Towards a Model for Embodied Emotions

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***Abstract*— We are interested in developing A-Life-like models to study the evolution of emotional systems in artificial worlds inhabited by autonomous agents. This paper focuses on the emotional component of an agent at its very basic physical level. We adopt an evolutionary perspective by modelling the agent based on biologically plausible principles, whereby Emotions emerge from homeostatic mechanisms. We suggest that the agent should be embodied so as to allow its behaviour to be affected by low-level physical tasks. By embodiment we mean that the agent has a virtual physical body whose states can be sensed by the agent itself. The simulations show the emergence of a stable emotional system with emotional contexts resulting from dynamical categorization of objects in the world. This proved to be effective and versatile enough to allow the agent to adapt itself to unknown world configurations. The results are coherent with Antonio Damasio's theory of background emotional system [1]. We demonstrate that body/world categorizations and body maps can evolve from a simple rule: self-survival.**

I. Introduction

The importance of Emotions has been emphasized throughout the years in several areas of research. An interesting path has been traced by several researchers. There are findings in neuroscience, psychology and cognitive sciences indicating the surprising role of Emotions in intelligent behaviour. Specially interesting for us are the studies looking at physiological interferences, and the relation between body and affective states, as well to the evolutionary mechanisms. Emotions have an important role in behaviour and adaptation in biological systems.

In our modeling approach we share the neurobiological and evolutionary perspectives to Emotions [1], as discussed in the following sections.

A. Our perspective on Emotions

Going back to the 19^{th} century we find the earliest scientific studies on Emotions: Charles Darwin'[2] observations about bodily expression of Emotions, William James' [3] search for the meaning of emotion and Wilhelm Wundt's [4] appeal for the importance of including Emotions among the research topics in psychology studies. But for many years, studies on behaviour focused on higher level processes of mind, discarding Emotions altogether [5]. Still the ideas changed considerably throughout time, and nowadays Emotions are the focus of many researchers.

The line connecting mind and body, and the role played by Emotions in rationality came emphasized after Walter Cannon [6]. He suggested that there are neural paths from our senses that flow in two directions - the experience of an emotion and the physiological responses occur together. Later Silvan Tomkins [7], [8], Robert Plutchik [9], [10] and Carroll Izard [11], [12], [13] developed similar evolutionary theories of Emotions. They claimed that Emotions are a group of identical processes of certain brain structures and that each of them has a unique concrete emotional content, reinforcing their importance. Paul Ekman proposed the basic (and universal) Emotions [14], based on cross-cultural studies [15]. These ideas were widely accepted in evolutionary, behavioural and cross-cultural studies, by their proven ability to facilitate adaptive responses.

Important insights come from Antonio Damasio [16][1][17], who brought to the discussion some strong neurobiological evidence, mainly exploring the connectivity between body and mind. He suggests that, the processes of Emotion and Feeling are part of the neural machinery for biological regulation, whose core is formed by homeostatic controls, drives and instincts. Survival mechanisms are related this way to Emotions and feelings, in the sense that they are regulated by the same mechanisms. Emotions are complicated collections of chemical and neural responses, forming a pattern; all Emotions have some regulatory role to play, leading in one way or another to the creation of circumstances advantageous to the organism exhibiting the phenomenon. The biological function of Emotions can be divided in two: the production of a specific reaction to the inducing situation (e.g. run away in the presence of danger), and the regulation of the internal state of the organism such that it can be prepared for the specific reaction (e.g. increased blood flow to the arteries in the legs so that muscles receive extra oxygen and glucose, in order to escape faster). Emotions are inseparable from the idea of reward or punishment, of pleasure or pain, of approach or withdrawal, or personal advantage or disadvantage.

From a neurobiological perspective, the sequence of events in the process of Emotion, can be summarized as:

1) engagement of the organism by an inducer of emotion;
2) signals consequent to the processing of the object's image activate all the neural sites that are prepared to

respond to the particular class of inducer to which the object belongs. These sites have been preset innately, although past experience has modulated the manner in which they are likely to respond;

3) emotion induction sites trigger a number of signals toward other brain sites (for instance, monoamine nuclei, somatosensory cortices, cingulated cortices) and toward the body (for instance, viscera, endocrine glands).

