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A new approach to modeling emotions and their use on a decision making system for artif cial agents

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Abstract—In this paper, a new approach to the generation and the role of artif cial emotions in the decision making process of autonomous agents (physical and virtual) is presented. The proposed decision making system is biologically inspired and it is based on drives, motivations, and emotions. The agent has certain needs or drives, that must be within a certain range, and motivations are understood as what moves the agent to satisfy a drive. Considering that the wellbeing of the agent is a function of its drives, the goal of the agent is to optimize it. Currently, the implemented artif cial emotions are happiness, sadness, and fear.

The novelties of our approach are, on one hand, that the generation method and the role of each of the artif cial emotions are not def ned as a whole, as most authors do. Each artif cial emotion is treated separately. On the other hand, in the proposed system it is not mandatory to predef ne neither the situations that must release any artif cial emotion nor the actions that must be executed in each case. Both, the emotional releaser and the actions, can be learnt by the agent, as happens in some occasions in nature, based on its own experience.

In order to test the decision making process, it has been implemented on virtual agents (software entities) living in a simple virtual environment. The results presented in this paper correspond to the implementation of the decision making system on an agent whose main goal is to learn from scratch how to behave in order to maximize its wellbeing, by satisfying its drives or needs. The learning process, as shown by the experiments, produces very natural results. The usefulness of the artif cial emotions in the decision making system is proved by making the same experiments with and without artif cial emotions, and then comparing the performance of the agent.

Index Terms—Artif cial emotions, decision making system, motivations, autonomy, learning.

1 Introduction

According to LeDoux [1], at the beginning of the Sixties, the artificial intelligence precursor Herbert Simon was convinced that including emotions in cognitive models was necessary to approximate the human mind. But only in recent years the well known emotional intelligence has been taken into account as an essential factor to understand and evaluate the human behaviour. Moreover, some researchers have realized the importance of emotions in intelligent thinking and behaviours [2] [3] [4]. Several studies have shown that emotions have influence on many cognitive mechanisms, such as memory, attention, perception, and reasoning [5] [6]. Besides, emotions play a very important role in survival, social interaction, and learning of new behaviours [7].

Based on these evidences, some researchers in artificial intelligence and robotics have concluded that emotions, or at least some emotionally inspired features (artificial emotions), are essential in their systems in order to improve their functionality (e.g. [8] [9] [10] [11] [4]).

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Rosalind Picard in [5] expounds some reasons for giving certain emotional abilities to machines: the first goal is to build robots and synthetic characters that can emulate living humans and animals; the second is to make machines that are intelligent; a third objective is to try to understand human emotions by modeling them. In our work we are interested in all of these goals. First, we are trying to develop social robots, whose main objective is the interaction with humans. In many social robots, human-robot interaction can be improved if the humans perceive the robot as a living being. Second, we are trying to develop intelligent autonomous robots and we think that the inclusion of artificial emotions can help us do so. And third, we are also interested in the use of robots as research platforms that could help us understand the psychological mechanisms of humans and animals.

To reach these three goals we think that a bio-inspired approach is necessary. There are some robots able to show emotions, but the internal mechanisms that control those emotions are fully different from the mechanisms in humans and animals. Many researchers in robotics have used emotions just to get the first (e.g. Aibo by Sony) or the second goal (e.g. Gadanho [8]) proposed by Picard. In order to do that, they have developed ad-hoc solutions adapted to specific problems. In our approach, we are interested not only in the behaviour of the robot, but also in the underlying mechanisms, trying to emulate natural ones for the robot, when possible.

The main goal of our research is to construct an autonomous and social robot. We have already developed a robotic platform called Maggie at the Carlos III University of Madrid, Spain. This robot has some social skills, e.g. playing games with the user, visual recognition capabilities, and speech dialogs [12].

The decision making system designed for this robot is based on a motivational system, and some artificial emotions have been included. Each of them have different appraisal mechanisms that release them and different roles. Before the implementation of this decision making system on the physical platform, and as a previous step, this work has been carried out using virtual autonomous agents, understood as software entities. The results presented in this paper correspond to this implementation and will prove that the agent, with our decision making system, performs better with the artificial emotions than without them.

This paper is organized as follows. Section 2 presents a brief reflection about whether robots need emotions. Later, the approach proposed in this paper is explained in section 3. Next, a review of some works related to this research topic is given in section 4. In section 5, a general description of our current framework is presented. In this section, the definition of some basic concepts such as drives and motivations is given, and the model (the appraisal process and the role) of each artificial emotion implemented is explained. Section 6 describes the implementation of the decision making system on the virtual agent in order to test it. The next section, section 7, presents the results of the experiments made in order to prove the usefulness of the artificial emotions in the decision making system. Finally, the main conclusions of this paper and future works are summarized in section 8.

2 Do robots need emotions?

This is probably, or at least it should be, the first question that many researchers have asked themselves when they first tried to include artificial emotions in their systems.

As stated in section 1, there are some authors who think that the inclusion of emotional features in machines will improve their intelligence, and their interaction with humans [13] [5]. Moreover, Michaud et al [9] found that there are psychological evidences that suggest that emotions can serve three important roles in designing autonomous robots: emotions to adapt to limitations, emotions to manage social behaviour, and emotions for interpersonal communication.

Arkin also considers the importance of artificial emotions for machines (robots in this case), besides their importance in human-robot interaction [11].

According to Arkin and Michaud, artificial emotions are essential for autonomy as well as for human-robot interaction. Moreover, in [4], Kelley states: "Emotions are necessary for the survival of the individual and the species. Therefore, all organisms on earth need emotional systems... Thus, a robot designed to survive in the world ... would require an equivalent system, one that instills urgency to its actions and decisions".

In this same line, Cañamero [10], Bellman [14], and Ortony [15], consider that robots need artificial emotions for the same reason that humans and animals need emotions: because they help them confront their environment. Besides, emotions are a requisite for establishing long term memories and providing opportunities for learning, from simple forms of reinforcement learning to complex planning.

Fellows [16] also defends that, since animals have emotions in a functional way, robots could be provided with features functionally related to emotions. He also mention that the emotions that could be implemented on robots must not be called emotions but "robot-emotions", since they are just an imitation of the functionality of human and animal emotions.

In relation to this same point, Sloman [3] thinks that we must distinguish among adult emotions, animal emotions, robot emotions, etc. Moreover, Sloman et al in [17] state that, first, the designer must define the set of requirements to be satisfied by the robot task and its environment. Then, depending on these requirements, the sorts of emotions that are possible (or desirable) for the robot will be determined.

Finally, Cañamero considers an interesting idea: "the inclusion of emotional elements in the architecture of our robots does not make them more valuable per se. On the contrary, we must be able to show accurately and precisely that (or rather whether) our results allow us to conclude that emotions improved the performance or the interaction capabilities of our robot and how. An obvious way of doing this is by running control experiments in which the robot performs the same task "with" and "without" emotions and comparing the results" [18].

This same idea is shared by Scheutz in [19], where he presents a method to evaluate the utility of emotion for the control of artificial agents. He introduces an agent model for virtual and robotic agents that is capable of implementing emotional states, and compares the utility of its emotional control mechanism in an evolutionary survival task to other agents that do not use emotional control.

Based on these ideas, in this paper we will prove the usefulness of our model of artificial emotions in the decision making system, by comparing the results obtained with and without them.

