Exploring the Role of Emotions in Autonomous Robot Learning

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Abstract

Autonomy is a very important property for a robot to have, yet implementing it in a robot is far from trivial, particularly when one requires the meaning of autonomy to include self-motivation, instead of mere automaticity.

The fact that emotions are considered to be essential to human reasoning and human motivation in particular, suggests that they might play an important role in robot autonomy. The purpose of the work reported here is to know if and how emotions can help a robot in achieving autonomy.

Experimental work was done in a simulated robot that adapts to its environment through the use of reinforcement learning. Results suggest that emotions can be useful in dividing the task in smaller manageable problems by focusing the attention in the relevant features of the task at any one time.

1. Introduction

In the field of robotics, the criteria used to define if a robot is autonomous or not are not well established. In general, simply requiring that, once the robot is finished, it does its task without human intervention is enough. The word's root meaning suggests an alternative definition of autonomy that has stronger requirements. Namely, a truly autonomous robot should also develop the laws that rule its behaviour.

> AUTONOMOUS — f. Gr. *αύτόνομος* making or having one's own laws, independent (f. *αύτο-* self, own + *νόμος* law) + -ous (The Oxford English dictionary 89)

Although it is still a very open research subject, there is much argument in favour of having truly autonomous systems. Having autonomous agents seems to be a clear advantage in several diverse fields, like for example robotics, animal robotics[1] (McFarland 94), agents theory (Ferguson 92) and interactive virtual environments (Blumberg 95). Although, arguments against having fully autonomous agents are easy to find (in general, the robot is supposed to do something useful and not whatever it wants), it is generally accepted that it is beneficial to have autonomy, at least to a certain extent which is still far from being achieved in today's systems. It is often difficult or even impossible for the designer to anticipate all possible scenarios the robot will be confronted with, autonomy can help the robot to deal with the unexpected situations.

To accomplish strong autonomy, a robot must have an adaptive controller that improves its performance by unsupervised learning when interacting with its environment.

In robotics, emotions are often used to modulate activity in a fixed controller (Cañamero 97; Bates *et al.* 94). The social role of emotions has been particularly explored. The external demonstration of emotions has been used as a sort of communication mechanism that allows the robot to report to others its internal state (e.g. its level of task achievement (Shibata *et al.* 96)) or makes the robot capable of generating empathy emotions in people, by creating an illusion of life in a believable character (Bates 94).

The present research focus on how to use emotions in the control of an autonomous robot that adapts to its environment using reinforcement learning. Emotions seem to have solved in mammals many cognitive problems involved in autonomous systems with multiple goals and uncertain environments (Oatley 87). It has been argued before in the field of Artificial Intelligence that emotions are the ultimate source of intelligence and might provide robots with the autonomy they need (Toda 94); doubts have even been posed on whether machines can exhibit intelligence without any emotions (Minsky 86).

The work was done under an animat philosophy (Wilson 91), by building bottom-up a biologically inspired complete agent by synthesis. A robot was equipped with a recurrent network model of "emotions" which incorporates the important computational features of Damásio's somatic marker hypothesis (Damásio 94). Yet, the developed model is based on a simplified

[1] Modelling of animal behaviour using robots.

hormone system and is far from the complexity of true emotions experienced by humans. Experiments were carried out on a simulated Khepera robot in an animal-like adaptation task.

In the next section, a detailed description of the emotion model developed is presented. The experiments done with this model are reported in the following section.

2. Emotions

People like to have a Cartesian approach to life in thinking that all their reasoning is purely logical and emotions are purely disruptive. In fact, individuals do not always make rational choices (Grossberg & Gutowski 87) and pure logical reasoning shows serious faults when used to model human reasoning in the field of Artificial Intelligence (Dreyfus 92). Recent neurophysiological research suggests that our thinking is not so detached and ungrounded. With the help of the emotions, the feelings provided by our body play an important role in reasoning. This is the central claim of the somatic-marker hypothesis[2] (Damásio 94).

Damásio makes a clear distinction between the concepts of emotion and feeling that will be used in the current work. Feeling designates the process of monitoring the body. Feelings offer us the cognition of our visceral and musculoskeletal state. Emotion is a combination of a mental evaluative process with dispositional responses to that process, mostly toward the body proper but also toward the brain itself. Emotions all generate feelings, but only some feelings generate emotions. If feelings are associated with emotions then the body signals will move from the background to the foreground of our attention.

