Learning Object Significance with an Emotion based Process

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Abstract

This paper presents an emotion based process generating cognition through learning. Two models are described which investigates the possibilities of designing cognitive systems based on emotion. In order to test these models through experiments, we used a mobile robot simulator, Webots, modeling the real Khepera robot. The first proposed model is the simplest since it uses only positive and negative reinforcement signals as well as proximity sensors. The robot learns to avoid obstacles based on reflex reaction and on reinforcement signals. The second model relying on appraisal theory is more complex. It involves the use of reinforcement signals, proximity sensors and a simulated color camera to learn, in particular, to associate visual stimulus with the appropriate behavior. Interesting simulation results demonstrate the significance of this promising approach.

Introduction

In the last few years, the emotion process yielded many investigations in various research fields, including Neurobiology (Damasio 1994; LeDoux 1996), Computer Science (Minsky 1987; Picard 1997) as well as Psychology (Salovey & Mayer 1990; Goleman 1995). All these authors hypothesize that the emotion process is a fundamental component of cognitive processes, and could probably be the center of cognition. As mentioned in (LeDoux 1996), p.25, “Minds without emotions are not really minds at all”, however, the precise role of emotion in the brain processes is not clear. It might be explained as a signal for cognition (LeDoux 1996), a representation paradigm for cognition (Damasio 1994), a way for independent processes to communicate and get synchronized (Minsky 1987), a decisional system for handling conflicts between goals and environmental conditions (Sloman 1987; Oatlley & Johnson-Laird 1987), or finally a way to adapt to the environment (Salovey & Mayer 1990; Goleman 1995). Each of these authors focuses on one of the aspects of emotion in cognition. However, it seems currently difficult to identify all these aspects and to prove the necessity of emotion in cognition. But we can try to see how it's possible to mix emotional processes to cognition and to observe whether or not they improve the efficiency of cognition.

In this paper, we assume that emotion can be seen as the basis of cognition because it provides a default functional model. The origin of human and animal cognition remains an open question. Along the phylogenesis, animals had, on one hand, to face their environment and to react as fast as possible to unknown events, and on the other hand, to define goals which they were not directly supposed to address. Object of this paper is to show how emotion based structures could contribute to the emergence of cognition by creating suitable learning conditions.

This paper is divided in three parts. First of all, we examine the different proposals of emotion models, in order to define our proposal in relation to others. Then we describe the experimental setting. Finally, we define two learning model based on emotion and report experimentation with them.

Emotion Models

Various computational models of emotion have been proposed (Dyer 1987; Frijda & Swagerman 1987; Elliot 1992; Scherer 1993; Chwelos & Oatley 1994; Ortony & O'Rorke 1994; Wright 1997; Armony *et al.* 1997; Canamero 1997). See also a review in Pfeifer 1988; Hudlicka & Fellous 1996; Picard 1997.Even if these models have been built for different reasons and relied on different theories, we think there are three features of these models :

Feature of emotion Generally these models are based on emotion labels (joy, fear, anger, etc.). However emotion labels are often controversial, as well as concerning their definition, their nature and the number of different labels (Ortony & Turner 1990; Ekman 1992). Moreover, in humans, the access to the label of emotion relies on consciousness, or at a lower level, on the categorization process. We think that it's more important to focus on the mechanism we can elicit and differentiate emotion rather than to define controversial label.

Input of the system Generally we can find stimuli based on an important significance (electric shocks, narration of emotional situations, goal conflicts, etc.). This association between emotions and specific kinds of stimuli induce a discrete representation of emotion : it seems that emotion serves to take in account this special stimuli (reflex reaction, conflict, etc.). But in our opinion, if emotion is important in cognition, it's not only to deal with this particular patterns, but with all patterns.

Origin Models are often presented as applications of a single theoretical model designed by specific authors. Without a survey of these different models, it's difficult to distinguish the most significative ones. There's currently no experimental proof demonstrating the relevance of such models. It seems to us that the choice of the theorical model is very relevant and that it's necessary to chose a model that can take into account other theoretical proposals.