Edmund Rolls [18], as Antonio Damasio [1], underlines the division of two concepts: Emotion and Feeling. The first corresponds to states derived from reinforcement stimuli; the second represents the real "feeling". A reinforcement signal brings information about reward and punishment. By the internal representation of an object, already biologically qualified as an emotion inducer (or acquired), generalization and association processes occur (e.g. fear: one snake ... all snakes). A perception followed by an emotional reaction can be the activation of a representation. The brain is modulated by reward/punishment processes, and its goal is to maximize rewards and minimize punishments [18].

We share some of Rolls ideas regarding the reward/punishment system, from the perspective in which the evolution of higher brain systems were guided by previous neurobiological predispositions [19]. Other implications of his ideas, specially in the relation between Emotion and Memory, are not part of our discussion. Nevertheless, this gives rise to an interesting discussion about interaction between affect and logic, Emotions and cognition. Sustained for an evolutionary perspective certain organizational principles in the brain might reflect emotional states.

For further details and references on Emotions, cognition and behaviour, please refer to [1] [19] and [20].

B. Arousal and Valence

An interesting approach to Emotions is the Dimensional Approach. In short, an emotion has at least two qualities: valence (pleasantness or hedonic value) and arousal (bodily activation). Both may be defined as subjective experiences [21]. Valence is a subjective feeling of pleasantness or unpleasantness; arousal is a subjective state of feeling activated or deactivated. A two dimensional model has been proposed to reflect the degree to which different individuals incorporate subjective experiences of valence and arousal into their emotional experiences [22]. In Fig. 1, there is a possible representation of this two-dimensional space.

C. Concept and Hypothesis

Due to a progressive change in theoretical studies in a broad range of areas, models of cognition, attention and behaviour now frequently include Emotions as part of the behavioural system. Emotional cues as states that might influence behaviour and adaptation is an idea that became stronger in the last decades, and gained special attention in computational models of cognition and behaviour [23], [24], [25], [26], [27], to cite but a few. Different perspectives were adopted when working with Emotions. While some of these models are

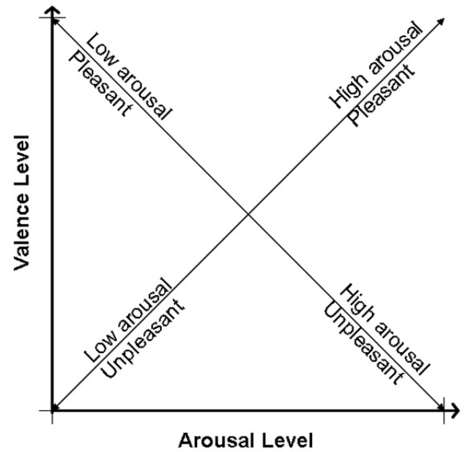

Fig. 1. Arousal-Valence Space.

inspired by different properties of an emotional system for task solving issues, and specific application (e.g. using facial expressions for social engagement), we are interested in using computational models to understand the basic mechanisms of the emotional systems. We are interested in studying how these systems evolved, which mechanisms do they use, and the role of the body.

We created a conceptual A-Life model to implement artificial worlds inhabited by autonomous emotional agents, modelling the agent based on biologically plausible principles. We focused on the idea of having an embodiment (in the sense that the agent has a virtual physical body whose states can be sensed by the agent itself) so that low level tasks (e.g. satiate body needs) influence its overall performance, by affecting its behaviour. A neural network endows the agent with cognitive capabilities, processing information related with its body, and its environment. The agent's emotional state is mirrored into a set Background Emotions. This term is used by Damasio [1] for the responses caused by "...certain conditions of internal state engendered by ongoing physiological processes or by the organism's interactions with the environment or both"[1].