Somatic markers are special instances of body feelings (visceral and non-visceral sensations) generated by emotions, that are acquired by experience based on internal preference systems and external events and which help to predict future outcomes of certain scenarios. They will force attention on the negative or positive outcome of certain options, that can be immediately defeated leaving fewer alternatives or can be immediately followed. This way, the somatic markers provide humans with a reasoning system that is free from many of the faults of formal logic, namely the need for much computational and memory power for having every option thoroughly evaluated.

Many emotions theorists agree that emotions are most helpful on focusing attention in the relevant features of the problem at hand (De Sousa 87; Tomkins 84; Plutchick 84; Scherer 84; Panksepp 82).

Inspired by the ideas that have been presented, an emotion model was developed that is described next.

[2] Marker because it marks an internal image and somatic because it is the body that does it.

2.1 Model

A large subset of theories of emotions is based on cognitive appraisal theories (Lazarus 82; Power & Dalgleish 97), although some evidence exists to suggest that emotions can be aroused without cognition (Zajonc 84).

Following the psychologists' main stream, most AI models of emotions are based on an analytic approach (Sloman *et al.* 94; Pfeifer 82; Pfeifer & Nicholas 85; Bates *et al.* 92) that tries to endow the model with the full complexity of human emotions as perceived from an observer's point of view. In opposition to this kind of approach, a bottom-up approach was followed here. In both ontological development and evolution the full richness of emotions is only achieved at a final stage. In the first stages of these processes only certain basic emotions are present and, later, other more complex emotions develop on top of these.

The model that was developed — figure 1 — is based on four basic emotions: Happiness, Sadness, Fear and Anger. These emotions were selected because they are the most universal emotions along with Disgust (Damásio 94) and are adequate and useful for the robot–environment interaction afforded by the experiments. Others might prove too sophisticated or out of place. For instance, there seems to be no situation where it is appropriate for the robot to feel disgust. Yet, if, for instance, toxic food was added to the environment, disgust would become useful to keep the robot away from it.

The emotions chosen are also usually included in the definitions of primary emotions[3] (Shaver *et al.* 87; Power & Dalgleish 97), which is a good indicator of their relevance and need. Other emotions, like love and hate, which some authors like to suggest as primary emotions, were not included because they do not seem very basic[4] and the present work does not have, for the moment, any social aims.

The model determines the intensity of each emotion based on the robot's current internal feelings. These feelings are: Hunger, Pain, Restlessness, Temperature, Eating, Smell, Warmth and Closeness. Each emotion is defined by a set of constant feeling dependencies and a bias. The values of the dependencies were carefully chosen to provide adequate emotions for the possible body states. For example, the sadness intensity will be

[3] It should be noticed that the paradigm of primary emotions is not undisputed, yet most of the arguments against it are marginal to the present usage. These arguments refer to the plausibility of translating all emotions in terms of graduations of primary emotions. The point here is that these emotions are more universal and fundamental and therefore more adequate to low reasoning animats in a simplified environment.

[4] There are even arguments against considering them as emotions, *e.g.* (Sloman 87).

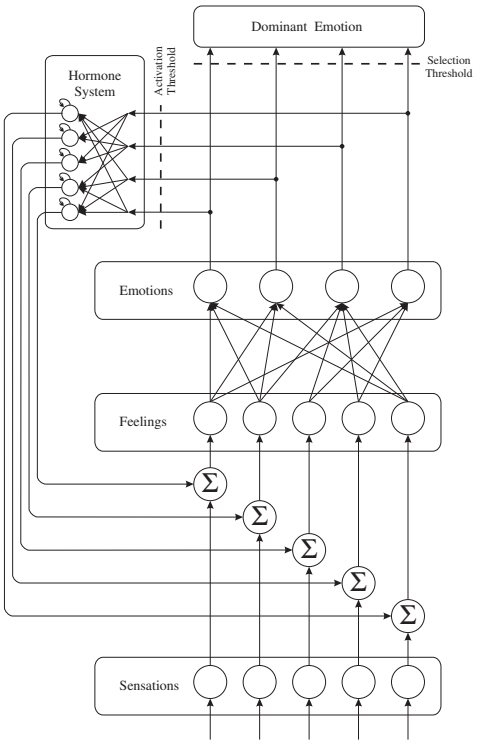

Figure 1 Emotions model.

high if hunger and restlessness are high and the robot is not eating.

