

Preference-Oriented Planning for Achieving Satisfactory Emotional States

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Abstract

During the last years the study of emotions and the characteristics of the human personality is increasingly relevant. This work proposes a deliberative emotional model for virtual agents based on their basic needs and preferences, implemented as an automated planning domain. The domain describes the knowledge of one agent living in a virtual world that has a set of basic physiological needs as feeding, hydration, rest, hygiene and entertainment. To cater for its needs, it must carry out different activities interacting with different objects over which it has preferences of one object over another. The selection depends on its preferences and directly affects its emotional state. So, the plans generated by the system attempt to fulfil the agent's physiological needs, choosing the objects required by each action to achieve the most satisfactory emotional state.

Introduction

Emotions have been shown in other fields to play an important role on rationality. Thus, the work on understanding and using emotions has been extended to the Artificial Intelligence field. Among other things, emotions can explain part of the interaction of the individual with the environment. This allows rational agents to approach all those objects and agents in the environment that cater for its needs and benefit its well-being. And, also, it allows those agents to move away of objects that endanger its survival (Breazeal 2003).

Emotions have been studied in Psychology, Neurology and Physiology from a wide variety of points of view and each field focuses the attention on different aspects. Despite everything, it seems there is some agreement to consider emotions as an inborn and subjective reaction to the environment, with an adaptative function, and accompanied of several organic, physiological and endocrine changes. Another point of agreement is that emotions are an outstanding factor in humans and living beings, because they modify the usual behaviour depending on changes in the environment. In the development of systems that interact with persons, as human behaviour simulators, emotions should not be ignored, because, on one hand, they may help on this interaction and, on the other hand, they constitute a decisive part of human reasoning and behaviour.

During the last years, several emotion-oriented systems have been developed, that normally follow Frijda's theory about emotions based on a functional hypothesis: emotions are functional most of the time (Frijda 1995). Thus, the use of emotions in artificial systems is needed to achieve an objective. As an example, Cañamero proposes a homeostatic approach to the motivations model. She creates a self-regulatory system, very close to natural homeostasis, that connects each motivation to a physiological variable, which is controlled within a given range (Cañamero 1997). When the value of that variable differs from the ideal one, an error signal proportional to the deviation, called drive, is sent, and activates some control mechanism that adjusts the value to the right direction. There are other architectures based on drives, as the Dorner's PSI architecture used by Bach (Bach & Vuine 2003) and also by Lim (Lim *et al.* 2005), that offer a set of drives of different type, as certainty, competence or affiliation.

Taking as reference Cañamero's and Gadanho's works on how to improve artificial emotions in robot's behaviour (Gadanho & Hallam 2001), Malfaz created a decision-making system based on emotions and machine-learning (through reinforcement learning) for social autonomous agents (Malfaz & Salichs 2006). Her agents developed artificial emotions, like happiness and fear, and learned a way of behaving that let them avoid some risks and keep a standard well-being.

However, most works on emotional agents are based on reactive behaviours, so there is no inference being done on medium-long term goals and the influence of emotions on how to achieve those goals. There are some works on emotions based on planning, but mainly oriented to storytelling. Examples are emergent narrative in FEARNOT! (Aylett *et al.* 2005) and the interactive storytelling of Madame Bovary on the Holodeck (Cavazza *et al.* 2007).

In the present work, a model of long term reasoning based on emotions has been designed following some ideas introduced by Avradinis and colleagues (Avradinis *et al.* 2003) using some concepts that already appear in Cañamero's and Malfaz's works, like motivations and the use of drives to represent basic needs. The model has been implemented as an automated planning domain that constitutes the reasoning core of a possible client in the virtual and multi-agent world AI-LIVE (Fernández *et al.* 2008). AI-LIVE is a

client/server application oriented towards the intensive use of Artificial Intelligence controlled Bots, and it was designed as a test environment of several Artificial Intelligence techniques. It borrows the idea from the popular video game THE SIMS, where the player creates individual characters (units) that have significant autonomy, with their own drives, goals, and strategies for satisfying those goals. In this implementation, we introduce the concept of how an agent prefers some objects and the influence of those on long term achievement of goals.

