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An architecture based on emotions for growing up artefacts

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Abstract: - Contrary to what was advocated for a long time, the emotions were identified as essential for the emergence of intelligent behavior in real complex environments. The present work propose an architecture using functionalities similar to those emotions have in human cognition for an evolving robot diving in a real world environment.

Key-Words: - emotional architecture, growing up, adaptive robot, emotion and cognition, Artificial Immune System application

1 Introduction

Many research works in robotics and autonomous systems are focused on getting an agent to learn to do some task such as recognizing an object or reaching a specific place. The task can be learned, but in most of these works the robot's task was predefined by the researcher. The next logical step is to project an autonomous robot that can dive in unpredictable environments[1][2]. That means to investigate how robots that are capable of `growing up' through experience can be designed.

Living systems, starting from a pre-structured set of functions, develop competence to better adapt to the environment all life long. Steels in [29] claimed that the new level can "slave" the level or the levels below, or it is possible to see a kind of co-evolution towards greater complexity.

By growing up we mean that a robot starts with only some basic skills and an ability to sense and react to the world and then it develops new skills that were not entirely engineered into it at the start. A living artefact grows up when its capabilities, abilities/knowledge, shift to a further level of complexity, i.e. the complexity rank of its internal capabilities performs a step forward.

Growing up is an emergent mechanism. This means that it cannot be reduced to its parts. In other words, it exists at one level of structure but cannot be fully explained in terms of structure at a lower level.

But how does 'growing up' happen in nature?

What kinds of procedures do people activate to turn up this process?

What mechanisms are trigged off?

In [22] an experiment conducted with children dealing with the abstraction process, one of the growing up steps in their development toward an adult age has been described. Many useful ideas concerning the implementation of a growing up artefact emerged during this experiment: only some of them are currently considered within the framework of epigenetic robotics [21]

Results in [22]showed that some predefined and preferential sensorially based paths were used. The growing up process emerges from the complex combination of the results of these pre-wired elaborations with a strong connection to the emotional system.

The relationship between emotion and the growing up process becomes even more interesting if we consider that the human brain is a highly distributed and massively parallel system.

Damasio in [7] pointed out that emotion plays a very significant role in the success of the cognition process, for example by speeding up memory searches using emotional cues, by reducing the space of analysis to a set of reasonable hypothesis, or by providing a way to compensate the uncertainty of data gathered by perception.

During its early years, the AI world showed an apparent lack of interest in emotion for several reasons. The first one is related to the common and long debated misconception that emotion is the opposite notion of reason. Acting emotionally has always implied that the action would be impulsive and unthought, and therefore always less appropriate or efficient than action taken after a long reasoning process.

Emotion and reasoning have historically been placed on opposite fields. The only interaction emotion was considered to have with reasoning was clearly of a destructive nature. The other reason for the absence of emotion-based concepts in robot architectures is quite basic: we simply did not know enough about emotion to build a comprehensive model.

Only after the 1980 researchers had the chance to observe the brain performing in real-time using instruments such as CAT, NMR and PET. These techniques allowed researchers to thoroughly analyze the structure of the brain and to visualize its activity patterns and internal interactions, providing deeper insights into emotional system. Contrary to what was advocated for a long time, many properties suggest that something analogous to emotions might play an important role in growing up artificial creatures. In fact emotions are involved in many cognitive steps like:

- Control of attention: emotions influence perception and orient reasoning by focusing the attention on the most relevant features to solve its immediate problem (i.e.., [3],[23]).
- Memory filters: emotions allow better recall of events that are congruent with current emotional state [3] or events that were learned while the agent was on a congruent emotional state (i.e [3]).
- Assistance in reasoning: emotional system quickly obtains perceptual cues that can be used to direct the access to the cognitive information relevant for the cognitive system's deliberation (i.e.[7])
- Experiences recording: behavior tendencies or even stereotyped responses are usually associated with particular emotional scenarios. These built-in responses allow for appropriate behavior to be automatically triggered in emergency situations, avoiding spending unavailable time on elaborate reasoning.

When modeling emotional system, only the functional aspect of emotions in cognition should be taken into account and not the replication of the experience of human emotions as reported by the individuals' subjective cognitive observations agents [9].

For example, if in a *fearful* situation the human heartbeat is accelerated in order to prepare the body for a possible powerful response: in an artefact this could correspond to speeding up the processor clock to cope with a “dangerous” flow of data, or boost the global performance of the robot. Even if that heartbeat acceleration is triggered by a hormonal discharge (which is a communication mechanism between the brain and the body), it might not make much sense to try to introduce the idea of a “synthetic hormone discharge”[6] because a similar communication mechanism can be simply performed by means of a hardware or software interrupt. However, in both cases it would probably not be possible to sustain such a powerful state for a long time either due to certain physical limits, as in the case of human beings, or to possible energy and temperature constraints in the case of artefacts .