Furthermore, based on what was suggested in (Damásio 94), the emotion state should also influence the way the robot feels. In general, the body reactions aroused by emotions also give rise to the emotions that create them. In this model each emotion tries to influence the body state in such a way that the result body state matches the state that gives rise to that particular emotion.

When an emotion is active, *i.e.* its intensity value is significantly large, then it will influence the body through a hormone system, by producing appropriate hormones.

The hormone system in the model is a very simplified one. It consists in having one hormone associated with each feeling. A feeling intensity is not a value directly obtained from the value of the body sensation that gives rise to it, but from the sum of the sensation and hormone value. The hormone values can be (positively or negatively) high enough to totally hide the real sensations from the robot's perception of its body.

The hormone quantities produced by each emotion are directly related to its intensity and its dependencies on the associated feelings. The stronger the dependency on a certain feeling, the greater quantity of the associated hormone is produced by an emotion.

On the one hand, the hormone mechanism provides a sort of fight between the emotions to gain control over the body which is ultimately what selects which emotion will be dominant. On the other hand, what the robot feels — its body image — is not only dependent on its sensations but is also dependent on its emotional state.

The hormones' values can increase quite rapidly, allowing for the quick build up of a new emotional state, and decrease slowly allowing for the persistence of an emotional state even when the cause that has given rise to it is gone, another of the characteristic features of emotions.

The dominant emotion is the emotion with the highest intensity, unless no emotion intensity exceeds a selection threshold. In this case, there will not be a dominant emotion and emotional state will be neutral. Emotions were divided into two categories: positive and negative. The ones that are considered "good" are positive (only Happiness, in the set of emotions used), the others are considered negative.

In summary, the model of emotions described provides not only an emotional state coherent with the current situation, but also influences the body perception. In order to evaluate the role of emotions in reasoning, this state should be used for the actual control of the robot, determining its behaviour (Albus 90; Wright 96a; Moffat *et al.* 93). The next section describes the experiments done in this *direction*.

3. Experiments

3.1 The Robot Task

The ultimate goal of the research reported in this document is to develop a fully autonomous real robot. This was one reason why self-sufficiency was considered a useful property to include in the system. Another reason for this choice is that is easier to think of emotions in the context of an animal-like creature with self-maintainance needs.

The robot's task consists in collecting energy from food sources scattered throughout the environment. These food sources are actually lights so that the robot is able to distinguish them with its poor perception capabilities. The robot needs this energy to use during its functioning. It will use up the energy faster if the velocity it applies to its motors is higher. This simple task was carried out with success in a study reported previously (Gadanho & Hallam 98) and it was felt that for a proper evaluation of the advantages of using emotions, the task should be made more difficult. It was chosen to make the survival problem more difficult by making energy harder to obtain. This was accomplished by two different means:

– *The robot can only extract a limited amount of energy from each food source.* In time, the food source will recover its ability to provide energy again, but meanwhile the robot will be forced to look for other

sources of energy in order to survive. The robot cannot be successful by relying on a single food source for energy, *i.e.*the time it takes for new energy to be available in a single food source is longer than the time it takes for the robot to waste it. When the food source has no energy, the light associated with it is turned off.

- *The robot has to perform elaborate behaviour to receive energy.* To gain energy from a food source, the robot has first to bump into it. If the food source still has energy left, it will make some of it available to the robot for a short period of time. At the same time an odour will be released that can be sensed by the robot. During this short period, the robot can acquire energy by receiving high values of light in its rear light sensors. This means that the robot must turn its back to the food source. To receive more energy the robot has to restart the whole process again by hitting the light again so that a new time window of released energy is started.

The robot's task can be translated into multiple goals: moving around the environment in order to find different food sources and, if a food source is found, extracting energy from it. Furthermore, the robot should not keep still in the same place for long durations of time or collide with obstacles.