3 OUR APPROACH

The proposed decision making system is based on drives (needs), motivations, artificial emotions, and the possibility of learning the right selection of actions. The goal is the maximization of the wellbeing of the agent, that is defined as a function of its drives. Therefore, following a homeostatic approach, the decision making process is oriented to satisfy these drives maintaining an internal equilibrium. As will be explained later, motivations can be viewed as what moves an agent to behave in a way that satisfies a certain need. In other approaches, as shown in section 4, these behaviours are previously linked with the need that must be satisfied, and they are called motivational behaviours. Nevertheless, in our approach, the behaviours are not necessarily previously motivated and the agent can learn, using a reinforcement learning algorithm, the right action to execute in every situation presented by the environment. In relation to the emotional reactions, we could give the agent the information about what to do in certain emotional states. This would be equivalent to say that these reactions, or action tendencies, are innate. Nevertheless, although this is true in some occasions, e.g. to smile when happy, in nature, for example, not everybody has the same fear reaction, some people run away, others hide, others get petrified, etc. In our approach, the agent could learn the action tendencies related to a certain emotion.

The reinforcement learning algorithm used in the implementation presented in this paper is the well-known Q-learning algorithm [20]. Using this algorithm, the agent learns the value of every action in every possible state. Therefore, a high value will mean that this action is well suited for that certain state. The learning process can be carried out from scratch, that is, the initial values, the q-values, are equal to zero. On the other hand, the agent can have some initial knowledge and, in this case, those initial q-values can be different from zero. This second option will reflect some inherited or innate knowledge about what to do in some situations, as happens in real life. In nature, many living beings are born with some inherited knowledge related to its survival, e.g. to eat when hungry, or to run away in presence of a big and angry animal. Nevertheless, there may be another knowledge that must be learnt during the life-span depending on the particular environment, e.g. how to behave in a social community.

The results presented in this paper correspond to an implementation in the virtual environment where no previous knowledge is assumed, so all the initial q-values are equal to zero and will be updated during the learning process. This experiment is made in this way in order to test the proposed implementation of the decision making process and we assume that its validity is proved based on the similarity of the learnt behaviours with the natural ones.

It is important to highlight that, in general implementations, this learning process is optional. This means that, for example, when implementing this decision making system on a social robot, we can decide to give it all the needed information, so the learning is not necessary. On the other hand, we can decide to give the social robot some initial knowledge related, for example, to recharging the batteries, and then let the robot learn other information, for example, the policy of behaviour related to human-robot interaction.

In the experiments presented in this paper, we focus our study on just three artificial emotions: fear, happiness, and sadness. These are adequate and useful for the complexity that the experiment can afford, as is suggested by Cañamero in [21]: "Do not put more emotion in your system than what is required by the complexity of the system-environment interaction". What is expected is that, when the decision making system is implemented on the real robot, the system will become much more complex. Then, new emotions will probably need to be included and maybe others must be re-defined.

In relation to the generation of the artificial emotions, most of the related works, as will be shown in the next section, have a releaser event, or a predefined situation that, in case of happening, triggers a certain emotion. We think that predefining just a finite set of emotional releasers, or events, makes the whole idea less natural. Although in nature there are some innate, or natural releasers, we think that others are learnt by the individual through its own experience.

In the presented experiments, the releasers are not related to predefined events. The agent is able to appraise its environment and, as a consequence, an artificial emotion is released. For example, in the case of happiness and sadness, they are released depending on the resulting variation of the wellbeing of the agent, whatever situation caused that. In relation to fear, using an appraisal mechanism, the agent will learn to identify the dangerous situation that is able to release it.

Using the proposed generation method of artificial emotions, the agent will be able to appraise its environment and release them in the presence of new situations or events without the necessity of pre-defining them. For example, a real robot would be able to release fear in front of a new emerging dangerous situation even if this event was not identified by the designer in advance. Again, in the general case, those releasers can also be pre-wired by the designer, converting them into innate releasers. For example, in the real implementation on Maggie (our real robot) we could establish some situations as innate releasers for fear, e.g. the detection of a downwards staircase, or entering a dark room.

Finally, in relation to the role of the artificial emotions in the decision making system, the role of happiness and sadness is to be used as the reinforcement function in the learning process. On the other hand, the role of fear will be to motivate the right behaviour in order to avoid a dangerous situation. This is, in fact, the unique role of fear according to Breazeal and Brooks [22]. As already stated, in the experiments presented, this emotional reaction will also be learnt by the agent and will be compared with the one expected from a living-being in order to show the validity of our approach.

4 Related work

4.1 Generating artif cial emotions: The appraisal method

Currently, most experts agree that natural emotions are produced by an appraisal of the situation of the agent in its relation with the world. This appraisal is conceived as a constituting element of emotion generation, mediating between events and emotions, explaining why the same event can give rise to different emotions in different individuals, or even in the same individual (usually at different times) [23]. Ortony in [15] gives a good example of this theory: members of the winning and losing teams in a football match have different emotional reactions from the same objective event.

In relation to the generation of artificial emotions, there are two main approaches: the emotional affective space model and the discrete model.

4.1.1 The affective space model

Many researchers think that the relation between situations and emotions is mediated by a set of intermediate variables. These variables act as dimensions of an affective space and each emotion is associated to a different zone of that space. For example, Breazeal follows this approach in her work with social robots [22]. She uses three dimensions, arousal, valence, and stance, to appraise nine artificial emotions. The precipitating event of an emotion is affectively appraised by labeling it with affective tags (arousal, valence, and stance). In addition, the drives (how well they are being satisfied) and the progress towards achieving the desired goal can also influence the robot's emotive state. For example, the success in achieving the goal of the behaviour is an antecedent condition for eliciting happiness, for fear is the presence of a threatening stimulus, etc.

Other authors such as Hollinger et al [24] also use an affective space to determine artificial emotions (12 in this case) for a social robot. In that case, the affective space is based on the Mehrabian PAD scale, where the axes represent pleasure, arousal, and dominance. In this approach, the emotion state of the robot varies according to its interaction with people. In fact, the emotional releasers are related to different color shirts, and each color has a certain coordinate in the PAD scale. This PAD scale is also used by Qingji et al [25] to develop a robot emotion generation mechanism. In this work, certain external events will produce variations in each dimension. For example, a person coming produces positive variations in every dimension, or if there is no human interaction for a long time, then the three dimensions of emotion decrease.

4.1.2 The discrete model

In relation to the discrete model, Lazarus [26] considers that the growing importance of cognitive-mediational or value-expectancy approaches to mind and behavior in social sciences has generated a renewed interest in emotions as discrete categories. This contrasts with the position that views emotions as a limited set of dimensions. In the discrete emotional approach, dimensions of emotional intensity are still used, but these are applied within each emotional category. In contrast, the dimensional approach minimizes the importance of distinctions among emotions because it is based on a factor-analytic search for the minimal number of emotional dimensions that account for the maximum emotional variation.

This discrete approach is followed by several authors. Cañamero [27] implements a set of artificial emotions (anger, boredom, fear, happiness, interest, and sadness) in her works with autonomous robots that can be activated as a result of the interactions of the robot with the world. In fact, these artificial emotions become active depending on different events, for example: anger becomes active when the goal of the agent is not finish, fear appears in the presence of enemies, etc.

Another example is the work carried out by Gadanho [8]. These implemented artificial emotions (happiness, fear, sadness, and anger) have some features such as having valence, coloring perception, etc. Moreover, the generation of the emotional state is related to certain related events. In this case, for example, the robot will be sad if it has a very low battery level, it will be afraid if it hits the wall, etc.

Velásquez [28] also proposes an emotion-based control for autonomous robots. In his work six emotions are identified (anger, fear, sorrow, happiness, disgust, and surprise). He considers natural (or innate) releasers and he also included the capacity of acquiring learned releasers. The natural releasers are, for example in the case of fear, situations in which its sensory systems would not work properly (dark environments) and the detection of archetypal predators. The learnt releasers correspond to the stimuli that they tend to be associated with and predictive of the occurrence of natural releasers.