Emotions are deeply related to the evaluation of the robot’s capabilities to achieve a given goal. Goal includes both explicit formulations of desirable future states that the artefact seeks to achieve, and implicit states that *must* be reached or maintained.

Emotions can reflect the robot’ s capability (knowledge, action set, physical robustness, etc.) to cope with the current state of the environment when trying to achieve one or more of its goals. For instance, *Frustration* may reflect the inability to deal with the environment when attempting to achieve a certain goal. *Fear* may reflect the occurrence of something (externally or internally) that can be judged as dangerous or punishing for the robot.

The objective of this paper is to enhance the performance of the robot and not to improve knowledge about the nature of emotions themselves. Nevertheless, to be more concise and easier to be followed in this paper, I will use a language which might implicitly attribute human emotions to the robot. I always refer to ‘emotional words’ with a very limited functional meaning.

2 The emotion models

Basic emotions are emotional phenomena that can be quite clearly differentiated. Although cognitive researchers are still debating which emotions exactly constitute the set of basic emotions[7], *Anger, Fear, Joy, Surprise, Disgust* are usually considered part of that set.

In nature emotion are not single values, but processes, functions with characteristic activation and permanence times

They have well-defined objects and are very intense and usually they occur over a reduced time span (few seconds or minutes). Because of their strong intensity, an agent is, most of the times, clearly aware of its existence.

The intensity of emotional feeling can be used as supplementary or alternative input to certain high-level cognitive processes, such as decision-making or learning [11],[28].

Real-life environments are usually inaccessible and continuously changing. People deal with this complexity everyday. However, when someone is asked to rate the overall life satisfaction in a certain situation, human being will not trigger a multi-criteria evaluation process to reach a conclusion. This task would certainly involve a great number of factors, some of them uncertain or difficult to identify and quantify. Instead, people will find the answer simply by asking themselves “How do I *feel* about my life in this situation?” [26].

Our emotional system seems to be capable of *condensing* large amounts of dispersed information into a single and easily identifiable information unit. In complex environments, this information may be difficult to obtain because sources are disperse and noisy. Alternatively, the amount of information available may be so large that artefacts will simply not have enough computational resources to process it. Therefore, the information

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condensation provided by the feeling of emotion can actually become a very functional property.

Internal condensation states encompass and condense a set of emotions such as *Pleasant/Unpleasant*[6],[31]. Contrary to basic emotions, these condensation state may have no clearly defined object or antecedent. They are usually less intense, they may remain unconscious to the agent for most of the time. These condensation states may be originated by an intense or recurrent occurrence of an emotion or simply by environmental factors. They may last for a longer time then emotions.

Since emotions are essentially linked to artefacts' goals and capabilities, these condensation states work as a very functional relevance filter.

Figure 1The robot KURT2 in the IEIIT environment

The pleasant or unpleasant states usually associated with emotions can act as reinforcement (e.g [29], [5]) and are frequently pointed to as a source of interruption of behavior ([25]). This allows emotional system to motivate the agent to approach or avoid certain emotional scenarios. It is often assumed that human decision making consists of the maximization of peasant states (generated by positive emotions) and minimization of unpleasant states (connected to negative emotions e.g., [29]). Mowrer in [24] proposed that during learning stimuli are primarily associated with emotions which then drive the behavior associations.

Emotional phenomena are capable of amplifying the most relevant data for the agent (external *and* internal), taking into account the artefact's current capabilities to deal with those events.

3 The robot

We used a wheeled mobile robot platform originally designed for sewage pipe inspection (KURT2). The robot (Figure 1) has been equipped with six wheels, twelve infrared sensors that allow the detection of object proximity and ambient light, and two sonar sensors as well. The robot carries a standard laptop running the control software The microphone of the laptop can be considered as another robot sensor for the environment noise.

During the EC SIGNAL IST-2000-29225 Project, the Systemic Architecture (summarized in Figure 2) has been implemented on this robot as described in [18],[13] .

Within this architecture, from a number of classifier is associated to each set of sensor signals . Each feature extractor uses a different signal processing technique like Artificial Neural Networks supervised and unsupervised, isomaps, chaotic signal characterization, fft etc.