In order to have the robot's emotional state compatible with its task, the emotions dependencies from feelings are such that:

- The robot is **happy** if there is nothing wrong with the present situation. It will be particularly happy if it has been using its motors a lot or is getting new energy at the moment.
- If the robot has very low energy and it is not acquiring new energy, then it's state will be **sad**.
- If the robot bumps into the walls then the pain will make it **fearful**, unless it is very hungry. In this case the pain, can be ignored.
- If the robot keeps too long in the same place it will start to get restless. This will make it **angry**. The anger will be kept for as long as the robot does not move away or change it's current action. If the action is changed the value of restlessness is reseted by the system.

All the experiments were carried out in a Khepera simulated robot (Michel 96) within a closed environment divided by several walls and containing a few lights (see figure 2).

3.2 The Adaptive Controller

Reinforcement learning techniques have already been successfully used in the field of robotics and were therefore selected for the learning algorithm. The main problem with reinforcement learning is that learning can be very slow, particularly if the task is very complex. Yet, behaviour decomposition of the task can reduce significantly the learning time or even make the task feasible. Behavioural decomposition usually consists in learning some predefined behaviours in a first phase and then finding the high-level coordination of these behaviours. Although the behaviours themselves are often learned successfully (Mahadevan & Connell 92; Lin 93), the behaviour coordination is much more difficult and is usually hard-wired to some extent (Mahadevan & Connell 92; Lin 93; Mataric 94). One problem in particular which is quite difficult and task dependent is determining when to change behaviour. This is not a problem in traditional reinforcement leaning where agents live in grid worlds and state transition is perfectly determined. Yet, in robotics, agent states change asynchronously in response to internal and external events and actions take variable amounts of time to execute (Mataric 94). The design of a reward function can also be a problem if there are multiple goals and immediate reinforcement is not always available. In this case, it is often impossible to have a direct translation to a traditional monolithic reward function (Mataric 94). Both of the two previous problems can be found in the task at hand. Furthermore, unlike traditional reinforcement learning tasks, the task of an autonomous robot is mainly one of continuously executing a task for as long as necessary in opposition to successfully completing a task and finishing. Another major difference is that the distinction between a learning phase and a performing phase had to be eliminated, because an autonomous robot is supposed to continuously adapt to its environment.

In our work we have chosen to have the primitive behaviours hand-designed and learn only the behaviours coordination in the hope that emotions might be useful in solving some of the problems discussed previously. Three primitive behaviours were hand-designed:

Avoid obstacles — Turn away from the nearest obstacle and move away from it. It the sensors cannot detect any obstacle nearby, then remain still.

Seek Light — Go in the direction of the nearest light. If no light can be seen remain still.

Wall Following — If there is no wall in sight, move forwards at full speed. Once a wall is found, follow it. This behaviour by itself is not very reliable in that the robot can crash. Yet, the avoid obstacles behaviour can easily help in these situations.

The controller developed — figure 3 — tries to maximise the evaluation received by selecting one of the three possible behaviours, taking into account the current robot feelings, and the previously received evaluations.

The controller has two separate modules:

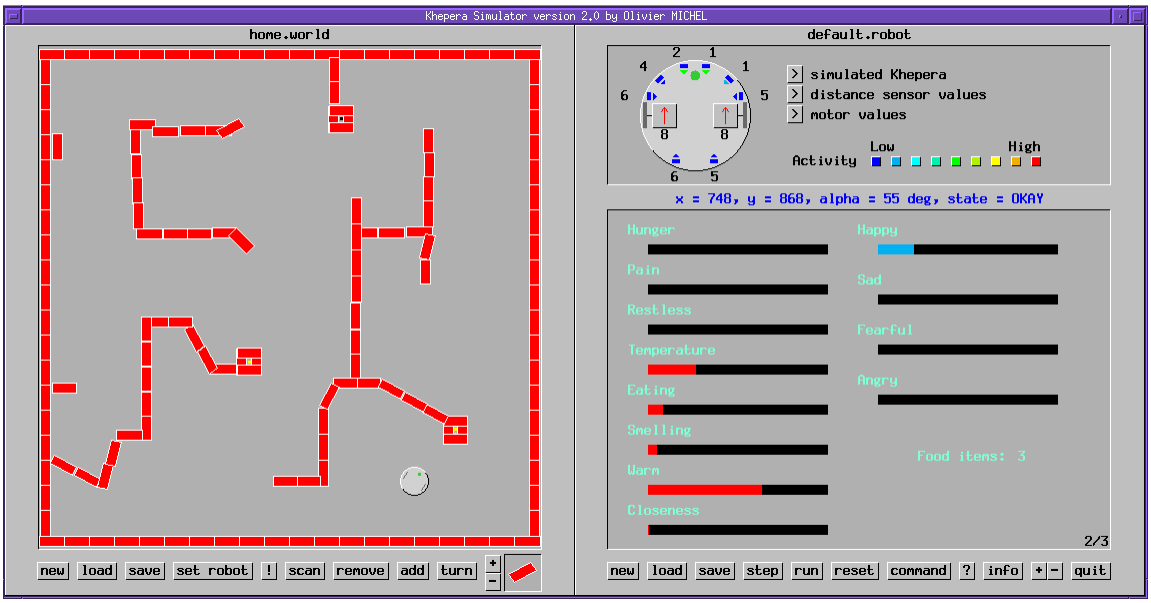

Figure 2 The robot and its environment.

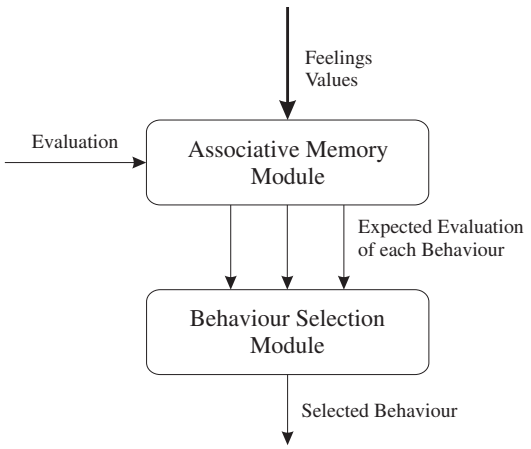

Figure 3 Adaptive controller.

Associative Memory Module — This plastic module uses feed-forward networks to associate the robot feelings with the current expected value of each one of the three robot behaviours. Q-learning (Watkins 89) was used in an implementation very similar to the one reported by Lin (Lin 92). Neural networks learned by back-propagation utility functions that model $util(x, a)$:

$$util(x, a) = R + \gamma eval(y) \quad (1)$$

The value R is the immediate reinforcement. The function $eval(y)$ is the expected cumulative discounted reinforcement starting from state y reached by executing behaviour a in state x. The discount factor (γ) was set to 0.9. For each iteration, the target value u will be given to the network whose behaviour was used in the previous iteration:

$$u = R + \gamma \text{Max}\{util(y, k) \mid k \in actions\} \quad (2)$$

Behaviour Selection Module — Based on the information provided by the previous module, this module makes a stochastic selection of the behaviour to take next. For a temperature T, the probability of selecting behaviour a is:

$$P(a) = \frac{e^{\frac{v_a}{T}}}{\sum_{i=1}^{6} e^{\frac{v_i}{T}}} \qquad v_i = \text{Value of behaviour } i \quad (3)$$

3.3 The Role of Emotions

From what was discussed previously in this document, both in terms of emotions and of the reinforcement learning paradigm, here are some possible emotions roles:

Reinforcement value The design of a reward function is one of the most crucial aspects to the success in a reinforcement learning task. Experiments showed that the use of a monolithic reward function in the task described earlier in this document is inadequate. This was to be expected taking into account that we are dealing with a multi-goal task with immediate and delayed reinforcements.

In robotics, the role of providing an evaluation of the state of the world is often attributed to emotions,

e.g., (Albus 90; Wright 96b). It is often assumed that human decision making consists in the maximization of positive emotions and minimisation of negative emotions, *e.g.*(Tomkins 84). It should be expected that a reward function directly obtained from the emotional state would work well. This can be easily accomplished with our model. At any moment in time, a value judgement can be obtained from the emotion system by considering the intensity of the current dominant emotion and whether it is positive or negative. Experiments were made that consisted in using as reinforcement the intensity of the current dominant emotion or zero if there was no dominant emotion. If the dominant emotion was a negative one then its (positive intensity) value would be negated. Results showed that such a naive approach is not very successful when a more than usually realistic emotion model is used (Gadanho & Hallam 98).