The paper presents first the model design. Then, we describe the domain that implements the model, and show some empirical results that validate the model. Finally, we draw some conclusions derived from the work, and propose future research lines.

Model Design

Our aim in this work is to include emotions in a deliberative system, including automated planning, in order to obtain more real and complex behavior of agents. These behaviors are necessary to implement a wide variety of applications such as agents that help users in their life, systems related with marketing and advertising, educational programs, systems that play video games or automatically generate text. The suggested model expects to show that the use of emotional features, with the establishment of preferences about certain objects in its environment, improves the performance of a deliberative agent by generating better plans.

It has been developed to represent the knowledge of one agent of the virtual world AI-LIVE. In this virtual world, an agent tries to cater for its needs or drives, its motivation (Toates 1986), through specific actions interacting with different objects. Five drives have been identified for the agent, which are easily identifiable in human beings as basic needs: hunger, thirst, tiredness, boredom and dirtiness. Along with the first three, widely used in many systems, we have added dirtiness and boredom, which are more domain-specific to add a wider variety of actions and get richer behaviors. These basic needs increase over time.

To cater for each of these basic needs, the agent must perform actions (Figure 1). For example, it should eat to satisfy its hunger or sleep to recover from fatigue.

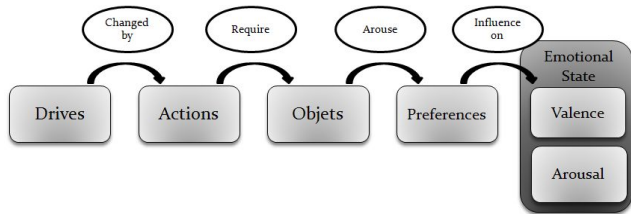


Figure 1: Conceptual diagram of the architecture, that shows the main concepts it manages and how they interact.

To carry out each of these actions, the agent needs to use objects of specific types. Thus, it will need food to eat, or a bed to sleep. There are different objects of each type in its environment and the agent prefers some over the others.

When an agent executes an action with an object, its emotional state is modified depending on the agent's preferences for this object.

In our design, we have chosen to implement a model widely-accepted in psychology. This model represents the emotional state of an agent as a two-dimensional space of two qualities: valence and arousal (Duffy 1941), instead of models that use a set of independent basic emotions usually preferred in the design of BDI agents. Valence ranges from highly positive to highly negative, whereas arousal ranges from calmed or soothed to excited or agitated. The first one is a measure of the pleasantness or hedonic value, and the second one represents the bodily activation (Barret 1998). In the proposed model, only the valence is modified by the execution of actions, so the valence value is modified when an agent executes an action with an object, depending on the agent's preference for this object. Our goal is that the agent generates plans to satisfy its needs and to achieve the best value of valence, the most positive.

Domain Description

We are using a classical domain-independent planner and a domain model described in PDDL (Fox & Long 2003) that contains all information about the world. This PDDL domain has been designed based on the concepts of drive, emotion and preferences to represent the knowledge of only one planning agent of the virtual world AI-LIVE.

Drives

Drives are represented in the domain through functions. The ideal value is established at zero for all drives, so when a drive has a value of zero, its need is totally satisfied. The distance to the ideal value implies the intensity of the need. The value of each drive is increased as time goes by to represent the increase of the need. To reduce it, the agent has to carry out actions. For instance, the agent can *eat* to reduce the drive *hunger*. In Figure 2 we show the description of the available drives used and the actions that are available to decrease the value of the corresponding drive.

Needs	Drives	Actions
Feeding	<i>hunger</i>	<i>eat</i>
Hydration	<i>thirst</i>	<i>drink</i>
Rest	<i>tiredness</i>	<i>sleep</i>
Hygiene	<i>dirtiness</i>	<i>bath</i>
Entertainment	<i>boredom</i>	<i>play</i>

Figure 2: Summary of the basic needs and their associated actions.

