them. In that way, it should be possible to develop a computational model of emotions that could be used in Artificial Intelligence.

Later, in 1991, Richard Lazarus finished his research on stress (Lazarus, 1991), which was a very relevant psychological problem during World War II that was when Lazarus began his investigation. This led him to the study of emotions and the subsequent development of *coping*, a key concept in his research that is usually related to stress.

Although all these theories try to define what emotions are, the OCC model provides a clearer definition: emotions are reactions to events, agents or objects and their origin is determined by the way in which the situation that triggers them is interpreted by the individual (Ortony et al., 1990).

## 2.2 Mood

Mood can be considered as an emotional situation occurring at a particular time and whose duration is longer than that of emotions (it can last for hours or days). In the field of emotion modelling, mood can act as a filter in the process of modelling emotions, so that generated emotional responses are as realistic as possible. Traditionally, mood has been modeled as a part of the emotional state, that is, as if it just were an additional emotion. However, mood differs from emotions because it reflects a more stable and lasting emotional state of an individual, and therefore must be treated separately.

From the point of view of the dimensional theory of Mehrabian (Mehrabian, 1995), mood can be defined as *an average of the emotional state of a person in a variety of daily life situations*. This theory is also one of the most popular recent computational models of emotion due to its simplification of mood in three traits: *Pleasure*, *Arousal* and *Dominance*. These three characteristics form a three-dimensional space for mood in which each of the dimensions is measured in numerical values ranging from -1.0 to 1.0. In this way, different combinations of these features can be established to classify different mood states. Examples can be seen in Table 1, in which +P and -P are used for pleasant and unpleasant, +A and -A for exciting and gentle, and +D and -D for dominant and submissive.

Each type of mood can then be defined by a value in each of the dimensions of Pleasure, Arousal and Dominance. For example, a person is in a relaxed mood if the values of Pleasure and Dominance are positive, and that of Arousal is negative.

| | |
|---|---|
| +P+A+D Exuberant | -P-A-D Boring |
| +P+A-D Dependant | -P-A+D Disdainful |
| +P-A+D Relaxed | -P+A-D Anxious |
| +P-A-D Submissive | -P+A+D Boring |

Table 1: Mood according to the PAD dimensional space

## 2.3 Personality

Personality in virtual agents can be expressed in many ways: through language (Mairesse and Walker, 2010) or non-verbal behavior such as facial expression (Bee et al., 2010) or gestures (McRorie et al., 2012). Personality theories have always tried to specify how many personality traits human beings have. Gordon Allport proposed a list of more than 4000 features (Allport, 1937), Raymond Cattell considered 16 personality factors (Cattell, 1957) and Hans Eysenck summarized them into a theory with only three factors (Eysenck, 1991). Many researchers consider that Cattell's theory was too complicated and that Eysenck's had too limited a scope. As a result of these investigations arose the theory that is known in Psychology as the *Big Five* model.

The Big Five (Barrick and Mount, 1991) is a theory that examines the structure of personality by considering five factors or personal traits represented like five different dimensions: extraversion, agreeableness, openness to experience, conscientiousness and neuroticism. Each of the five personality dimensions represents a range between two extremes. For example, extraversion represents the continuous range between the most extroverted and the most introverted trait. The characteristics of each of the dimensions are briefly described below:

- **Openness to experience**: people who have this trait tend to be curious about the world and other people, and are eager to learn new things and enjoy new experiences. On the other hand, people who are not very open are much more traditional and resist new ideas because they do not like changes.

- **Conscientiousness**: high conscientious people have control over their impulses, plan their tasks with time and think about how their behavior can affect others. On the opposite side, low conscientious people overlook important tasks and, in general, do not complete things they are in charge of.

- **Extraversion**: people who have a high level of extraversion tend to be more sociable, enjoy meeting new people and initiating new conversations. Introverted people are reserved and find it difficult to start a conversation. They prefer loneliness because social events can be exhausting for them.

- **Agreeableness**: people who have a high level of agreeableness tend to be more cooperative and feel empathy and concern for others, while those who have a low level tend to be more competitive and may come to be argumentative or untrustworthy.

- **Neuroticism**: people with a high level of neuroticism tend to get irritated and depressed more easily, with a tendency of experiencing drastic changes in mood. On the contrary, a person who is not neurotic is emotionally stable and rarely feels sad or depressed.

The Big Five schema is used in many modern computational models that consider personality traits for the simulation of emotions. For example, ALMA (Gebhard, 2005) includes this model in the personality profile of its system and relates personality to emotions and mood through a mapping of values that fits the three-dimensional PAD model on which its architecture is based.

# 3 Computational Models of Emotion, Mood and Personality

A computational model of cognition is responsible of providing the necessary information to understand cognitive functions, describing the entire process through algorithms and programs (Sun, 2008). In this work, we are interested in computational models of emotion, and related issues like mood and personality.

Computational models of emotion are usually based on psychological theories as a basis for building an effective computational model. They usually try to define what an emotion consists of or how to understand emotional states like fear or happiness. However, as we have seen in Section 2.1, there are many psychological theories about emotions which differ in points as important as the involved cognitive processes or the representations of emotions. That makes the development of a computational model of emotion a quite complex task.

In the field of Artificial Intelligence, computational models of emotion are used to design autonomous agents that are able to interact with other agents or people, using verbal and non-verbal behaviour (Marsella and Gratch, 2014). Therefore, they must be able to address how emotions arise and change in relation to different conditions, from simple events to complex situations that involve more agents. In addition, emotions must be directly related both to the dynamics of how the environment works and to the mechanics of the individual's cognitive and behavioural processes.

## 3.1 Most Influential Computational Models and Architectures

Since there are many computational models of emotion used in affective computing, it is almost impossible to compare them all. For this reason, in this work this comparison has been limited to those models that have had a high influence in this area, analysing the general properties of each of them. These models are:

- **FLAME (Fuzzy Logic Adaptive Model of Emotions) (El-Nasr et al., 2000)**. FLAME is a model of emotion and mood that uses fuzzy logic to process events and obtain new emotional states. This model is based on the OCC model and includes algorithms to learn patterns of events, expectations and relationships between objects, among others. FLAME is widely used to control the behaviour of agents in virtual environments.

- **EMA (EMotion and Adaptation) (Marsella and Gratch, 2009)**. EMA is a computational model of emotion designed to provide very realistic emotional responses in virtual agents. This model is widely influenced by Lazarus' theories.

- **FAtiMA (Fearnot AffectTIve Mind Architecture) (Dias et al., 2014)**. FAtiMA is a cognitive architecture based on the OCC model that is specially designed to create intelligent agents that are able to use emotions and personality in order to influence their behaviour and be used in different scenarios. Due to its complexity, in 2014 a modular and simpler version of FAtiMA was developed that only contains some of its components to make the architecture more understandable and usable.