It seemed to us very important to take into account these different aspects before we designed our simulation model. This model includes the following features (1) It focuses on the process of the emergence of emotion. The question of the labels of the emotions will be addressed in further investigations. (2) It doesn't necessarily make use of an experimental framework with stimuli associated to a strong significance, directly connected to emotion. (3) It shares a number of features with other known models.

In our model, emotion is represented trough the two common levels of emotion : level of process which can elicit and differentiate emotion (evaluation of stimuli) and level of state which can give information about the system. This two levels have two distinct implications : evaluation serves two extracts relevant information in order to be taken into account. State is directly linked up with process (in order to learn to change the goal). We make two experiments to explore this design. In the first experimentation evaluation it's a simple bad/good signal which creates an association. The second experimentation signal is based on the appraisal theory that creates a scheme.

Experimental Set-Up

We used of an Artificial Life (ALife) paradigm which has proved to be useful for investigating cognition (Parisi 1997). In order to proceed experiments, we used the Webots simulator (Cyberbotics 1998) which is a realistic mobile robot simulator modeling a real robot: Khepera (Mondada, Franzi, & Ienne 1994). This mini mobile robot (55mm diameter) is equipped with 8 infrared sensors allowing it to detect surrounding obstacles, and two independent motors driving the wheels (see figure 1). Several extension turrets are available, like for example a gripper to grasp objects, or a color vision turret with a resolution of 160x120 pixels which we used in our experiments.

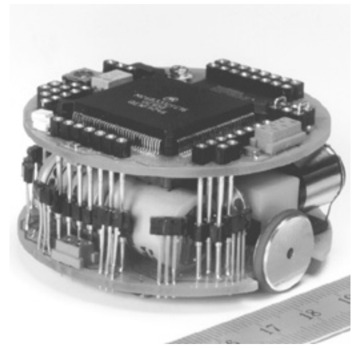

Figure 1: Real Khepera.

Webots is compatible with the Khepera robot. C programs developed within Webots can be transferred directly to the real robot. A supervisor module helps monitoring experiments with simulated and/or real robots. Simulation capabilities include all major Khepera extension turrets, especially gripper and vision turret. Vision is synthesized through an OpenGL 3D rendering of the scene around the robot. A environment editor and a programmable graphical user interface allow the customization of experimental frameworks.

The environment we design is a city with buildings, a river, and green spaces. Each of these elements has a specific color. Robot have to move across the city and learn how to avoid different kinds of obstacles.

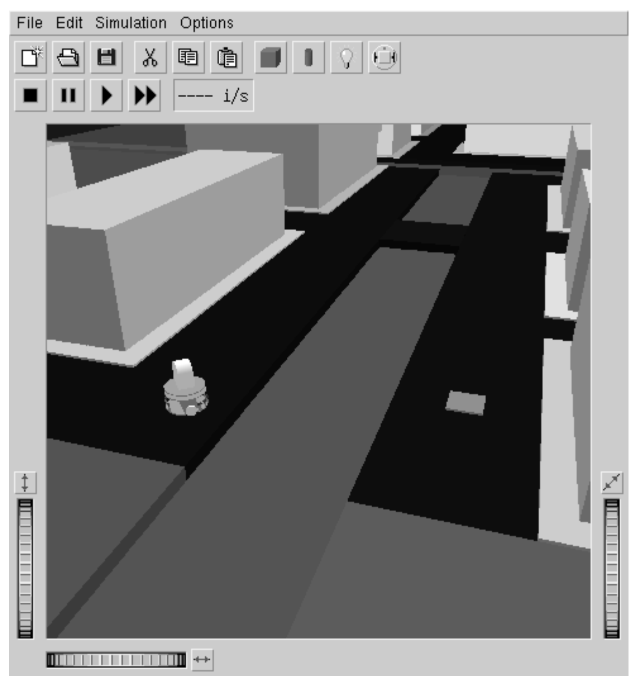

Figure 2: The virtual world (Webots simulator).