Objects

Objects describe the different elements of the virtual world AI-LIVE. Objects may be of two kinds: physical objects and rooms. Physical objects represent resources needed to carry out the actions to cater for needs, and are infinite. Rooms describe physical spaces, where the agents may move and physical objects may be situated. Both are represented in

PDDL as types and the specific objects will appear in the problem description as instances of those types.

Preferences

Preferences describe the agent's personal preferences for each one of the physical objects of its environment. They are represented as PDDL functions of the form:

```
(= (preference apple) 5)
```

These values are not modified during the planning process and they are between zero, for the detested objects, and ten, for the favourite ones. Since we only have an agent in this version of the architecture, there is no need to add the agent as an argument of the predicate. We will expand those fluents with the agent in the next version, where multiple agents will interact in the same environment. Also, in the next version, the preferences will be able to change over time as defined in (Fernández *et al.* 2008).

Emotional State

The agent's emotional state is determined by two components: valence and arousal. In this paper, we have only used the first one, which represents whether the emotional state of the individual is positive or negative and to which degree. Therefore, we have to compute the variation in the valence with respect to the objects preference, for each action. Imposing a maximum increment/decrement of 0.1 and considering the middle point of the preference function as a threshold (with higher values, the valence increases; and with lower values, the valence decreases), the variation suffered by the valence depending on the agent's preference can be represented as:

$$\Delta V = (p - \frac{p_{max} + p_{min}}{2}) * \frac{0.1}{\frac{p_{max} - p_{min}}{2}} \quad (1)$$

where V refers to the value of the valence, p to the value of the agent's preference for the used object, p_{max} to the maximum value of preference and p_{min} to the minimum value of preference.

So, considering the used maximum and minimum preference values, of 10 and 0, respectively, the variation suffered by the valence can be represented as:

$$\Delta V = (p - 5) * 0.02 \quad (2)$$

where V refers to the value of the valence and p to the value of agent's preference for the used object.

A valid metric for current planners must consist in minimizing/maximizing an increasing/decreasing monotonous function; no action can have an effect that has the opposite effect: decreasing/increasing its value. In our model, the objects used in the actions can cause both valence increment (when the agent prefers the object) and a decrement (when it does not like it). Therefore, it is not possible to use the valence directly as the metric. Instead, we use an increasing monotonous function (v -valence) that the planner tries to minimize. Each action increases v -valence, with positive values between 0 and 1 depending on the preference for the object used, as follows:

```
(increase (v-valence) (- 1 (* 0.1 (preference ?object))))
```

So, considering the previous expression and working out the value of $preference$, the variable p of the Formula 2 can be replaced for its value, as follows:

$$\Delta V = (\frac{1}{2} - v) * 0.2 \quad (3)$$

where V refers to the value of the valence and v to the value of v -valence for the used object.

Consequently, the final value of valence after an action can be calculated as follows:

$$V_{i+1} = V_i + [(\frac{1}{2} - v) * 0.2] \quad (4)$$

where V refers to the value of the valence and v to the value of v -valence for the used object.

Thus, knowing the number of actions of the plan that change the v -valence, l , we can normalize the set of all variations as:

$$V_{final} = V_{initial} + [l * (\frac{1}{2} - \frac{v}{l}) * 0.2] \quad (5)$$

where V refers to the value of the valence, v to the value of v -valence for the used object and l to the number of actions of the plan that change the v -valence.

The metric used consists on minimizing that value:

```
(:metric minimize (v-valence))
```

Actions

Actions defined in the domain describe several activities that the agent may carry out. There are three types of actions:

- **Actions to cater for its needs:** Each one of these actions needs one object of a specific type to decrease in one unit its corresponding drive value. These actions also cause an increase in the rest of drives values in a fixed quantity (0.1) to represent the effect of time over the agent needs. In this group the actions are `eat`, `drink`, `sleep`, `bath` and `play`. In Figure 3, we show an example of this type of action. As we can see, the action reduces in a big quantity the relevant need (hunger in this case) and increases the rest of drives to simulate the pass of time.

```
(:action EAT
:parameters (?food - food ?room - room)
:precondition (and (in ?room) (at ?food ?room))
:effect (and (decrease (hunger) 1)
              (increase (boredom) 0.1)
              (increase (dirtiness) 0.1)
              (increase (tiredness) 0.1)
              (increase (thirst) 0.1)
              (increase (v-valence)
                (- 1 (* 0.1 (preference ?food))))))
```

Figure 3: Example of action (EAT) to cater for a need (hunger).