- **ALMA (A Layered Model of Affect) (Gebhard, 2005)**. ALMA is a programming framework that implements the OCC model and the Mehrabian dimensional theory (PAD) and incorporates emotions,

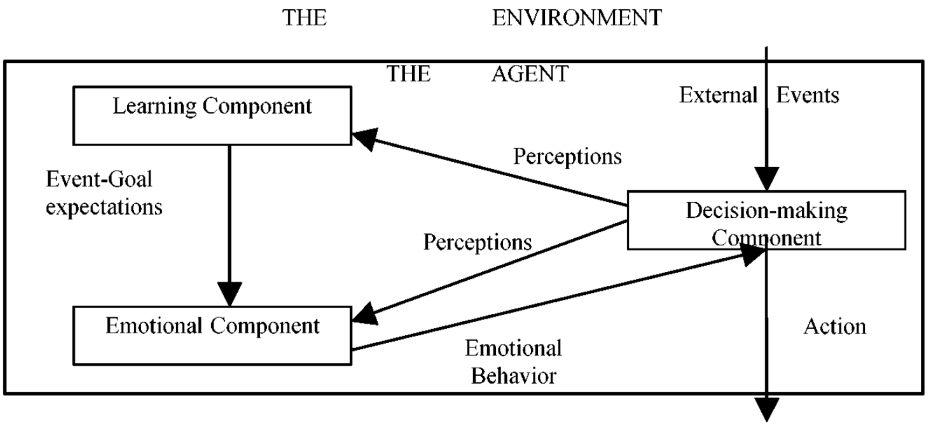



Figure 1: Abstract representation of an agent architecture (El-Nasr et al., 2000)

mood and personality. This tool allows developers to build their own computer models of emotions for multiple applications.

It is important to note that each of these models has different objectives. Some are specially designed to provide a formal basis for a theory, others aim to develop a programming tool, such as ALMA, and others such as EMA seek to develop an application. In addition, we can see that the OCC model is the most popular one. In this work we have used FLAME as the computational model of emotions for our virtual agents. Among other features, the use of fuzzy logic makes it very useful when treating with uncertainty issues related to emotional states.

## 3.2 FLAME

FLAME (Fuzzy Logic Adaptive Model of Emotions) (El-Nasr et al., 2000) includes two new features with respect to the OCC model in which it is based (Roseman et al., 1990; Ortony et al., 1990). The first one is the representation of emotions with fuzzy logic in order to perform a mapping of events and expectations on behaviors and emotional states using rules. The second is the incorporation of machine learning techniques, so the agents relate to the objects and events of the environment as well as to the user's objectives and expectations, giving rise to different responses.

Regarding the architecture of the model, FLAME defines three main components: an emotional component, a learning component and a decision-making component. Following the representation of the architecture in Fi-

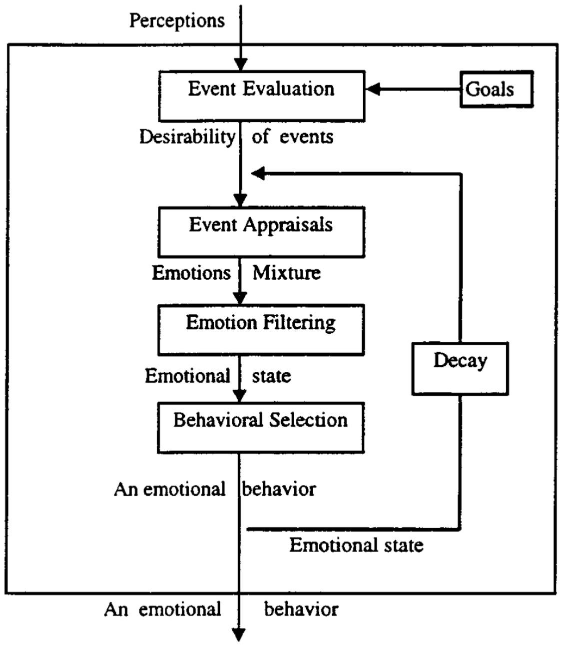



Figure 2: Representation of the emotional component in FLAME (El-Nasr et al., 2000)

gure 1, the process starts when the agent perceives external events from the environment. These perceptions are processed by the learning and emotional components. However, the emotional component uses expectations and relationships between events and objectives to generate emotions. In addition, an emotional behaviour is generated, which will be used as input for the decision-making component. The final action to be performed by the agent will have to consider the mood, emotional state and emotional behaviour obtained during this process.

In Figure 2 the processes that make up the emotional component are shown. When an event happens, the agent obtains information from the environment. This information is propagated through the component so that the output produced by each process serves as an input to the next one. First, the evaluation process is responsible for identifying the objectives that are affected by the event and for associating the degree of impact that the event has on these objectives. Next, the level of desirability of the event is computed according to the impact and the importance of the affected objectives. All this process is performed using fuzzy logic rules.

Once the level of desirability is calculated, it is transferred to the classification process to calculate the new emotional state of the agent. Subsequently, the filtering component will be responsible for considering the mood of the agent to detect dependencies with previous emotions. Finally, the reaction of the agent to the event is selected from the emotional state obtained in previous processes. The emotional state and intensity of the emotions of the agent will not be immutable until a new event happens, but will decrease as time goes by.

# 4 Fuzzy Logic

When describing the emotional state of a person, it is quite usual to use vague expressions such as *Peter is very tired* or *Lucy is a bit angry.* A human being is able to understand and interpret these undetermined expressions without problems. However, a machine will have trouble to interpret information that is not expressed using absolute values. Fuzzy logic is very useful in this kind of contexts, due to its ability to solve complex and undefined problems, as opposed to the difficulty of solving them using the traditional procedures of classical logic.

## 4.1 Fuzzy Sets

The term *fuzzy set* was first used by Lotfi A. Zadeh in his theory of fuzzy sets (Klir and Yuan, 1995). This theory was presented as a generalization of the classical set theory and its main function is to associate the degree of membership of elements in a set. In this way a proposition is not totally false or true, but it can be partially satisfied. This association process is known as *fuzzification.*

Fuzzy sets can be seen as a generalization of normal or *crisp* sets. Fuzzy logic is a multi-valued logic, so it is necessary to use a range to define the continuous values that an element can have. Therefore, it is possible to use this range of values to indicate the degree of membership of an element in the set. Therefore, the *membership function* $\mu_A$ from a fuzzy set $A$ has the following definition:

$$\mu_A = X \to [0, 1]$$

where $\mu_A(x) = 1$ indicates that $x$ completely belongs to $A$, $\mu_A(x) = 0$ is the opposite case where $x$ is not in $A$ and $0 < \mu_A(x) < 1$ if $x$ is partially in set $A$. The *degree of membership* of element $x$ to the fuzzy set $A$ is calculated in this way.

In addition, the membership functions allow graphical representation of fuzzy sets. When the calculations are not very complex, it is usual to choose simple functions to facilitate the operations of the system. The most used functions are the triangular and trapezoidal ones, as they have parameters that can be adjusted to achieve the desired domain. The traingular functions are defined in the following way:

$$\mu_A(x) = \begin{cases} 0, & x \leq a \\ \dfrac{x-a}{m-a}, & a < x \leq m \\ \dfrac{b-x}{b-m}, & m < x < b \\ 0, & x \geq b \end{cases}$$

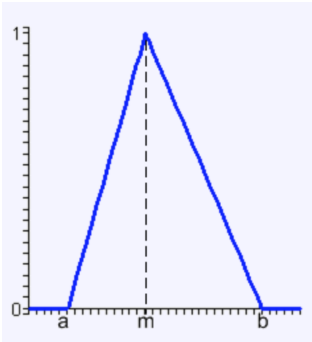
with $a$ and $b$ being the lower and upper limit, respectively. The medium value $m$ is the maximum value of the function, that can be asimmetric (Figure 3a). The trapezoidal function adds extra parameters to its definition to complete a trapezoidal form:

$$\mu_A(x) = \begin{cases} 0, & (x < a) \text{ or } (x > d) \\ \dfrac{x-a}{b-a}, & a \leq x \leq b \\ 1, & b \leq x \leq c \\ \dfrac{d-x}{d-c}, & c \leq x \leq d \end{cases}$$

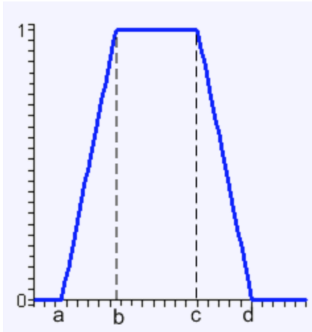
with $a$ and $d$ being the lower and upper limit, respectively, and $b$ and $c$ the maximum values of lower and upper limits (Figure 3b). The triangular function can be seen as a particular case of the trapezoidal function where $b$ and $c$ values are equivalent.