Another approach is presented by Murphy et al in [29], where an emotion-based control for multi-agent systems is proposed. In their approach, the artificial emotions "provide the ongoing monitoring function and from that monitoring, emotional states are generated". The implemented artificial emotions are: happy, confident, concerned, and frustrated. Each of these artificial emotions is released depending on the task progress. In [9] [30], Michaud et al present a similar approach to artificial emotions in the sense that they also consider that emotions monitor the accomplishment of the goals, and these goals are represented using motives. The emotional model is a 2D bipolar model with four emotions, Joy/Sadness and Anger/Fear, each emotion defined from 0 to 100 percent. Joy/Sadness monitors a decrease or increase in the motives energy level, indicating the presence or absence of progress toward accomplishing the goal associated with activated motives. Anger/Fear examines oscillations or constancy in the energy level, indicating difficulty or not progress toward goals.

4.2 The role of the artif cial emotions

There are several points of view in relation to the functionality of the implemented emotions in the decision making systems of agents. Which role must they have? How do they influence the decision making process?

Some researchers implement artificial emotions in their systems in order to improve the human-robot interaction. This is the case, for example, of Breazeal [7] [22], whose work is oriented to this issue in social robots. Apart from the external expression of emotions, they are able to elicit an adaptive behavioural response that serves either social or self-maintenance functions. In this model, each artificial emotion has an observable response. This work proved that the interaction with the robot is more intuitive, natural and enjoyable for the person.

In this same line, Hollinger et al [24] prove the usefulness of emotional modeling to improve the human-robot interaction, but in a much simpler way than Breazeal. In this work, the robot state is translated into a particular set of sound and movement responses.

In other cases, the main role of the artificial emotions is not focused on the improvement of the human-robot interaction but on how these emotions affect the decision making system of an autonomous robot.

In the case of Velásquez [31] [28], he was one of the first researchers in considering an emotion-based decision making system for autonomous robots. In this approach, emotions play a much larger role than just that of facilitating emotional expression. They are able to activate different behaviours, facilitate attention, establish appropriate emotional expressions useful for social interactions, and finally, they provide the means by which the robot can learn from past emotional experiences and modify its behaviour accordingly.

Another approach is presented in the works carried out by Cañamero [27] [10] [18], where the implemented artificial emotions work as monitoring mechanisms to cope with important situations related to survival. In these works, the decision making process is based on a motivational system. The motivation with the highest value will organize the behaviour of the agent in order to satisfy its related internal need (motivational behaviour). The artificial emotions in this approach influence the decision making process in two ways. First, by modifying the intensity of the current motivation and, as a consequence, the intensity of the behaviour. Second, by altering the perception of the body state.

Other authors have also used emotions as monitoring systems, such as Murphy et al [29]. Nevertheless, in their approach emotions monitor the ongoing task (not the environment, as Cañamero) and they also influence the decision making process by allowing the robot to adapt its behaviour and to select new ones in order to fulfill the overall mission. In this approach, each artificial emotion is associated with action tendencies. For example, if the robot is "frustrated", it will change the current strategy; if it is "confident", it will continue the normal activity, etc.

Michaud et al [9] [30] also implemented artificial emotions to monitor the accomplishment of the goals and the overall states of the agent, as Murphy [29]. In their EMIB control architecture, emotions are not represented explicitly but they are represented as a background state, allowing them to affect and to be affected by all the modules of the architecture. Therefore, for example, they can adapt the way the agent responds to stimuli or express emotional states; influence behaviours by changing some of their parameters; associate the state of the agent with particular event; affect the goal of the agent via its motives.

Other approaches take advantage of some functions attributed to emotions in human behaviour and try to implement them in their systems in order to improve the behaviour of an autonomous robot. This is the case of the work presented by Gadanho [8], where the artificial emotions influence the decision making process in two different ways. In this approach the robot adapts to its environment using a reinforcement learning algorithm. According to the authors, since it is frequently assumed that the human decision making process consists on maximizing the positive emotions and minimizing the negative ones [6], the reinforcement function was designed in such a way that it extracts the value of the judgement of the emotional system by considering the intensity of the dominant emotion, and if it is positive or negative. On the other hand, emotions have a role related to behaviour interruption processes in order to deal with new and unexpected situations (as Sloman proposed [17]). Gadanho takes this role as an inspiration to explore its utility on determining the state transitions in the reinforcement learning system.

4.3 Main differences with our approach

There are many other approaches than the ones described in the previous sections, but these are the ones that have mainly inspired our research. In this section we state the main differences between our approach and the ones already presented.

Firstly, in our work we follow a discrete emotional approach and we consider, as Lazarus, that in many occasions appraisal occurs in a holistic fashion, and it is based on theme evaluation rather than on analytical processing using evaluation dimensions.

The design of the decision making system has been inspired mainly by Cañamero's, Gadanho's, and Breazeal's (and therefore Velásquez's) works. All of them use drives, motivations, and emotions in order to select the behaviours. This approach is perhaps more similar to the ones proposed by Cañamero and Breazeal in relation to the modeling of motivations, with the main difference that we do not have necessarily any related behaviour that satisfies the associated need (motivational behaviours).

Regarding the implementation of artificial emotions, the approach proposed in this paper is different from the ones presented in this section in relation to the following points:

Each artificial emotion is treated separately, they are not introduced in the system as a whole entity, as in other approaches. We think that the relation between situations and emotions is specific for each emotion, and each emotion requires a particular study to establish this relationship. Moreover, the role of each artificial emotion in the decision making system is different, as well as the emotional reaction, that could be learnt.

Happiness and sadness are defined as the positive or negative variation of the wellbeing. This definition could remind of the idea proposed by Murphy and Michaud, who implemented the notion of emotion as a monitoring progress toward goals. Nevertheless, in our approach, the information given by these increments is not related to the fulfillment of a certain task, but to the overall performance of the agent.

The role of happiness and sadness as the reinforcement function in the learning process was inspired by Gadanho´s works. Nevertheless, Gadanho did not obtain good results using this reinforcement [8]. Our approach differs from Gadanho's in the generation of the artificial emotions, since they are related to pre-defined events and they did not provide useful information for the reinforcement function.

The novelty related to the artificial emotion Fear is based on the appraisal mechanism introduced. This mechanism, as will be explained later, allows the agent to learn to identify a new emerging dangerous situation, unknown by it, by considering the worst experiences in the learning process. Although Velásquez also proposed a method to learn emotional releasers, the mechanism requires the previous definition of a natural releaser. For example, as explained in [31], the presence of a natural releaser (being punished) causes the fear emotional system to become active, and the other present stimulus (being in presence of a person) is then associated to fear as a new learnt releaser.

Finally, another novelty of our approach is the possibility of learning the emotional reactions. More specifically, the agent is able to learn to avoid a dangerous situation by generating a scape behaviour not previously programmed.

In general, the advantage of our decision making system is the implementation of artificial emotions in conjunction with the learning process. This combination makes the system more flexible since it does not need to be provided of previous information about emotional releasers or reactions.

5 Current Framework: The Decision Making System

As said in section 3, the agent has certain internal needs, or drives, and motivations. The goal of the decision making system of the agent is to survive, maintaining all its needs within acceptable ranges. The general idea of this decision making system is shown in figure 1.

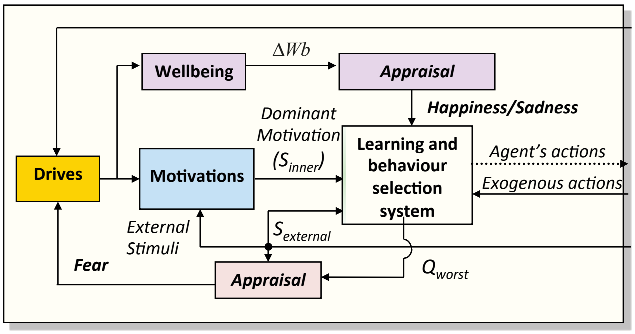

Fig. 1. The decision making system

5.1 Drives, motivations and wellbeing of the agent

The internal state of the agent can be parameterized by several variables, which must be around an ideal level. When the value of these variables differs from the ideal one, an error signal occurs: the drive. Therefore, the drives can be seen as the internal needs of the agent.