The agent learns through a reward and punishment system, to adapt itself to the environment by interacting with it. Our algorithm is inspired on Rolls' "Stimulus-Reinforcement Association Learning" [28]: (:..) stimuli or events which, if their occurrence, termination, or omission is made contingent upon the making of a response, alter the probability of the future emission of that response. Moreover, some stimuli are unlearned or primary reinforcers (e.g. pain), while others may become reinforced by learning, because of their association with such primary reinforcers: the secondary reinforcers"[2]. We use the arousal/valence dimensions referred in the previous subsection, to scale and quantify the interactions results. This way we intend to create the basis of we believe to be essential for the emergence of an emotional system (in the sense

[1]page 52.
[2]page 601.

that acts such like mechanism): a body, a brain, and their interaction.

In this model, Emotions act as an adaptation mechanism. We implemented the agents' background structure, which will eventually allow us to contextualize the foreground emotional system (and the so called Basic Emotions [14]), in order to define the agents's foreground (to use Damasio' terminology) emotional state.

The aim of this exercise is to design an embodied agent-based cognitive model and establish how an emotional system can emerge from self-regulatory Homeostatic Processes, by the interaction between a body and a brain. For that we propose a model of these biological mechanisms. The objective is to understand the role and the importance of Emotions in self-survival tasks; hence one of the reasons to implement a single-agent system at this stage. We also are interested in studying how the regulation of the Homeostatic Processes can influence world categorization and decision making (currently at a low level and for single tasks). We also analyze how Emotions act as a system of internal rewards, that preserve the system, and permit continuous adaptation process in self-survival tasks, by signalling and scaling pleasant or unpleasant interactions.

II. The Simulation Environment

The simulation environment (programmed in C++) is represented as a two-dimensional world populated by several objects (See Fig. 2). An autonomous agent inhabits this artificial world and is able to move within the borders that define its limits. The objects have different representations (see Table I). Each one of them is related with a physiological interference. We also created obstacles in the world that, in the simplest case, are only the topological limits (or borders) of the world; these borders are considered as sources of pain.

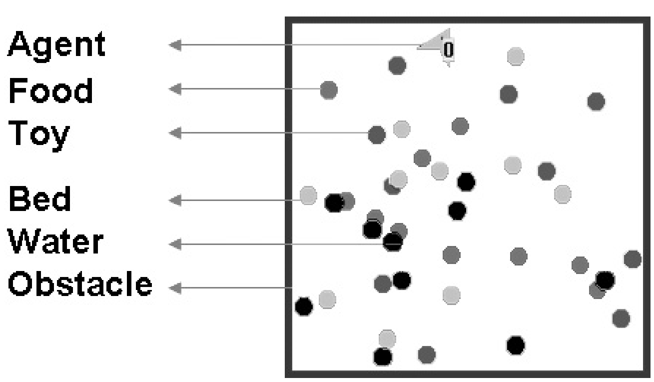

Fig. 2. The artificial world.

In short, we have an autonomous agent, which has to adapt itself to a world by controlling self-survival tasks, and by attributing emotional meanings to objects; objects might have different meanings for different situations. No representation or meaning of these objects is given to the agent beforehand. In order to design the autonomous agent, its structure includes cognitive, emotional and embodiment systems, endowing the agent with capabilities of interacting with the world, sense the body and the world, and learn from that.

Object color	**Representation**	**Physiological interference**	**Motivation**
Red	Food	Increase Blood Sugar	Eat
Green	Bed	Increase Energy	Rest
Blue	Obstacles	Increase Pain	-
White	Water	Increase Vascular Volume	Drink
Pink	Toy	Increase Endorphine	Play

TABLE I

Objects representation and interferences.

III. The Autonomous Agent

We developed a versatile structure for the agent, which will allow us to extend it as the project develops; e.g., the creation of a truly interactive artificial society. Currently, the agent comprises three main formalized systems: Perceptual System, Nervous System and Motor System. These structures will be developed at a later stage in order to incorporate more complex interaction interfaces between agents and interaction with more complex objects (possibly associated with higher level tasks in the world). As a basis to create this system, information is stored as "genomic" structure, that represents the characteristics of the body and nervous system of the agent. We emphasize the fact that no structure was explicit coded for Emotions: we are studying the possibility of an emergent phenomena due to the modelled biological system.