## 4.2 Use of linguistic variables in fuzzy rules

Linguistic variables are variables that represent elements without a clear definition through words or sentences in natural language. Mainly, they are composed of a primary term and a modifier. Primary terms (high, strong, sad, etc.) are used to construct fuzzy sets, and modifiers (very, too, a little, etc.) are used to calculate the other fuzzy sets of compound terms. For example, in Figure 4 we can see the linguistic variable *height* with fuzzy sets *very low*, *low*, *medium*, *high* and *very high* to represent the values the variable can take.




(a) Asymmetric triangular function




(b) Trapezoidal function

Figure 3: Representation of membership functions.

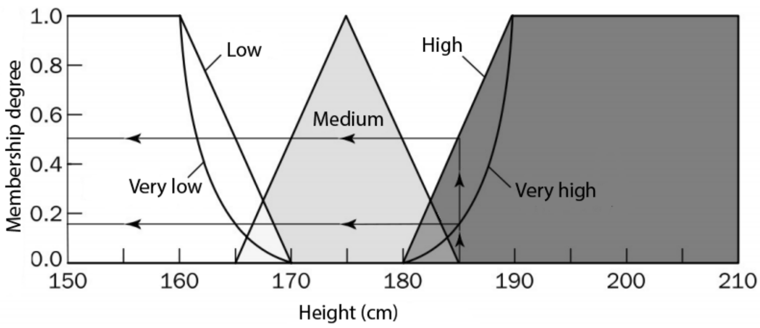



Figure 4: Use of *very* modifier to determine the membership degree of the height variable.

In order to represent natural language sentences in terms of linguistic variables, we use *fuzzy propositions*. This concept is based on replacing the possible variables and their corresponding values with symbols that help to process the propositions. For example, the fact *Peter is not a millionaire* can be represented as *P is not M* using the logical connector *not*. This transformation facilitates the processing of facts through the so-called *fuzzy rules* expressed in the form of an *if-then* sentence like IF <fuzzy_proposition> THEN <fuzzy_proposition>. In classic rules, if the antecedent is fulfilled then the consequent will also be fulfilled. On the contrary, fuzzy propositions are valid depending on the degree of membership. For example, in Figure 4 a height of 185 cm would have a degree of membership of 0.5 in the fuzzy set *very high*.

One of the most influential inference types is the inference of Mamdani

(Pourjavad and Mayorga, 2017), used in many computational models of emotions such as FLAME. Given that the system described in this chapter is based on this model, it is convenient to explain in more detail the four steps followed by Mamdani's inference:

1. **Fuzzification of input variables**: the crisp values of input variables are checked to calculate the degree of membership they have in each of the previously defined fuzzy sets.

2. **Evaluation of fuzzy rules**: once the fuzzy input variables are obtained, all the rules are evaluated by checking if the antecedents are fulfilled. The final value obtained will be used to determine the fuzzy set to which the consequent belongs.

3. **Obtaining output variables from the rules**: membership degrees from all the consequents must be combined, so that a single fuzzy set is obtained for each of the output variables.

4. **Defuzzification of the results**: the fuzzy sets from the previous step are transformed into output crisp values. There are multiple techniques to carry out this process, among which the Middle of Maximum (MoM) and the Center of Area (CoA) stand out.

# 5 A Model of Virtual Characters Using Fuzzy Logic

As described previously, the aim of this work is to build a model of virtual characters that can simulate emotions caused by the events that occur in a virtual environment, using fuzzy logic (see section 4) and computational modelling equations. In addition, this model provides components that can filter emotions in order to obtain a more complex emotional state through the use of the character's mood and personality. In this section we describe how this model has been designed.

The proposed model takes the computational model used in FLAME ((El-Nasr et al., 2000) see section 3.2) as a starting point in order to obtain the emotions according to the events that take place in the virtual environment. These events can occur either when a character interacts with an object of with another character. In the first case, there must be some relation between the character or the object so that an emotion can arise (e.g. a character gets angry when another character takes its beverage, as it may understand that the beverage is being stolen). If there is no relation between the character and the object, then the event will not have any emotional impact.

In the following subsections we describe the main features and mechanisms used to define a computational model of emotion, and the relationships that exist between them to determine an emotional state in response to an event. Subsequently, we explain how we have integrated mood and personality into this model in order to create a richer emotional model of virtual characters.

## 5.1 Emotions

According to the FLAME model, the agents that inhabit a virtual environment receive information from the events that occur in the environment through the agent's *perceptions*, which are then sent to their emotional component. This element processes perceptions and uses the outputs of an inductive learning component (that calculates the expectation of an event) in order to simulate an emotional state. In the proposed model, we have substituted the learning component with one based on the frequency of events, as the number of events that are likely to happen is restricted and a learning-based element is not likely to provide good results. In our case, the expectation of an event will be calculated according to its frequency: the more frequently it occurs, the higher the expectation of that event will be. This complies with the role of the expectation of an event, which reduces the intensity of the emotions it causes when an event repeats frequently.

The first process of the emotional component is the *event evaluation* (see Figure 2) where the system captures and processes the environment variables when the event occurs. In the proposed model, this evaluation is made in two steps. In the first one, the goals affected by the event are identified, along with the impact that the event has on them. In the second one, the rules to obtain the desirability of the event are calculated according to the impact calculated in the previous step and the importance of the goals. Therefore, the event evaluation process describes three variables that determine the emotional state:

- **Importance**: this variable expresses de the importance of the character's goals affected by the event.
- **Impact**: this variable represents the impact of the events on the character's goals.
- **Desirability**: this variable shows the level of desirability of the event according to the importance and impact on the character's goals.

All the characters endowed with emotions have goals with a certain associated *importance* for the character. During the evaluation process, once the affected goals have been identified, their corresponding importance is fuzzified using fuzzy sets, according to the precission desired for the classification of the corresponding crisp values. However, it is also necessary to consider that the inference process will turn more complex if the set granularity increases. In this case, we have empirically determined that in order to classify the event importance it is enough to use just three sets: *NotImportant*, *SlightlyImportant* and *ExtremelyImportant* (see Figure 5).