- **GET-GOAL action:** It is a fictitious action (Figure 4) that allows us to use numerical values in the goals for the problems definition because not all planners support the definition of numerical goal in the problem file. Drives values are not modified through this action.

```
(:action GET-GOAL
:parameters ()
:precondition (and (< (boredom) 10)
                  (< (dirtiness) 10)
                  (< (hunger) 10)
                  (< (tiredness) 10)
                  (< (thirst) 10))
:effect (and (goal)))
```

Figure 4: Get-goal action.

- **GO action:** It is an action that does not cater for any need and represents the agent movement. Its execution produces the same increase (0.1) on all the drives, and v-valence is increased with the minimum value (0.1) too (Figure 5).

```
(:action GO
:parameters (?room-from - room ?room-to - room)
:precondition (and (in ?room-from))
:effect (and (increase (boredom) 0.1)
            (increase (dirtiness) 0.1)
            (increase (hunger) 0.1)
            (increase (tiredness) 0.1)
            (increase (thirst) 0.1)
            (increase (v-valence) 0.1)
            (not (in ?room-from))
            (in ?room-to)))
```

Figure 5: Go action.

Goals

The agent's motivation is to satisfy its basic needs, so goals consist of a set of drives values that the agent has to achieve. The GET-GOAL action is included to add these numerical values in the goals (so they are in the domain definition instead of in the problem file). The effect of the GET-GOAL action is the goal predicate and it is the only one in the goal section of the problem file.

Experiments and Results

The main focus of this experimentation is to compare the results obtained with a model that uses preferences and another one that does not use them. Thus, we show that the model is valid and the advantages of using preferences in this type of problems.

Experimental Setup

We have defined several kinds of problems for this domain, considering a static world. In each of the problems we have established a specific initial need in one or more of the drives, which are called dominant drives. Each of these dominant drives will have a initial value significantly higher

(50) than the rest of drives (10). The value set as a goal for each of the drives in all cases is to have a value below 10. Furthermore, for each action, the agent has three objects to choose from, with varying degrees of preference: preferred (9), indifferent (5) and hated (1).

We compare the performance of the emotion-based model with that of an alternative model in which the agent has no preferences for any object. This alternative model has been implemented by using the same domain and by generating different problems in which the preference of the agent to each object is the same: the average value of preferences of the agent's original problem (5). So, we have varied the number of dominant drives and the model used. We measure the value reached in the metric (v-valence), the length of the solutions and the time invested on planning.

Two different planners have been used to solve the problems: METRIC-FF (Hoffman 2002) and SGPLAN (Chen *et al.* 2004).

Results

Figure 6 shows the time spent by the planner METRIC-FF to solve each generated problem. The time in seconds spent by the planner when using the model with preferences is usually more than not using them. This is due to the bigger number of generated nodes to achieve a better metric value because, in the model without preferences, the planner chooses the first object of each type and ignores the rest.

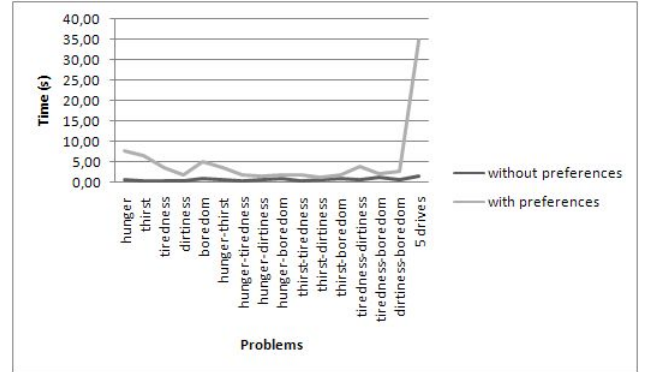


Figure 6: Planning time (in seconds) using METRIC-FF.