The word motivation indicates the dynamic root of behaviour, which means those internal, rather than external factors, that urge the organism to action [32].

The motivational states represent tendencies to behave in particular ways as a consequence of internal (drives) and external (incentive stimuli) factors [27]. In other words, the motivational state is a tendency to correct the error, the drive, through the execution of behaviours.

In order to model the motivations of the agent, we used Lorentz's hydraulic model of motivation as an inspiration [33]. Other authors [22] [34] have also used this approach to model motivations. In Lorenz's model, the internal drive strength interacts with the external stimulus strength. If the drive is low, then a strong stimulus is needed to trigger a motivated behaviour. If the drive is high, then a mild stimulus is sufficient [35]. This approach explains the fact that we do not always eat because we are hungry (the drive) but because we like the food (external stimulus) we have in front of us. Therefore, the intensities of the motivations are calculated as follows:

$$\begin{array}{l} \text{If } D_i < L_d \text{ then } M_i = 0 \\ \text{If } D_i \geq L_d \text{ then } M_i = D_i + w_i \end{array} \tag{1}$$

where M_i are the motivations, D_i are the related drives, w_i are the related external stimuli, and L_d is called the activation level.

On the other hand, the wellbeing of the agent is defined as the degree of need satisfaction. Therefore, when all the drives of the agent are satisfied, their values are zero and the wellbeing is maximum.

$$Wb = Wb_{ideal} - \sum_i \alpha_i \cdot D_i \tag{2}$$

where α_i are ponder factors that determine the weight or importance of each drive on the wellbeing of the agent, and Wb_{ideal} is the ideal value of the wellbeing of the agent.

By varying the values of α_i, the behaviour of the agent may be different. As will be explained later, the agent uses the variations of the wellbeing as the reinforcement function in the learning process. Therefore, if one of the drives has a high α_i, then a big reinforcement is expected when this drive is satisfied. For example, if the α_i related to a possible social need is higher than the rest of needs, then the agent will be more sociable.

5.2 The learning process

As already stated, the reinforcement learning method used in the experiment presented in this paper is the Q-learning algorithm [20]. Its goal is to estimate the $Q(s,a)$ values. The $Q(s,a)$ value is the expected reward for executing action a in state s and then following the optimal policy from there. Every $Q(s,a)$ is updated according to:

$$Q(s,a) = (1-\beta) \cdot Q(s,a) + \beta \cdot (r + \gamma V(s')) \tag{3}$$

where $V(s') = \max_{a \in A} (Q(s',a))$ is the value of the new state s' and is the best reward the agent can expect from s'. A is the set of actions, a is every action, r is the reinforcement, γ is the discount factor, and β is the learning rate.

Another important feature of this current implementation is that the agent knows the actions that can be executed with every object, but it does not know the model of its environment. This means that the agent knows neither the consequences of executing an action (the next state) nor the reward that will be received. Therefore, the agent must learn the right policy of behaviour using a model-free approach.

In this system, the state $s \epsilon S$ of the agent is the combination of its inner state, S_{inner}, and its external state, $S_{external}$: $S = S_{inner} \times S_{external}$ where S is the set of states of the agent, S_{inner} is the set of inner states of the agent, and $S_{external}$ is the set of external states of the agent.

Once the intensity for every motivation is calculated using (1), these compete among each other to be the dominant one. The one with the highest value will be the dominant motivation and will determine the inner state of the agent. According to (1), a situation where none of the drives has a value higher than the activation level L_d can occur and therefore, all of the intensities of the motivations are equal to zero. In that case, there is no dominant motivation and it can be considered that the agent has no needs, it is "OK".

On the other hand, the external state is the state of the agent in relation to all the objects that the agent can interact with: $S_{external} = S_{obj_1} \times S_{obj_2} ...$ where S_{obj_i} is the set of states of the agent in relation to object i.

In a previous work [36], it was decided that in order to reduce the complexity of the learning process, the states related to the objects are treated as being independent from each other. Therefore, the agent learns how to behave in relation to every object separately. This implies that the nomenclature of Q values changes to $Q^{obj_i}(s,a)$. The super-index obj_i specifies the object that the agent is dealing with, $a \in A_{obj_i}$, A_{obj_i} being the set of actions related to object i and s the state of the agent in relation to object i.

5.3 Appraisal processes

As introduced in section 4, we think that emotions are elicited from the subjective appraisal of the environment of the agent. Moreover, we follow a discrete approach for generating our artificial emotions (happiness, sadness, and fear).

Many psychologists have proposed schemes for representing the conditions under which emotions are elicited. Ortony proposed a great simplification of the OCC model [37] for building believable artifacts in [15]. This complete model was reduced to a set of five positive reactions and five negative ones. Ortony assumed that these categories have enough generative capacity to endow any affective agent with the potential for a rich and varied emotional life. In our work, we take the ones involved in the presented experiment into consideration.

5.3.1 Appraisal in happiness and sadness

According to the reduced model of Ortony, happiness occurs because something good happens to the agent (positive reaction) and sadness appears when something bad happens (negative reaction). In our system, happiness can be related to a reduction of a need (e.g. a positive reaction because the agent eats) and sadness to an increment of a drive (e.g. a negative reaction because the agent was robbed). Taking into account that the wellbeing of the agent is a function of its needs, happiness and sadness are related to the positive and negative variations of the wellbeing (ΔWb):

$$\begin{array}{l} \text{If } \Delta Wb > 0 \Rightarrow \text{Happiness} \\ \text{If } \Delta Wb < 0 \Rightarrow \text{Sadness} \end{array} \quad (4)$$

It is important to note that low wellbeing does not imply sadness as well as high wellbeing does not implies happiness. These emotions are related to increments or decrements of the wellbeing (positive and negative reactions). This means that, for example, a good news when one is hungry or tired would imply happiness. The intensity of these emotions is proportional to the variation suffered by the wellbeing.

Using this approach, we think that we are able to consider every event or situation that produces a positive or negative appraisal of the environment (internal and external) of the agent. Again, there is not a fixed set of situations that elicits happiness or sadness. This approach, in our opinion, seems more similar to the natural one.

5.3.2 Appraisal in Fear

According to Ortony [15], fear is a negative reaction related with the possibility of something bad happening. In our approach, the possibility of something bad happening means that the wellbeing of the agent may decrease (a need may be increased).

Fear is normally associated with avoiding dangerous situations. Those situations could be considered as situations were something bad could happen to the agent, but it does not have any control over it.

An example would be the following: if we are walking on the street and we meet someone that kicks us for no reason, we do not have any control over that action. The received punishment is not due to any of our actions, but this depends on the other person. The result is that at the end, we will be afraid of being next to that person, since it may hit us.

In our approach fear will appear when the agent is in this kind of situation that can be considered as "dangerous". This means that the appraisal of this situation is the elicitor of the Fear emotion.

An "exogenous" action is the one that it is not executed by the agent, but by another object from its environment. These actions affect to the situation of the agent and to the reinforcement received. In order to differentiate the effects from the actions of the agent and the effects from the exogenous actions, our implementation is centered on the specific situation when the agent is "doing nothing". In this case, the assumption is that all the changes experienced by the agent are a consequence of external elements.