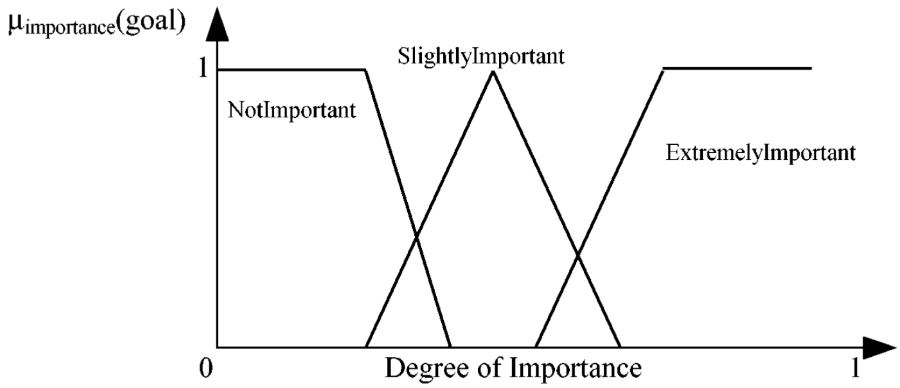



Figure 5: Membership functions for the variable *importance*

After calculating the importance of the event, the *impact* degree that the event causes on the goals is set. Given the significance of the character's goals on the model, it is necessary to use a higher precission to fuzzify the impact than in the case of the importance of the event. In this case, it has been empirically determined that using five fuzzy sets allows us to model the impact with enough precission: *HighlyPositive*, *SlightlyPositive*, *NoImpact*, *SlightlyNegative* and *HighlyNegative* (see Figure 6).

Finally, the level of *desirability* of the event from the character's point of view is established according to the values of the *impact* and the *importance* we have just calculated. The possible values for the desirability are *HighlyUndesired*, *SlightlyUndesired*, *Neutral*, *HighlyDesired*, *SlightlyDesired* (see Figure 7). The value of the desirability is established using a set of fuzzy rules (see section 4.2) like the following ones:

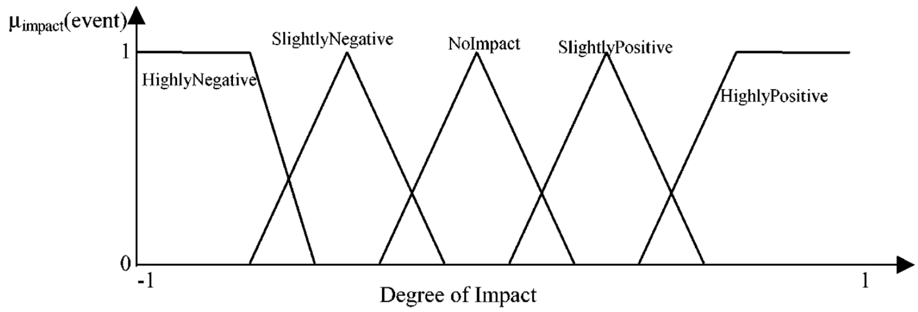



Figure 6: Membership functions for the variable *impact*

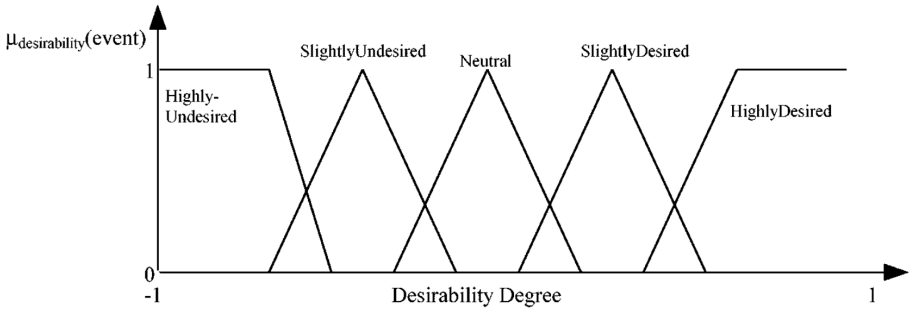



Figure 7: Membership functions for the variable *desirability*

IF Impact($G_1$, $E$) is $A_1$
AND Impact($G_2$, $E$) is $A_2$
...
AND Impact($G_k$, $E$) is $A_k$
AND Importance($G_1$) is $B_1$
AND Importance($G_2$) is $B_2$
...
AND Importance($G_k$) is $B_k$
THEN Desirability($E$) is $C$

where $G_i$ are goals and $E$ is the event that has triggered the rules. Applying the membership functions of the impact and the importance, we obtain fuzzy sets that can be trivially matched in the rule antecedents with the values of the different $A_i$ and $B_i$. If all the antecedents hold, the set $C$ is associated to the desirability of the of the event $E$ (i.e. if the event $E$ has an impact $A_i$ on the goals $G_i$ and each goal $G_i$ has an importance $B_i$, then the desirability of the event $E$ is $C$).

If we have a character that needs to send an urgent text message and another character steals its smartphone, this event may have a negative impact on the goals of the first character, so it can be easily seen that the event is undesirable. A fuzzy rule that defines this situation is

| |
|---|
| IF *Impact*(send text message, stolen phone) is *HighlyNegative*<br>AND *Importance*(send text message) is *ExtremelyImportant*<br>THEN *Desirability*(stolen phone) is *HighlyUndesired* |

In order to create and process the rules complying with the properties of the classical sets and at the same time allow to use them in an easy way, we have chosen the Mandani inference model (see section 4.2). This method allows us to create IF-THEN rules and nest additional antecedents in order to create more complex rules. The simplicity of the well defined steps of this model makes it easy to obtain a final *crisp* value using different fuzzification and defuzzification methods.

In the current model, we have decided to use the *Middle of Maximums (MOM)* method to defuzzify the value of the desirability of an event. Provided that we are only using five basic emotions for the characters (joy, sadness, fear, anger and surprise), we have considered that it is precise enough for our purposes, even though other methods, such as the *Centroid*, may be more acute (and computationally more expensive). The result of the defuzzification process is a crisp value that represents the desirability of an event, which is subsequently used to calculate (using the formulas proposed in the next sections) the intensity of the emotions of a character that are triggered by that event.

### 5.1.1 Emotion Classification

One the expectation of an event has been identified and all the rules have been processed, and therefore, the fuzzy set corresonding to the desirability of the events has been processed, we can calculate the emotional state of the agent using *affective computing* equations, which depend on both the expectation and the desirability of the events. The source of these equations is in the relation between the emotions and the desirability of an event, based on the definitions provided by Ortony et al. (1990), as shown in Table 2.

The proposed model considers both the desirability and expectation of an event as variables needed to calculate the intensity of emotions. However, variables such as the implication or the approval of other characters is beyond the scope of this work. Therefore, in this work we use some of the emotions proposed in FLAME which do not depend on social norms, but just on the

| Emotion | Rule |
|---|---|
| Joy | Ocurrence of a desirable event |
| Sadness | Ocurrence of an undesirable event |
| Disappointment | Ocurrence of a disconfirmed desirable event |
| Relief | Ocurrence of a disconfirmed undesirable event |
| Hope | Ocurrence of an unconfirmed desirable event |
| Fear | Ocurrence of an unconfirmed undesirable event |
| Pride | Action carried out by the character approved by other characters |
| Shame | Action carried out by the character disapproved by other characters |
| Reproach | Action carried out by other character disapproved by this character |
| Admiration | Action carried out by other character approved by this character |
| Anger | Complex emotion: sadness + reproach |
| Gratitude | Complex emotion: joy + admiration |
| Gratification | Complex emotion: joy + pride |
| Remorse | Complex emotion: sadness + shame |

Table 2: Rules for modelling emotions in FLAME

character's own actions and decisions: joy, sadness, fear, anger and surprise (see Table 3).

The emotions of joy, sadness and fear have been modelled according to the equations proposed by Price et al. (1985) and adapted so that they can be used in terms of the desirability and expectation of an event.