However, the time spent by SGPLAN is the same for both models as Figure 7 shows. When this planner searches a solution, it does not search for the best one, in terms of metric value. So, the time invested does not depend on the quality of the solution, but on the difficulty to find a solution. We can also see that SGPLAN takes much less time than METRIC-FF for solving the problems.

Figure 8 shows the length of plans generated by METRIC-FF, that is a bit higher in the model with preferences because the planner searches to obtain a best metric value executing more actions.

Figure 9 shows the length of plans generated by SGPLAN. In this case, the length of the plans is the same for both models because SGPLAN does not consider the quality of solu-

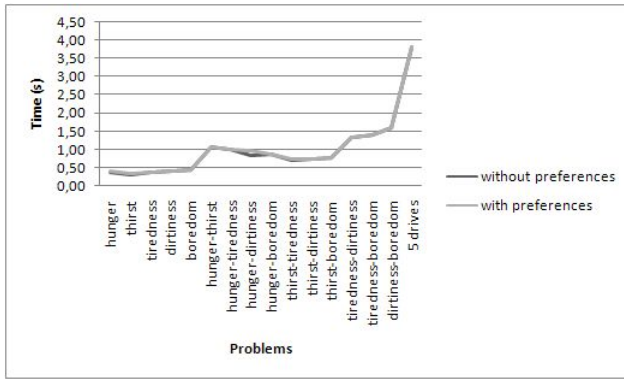


Figure 7: Planning time (in seconds) using SGPLAN.

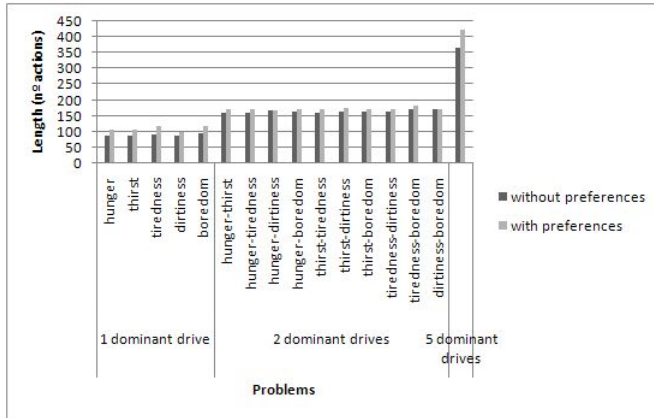


Figure 8: Length (number of actions) of plans using METRIC-FF.

tion, in terms of metric value. So, the solution shown is the same for both models.

Figure 10 shows the end value of the metric (v-valence) in each problem, using METRIC-FF. This shows that in all cases the value obtained by the model that uses preferences is significantly better than not using them.

Using SGPLAN the end value of the metric (v-valence) is the same for both models, as Figure 11 shows, because this planner only searches for a valid solution without considering its quality.

Conclusions and Future Work

This paper proposes a model of long term reasoning based on emotions, drives and preferences in autonomous agents, implemented as a planning task. The domain includes a representation for emotional states, drives, preferences, actions, objects and a suitable metric. The emotional state is modeled by one function: valence. And, actions produce variations in the valence depending on the preference value of the used object. The goal is to generate plans that maximizes the valence. Given that current planners only deal with monotonous functions as metric functions, we con-

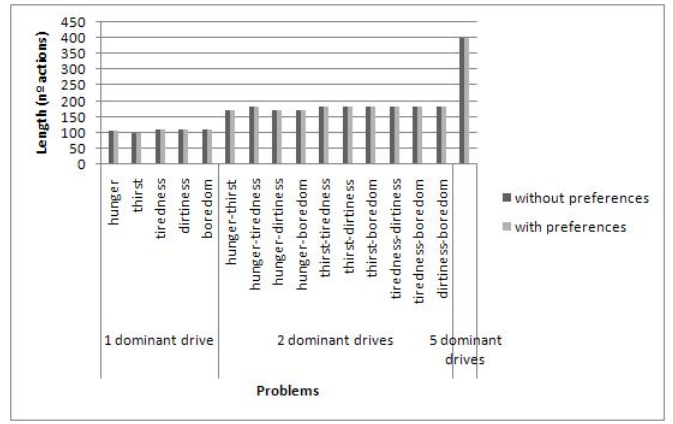


Figure 9: Length (number of actions) of plans using SGPLAN.