For the appraisal of dangerous situations, the worst Q values registered are stored:

$$Q^{obj_i}_{worst}(s,a) = \min(Q^{obj_i}_{worst}(s,a), r + \gamma \cdot V^{obj_i}_{worst}(s')) \quad (5)$$

where $V^{obj_i}_{worst}(s') = \max\limits_{a \in A_{obj_i}} (Q^{obj_i}_{worst}(s',a))$ is the worst value of object i in the new state.

Then, it is considered that the situation is:

$$\begin{array}{l} \text{"Dangerous" if } Q^{obj_i}_{worst}(s, Nothing) < L_{fear} \\ \text{"Safe" if } Q^{obj_i}_{worst}(s, Nothing) \geq L_{fear} \end{array} \quad (6)$$

where L_{fear} is the minimum acceptable value of the worst expected value when the agent is doing nothing.

5.4 The role of the artif cial emotions

As presented in section 4, the functionality of the artificial emotions in agents is quite diverse. In our approach, as already introduced, happiness and sadness are used as the reinforcement function in the learning process, and fear will motivate behaviours oriented towards self-protection.

5.4.1 The role of happiness and sadness

Rolls [6] proposes that emotions are states elicited by reinforcements (rewards or punishments), so our actions are oriented towards obtaining rewards and avoiding punishments. Following this point of view, in this proposed decision making system, happiness and sadness are used as the positive and negative reinforcement functions during the learning process, respectively. As stated in section 4, this is also the role used by Gadanho in her works, although she obtained poor results [8]. Maybe, those bad results were due to the definition used for emotions and to the fact that, according to her definition, they do not really provide a good evaluation of what is going on at any single moment.

5.4.2 The role of fear

In this approach, fear is considered as a motivation. The role of the artificial emotion Fear is inspired by the idea that emotions can also constitute motivational factors and constitute "value systems" that affect the selection of goals and goal-directed behavior [18]. Another point of view is given by Arkin [11], who says that emotions constitute a sub-set of motivations which give support to the survival of an agent in a complex environment.

Moreover, Breazeal [7] also states that emotions are an important motivational system for complex systems. In fact, according to her [22], the unique function of fear is to motivate avoidance or escape from dangerous situations. This response protects the robot from possible harm when faced with a threatening stimulus. This is, in fact, the approach that is followed in our work.

6 Testing the decision making system

In order to test the decision making system represented in the previous section, a very simple virtual world is developed. This virtual environment, created using a text-based role-playing game called CoffeMud, has been extensively described in a previous work [38]. The objects that are present in this world can be classified in: passive, which are not capable of executing actions (food, water, medicine, and the world), and active, which can execute actions (another agent).

All the parameters set in this implementation will shape a specific personality for the agent. Changing these parameters, new personalities will be exhibited by it. The performance with different personalities will be studied in the future.

6.1 Drives and motivations

The considered drives and motivations are the following: Hunger, Thirst, Weakness, Loneliness, and Fear.

These drives and motivations have been selected taking the needs of the agent in the virtual world into account. The Hunger and Thirst drives are related to the consumption of food and water. The Weakness drive is related to the tiredness of the agent due to its movement. Therefore, it is related to the need of recovery (consumption of medicine). The Loneliness drive is the social need included in order to favor the social interaction (to interact with another agent). Finally, Fear is a motivation, but it is also included as a drive just for its inclusion in the wellbeing function, and therefore, for its consideration in the reinforcement. In fact, the Fear motivation has the same value as the drive.

As expressed in equation (1), in order to calculate the value of the rest of motivations, every drive has a related external stimulus, the motivational stimulus. Those stimuli are: food for Hunger, water for Thirst, medicine for Weakness, and another agent for Loneliness. In the presented experiments, the values related to this equation were selected by the designer: the motivational stimuli is $w_i = 1$, and the activation limit of motivations is $L_d = 2$.

Every drive starts with value zero and they vary their values according to different dynamics. The Hunger, Thirst, and Loneliness drives increase their value as the time passes. Moreover, these drives, after being satisfied (their value are zero again), do not start to increase again until a certain amount of time later. This is for reflecting the fact that, for example, after eating one does not feel hungry again until some hours later. We call this time the satisfaction time. In table 1 the increments each drive suffers at each simulation step and their satisfaction times are shown.

TABLE 1
Drives dynamics

Drive	Increment	Satisfaction time
Thirst	+0.1	50
Hunger	+0.08	100
Loneliness	+0.06	150

As is shown, the Thirst drive is more urgent than the Hunger drive (the growing rate of Thirst is higher and it begins to grow again sooner than Hunger). This has been designed this way since, according to physiological studies, one is thirsty more frequently than hungry [39]. The Loneliness drive has been set to be less urgent since it is not a basic need in a general frame.

In the case of the Weakness drive, its variation depends on the movement of the agent:

$$\Delta D_{weakness} = \begin{cases} 0 & if\ the\ agent\ keeps\ still \\ 0.05 & (at\ each\ step)\ if\ the\ agent\ moves \end{cases} \tag{7}$$

Finally, the dynamics of the Fear drive/motivation depends on the appraisal of a dangerous situation:

$$D_{fear} = \begin{cases} 0 & if\ the\ agent\ is\ in\ a\ safe\ situation \\ 5 & if\ the\ agent\ is\ in\ a\ dangerous\ situation \end{cases} \tag{8}$$

As is observed, the value of the Fear drive/motivation when the agent is in a dangerous situation is quite big in comparison with the growing values shown on table 1. This value has been selected to be high for giving the chance for being the dominant motivation when the agent is in this kind of situation.

6.2 Wellbeing

Adapting equation (2) to the selected drives:

$$\begin{aligned} Wb = Wb_{ideal} - (&\alpha_1 D_{hunger} + \alpha_2 D_{thirst} \\ &+ \alpha_3 D_{weakness} + \alpha_4 D_{loneliness} + \alpha_5 D_{fear}) \end{aligned} \tag{9}$$

where $Wb_{ideal} = 100$. In the experiments, all the drives have the same importance and therefore all the ponder factors are equal to each other: $\alpha_i = 1$.

6.3 State of the agent

In this scenario the inner state of the agent, which is determined by the dominant motivation, is defined as: $S_{inner} = \{Hungry, Thirsty, Weak, Alone, Scared, OK\}$.

In relation to the external state, the state related to every passive object, except for the world object, is the combination of three binary variables, so

$S_{obj} = Being\ in\ possession\ of \times Being\ next\ to \times Knowing\ where\ to\ find.$

In relation to the world object, at the moment, the state of the agent according to the world is unique since the agent is always in the world.

Finally, in relation to another agent, the state depends on the value of a binary variable: $S_{agent} = Being\ next\ to$

6.4 Actions of the agent

The sets of actions that the agent can execute, depending on its state in relation to the objects, are the following: $A_{food} = \{Eat,\ Get,\ Go\ to\}$, $A_{water/medicine} = \{Drink\ water/med,\ Get,\ Go\ to\}$, $A_{world} = \{Keep\ still,\ Explore\}$, and $A_{another\ agent} = \{Steal, Give, Greet, Nothing, Kick\}$.

Among all these actions, there are some which cause an increase or decrease of some drives, as shown in table 2, leading to a variation of the wellbeing of the agent.

TABLE 2
Effects of the actions on drives

Action	Drive	Effect
Eat	Hunger	Reduce to zero
Drink water	Thirst	Reduce to zero
Drink medicine	Weakness	Reduce to zero
To be greeted	Loneliness	Reduce to zero
To be stolen	Loneliness	Increase 1
To be given	Loneliness	Reduce to zero
To be kicked	Loneliness	Increase 1
To be kicked	Weakness	Increase 20
Explore/ go to	Weakness	Increase 0.05

As observed, for testing purposes, the punishments received when the agent is robbed or kicked has been selected in such a way that these values are much bigger than the growing rate of these drives shown in table 1.