First experiment: Using a reflex reaction to avoid obstacles

Aim

In a first approach, we assume that emotion can be characterized by a reaction to positive and negative signals. Pfeifer (Pfeifer 1994) proposes an experiment in which such a signal is used to learn obstacle avoidance. This experiment appears to be interesting because emotion as a system of positive and negative signal emission is often used to create affective computing (see Picard 1997 ; chapter 5).

Model

Design The model is made up of four parts:

1. A reflex structure which produces a motor reaction in the opposite direction to an obstacle hit on an infra-red sensor.
2. An association matrix between the motor behavior and the sensor inputs provided by the infra-red sensors. This matrix is initially empty, i.e., each component is set to zero.
3. A signal, creating an association in the matrix each time the robot hits an obstacle.
4. A behavior system deciding either (1) to go straight when no hit and no known association occurred, (2) to fire a reflex behavior if a hit occurred or (3) to associate a motor configuration to a known sensor pattern.

Mathematical model An association matrix is defined :

- Each proximity sensor returns an integer value ranging from 0 to 1023 which is in turn transformed into an integer value ranging from 0 to 4. We consider only the six front sensors, therefore, there are $5^6 = 15625$ sensors configurations.
- Motor speed is an integer value ranging from -20 to 20 which is in turn transformed into an integer value ranging from 0 to 4. There are two motors, therefore, there are $5^2 = 25$ motors configurations.
- The matrix (sensor configuration * motor configuration = 25 * 15625) contains the weight for this association.

Learning rule: In the association matrix increment the weight between immediate motor reflex and previous sensors configuration

Algorithm

```
For each step
   Compute hit
   If hit > 0
      Compute motor reflex
      Do learning rule
      Do behavior (proceed motor reflex)
   If hit = 0
            Search the association matrix for the
                       strongest weight with this
                       sensor configuration
            If strongest weight > threshold (50)
               Do motor configuration associate
            Else do default behavior (Move forward)
```

Results

During the experiment, number of hits was recorded. After some time, we observed a decrease of the number of hits following a curve with three plateaux (see figure 3) :

Part 1 The robot learns rapidly how to avoid discrete obstacles (situated on the sides of the robot).

Part 2 The robot needs some more time to learn to avoid front obstacles and corner obstacles (such obstacles require a rotation of more than 90 degrees which change dramatically the trajectory of the robot).

Part 3 The number of hits slowly reaches zero, the robot learned how to avoid obstacles in the most current configurations found in its environment.

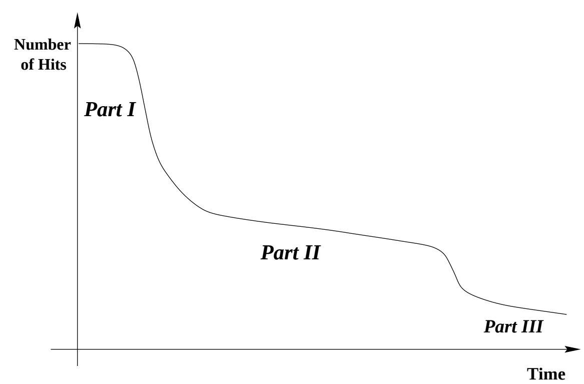

Figure 3: Evolution of the number of hits along the time.

Discussion

The number of hits, however, will never reach zero. Several problems inherent to the signal remain:

No signal: the sensors of the robot are not uniformly arranged around the robot and the robot may be unable to detect a small obstacle close to its wheels.

Strong or non-uniform signal: learning is sensitive to signal quality. A too strong signal leads to robot to spin round while a non-uniformly represented signal on sensors makes the robot follow the walls.

Inappropriate signal: each signal having an independent action on learning, a reinforcement action might turn out to be inappropriate in the next few iterations. For example, in some cases learning to turn left might lead to avoid obstacles in front of the robot, but doesn't always prevent from hitting an obstacle which might be on the left hand side of the robot, yielding a contradictory reinforcement signal.