Nevertheless, an emotion dependent reward function can be very helpful. Emotions permit the robot to focus attention only in the relevant features at any one time. For instance if the robot is very fearful, it should probably concentrate in avoiding obstacles and not pay attention to its hunger. This can be translated to a reinforcement function that gives rewards according to robot state. In the experiments made, the robots that used this kind of approach performed quite well and were the most successful found.

DETERMINING STATE Another mechanism that was experimented was having emotions influencing the robot perception. When the robot learns associations between states and rewards through its neural networks, it is actually using feelings to determine state by using them as network inputs. In the emotion model developed, feelings are influenced by emotions through the hormone system. So the robot state is emotion dependent. What the robot learns to associate with rewards it is actually being distorted by emotions. It is being changed to be more compatible with the active emotions, thus making the relevant features of the environment more evident. For the moment no significant differences where found in using this kind of perception or using an alternative perception that is not influenced by hormones. This shows that the robot can cope with a distorted view of reality, but does not show that emotions can be useful in this domain. Yet, the fact that were no differences found can be purely task dependent.

TRIGGERING STATE TRANSITION In a robotic environment, a new state can be found for virtually every step. The perception of the world will always be at least slightly different from step to step due to noise. Nevertheless, making a new re-evaluation of the system every step by selecting a new behaviour and performing an evaluation on the previous behaviour does not make sense. The problem is not so much one of too much computational waste, but mostly of not making a correct evaluation of the achievements of the behaviours. It the behaviour is evaluated and eventually replaced every step, then it will not have time to develop to its full potential and will be reduced to small individual actions that will look almost random. This will make it difficult for the learning system to understand what are the advantages of each one of behaviours. This was actually tried out and the results were quite disastrous. On the other hand, if the behaviours are left running for too long, events may occur that will make them inadequate to the new situation. The ideal would be to know when a significant change has occurred in the environment that makes a re-evaluation necessary. Using emotions to trigger state transition seems reasonable, because emotions can provide a global summarised vision of the environment. Any important change in the environment is liable to be captured by the emotional state.

Experiments were made to test if emotions could really fulfill this role. In practice, the learning controller was triggered whenever:

- there was a change in the emotion that was dominant;
- the current dominant emotion value was statistically different from the values recorded since a state transition was last made.

Although this method of triggering the controller is adequate to provide good results, it must be said that simpler alternative methods were found during our experiments that did as well. This problem is still under research, namely an exploration of the system parameters is still under way.

4. Conclusions

The model of emotions behaved appropriately when tested on the animat, in the sense that the robot consistently displays plausible contextual emotional states during the process of interacting with the environment. Furthermore, because its emotions are grounded in body feelings, and not direct sensory input, it manages to avoid sudden changes of emotional state, from one extreme emotion to a completely different one. The more different the emotions are, the more difficult it is to change from one to the other. The physiological arousal caused by emotions has been repeatedly left out of cognitive theories of emotions[5], because it is not considered cognitively interesting, yet without it emotions lack their characteristic inertia (Moffat *et al.* 93).

[5] The FEELER system (Pfeifer 82) can be considered an exception.

Furthermore, experiments showed that emotions can be used as an attention mechanism at different levels of a reinforcement learning task:

- Modulation of the reinforcement function is by itself a powerful attention mechanism in a reinforcement learning task that can be successfully fulfilled using emotions.
- The robot current state can be influenced by the use of hormones. This can make more evident the aspects of the environment that are directly related with the current emotional state.
- Determining the occurrence of state transition, by looking at sudden changes in the emotional system state.

These were three different mechanisms that worked well experimentally. Each one of them had different levels of performance when compared with alternative methods. For the time being, it is difficult to tell if the second two mechanisms can be replaced by simpler approaches with no detriment to final performance. Preliminary results suggest as much, but a thorough examination is necessary before such conclusions can be taken.

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