7 Experimental results

In this section we will prove the usefulness of the model of the artificial emotions proposed. First, we compare the performance of the agent in the same experiment, except we use one of the two reinforcement functions: the wellbeing and happiness/sadness. We will try to prove that the use of these artificial emotions as the reinforcement helps the agent perform better in its environment.

Secondly, we propose an experiment were a dangerous situation can emerge and must be avoided by the agent for its own benefit. We will prove that only if the agent has the mechanisms to appraise this situation and release fear, it will be able to scape and protect itself.

In these experiments, as previously stated, the agent does not have any previous knowledge about what to do in any situation. Therefore, it must learn everything from scratch. The results will also prove that the policies of behaviour learnt are similar to the ones expected in nature, proving the validity of the decision making proposed.

In order to analyze the performance of the agent, we study its wellbeing along the whole experiment. Not only will the average value be considered but also its stability (to guarantee the internal equilibrium). The optimal situation would be that during most part of the experiment the wellbeing is approximately its ideal value ($Wb_{ideal} = 100$).

7.1 Utility of happiness and sadness

Taking the ideas proposed by Rolls [6] into account, we implemented happiness and sadness as the reinforcement function. Nevertheless, we decided to compare the performance of the agent using another reinforcement function in order to prove which one is the best for our implementation. Considering that Gadanho in later works [40] used a wellbeing signal as the reinforcement function obtaining satisfactory results, we decided to take the wellbeing of the agent as the alternative reward. This selection also seems quite reasonable since the wellbeing gives us a good information about the performance of the agent.

In order to compare the performance of the agent using both reinforcement functions, two experiments were carried out fixing the values of the following parameters related to the learning process: the learning rate is $\beta = 0,3$, and the discount factor is $\gamma = 0,8$.

In both experiments, the agent lived alone in the environment so the Loneliness drive was not considered as well as the Fear motivation, whose usefulness will be proved in the next section.

Figure 2(left) shows the wellbeing of the agent while it is using its own wellbeing as the reinforcement. As can be observed, during the whole life of the agent, the wellbeing is continuously varying. According to these results, the conclusion is that the agent does not learn a good policy of behaviour since, although the average value of the wellbeing is 73.9, the range variation is quite large $Wb \in [40, 100]$.

On the other hand, when happiness and sadness are used as the reinforcement function, the wellbeing of the agent is greater than 90 most of the time, $Wb \in [90, 100]$ (see Figure 2(right)). In fact, the average value of the wellbeing is 98.7. These observations imply that the agent learnt a correct policy of behaviour, meaning that the sequence of actions learnt by the agent leads it to satisfy the drive related to the dominant motivation.

As a conclusion, we have showed that happiness and sadness, defined as positive and negative variations of the wellbeing, are a good reinforcement function for learning to behave maximizing the wellbeing. The results showed that using the proposed decision

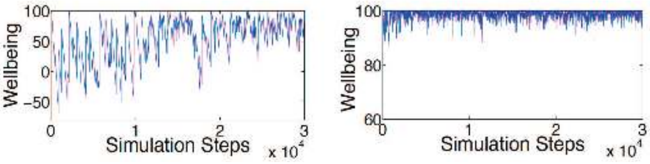

Fig. 2. Wellbeing of the agent when using both reinforcement functions: (left)Wellbeing; (right)Happiness/Sadness

making system, the learnt policies of behaviour are the ones expected in nature, for example, the agent learned that if it is hungry, it must go were the food is, then take it, and finally eat it.

7.2 The utility of fear

In this section, we present the results obtained from two experiments in order to prove the usefulness of the model of the emotion fear in our implementation: the agent with Fear motivation and the agent with no Fear motivation. In these experiments, there is a dangerous situation unknown by the agent in advance. Only if the agent has the capacity of appraising this kind of situation, it will be able to avoid it.

7.2.1 Description of the experiments

In order to carry out these experiments the agent lives with two kinds of opponents:

A neutral agent who randomly selects, with the same probability, among the following actions: $A_{neutral} = \{Greet, Steal, Give\}$

A dangerous agent, who:

95% of the times chooses its actions with the same probability among the following actions: $A_{dangerous_{95\%}} = \{Greet, Give\}$

Meanwhile, the other 5% of the times: $A_{dangerous_{5\%}} = Kick$

Therefore, the dangerous agent is only the one that, very occasionally, kicks the opponent. It seems obvious that the interaction with the second opponent may be dangerous, although the agent, at the beginning of its life, will not be aware of it.

Each experiment consists of two phases: the *learning phase* and the *steady phase*. During the learning phase, the agent starts with all the initial Q values equal to zero. The agent, through its experience in the world, learns and updates its Q values. Once the learning phase has finished, the steady phase starts. In this last phase, the agent “lives” according to the learnt Q values, it exploits the learnt policy of behaviour and stops learning. Therefore, in this steady phase the executed actions are the ones with the highest Q values. The learning phase consists of 25000 simulation steps and the steady phase of 5000 simulation steps.

7.2.2 Results of the agent with Fear as a motivation

In this experiment, the mechanisms to make the appraisal of a dangerous situation described in section 5.3.2 by equation (6) are implemented. In this experiment, the exogenous actions can only be executed by another agent; therefore, the appraisal mechanism is centered on the worst Q value registered while the agent was interacting with another agent and its own action was "doing nothing". Based on previous experiments, the limit introduced in (6) is established as $L_{fear} = -4$.

Figure 3 shows the evolution of the wellbeing of the agent when it has Fear as a motivation. The first observation is that there are some drops, that disappear as the experiment evolve. These drops correspond to the peaks of the weakness drive as is shown in figure 4. As can be observed, those sudden increments are most common at the beginning of the experiment, and it can be appreciated how the number of peaks suddenly decreases in the middle of the learning phase. The magnitude of those peaks is equal or bigger than 20, which is the punishment received when the agent was kicked. This means that at the beginning of the experiment the agent was hurt, but finally, it was able to avoid being kicked.

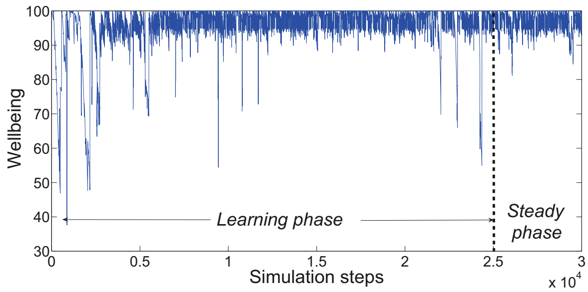

Fig. 3. Wellbeing of the agent with Fear motivation

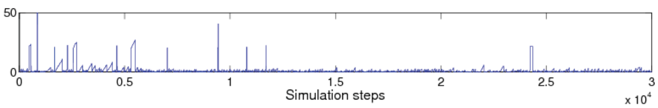

Fig. 4. The Weakness drive with Fear motivation

Therefore, what could be concluded was that the agent was able to identify that being next to the dangerous agent was a dangerous situation, and then it learn to avoid that situation. Moreover, analyzing the results obtained, what was also observed was that the number of interactions with the dangerous agent, during the steady phase, was just four times, while it interacted a total of 376 times with the neutral opponent. Those numbers reinforce the idea that the agent avoided being next to the dangerous agent. Nevertheless, let us now analyze how the appraisal mechanism worked.

First, in order to start with this analysis, the Q_{worst} vectors, which store the worst values related to the interaction with the dangerous and the neutral agents, are shown. Figure 5(left) shows that the worst Q value registered when the agent interacts with the dangerous agent is -20, due to the punishments received when interacting with it. This value is lower than the proposed limit L_{fear}. Therefore, from the moment that this worst value passes the value of the limit, in simulation step 2200 approximately, every time that the agent is next to the dangerous opponent, according to equation (6) this is identified as a dangerous situation, and then the Fear drive increases five units, according to equation (8), as shown in figure 6.