A. Perceptual System

In order to perceive the world, an agent contains a retina (here represented as a color array) that resembles a biological retina on a functional level, inspired in LIVIA [29] and GAIA [30]. It senses a bitmap world (environment) through a *ray tracing* algorithm, which is inspired on the photons travel from the light-emitting objects to the retina. At each time step, an agent fetches in a certain number of directions for visual input from its world. Each light ray that hits the sensing cells is traced to its origin in order to determine its intensity and colour, which feeds directly a color array. This array is then relayed to the nervous system. Each of the five colors is mapped into 4 neurons in the neural network input, as seen in Fig. 3. The directions in which the agent fetches the objects is calculated by Equation 1 (where *i* stands for the direction index, and α_i the fetching angle for each direction).

$$\alpha_i = \frac{2 \cdot \pi \cdot i}{retina\_size} \tag{1}$$

Another characteristic is the attenuation of visual cues in function of the distance of the objects in relation to the agent. There is a maximum value for distances in which the agent can see (*sight_range*). Colors are linearly attenuated according to their distance from the agent. That is, a *foggy world* was created. Currently, the agent has a sight range of 80 pixels in a 250x250 bi-dimensional world. Both *retina_size* (number of fetching angles) and *sight_range* are coded into the "genomic" structure of the agent.

B. Nervous System

The nervous system includes a feed-forward neural network (NN) with a genetically encoded structure (fixed during life-time). The neural network is organized in layers: an input layer (two groups: retina and body sensors), an output layer (two groups: motivations and motor control) and a hidden layer (with excitatory-only and inhibitory-only neurons). We distinguish between excitatory and inhibitory hidden groups due to the fact that the agent will have to perform tasks related to the activation or inhibition of certain behaviours. In the current version of the nervous system, each neuron of a layer connects to all neurons of the following layer. The inputs are propagated to the output through the synapses, processing one layer at the time from the input to the output. Each area has projections (a group of synapses) to any other area of the following layer. In Fig. 3, we present the NN architecture. Table II shows the current values that define the NN architecture.

Group	Number Neurons	Number of Synapses
Retina	20	$20 \cdot 16 = 320$
Body Sensors (Drives)	5	$5 \cdot 16 = 80$
Hidden Layer	16 (8 excit.+8 inhib.)	$16 \cdot 9 = 144$
Motivations	6	0
Motor Control	3	0

TABLE II

THE VALUES FOR THE NEURAL NETWORK ARCHITECTURE.

The activation function for the input neurons is presented in Equation 2, while the activation for all other neurons is calculated by Equation 3.

$$F_{input} = \left(\frac{\tan^{-1}(x)}{\pi/2} \right) \tag{2}$$

$$F = \left(\frac{1}{1 + \exp^{-\alpha \cdot x}} \right) \tag{3}$$

C. Motor System

The concept of Emotions, and body relatedness imply the notion of an interactive embodiment system.

We created a simple structure for this: the agent controls a motor system through linear and angular speed signals, allowing it to travel around the world (including obstacle avoidance and object interaction). These signals are provided by the neural network, which means that motor skills also have to be learned. With this capabilities the agent will be able to navigate in its environment, approaching or avoiding certain states. This constitutes an important aspect for this study.

D. Embodied Emotional Process

As a starting point, we shall highlight one important aspect: rather than model emotional systems, we are interested in modeling the basic biological interactive elements (body and brain) from where Emotions and Feelings might emerge. In other words, we are interested in modelling the conditions for the emergence of Emotions, instead of programming Emotions.