However, anger is a complex emotion which depends on a combination of sadness and reproach, defined as an action disapproved by other characters. A repriachable actin could be stealing a cellphone, which would make all the characters angry, and not only the one owning the stolen phone. As we are not considering reproach, our current proposal is to consider anger as a combination of sadness and fear.

Surprise is an emotion that is not included in FLAME, but we have decided to consider it in our model in order to complete the set of basic emotions proposed by the discrete theories of emotion (see section 2.1).

| Emotion | Rule |
|---|---|
| Joy | Occurrence of a desirable event |
| Sadness | Occurrence of an undesirable event |
| Fear | Occurrence of an unconfirmed undesirable event |
| Anger | Complex emotion: fear + sadness |
| Surprise | Occurrence of an unconfirmed, desirable or undesirable, event |

Table 3: Theoretical foundation for modelling emotions

### 5.1.2 Equations for the intensity of emotions

After establishing the theoretical foundations to model emotions, it is possible to create the equations that calculate the intensity of emotions in terms of the *desirability* and the *expectation* of an event, obtained when processing the rules that model the emotions. The original equations were designed by Price et al. (1985) (see Table 4) and each of them uses a pre-calculated coefficient that provided good experimental results.

| Emotion | Equation |
|---|---|
| Joy | $(1.7 \times expectation^{0.5}) + (-0.7 \times desirability)$ |
| Sadness | $(2 \times expectation^{2}) - desirability$ |
| Disappointment | $Hope \times desirability$ |
| Relief | $Fear \times desirability$ |
| Hope | $(1.7 \times expectation^{0.5}) + (-0.7 \times desirability)$ |
| Fear | $(2 \times expectation^{2}) - desirability$ |

Table 4: Intensity of emotions in the FLAME model

In the proposed model, we had to test these equations and adjust the values of the coefficients in order to obtain a behavior that was closer to what we expected. In the case of the emotions not considered by FLAME, such as surprise, or with undefined equations, such as anger, the proposed equation has the same structure of the existing formulas, as shown in Table 5.

### 5.1.3 Emotion Inhibition

Once the emotional state has been determined using the previous equations, it is necessary to establish how some emotions affect others. For example, sadness is usually affected by emotions such as anger or fear (Bolles and Fanselow, 1980). In general, emotions with a higher intensity tend to influence

| Emotion | Equation |
|---|---|
| Joy | $(1.2 \times expectation^{0.5}) + (-0.6 \times desirability)$ |
| Sadness | $(2 \times expectation^{2}) - desirability$ |
| Fear | $(2 \times ((1 - expectation)\,/\,4)^{2}) - desirability\,/\,2$ |
| Surprise | $\lvert expectation \rvert \times (1 + desirability)$ |
| Anger | $(Fear \times Sadness) + expectation\,/\,2)$ |

Table 5: Intensity of emotions in the proposed model

the rest, so a filtering process is needed in order to calculate the threshold over which an emotion starts influencing others.

The relationship between two or more emotions that can suppress other emotions is known as *inhibition*. Some models of emotions use techniques in which weak emotions opposed to the more intense ones are inhibited (Velásquez, 1997). For example, sadness would tend to inhibit happiness if it had a higher intensity. In the current model, opposite emotions are inhibited according to their intensities, but negative emotions (fear, anger and sadness) are preferred over positive ones (joy) as they tend to be more persistent and dominant.

The main inconvenient when using these techniques is deciding when an emotion should not influence another one. For example, when a series of events where sadness and joy change continuously, as soon as the intensity of one of them exceeds the intensity of the other, then the second emotion would be inhibited, and this alternation could last forever. This conflict can be solved by defining an error range, so that when opposing emotions have similar intensities, the inhibition is not possible. In case the difference between the intensities exceeds the error range, then the more intense one can inhibit the other. However, the real problem is that we are not taking into account the big picture of the whole emotional state, as this inhibition may not be reasonable.

In the following sections (5.2 and 5.3) we propose a solution to this problem by taking into account the mood of the character and, subsequently, we show the influence of other factors such as the character's personality in order to model a more realistic emotional response.

### 5.1.4 Emotion Decay

The last step to simulate emotions is to use a method that allows us to fade the emotions of the agents in the absence of new events. When the stimulus that triggers an event disappears, the emotion does not vanish instantly. Instead, it decays with time. This process of emotional decay can be modeled in different ways. In the current model, we propose the use of two constants to define how both positive and negative emotions decay. For positive emotions, we define a constant $\phi$, and for the negative ones a constant $\varphi$, such that $\phi < \varphi$. This way, similarly to what usually happens with humans, negative emotions tend to be more persistent than positive ones, which decay faster. Emotion decay is progressive until their value goes down to 0.

## 5.2 Mood

At this stage, the mood can help us filter the interactions between the different emotions in order to solve the inhibition problem. Mood can be represented as a summary of past emotions by means of a factor that can be either positive or negative. This value depends on the intensity of the character's emotions, either negative (sadness, rage or fear) or positive (joy).

When a new event is triggered, the intensities of the different emotions are likely to vary, as they are not constant over time, but just using the last emotional state of a character in order to decide whether it is in a good or bad mood may be misleading. As an example, let's imagine two characters, David and Laura, who are walking along the river shore. Suddenly, a thief steals David's wallet. David starts chasing the thief, but a bicycle runs over him and makes him fall into the river. Laura helps David get out of the water and returns him his wallet, which the thief lost while he was running away.

While all these events were happening, David's mood was worsening with every new mishap. If the mood only takes into account the last emotional state generated by the emotional component, the when the story finishes David should be happy because he managed to retrieve his wallet, forgetting about his stolen wallet, the bicycle running over him and falling into the river, which would not be very realistic. Instead, the mood component should take all these events into account, over a time window of a certain length, in order to generate a more believable mood value.

### 5.2.1 Time window definition

The solution we have adopted to solve this issue is to calculate the mood value using the emotions generated over the last $n$ time units. We have heuristically determined that using the last 5 time slots offers the most coherent results, since using a longer time frame makes the mood consider events which are not recent enough. Similarly, using a shorter time frame makes the mood too similar to the case in which only the last event is considered. The equations used to calculate the mood value are:

$$
mood = \begin{cases} positive & \text{if } \sum_{i=-n}^{-1} I_i^+ > \sum_{i=-n}^{-1} I_i^- \\ neutral & \text{if } \left| \sum_{i=-n}^{-1} I_i^+ \right| - \left| \sum_{i=-n}^{-1} I_i^- \right| > 10\% \\ negative & \text{if } \sum_{i=-n}^{-1} I_i^+ < \sum_{i=-n}^{-1} I_i^- \end{cases}
$$

where $n$ is the number of time slots (i.e. the size of the time window), $I_i^+$ is the intensity of the positive emotions in instant $i$ and $I_i^-$ is the intensity of the negative emotions in instant $i$.

To illustrate how the calculation of the mood works, we can use the following example: the current mood has a negative value as a result of three negative emotions (sadness, anger and fear) versus a positive one (joy), all of them with a medium intensity. An event is triggered and the new emotional state shows that joy has an intensity of 0.45 and anger has an intensity $\leq 0.20$. In this case, anger inhibits joy even though the intensity of joy is greater than the one of anger, since the mood of the character at that moment was negative.

### 5.2.2 Emotion filtering using mood

In order to prevent the mood to always be influenced by the intensity of the emotions, we must define a tolerance value between the positive and negative emotions. For example, in FLAME this value is 5%, but it can be any value that adjust the behaviour of the system providing coherent results. In this case, if an emotion has a value $v$, any emotion with a value $\pm 5\%$ will depend on the mood in order to obtain its final intensity.