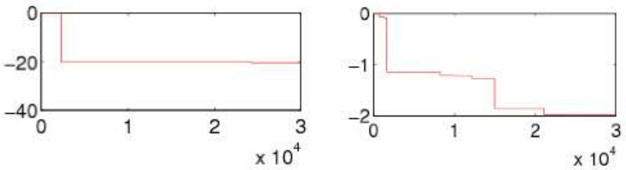

Fig. 5. (left)Q_{worst} values of the dangerous agent; (right)Q_{worst} values of the neutral agent

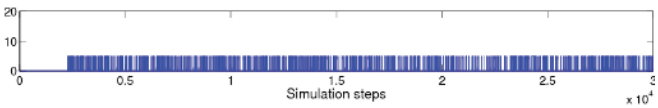

Fig. 6. The Fear drive with Fear motivation

On the other hand, for the neutral agent this value is -2, greater than L_{fear}, see figure 5(right). This means that being next to the neutral agent is a safe situation.

As has been shown, the appraisal mechanism is able to elicit Fear when the agent is in a dangerous situation. Once Fear is elicited, it could become the dominant motivation and then, the agent must learn what to do in those dangerous situations. If this happens, the agent must decide among all the available actions and select the one with the highest Q-value. Again, analyzing the results, the action with the highest value corresponds to a movement related action ("go for food"). Therefore, the agent decides to move away and once it is alone, it is in a safe situation, it will choose the next action to execute. As a conclusion, when the agent is next to the dangerous agent, it prefers to move rather than to interact with it: the agent "runs away" from that situation.

This fact is very important: the agent learns that when it is scared, the appropriate action is to escape. This escape action is not an *a priori* programmed action, the agent just values the movement actions very positively. This is reasonable since, if the agent is scared ($D_{fear} = 5$) and it moves to another room where it is alone, it will not be afraid since it is in a secure situation ($D_{fear} = 0$). This movement action has a positive reinforcement of 5.

In summary, when Fear is introduced as a motivation, the agent learns that when it is next to the dangerous agent, it is in a "dangerous situation", and the emotion Fear is elicited. If Fear becomes the dominant motivation, it prefers to move rather than to interact with it: the agent "runs away" from that situation, which is, in fact, the role of this emotion in our decision making system.

7.2.3 Results of the agent with no Fear motivation

In this second experiment, the agent lives in the same environment, with the same opponents but it does not have the mechanisms to appraise a dangerous situation. The agent will select its own actions based on the Q values learnt through its interaction with the environment. In this case, the wellbeing varies as shown in figure 7.

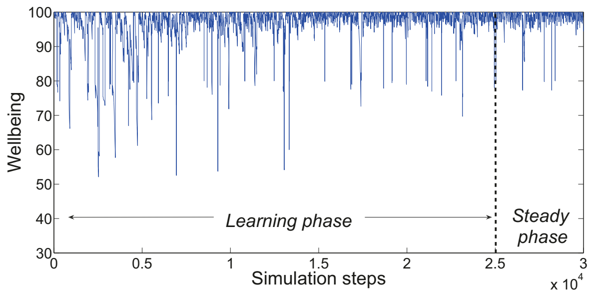

Fig. 7. Wellbeing of the agent with no Fear motivation

As can be observed, there are several drops in its wellbeing along the whole experiment. Again, these drops are due to the number of times that the agent was kicked, and as a consequence, the weakness drive presents many peaks of magnitude 20, see figure 8.

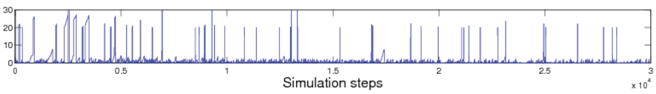

Fig. 8. The Weakness drive with no Fear motivation

This tells us that the agent interacts many times with the dangerous agent although this opponent may sometimes kick it. In fact, during the steady phase, the number of times that the agent interacts with the neutral agent is 326 and with the dangerous one is 214. In comparison with the four times that the agent interacted with the dangerous opponent when it has the Fear emotion implemented, this number is quite high. The reason why the agent interacts with the dangerous agent so many times, although the dangerous agent behaves badly towards the agent occasionally, is that the Q values related to the social interaction are high. This is because the agent uses the Q-learning algorithm for calculating the value of its actions. The consequence is that the Q value of each action during social interaction ponders the number of times that this action caused good and bad results. When the agent interacts with the dangerous opponent, the number of times that this opponent treated it well is much higher than the number of times that this one kicked it (the probability of this happen is 5% of the times). Therefore, it makes sense that the Q values related to the interaction with the dangerous agent are not low. As a consequence, when the agent is next to the dangerous agent, it does not consider the possibility of being hurt and, in many occasions, it decides to interact with it. It is not able to identify the dangerous situation and avoid it.

8 Conclusions and future works

In this paper, a new approach to the model of artificial emotions in autonomous and social agents is presented. These artificial emotions are included in the decision making system of the agent which is based on drives and motivations. The goal of the agent is to behave in order to maintain a certain equilibrium by satisfying its internal needs.

The model of artificial emotions includes the appraisal method as well as their role in the decision making system. This implementation has followed a novel approach in comparison with other approaches related to the use of artificial emotions on robots/virtual agents. On one hand, in our approach, the model of each artificial emotion is different for each of them. This means that there is not a general definition of how the artificial emotions are released and what their role as a whole entity is. Each of them is considered separately. On the other hand, the combination of the implementation of artificial emotions and the learning process allows the agent: to release these artificial emotions when coping with different situations which have not been pre-wired by the designer, and to learn to behave in order to maximize its wellbeing (including the emotional reactions).

In relation to the appraisal methods, the approach presented makes the decision making system more flexible. The designer does not need to decide a fixed set of situations or events that release the artificial emotions in advance. Using the proposed appraisal methods, the agent is able to elicit, for example, fear, to deal with new emerging threats in the environment.

Moreover, in the experiments presented, the agent has to learn how to behave from scratch, therefore, there are not emotional reactions previously linked with the released artificial emotion, nor motivational behaviours. In the general approach, we also said that we could give some previous information to the agent, as an innate knowledge. Nevertheless, this implementation helped us to test the decision making system and the usefulness of the artificial emotions.

One of the main conclusions of this work is obtained from the results of the first experiment: the use of happiness and sadness as the reinforcement function makes the agent learn the right policy of behaviour. The agent is able to survive maintaining its wellbeing within an acceptable range. In fact, the observed behaviour is the one expected in nature. This means that, for every dominant motivation, the agent is able to select the right sequence of actions in order to satisfy the corresponding drive, e.g. to drink water when thirsty, etc.

The second main conclusion is given by the other experiment carried out in this paper. The results prove that only when the agent has the appraisal mechanism to elicit fear, then it is able to identify a dangerous situation. Moreover, it also learns the expected emotional reaction for this artificial emotion: to escape from dangerous situations, which is its main role.

As stated along this work, the validity of these conclusions comes from the fact that the learnt behaviours using the decision making are the ones expected in nature.

Currently, a first and very simple implementation of the decision making system (without artificial emotions) is being carried out on Maggie, the social robot developed in the Carlos III University. The current environment is our laboratory, where different objects are introduced for interacting with Maggie. These objects are a docking station, a TV, and the people who work there. In order to perceive these objects, Maggie uses different sensors, such as laser, RFID tags, and cameras for artificial vision. The new drives are designed taking the social aspect of the robot into account (entertainment need, a social interaction need, and a survival need).