The sensory path (upstream) was designed to perform unsupervised categorization. Within the systemic architecture [18],[13], the action generators (AG) within higher levels generate control commands for the action generators in the level directly below. In addition, each action generator takes into account (input), the sensory information processed and classified within it's very building block. Thus the generated action depends on the commands (from higher levels), depends on the sensory information (same building block) and depends on the momentarily realised function within the action generator. The function of the action generator is influenced by the learning rules, following the goals and the paradigms of the schedule of development.

With this architecture, the robot learns through experience, and the learned behaviors gradually take over control from the initial basic-driven system.

KURT2 learns information that are relevant for its sensors, in its percepted world. Often these 'objects' are not perceptible or interesting elements for human beings.

The systemic architecture equipped KURT2 with some basic capabilities/abilities such as the ability to independently extract information from sensors, the ability to memorize interesting objects encountered along its path, and the ability to avoid obstacles and to follow the wall.

By utilizing these basic abilities, the robot can build a map of the environment, recognizing a route it has already taken or identifying an object it already met.

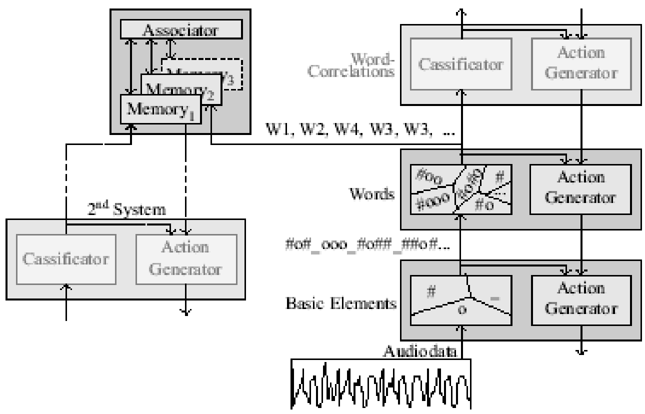

Figure 2 Systemic Architecture (from [19]) example of the audio subsystem

These abilities are equivalent to the paths sensorially based that children used in the experiment described in [22]: they

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allow the construction of a knowledge system strongly sensorially based.

During the experiments with the KURT robot with the Systemic Architecture the need of an Internal Values System allowing autonomous selection of actions coherent with drives emerged. This produced the architecture showed in

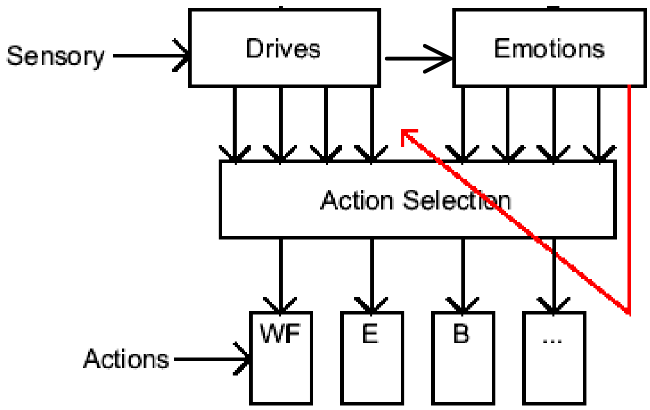

Figure 3Internal Value System

The core of the implementation (from [13]) is an action selection (AS) unit (shoen in Figure 3) which can choose between several actions to activate. It is possible to activate several actions in parallel, and/or for a predefined temporal interval. The envisaged actions have a complexity of: WF Wall Following, B Braitenberg

motivated obstacle avoiding movements, E Explorative moves, ...

The action selection rely on, and depend on . sensory values, and internal values called drives and emotions.

In a first implementation, the action selection was depending on the actual state of the set of scalar values that are denoted drives. These drives are a vector of internal values, representing an internal robot state. Thus the drives influence the action selection, and thereby are responsible for the chosen action, which in its consequence yield the behaviour, makes the robot move, and thereby will cause a change of sensory values (closing the loop to the drives).

The next implementation stage Has been to include a second set of internal values emotions. The emotions were depend explicitly on time and on the state of the drives-vector. They shall reflect if the drives have been fulfilled.

At first, in contrast to the output of the modules within the upstream path of the systemic architecture (typically classifiers) which are normally learnt in an unsupervised way, the values of the drives and the emotions were engineered.

4 The Internal Value System

Let us suppose that at the start, the robot is given some basic motivations such as ‘moving around the environment’, ‘ to explore the environment’, ‘to be social’. The robot should learn through experience, and the learned behaviors should gradually take over control from the instinct-driven initial system.