In the proposed model, the result obtained at the end of this process is a number that indicates whether the mood is positive, neutral or negative. This value is then used to filter the emotions obtained after processing the rules that model them, running Price's equations and getting the emotional state. In the case of positive emotions, when a new event is triggered, the filtered emotion is calculated according to the following formula:

$$
I_m^+ = \begin{cases} I^+ - (mood/windows \times desirability) & \text{if } desirability < 0 \\ I^+ + (mood/windows \times desirability) & \text{otherwise} \end{cases}
$$

where $I_m^+$ is the intensity of a positive emotion after filtering it with the mood, and $I^+$ is the intensity of the resulting emotion after using the emotion equations. The value of the mood is divided by the maximum value that can be obtained subtracting the summation of the positive and negative emotions (number of time windows). If, for example, all the negative emotion of the time windows had a value 0.0 and the positive ones had a value of 1.0, then the resulting intensity would only depend on the desirability and the current intensity. In case the mood were neutral, the emotions would be processed as if there was no mood.

In order to calculate the negative emotions, we proceed in a similar, but subtracting the value of the intensity if the event is desirable:

$$I_m^- = \begin{cases} I^- - (mood/windows \times desirability) & \text{if } desirability > 0 \\ I^- + (mood/windows \times desirability) & \text{otherwise} \end{cases}$$

The only emotion that is not comprised within either positive or negative emotions is surprise. Offering an unexpected gift or bringing bad news are opposite actions where surprise might reach high levels, so none of the previous equations is valid for surprise. On the contrary, we need more variables apart from desirability to determine whether the intensity is going to increase or decrease. The filtering function for surprise is defined as follows:

$$I_m = \begin{cases} I_s - (mood/windows \times desirability) & \text{if } desirability < 0, \ mood < 0 \\ I_s + (mood/windows \times desirability) & \text{if } desirability < 0, \ mood > 0 \\ I_s + (mood/windows \times desirability) & \text{if } desirability > 0, \ mood < 0 \\ I_s - (mood/windows \times desirability) & \text{if } desirability > 0, \ mood > 0 \end{cases}$$

Considering the current mood, we can define 4 different cases of opposed situations to calculate the intensity of surprise. For example, if Mary gives away a smartphone to Carl, who is not in a good mood because he has dented his car door parking it, his surprise will be remarkable, because Carl would not be expecting something positive to happen. On the contrary, if Mary gives Carl a parking manual, he will be in a worse mood and surprise will not increase nearly as much as his negative emotions.

### 5.2.3 Integrating short term memory

In the proposed model, mood captures the last time windows of the emotional state in order to determine whether it is positive or negative and, according to this value, it recalculates the equations of the emotional modeling. In addition, the proposed mood filtering equations (see section 5.1.3) manage to simulate emotions according to what has happened in the last $n$ time windows. However, the mood currently only uses the obtained value as a general influence of the emotional state in previous moments. This can make the system behave as if it were only reacting to isolated events, obtaining incoherent results.

In order to clarify how the mood works, we are going to illustrate it through an example. Let's suppose a simulation where the mood of all the characters is neutral, and we have a character named Jester who is in a canteen. Jester steals Robert's cellphone, where Robert is another character who is standing close to the bar. Immediately after that, Jester also decides to steal Robert's beverage.

When Jester steals the cellphone, Robert's mood moves from neutral to negative, provided that in the emotional state calculated in each time window, the intensity of negative emotions is higher than the one of positive emotions. During this process, the mood has not been taken into account to obtain the value of emotions, since the character initially had a neutral mood and the subsequent filtering process has no effect. On the contrary, When Jester steals Robert's beverage, the emotions are calculated using a negative mood, so the negative emotions increase more than when the mood is neutral.

However, Robert considers his cellphone is more important than his beverage. If, after the first robbery, the intensity of anger is 0.70 and sadness and fear have both a value of 0.50, the mood will be quite negative when the second robbery is processed. Provided that the beverage is less important than the cellphone, the intensity of anger starts in 0.20 and filtering the mood the resulting value might not exceed 0.30.

As a result, after the first robbery the character's anger has a value of 0.70, and after the second one the value is only 0.30 (i.e. after the second robbery the character is less angry than after the first, which is incoherent even though the importance of the beverage is lesser than the one of the cellphone). This effect makes it look as if mood were not taking into account all the previous actions, and would only react independently to each event. If the events had happened in the inverse order, this error would not have been perceived as the intensity of the negative emotions after the second robbery are higher than after the first.

In summary, mood alone is not enough to obtain coherent results, so we need to consider the history of previous emotions and events, storing them in what is called a *short-term emotional memory* (Ortony et al., 1990) integrated in the mood. The purpose of this new element is to aggregate the intensities of the previous emotions to the current mood, so that we can perceive the effect of previous actions on the current mood.

In emotions such as surprise, fear and joy we have used the average of the intensity before the event is triggered and after the mood has been filtered. Sadness and anger are persistent negative emotions, so their calculation is a little more complex. In the case of sadness, the final intensity is the maximum of the two intensities. The equation for anger also depends on the expectation, and is as follows:

$$max(new\_anger, old\_anger) + min(new\_anger, old\_anger) \times expectation$$

## 5.3 Personality

Using the equations defined by Price et al. (1985) is the basis for the emotional modeling of the characters, and the use of mood allows us to model the emotions considering the previous events that the character has experienced, preventing their reactions to specific events to be always the same, irrespective of what has happened previously. However, using the current model, all the characters will behave in the same way, as there is nothing to allow them to behave differently. The element that can allow us to solve this issue is personality, as characters with different personality will react differently to the same event. In this section we are going to describe how we have integrated the Big Five personality model (Barrick and Mount, 1991) to add a little more complexity and realism to the emotional simulation of characters.

### 5.3.1 Mapping personality traits

In the existing literature, the *Big Five* model is integrated with mood through a value mapping that fits the PAD model (see section 2.2). In our case, we are not using the PAD model but fuzzy logic, as it offers a wider range of possibilities to represent emotions instead of just a fix set of values. In addition, we have used FLAME as a reference to model and integrate both emotions and mood, but it does not consider the personality traits of an agent. In this case, we have mapped the emotions with the personality traits described in the *Big Five* model using the descriptions provided by ALMA (Gebhard, 2005) (see Figure 8).

| Trait | Refers to | If low score |
|---|---|---|
| Openness | Imaginative, prefer variety, independent | Down-to-earth, conventional, low aesthetical appreciation |
| Conscientiousness | Well-organized, careful, reliable, self-discipline | Disorganized, careless, weak-willed |
| Extraversion | Sociable, affectionate, optimistic | Reserved, sober |
| Agreeableness | Trusting, helpful | Suspicious, cynical |
| Neuroticism | Anxiety, experience negative emotions, vulnerable | Secure, calm, self-satisfied |

Figure 8: Personality traits in ALMA (Gebhard, 2005)

The result of this mapping can be seen in Table 6, where each personality trait has both a high and a low value which matches the level of intensity of the personality trait and how the character's emotions are affected by that trait depending on their intensity. For example, an agreeable character tends to be happy and calm, while a low level of agreeableness makes a character angry and sad. The emotions that appear in the *High level* and *Low level* sets of a personality trait may not be completely opposed to one another, and it is possible not to have the same emotions in both sets, as in the case of agreeableness.