In the next future, we plan to make this environment more complete by introducing new object and actions. Therefore, we must study how our decision making system scales when facing this new environment. In relation to the artificial emotions, as already stated, as the complexity of our system becomes bigger we will consider the implementation of new artificial emotions or even the re-definition of the existing ones. The inclusion of new emotions will probably be based on Ortony's proposal again. Therefore, in the case of, for example, the anger emotion, which is related to a negative reaction related with an other-initiated blameworthy act, could be elicited from another appraisal of the situation of something/someone making the consecution of its goal difficult.

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REFERENCES

[1] J. LeDoux, *El cerebro emocional*. Ariel/Planeta, 1996.
[2] A. Damasio, *Descartes' Error - Emotion, reason and human brain*. Picador, London, 1994.
[3] A. Sloman, *Emotions in Humans and Artifacts*. MIT Press, 2003, ch. How many separately evolved emotional beasties live within us.
[4] A. Kelley, *Who needs emotions? The brain meets the robot*. Oxford University Press, 2004, ch. Neurochemical networks encoding emotion and motivation: an evolutionary perspective.
[5] R. W. Picard, *Emotions in Humans and Artifacts*. MIT Press, 2003, ch. What does it mean for a computer to have emotions?
[6] E. Rolls, *Emotions in Humans and Artifacts*. MIT Press, 2003, ch. Theory of emotion, its functions, and its adaptive value.
[7] C. Breazeal, *Designing Sociable Robots*. The MIT Press, 2002.
[8] S. Gadanho, "Reinforcement learning in autonomous robots: An empirical investigation of the role of emotions," Ph.D. dissertation, University of Edinburgh, 1999.
[9] F. Michaud, P. Pirjanian, J. Audet, and D. Ltourneau, "Artificial emotion and social robotics," *Distributed Autonomous Robotic Systems.Springer Verlag, Hiedelberg, Germany*, pp. 121–130, 2000.
[10] L. Cañamero, *Emotions in Humans and Artifacts*. MIT Press, 2003, ch. Designing emotions for activity selection in autonomous agents.
[11] R. C. Arkin, *Who needs emotions? The brain meets the robots*. Oxford University Press, 2004, ch. Moving up the food chain: Motivation and Emotion in behavior-based robots.
[12] M. A. Salichs, R. Barber, A. M. Khamis, M. Malfaz, J. F. Gorostiza, R. Pacheco, R. Rivas, A. Corrales, and E. Delgado, "Maggie: A robotic platform for human-robot social interaction," in *IEEE International Conference on Robotics, Automation and Mechatronics (RAM 2006). Bangkok. Thailand*, 2006.
[13] M. Minsky, *The Society of Mind*. Simon and Schuster, 1986.
[14] K. L. Bellman, *Emotions in Humans and Artifacts*. MIT Press, 2003, ch. Emotions: Meaningful mappings between the individual and its world.
[15] A. Ortony, *Emotions in Humans and Artifacts*. MIT Press, 2003, ch. On making Believable Emotional Agents Believable, pp. 188–211.
[16] J. Fellows, "From human emotions to robot emotions," AAAI 2004 Spring Symposium on Architectures for Modelling Emotion: Cross- Disciplinary Foundations.SS-04-02. AAAI Press., Tech. Rep., 2004.
[17] A. Sloman, R. Chrisley, and M. Scheutz, *Who needs emotions: The brain meets the machine*. Oxford University Press, 2005, ch. The architectural basis of affective states and processes.
[18] L. Cañamero, "Emotion understanding from the perspective of autonomous robots research," *Neural Networks*, vol. 18, pp. 445–455, 2005.
[19] M. Scheutz, "Useful roles of emotions in artificial agents: a case study from artificial life." in *AAAI 2004*. AAAI press, Menlo Park, 2004, pp. 42–48.
[20] C. J. Watkins, "Models of delayed reinforcement learning," Ph.D. dissertation, Cambridge University, Cambridge, UK, 1989.
[21] D. Cañamero, "Emotions and adaptation in autonomous agents: a design perspective," *Cybernetics and systems: International Journal*, vol. 32, pp. 507–529, 2001.
[22] C. Breazeal and R. Brooks, *Who needs emotions: The brain meets the robot*. MIT Press, 2004, ch. Robot Emotion: A Functional Perspective.
[23] P. Petta, *Emotions in Humans and Artifacts*. MIT Press, 2003, ch. The role of emotions in a tractable architecture for situated cognizers, pp. 251–288.
[24] G. Hollinger, Y. Georgiev, A. Manfredi, B. Maxwell, Z. Pezzementi, and B. Mitchell, "Design of a social mobile robot using emotion-based decision mechanisms," in *Intelligent Robots and Systems, 2006 IEEE/RSJ International Conference on*, 2007, pp. 3093–3098.
[25] G. Qingji, W. Kai, and L. Haijuan, "A robot emotion generation mechanism based on pad emotion space," in *Intelligent Information Processing IV*, ser. IFIP Advances in Information and Communication Technology, Z. Shi, E. Mercier-Laurent, and D. Leake, Eds. Springer Boston, 2008, vol. 288, pp. 138–147.
[26] R. S. Lazarus, *Appraisal processes in emotion: Theory, methods, research*. New York: Oxford University Press, 2001, ch. Relational meaning and discrete emotions, pp. 37–67.
[27] L. Cañamero, "Modeling motivations and emotions as a basis for intelligent behavior," in *First International Symposium on Autonomous Agents (Agents'97), 148-155. New York, NY: The ACM Press.*, 1997.
[28] J. Velásquez, "An emotion-based approach to robotics," in *1999 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 1999.
[29] R. Murphy, C. Lisetti, R. Tardif, L. Irish, and A. Gage, "Emotion based control of cooperating heterogeneous mobile robots," *IEEE Transactions on Robotics and Automation*, vol. 18 (5), pp. 744–757, 2002.
[30] F. Michaud, "Emib computational architecture based on emotion and motivation for intentional selection and configuration of behavior producing modules," *Cognitive Science Quaterly*, vol. 3-4, pp. 340–361, 2002.
[31] J. Velásquez, "Modelling emotion-based decision-making," in *1998 AAAI Fall Symposium Emotional and Intelligent: The Tangled Knot of Cognition*, 1998.
[32] J. Santa-Cruz, J. M. Tobal, A. C. Vindel, and E. G. Fernández, "Introducción a la psicología," 1989, facultad de Psicologa. Universidad Complutense de Madrid.
[33] K. Lorenz and P. Leyhausen, *Motivation of human and animal behaviour; an ethological view*. New York: Van Nostrand-Reinhold, 1973, vol. xix.
[34] Z. Liu and Y. Lu, "A motivational model for virtual characters," in *Proceedings of the Seventh International Conference on Machine Learning and Cybernetics, Kunming*, 2008.
[35] K. C. Berridge, "Motivation concepts in behavioural neuroscience," *Physiology and Behaviour*, no. 81, pp. 179–209, 2004.
[36] M. Malfaz and M. Salichs, "Learning to deal with objects," in *Proccedings of the 8th International Conference on Development and Learning (ICDL 2009)*, 2009.
[37] A. Ortony, G. L. Clore, and A. Collins, *The Cognitive Structure of Emotions*. Cambridge University Press. Cambridge, UK, 1988.
[38] M. Malfaz and M. Salichs, "Using muds as an experimental platform for testing a decision making system for self-motivated autonomous agents," *Artificial Intelligence and Simulation of Behaviour Journal*, vol. 2 (1), pp. 21–44, 2010.
[39] R. Gautier and G. Boeree, *Teorias de la personalidad: una selección de los mejores autores del S. XX*, E. UNIBE, Ed., 2005.
[40] S. Gadanho and L. Custodio, "Asynchronous learning by emotions and cognition," in *From Animals to Animats VII, Proceedings of the Seventh International Conference on Simulation of Adaptive Behavior (SAB'02), Edinburgh, UK*, 2002.

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