These problems may be tackled in three different ways (1) Hardware improvement: improve the quality, number and arrangement of sensors. However, this might not be sufficient to tackle all problems. (2) Cognitive improvement: improve the learning process by implementing a powerful categorization system (like an ART network). (3) Affective improvement: improve the nature of the reinforcement signal (significance, gradually). This idea will be used in the second experiment.

Second experiment: Using appraisal to learn obstacle avoidance

Aim

This experiment will introduce the concept of appraisal which is fundamental in some theories of emotion (Frijda 1993; LeDoux 1996; Roseman, Antoniou, & Jose 1996; Scherer 1997; Leon & Hernandez 1998). The appraisal is the capacity to evaluate the relevance of a stimulus, using criterions based on the novelty, the displeasure, the significance to the goal, the potential of control and the ratio to the norm. In the previous experiment, we used only the pleasure/displeasure criterions. The second experiment will introduce new appraisal criterions.

Model

General Purpose A first attempt to survey and merge the different models of emotion was proposed (Leventhal & Scherer 1987). They demonstrated how an appraisal model, SEC (Scherer 1984; 1993), could be compatible with a hierarchical model of emotion. We found this model very interesting because it contains several levels and several components which seem relevant to emotion. Moreover, in our opinion this model seems compatible with other well known models (Damasio 1994; LeDoux 1996). These models feature:

Several layers: in which evaluations occur (sensory-motor, schematic and conceptual layers, according to Leventhal, first and second ways of evaluation, according to Ledoux).

Appraisal: stimuli are evaluated along given dimensions (SEC for Scherer, evaluations related to the body for Damasio).

Action state: evaluation produces a mobilization of cognition (alert process, according to Ledoux) or a representation framework.

Design The proposed model incorporates directly these features (see figure 4). We attempted to design an overall architecture relying at most on local computation (Minsky 1987; Brooks 1991). It's made up of the following items:

1. A linear evaluation system, where each evaluation stage is in turn used for the next evaluation, corresponding to the SEC model (first and second appraisal box).

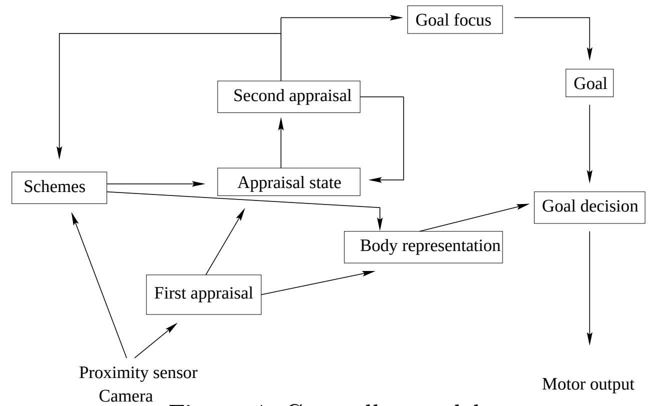

Figure 4: Controller model.

2. Two state systems: the first one provides a representation of appraisal while the second one provides a representation of the physical body (appraisal state and body representation box).
3. Two cognitive processes: The first one takes care to the attention selection and the second one handle the decision for the next move. The state systems can influence directly upon these two processes (goal focus and goal decision box).
4. A database of goal (goal box).
5. Three levels: sensory-motor (first appraisal box), schematic (scheme box) and conceptual (second appraisal box). The schematic level creates association schemes between significant patterns and actions.

Mathematical model We define two different processes : cognition and emotional processes. Each process is parallel and independent. Each emotion process is defined by an appraisal sequence defined as following:

Novelty compares the difference between a stimulus and a stack which contains previous stimuli (if difference $>$ threshold, return novelty, else return 0)

Pleasantness compares novelty result with an internal tendency, return -1 (disagreeable), 0 or 1 (pleasantness)

Goal significance accords behavior significance at previous pleasantness, return (if significance > 0 make behavior associate with this process)

Coping if significance > 0 and pleasantness < 0, start a counting (if value $>$ threshold, return negative coping (impossible to react), else return positive coping (possible to react)). Stop and reset counting if there are a change in significance dimension or pleasantness dimension.