This mapping is used in order to obtain other factors such as the mood, which increase or decrease the intensity of emotions. These values are fix and do not change over time, as personality does not change with time, in contrast to what happens with mood.

The input to the process of filtering the emotions with the personality traits are the emotions that have already been already filtered using the mood. After that, the personality influences the emotions according to the values that appear in Table 6. Each positive or negative sign of the emotion in the table represents a change in the value of that emotion by a certain value $\delta$. For example, a personality with a high level of openness will increase

| Traits | High level | Low level |
|---|---|---|
| Openness | ++joy, -surprise, -fear, -anger, -sadness | +surprise, -joy, +fear |
| Conscientiousness | -surprise | +surprise |
| Extraversion | +joy, -fear, +anger | +fear, -anger |
| Agreeableness | +joy, −anger | -anger, -sadness |
| Neuroticism | +anger, +fear, +sadness, +surprise | -anger, -fear, -sadness, -surprise |

Table 6: Mapping of personality traits and emotions

$2 \times \delta$ the value of joy with respect to the value it had after filtering it with the mood. We have determined empirically that a value of $\delta$ in the range of $10\% - 15\%$ offers coherent results according to what different users expected testing the model.

# 6 Implementation of the model

This section describes the methods that have been adopted to build the model proposed in the previous section using the Unity 3D video game engine. The project is developed in the programming languages C# and XML, this last one used for loading configuration files.

The architecture of the emotional agent (Figure 9) is composed of three main components: emotions, mood and personality. The agent communicates with the fuzzy component, which contains the rules and sets defined by the user to calculate the desirability of the event in order to obtain the emotional state. Next, the implementation of how each component has been carried out will be explained.

## 6.1 Virtual environment

The virtual environment contains information that is generated while the agent explores the environment or represents facts known by all agents. It's used as input of the simulating emotions process in virtual agents and it can be classified in two groups of information about the environment: objects and events.

The objects are represented in Unity through *GameObjects*, which represent containers of all the components that implement the real functionality. All the objects store information that allows to define a relationship between

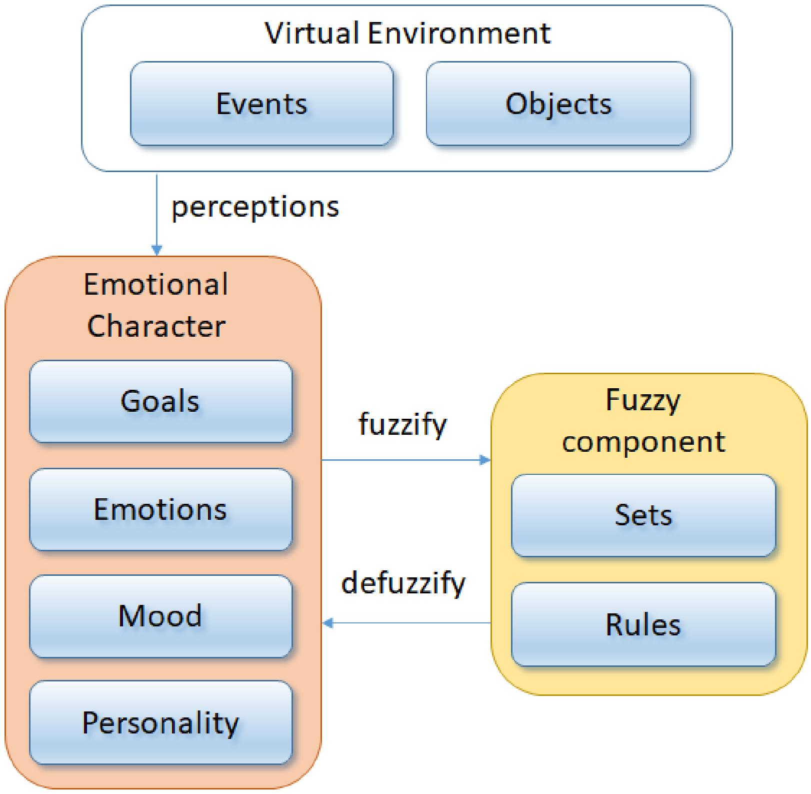



Figure 9: General view of the system architecture

a certain element of the environment and a character, through the importance it has for the character.

Application events can be produced in two ways using behavioral scripts in objects and characters of the virtual environment: when an action is performed on an object of the environment or during the interaction with another character. In the case of actions, there must be a relationship between the object and a character to simulate an emotion about it. If there is no character related to the object, the event will have no effect in the application.

Emotions are modeled from events, so it is necessary to define which may occur. The information of the available events keeps the *expectation* that they will happen and a weight that represents the degree of acceptance of the event share by all the agents.

In this system, the expectation begins at a minimum value and it will increase as the same event is repeated until it reaches the maximum value. This means that the event has occurred so many times that the impact it


Figure 10: General view of the virtual environment

will have on the character will be minimal. An example that we can find in the application is the theft of an object. The player steals a soda from a character and then his mobile. The second robbery will have a greater expectation because it has already experienced it before, which causes that emotions like surprise to be seriously depleted.

## 6.2 Message controller

Asynchronous messages allow the instructions of a function to not be blocked by waiting for the results of previous operations. This is very beneficial in case that several events happen consecutively and it is necessary to execute operations regardless of the order and without affecting the final result. Therefore, all environment elements communicate the event they produce using the asynchronous message passing mechanism provided by Unity. The message is sent to a function of the program to be executed and the receiver searches among all its behavior scripts if there is a function that corresponds to the requested one. In case of not finding it, the event won't be processed. On the other side, the indicated function will capture the message while the flow of operations invoked by the event continues its course.

The *Camera* is another object of the game that captures and shows the


Figure 11: Depiction of the character's emotions

virtual world created in Unity during the simulation. The execution of certain events may change the user interface, for example in giving *feedback* to the user of what is happening. These changes are updated with the asynchronous messages mechanism, so that the camera communicates with the message controller which is responsible for managing the reception of messages.

When an action related to an object is executed, the message controller obtains the identifier of the owner or the person involved in the event to know which character to send an asynchronous message with all the information of the event and the object. At the end of the process, the object disappears from the scene with its corresponding. In this way, possible conflicts are avoided in case the player tries to repeat the action several times because the event expectation will reach the maximum value, leaving the owner of the object completely insensitive to the event.

The re-sending of messages ends in the emotional component, the responsible for generating the final emotional state. Each virtual agent has a script that allows to simulate emotions and contain the current state of the intensity of the emotions, the mood as a multiple emotional states, the goals and the personality traits.

## 6.3 Emotional component

Each agent keeps its own objectives within the behavior scripts and they follow a data structure similar to the events. The objectives of each agent

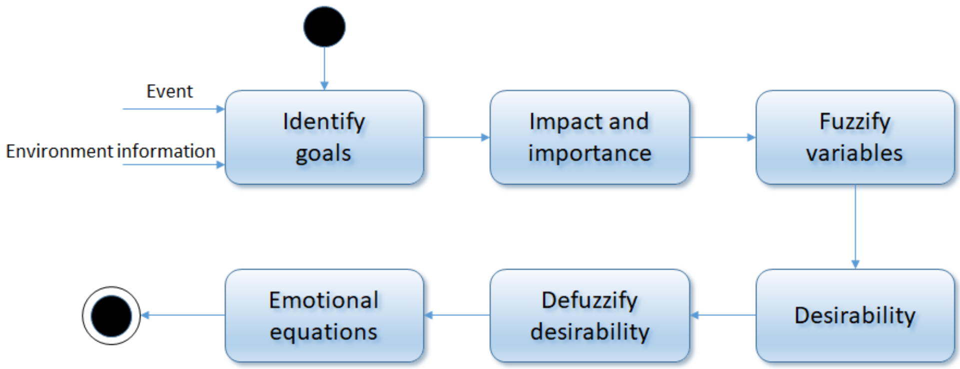



Figure 12: Flow of the simulation of emotions

don't belong to the environment information which is shared between all the agents but it depends on each one to manage their own objectives.