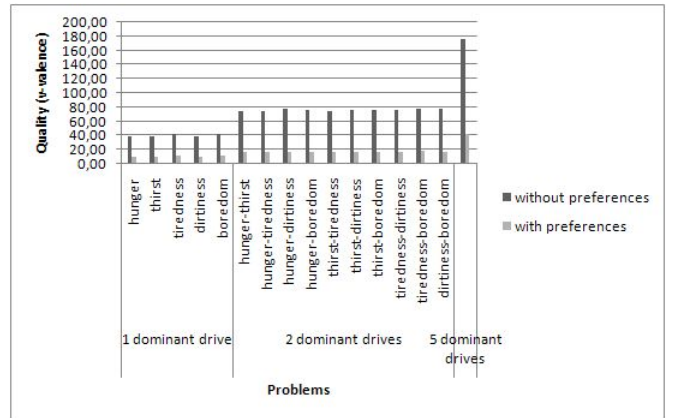


Figure 10: Quality (v-valence) of the plans computed by METRIC-FF.

verted the non-monotonous valence into a monotonous one, v-valence. We have also simulated time by increasing the value of drives as effects of the actions.

The results of the experiments show that while the time to solve the problems increases, the quality of solutions (measured as the value of the v-valence) greatly improves when preferences are used in the planning process of METRIC-FF. Results also show that SGPLAN is not appropriate for this domain, given that the quality of its plans is worse than the ones of METRIC-FF when using preferences.

In the next future, we would like to model the other component of the emotional state: arousal. In contrast to valence, that clearly distinguishes positive and negative values, arousal can not be classified in general as good and bad, and its best values depend on the situation. Also, we would like to relate the agent's emotional state to the goal generation and the preconditions of the actions.

The proposed model is the first step in the development of a richer and more complex architecture. We would like to develop the importance of the passing of time as a subjective and individual actions' factor. Another idea to implement

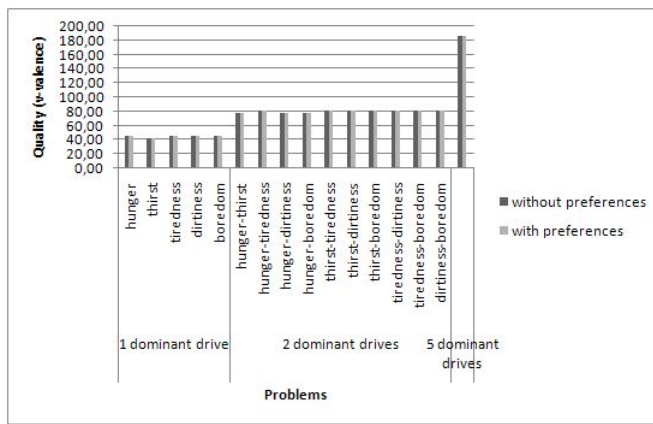


Figure 11: Quality (v-valence) of the plans computed by SGPLAN.

is to add new drives and domain actions, that are related with the same drive; as play, read or listen related with the drive `boredom`. Thus, agent has preferences over actions too. In either case, preferences can relate to agent's emotional state as well as objects and actions. Also, we would like to include the idea of well-being, which will focus the agent to keep all its needs below a certain level along time. The physiological well-being of the agent will influence its emotional state altering the values of valence and arousal. This idea is very related to the continuous planning to control the behaviour of virtual agents (Avradinis *et al.* 2003). Another future work is to incorporate multi-agent actions to the domain, especially those related to the processes of social interaction, by including some component that reasons about interaction, collaboration and communication, where the agent communicates emotions, ideas and thoughts, as well. These actions would involve two (or more) agents and depends on the agents personality, their emotional states and the relationship between them.

Acknowledgements

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