Internal state contains average value returned by each emotional process. Body representation contains end of appraisal sequence (goal significance) following four body representations (right and left side ; front and behind).

Cognitive process : There are five goals (default goal (move forward) and secondary goal (turn left, turn right, follow left wall, follow right wall)). Each goal is defined by a value in the body representation. Goal focus process choses a single goal. Goal decision process merges current actually body representation and expects body representation (goal).

Learning rule In the previous controller, associations are independently and continuously learned. In this model, learning occurs each time the mean state contains a strong displeasure value. This produces a new scheme containing the newer stimulus as a sensory input. The process then waits to observe which goal is associated to this stimulus and check whether this goal allows to come back to a normal state. If this normal state is reached within a small amount of time, the representation is associated to the scheme, otherwise, the scheme is destroyed.

Algorithm

```
For each step
    do first appraisal sequence
       (-> check sensors)
    change body representation
    change state
    do schematic process
       (-> check each schemes existence)
    change body representation
    change state
    do second appraisal sequence
       (-> check changes in state)
    change goal focus
    change state
    do learning rule
    do cognitive process
```

Experiment

This experiment involves the use of the infra-red sensors for distance measurement as well as the 2D color camera. Only the bottom line of the camera is analyzed to extract relevant information about the closer obstacle to the robot. The color information (density and mean localization) provides informations on surrounding obstacles. The task of the robot is to learn to move towards areas in which the number of obstacles is minimum.

There are several level of difficulty the Khepera robot has to address: (1) Avoid the obstacles perceived by the infra-red sensors. (2) Avoid the areas where it's not possible to go (river, green spaces). This is made possible thanks to the supervisor module of the Webots simulator allowing to send signals to the robot when it enters such an area (just like policeman would do). (3) Avoid areas where it's unable to go (plates on the ground which the robot cannot climb up), but which provides no signal (the infra-red sensors cannot detect them because they are too low). (4)Learn to distinguish between obstacles and non-obstacles based on the color information from the camera and learn to avoid obstacles from their position.

Results

Obstacle avoidance In any configuration, the robot avoid various obstacles. The avoidance of objects perceived by the infra-red sensors occurs at the low sensory-motor level. The avoidance of obstacles which are not perceived occurs at the schematic level and corresponds to a temporary change of goal. This change is a consequence of either a danger signal, or an internal appraisal (evaluation of the movement based on the motor commands).

Learning Learning landmarks from color information was first performed by associating color areas to a process responsible for goal changing. But this yielded to instabilities in the system where the robot unable to come back to its initial goal or to continue the obstacle avoidance behavior. Hence, we used schemes relying on a body representation rather than control. This way, when a robot faces an obstacle, it associates the presence of an object to the creation of a pattern representing its body, that is, it creates a illusion of the object in front of its sensors, so that it can always avoid the obstacle and go towards obstacle-free areas.

Discussion

The model we used is rather complex for such a simple task. This complexity is an important factor of instability for the goal and decision levels: the robot either always remains on the same goal or it always changes its mind. However, we believe that the scheme creation capability is a very powerful and could be generalized to more complex systems. But it would be mandatory to define precisely the different levels of the influence of reactions on the cognitive processes (attention selection, creation of representation, etc.).

Conclusion

This paper investigates the role of emotion in cognition. We showed how emotion can be seen as an evaluation system operating automatically either at the perceptual level or at the cognition level, by measuring efficiency and significance. The information produced is not intended to be processed by a cognitive system handling classes. Rather, it's intended to induce changes at the attention and representation levels.

It seemed to us that the encapsulation of these two levels is at the origin of emotion. We think that the corresponding processes are continuously active in cognition, at least meaning that everything is all right. The various emotion feelings result from the strength of the evaluation of stimuli, ranging from vague feelings to emotional shocks. It seems now necessary to perform to a validation of these results by experimenting on human beings and comparing our model to humans controlling the robot based on the same inputs and outputs capabilities.

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