The emotional component is the basis of the simulation of emotions to obtain a basic emotional state. Therefore, it is a required component for the good performance of the model but it doesn't need any initial configuration by the user because all the operations that calculate the intensity of emotions are predefined and described in section 5.1.

The Figure 12 shows the process of the emotional component which receives the event and the information of the object involved as the input. First, the character goals affected by the event are identified and the event expectation is increased. Next, the rules manager of the fuzzy component generates the variables of impact and importance of the goals based on the acceptance degree of the event, the goals weight and the importance of the object. Then, they are *fuzzified* in order to process the rules and obtain the fuzzy set of desirability, which is immediately *defuzzified* to use a crisp value and calculate the emotional equations of the section 5.1.2. In this way, we get the most basic emotional state that this model can simulate.

Finally, the decay of emotions continues as time goes by. In this model, it has been decided that the intensities decay every second during the simulation. Unity provides the static variable *Delta.Time* that takes the time in seconds that it takes to complete a frame. So every second the emotions intensities will decrease using decay constants for positive and negative emotions (section 5.1.4).

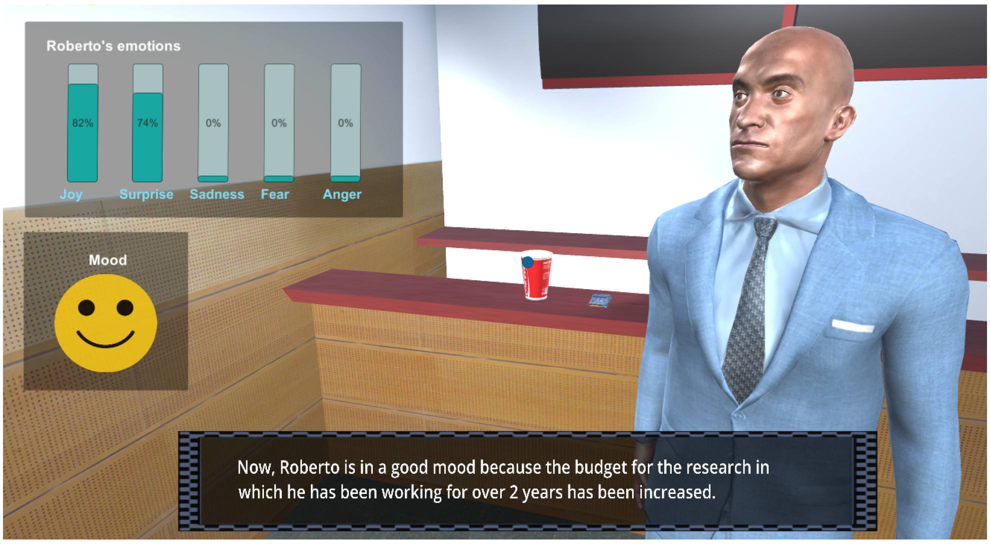



Figure 13: Depiction of the character's emotions and mood

## 6.4 Mood component

The model of characters can add the mood component to make the emotion simulation process more complex. The incorporation of the mood is optional to allow the user to decide if he only uses the emotional equations or combines both components to get a more realistic emotional state.

To carry out this task, the model allows the use of configuration files in a markup language so standardized and easy to use for anyone, such as XML. In this way, the user can easily decide if he incorporates this feature through the configuration described in the corresponding files.

There are many ways to parse an XML file but in Unity but the most practical one is to use the *XMLSerializer* library, available with languages such as C#, .Net and Javascript. This library allows reading operations of XML annotations and communicates to the container how the file should be parsed.

### 6.4.1 Monitoring of emotional intensities

Once the configuration is established and as soon as the system execution begins, it will be loaded together with the environment data (goals of each character, objects and possible events). From that moment, the mood will begin to store the most recent emotional states to calculate the difference between positive and negative emotions. The continuous update of the intensities causes that the simulation of emotions is always conditioned by the


Figure 14: Depiction of the character's emotions, mood and personality

mood. To avoid this problem, we use a margin of error between the positive and negative emotions in which the mood doesn't perform. It has been taken a tolerance value of 10%, because of its good results during the simulation.

The section 5.2.1 explained the importance of choosing the right number of time windows to capture the intensities of emotions. The value that gave the best results in Unity was 15, so it was used as the maximum number of windows.

Finally, we implemented the short-term memory as an extension of the mood. After the calculation of the new emotions and applying the filtering, the short-term memory is responsible for requesting the last emotional state and combine it with the old intensities according to the equations of the section 5.2.3. And this is the last step to achieve the final emotional state of mood processing.

## 6.5 Personality component

The personality is treated as a component that stores the personality traits of an agent. These features are predefined by the user through XML files before the simulation starts and last until the end of it. The input data received by the personality component are the intensities generated by the emotional equations or, if the mood is enabled, those obtained after this phase. The output is the emotional state that combines personality traits with emotions.

The incorporation of the personality to the behavior of a character is optional, as it was with the mood. En case of adding it, again the modeling of emotions would be even more complex because the results will be much more coherent than they were until now.

The personality of an agent is immutable, so from the initial charge, the character has the same value for each trait of the Big Five until the end of the execution. Each of them serves as a factor to increase or decrease the intensities of the mood processing, multiplying the factor by the intensities. Its increase or decrease addresses the descriptions in the Table 6 and varies from 15% to 30% as it is explained in the personality traits mapping (Section 5.3.1). And this is the last step of the simulation of emotions in the most complete way, combining emotions with mood and personality.

# 7 Conclusions

Our research on computational models and psychological theories of emotion culminated in the adoption of the FLAME computational model as a basis for the process of generating emotions. It was chosen mainly for its model of emotions based on fuzzy logic techniques, but its processing remains stuck when combined with the concept of mood, since the underlying model continues to respond independently to events. In this chapter, a model of emotion simulation for virtual characters has been described, using fuzzy logic for emotion simulation and incorporating new elements to enrich it with mood and personality traits.

The mood solves the problems some models have when a character forgets what has happened immediately before. It also adds new features to improve the emotional state of the output. Regarding personality traits, we have chosen to rely on the model that has become a psychological standard: the *Big Five*. *The Model of the Big Five* addresses the personality from the five-dimensional point of view and the descriptions of the emotions that were used to formulate an approach to the human personality.

Once the theoretical design of the model was established, we have integrated it into humanoid characters within a virtual environment created in Unity 3D. It has been implemented mainly by separating the emotional, personality and mood components, so that different combinations can be made, separating the personality or mood from the emotion generation process.

After performing some tests to check how the system behaved in Unity 3D, both expert and inexperienced users were asked to perform evaluations to check the realism of the model and assess the coherence of the generated emotions. Given the results of the evaluation, it is worth to mention that if the mood and personality had not been implemented, the results obtained would have been much worse than expected.

In the current implementation, it is still pending to show the resulting emotions both in the facial expression and the body posture of the characters, to better reflect in the 3D environment what the emotional state of the characters is.

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