Let us define the main emotions of the robot as:

Negative emotions (generating unpleasant state):

- *Anger*: Mechanism triggered when the accomplishment of a goal is menaced. Anger is a mechanism capable of blocking influences from the environment.
- *Restlessness*: Mechanism intended to stop a repetitive behavior that is proving to be inefficient. The triggering event is a prolonged inefficient behavior.
- *Fear*: An emotional state triggered by the presence of ‘enemies’. It functions as a Defensive Mechanism.
- *Sadness*: Mechanism that is triggered by the inability to attain a specific goal and results in a global reduction in the activity . When the robot is “ Sad”, it enter a suspended state waiting for the occurrence of changes in the environment or in their internal state.

Positive emotions (generating pleasant state):

- *Happiness*: Mechanism intended to obtain re-equilibration after the accomplishment of a goal.
- *Interest*: Triggered by the presence of a novel object in order to stimulate the interaction with it.

The emotion' 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 gave rise to it is gone. The time scales involved in the persistence of an emotion after the stimulus is gone (particularly when in the presence of a new stimulus that favors another emotion) are quite small.

An emotion only influences the internal state if its intensity value is significantly large, i.e. its value is above an activation threshold. On the one hand, there is a competition between the emotions to gain control over the states which is ultimately what selects which emotion will be dominant.

The robot states are also dependent on its perceptions and on its condensation state.

The perceptions (external features) available to the robot are:

- *hearing*
    - o a sound is heard
    - o a loud sound is heard (negative reinforcement);
- *Eating*: high when the robot is acquiring energy,
- *Proximity:* reflects the proximity of the nearest obstacle perceived by the distance sensors; it can be in front, on the left and on the right end; the robot can perceive the presence of
    - o Sudden obstacle
    - o Obstacle
- *Bump*
    - o into an unforeseen obstacle (can cause high pain)
    - o into un obstacle (can cause light pain)

The Internal States Variables (internal features) are:

Negative states (generating unpleasant state)

- *Hunger* The robot's energy deficit;
- *Pain* i.e. if the robot is bumping into obstacles or if it receive a negative reinforcement
- *Boredom* Increases if the robot does not move;

Positive states (generating pleasant state)

- *Active* when robot is moving
- *Social* when the robot perceive an object slowly moving an object slowly moving

The possible actions are

- *exploration and map making*
- *obstacle avoidance*
- *flee*
- *wall following*
- *to push an object*
- *to turn left and right ,*
- *to move forward,*
- *to stop moving,*
- *to move backwards*
- *to attack*

Each action is performed for one step of time.
Emotions and Internal system values generate two condensation categories: *unpleasant* and *pleasant*.
The robot is happy if there is nothing wrong with the present situation. It will be particularly happy if it can receive a reward.
If the robot has very low energy and it is not acquiring energy, then its state will be sad or aggressive.
It will attack if it percept an unexpected object, with a loud noise.
If the robot bumps into obstacles then it will leave.
If the robot stays in the same place too long it will start to get restless. This will make it angry. The anger will persist for as long as the robot does not move away or change its current action. A hungry robot will tend to be more angry.
This way a value judgment can easily be obtained from the emotion model by considering the intensity of the current condensation state. The dominant emotion is the one with the highest intensity, unless no emotion intensity exceeds a selection threshold . In this case, there will not be a dominant emotion and the condensation judgment is *neutral*.
The Internal Value System should be a complex system able to deal with problems such as Parallel processing, long-lasting memory, self-knowledge, contextual recognition, noise tolerance and ability to generalize. In [8] De Castro says that, are naturally solved by the immune systems.

5. The immune system

The immune network model was first proposed by Jerne in [17] Jerne suggested that antibodies recognize foreign antigens, and are connected together in a large-scale network formed by chains of stimulation and suppression between communicating antibodies. Although still controversial in immunological circles, this model has been successfully adopted by many AIS practitioners, producing diverse applications from data-mining systems [30] to simple robot-control architectures ([16],[15],[14])
According to Jerne, an antibody-molecule has certain mechanisms for the reciprocal recognition. When recognizing each other, there is either a negative or a positive stimulus. A positive stimulus leads to an activation of the b-cell, causing the b-cell to clone itself and produce antibodies. Negative stimulus leads to suppression of the b-cell and later even to the dismissal of the b-cell from the network.

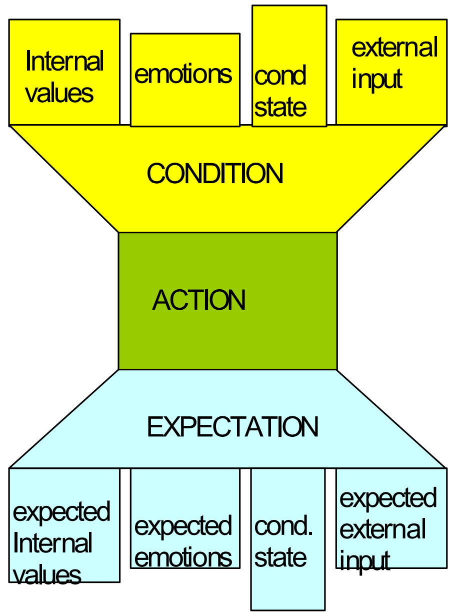

Figure 4Schematic representation of a RLA node

In this model this information of the robot experiences is held as a collection of *rule-like associations* (RLAs). Each RLA is a node in a network and consists of a (partial) description *C* of starting information (emotion status, internal values, condensed mood, external input) a robot action command *A* and a partial description of the expected effects *E*(emotion status, internal values, condensed mood, external input) of doing the action(see Figure 4). After creation, an RLA therefore expresses some of the expected results of doing action *A* in a context *C*, and weighted network links express the sequencing information; a sub-path involving strongly positive weights would express an episode. In immunological terminology, antibodies correspond to these RLAs, and antigens correspond to input data; the *C* and *E* parts of an RLA can be regarded as paratope and epitope. Much as in Jerne's immune network hypothesis, connections are formed and adjusted by a process of *recognition* between the paratope of one antibody and the epitope of another, and result in stimulation and suppression of one antibody by another, according to a dynamical equation suggested by Farmer in [10]. For further details see [14][15]

5.1 The algorithm

The RLA chain is a memory that maintains a record of relationship between conditions, actions taken, and the consequences of those actions. This episodic memory enables the robot to learn how to interact with the environment and to naturally form and round concepts within the RLA network.
The basic learning algorithm works as follows: The system is presented with environmental features extracted by the systemic architecture, an internal status vector , an emotional vector and a mood status that is function of previous internal values and emotions. Initial RLA values are randomly choosen. The algorithm then selects an RLA whose condition part is closest to the input situation (antigen). The system takes appropriate action based on the RLA (antibody). The algorithm evaluates whether the RLA correctly predicted the expected outcome from taking this action. If the system behaviour is in line with the desired outcome, the RLAs which produced this system behaviour receive positive reinforcement. This increases an RLA's weight corresponding to concentration in the immune system analogy. In the case of negative reinforcement, the RLA chosen is cloned and mutated (*clonal selection*) and the concentration is decreased. Also, RLAs that are connected to the RLA which generated negative reinforcement receive negative feedback.

6. Results

During the test runs it could be observed that the behavior at the beginning was always totally arbitrary, because of the initially randomly generated RLAs. After some time a clear improvement of the quality of the desired behavior improved. Increasing the number of iterations increasingly stabilizes the behavior, the robot follows one of its goals.
The links between RLAs can be used to express a sequence of condition/action pairs, so that strongly connected paths in the network represent a history of robot actions i.e an episodic memory, which is potentially useful for planning.
The emotion depends on the perceptions, but the emotion is still active long after the perception has been set to zero. In particular, the pain will quickly build up during the collision. This will make the fear emotion grow stronger and possibly overtake other existing emotions. When the robot finally manages to cease the collision, it still have pain not because the pain perception is still there, but because the mood associated with pain has a high value. So the fear emotion will persist and gradually decreases in value. This means that while the robot is gaining distance from the obstacle, the fear will still be there. Nevertheless, it will usually fade away as soon as a short distance is gained and the risk of further collisions has diminished.
A behavior similar to the emotional conditioning presented by Velasquez in [32]has been learned by Kurt2, where the fear emotional system acquires a new releaser for loud sounds. In that situation, KURT2 is being disciplined and as a result is subjected to some Pain. Pain will promote the activation of fear that in turn activates the flee behavior. Initially, the loud sound does not activate the fear emotional system by itself, and therefore the flee behavior will not be triggered. However, if both pain and stimulus loud sounds start occurring simultaneously the fear emotional system develops a new (learned) releaser associated with loud sounds. After some simultaneous occurrences of both stimuli, the new releaser will be able to activate the fear emotional system whenever loud sounds are sensed, promoting the subsequent activation of the flee behavior.

7. Conclusion

The model of emotions behaves appropriately when tested on the robot, in the sense that the robot consistently displays plausible contextual emotional states during the process of interacting with the environment. In particular the robot KURT2 learned the follow me behavior associating human voice and slowly moving obstacle. Furthermore, because its emotions are grounded in subjective “states", and not direct sensory input or “perceptions", it manages to avoid sudden changes of emotional state, from one extreme emotion to a completely different one. The more different the two emotions are, the more difficult it is to change from one to the other.

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