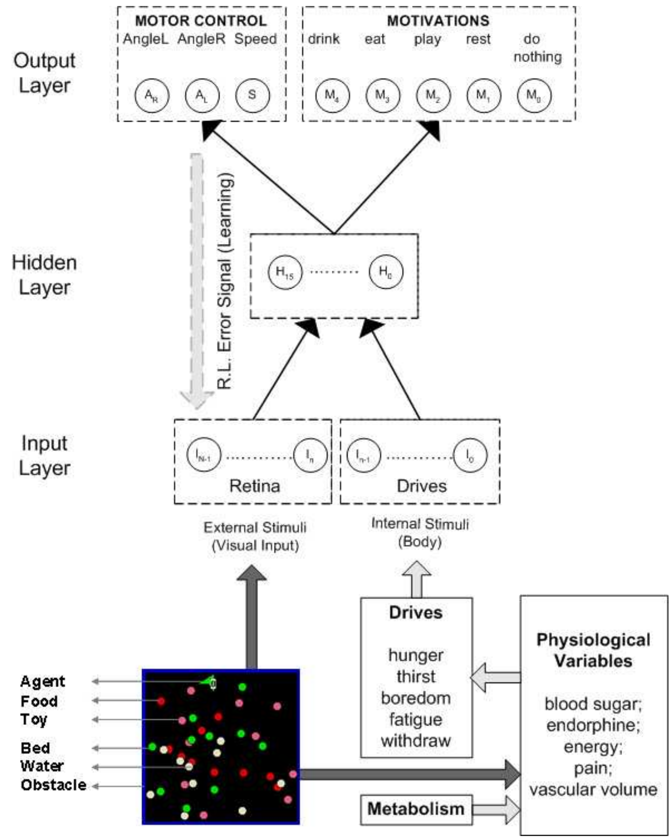

Fig. 3. Body/Brain interaction. System overview.

Fig. 3, gives a simple overview of the system. Inspired by Izard's work [13], we categorized the stimuli sensed by the agent as follows:

1) Somatic - body state (physiological data, drives);
2) World Perception (vision);
3) Body - external interactions (pain).

The agent perceives the world through a retina, and this signal is used to feed a set of input layers of the NN, together with its internal body state.

The body state consists of a map of the agent's body. We introduce a set of Physiological Variables into the agents embodiment (see Tables III and IV) that reflect the state of the agent's body. They range from a minimum to a maximum values, centered on an ideal value. Physiological state is affected by the agent's interaction with the environment (metabolism and objects).

E. Drives and Motivations

The Drives define the current and past body states that drive the agent attention towards specific needs. They are controlled only by the agent body, which reacts to its environment, with no other interference. They translate physiological changes into specific alarms or urges to action (e.g hunger if blood

Physiological Data	Range	Variation
Blood Sugar	10 - **30** - 50	metabolism: $K_{BSugDec}$*speed food: $K_{BSugInc}$*FoodValue
Endorphine	0 - **20** - 40	metabolism: K_{EndInc} toy: K_{EndDec}*ToyValue
Energy	100 - **120** - 140	metabolism: K_{EnDec}*speed bed: K_{EnInc}*RestValue
Vascular Volume	5 - **25** - 45	metabolism $K_{VVolDec}$*speed water: $K_{VVolInc}$*WaterValue
Pain	**0** - 20	metabolism $K_{PainDec}$ obstacles: $K_{PainInc}$*speed

TABLE III

PHYSIOLOGICAL DATA, DRIVES, AND THEIR DYNAMICS.

Constant	Value
$K_{BSugDec}$ $K_{BSugInc}$	-0.0050 0.50
K_{EndDec}) K_{EndInc}	-0.50 0.0020
K_{EnDec} K_{EnInc})	-0.0030 0.50
$K_{VVolDec}$ $K_{VVolInc}$	-0.0080 0.50
$K_{PainDec}$ $K_{PainInc}$	-0.005 0.50

TABLE IV

PHYSIOLOGICAL VARIABLES CONSTANT VALUES

sugar is low). They vary from a minimum of -10, and to a maximum of 10. The value indicates the excess or absence of certain stimuli in the body, specifically certain physiological needs (by excess or deficit). In any moment the agent can be hungry or not hungry, tired or energetic, etc. This takes in consideration the existence of a "temporary memory": in each moment the drive contains physiological information from the last M (see Equations 4 and 5) time steps. M corresponds to the agent' memory size, where past states influence is attenuated, while ΔV_i corresponds to the deviation of the drive value from its homeostatic position (value between -10 and 10).

$$DriveValue(t) = K * \sum_{i=0}^{M} \left(\Delta V_i * K_i \right) \tag{4}$$

$$K_i = \frac{1}{i+2}; K = \frac{1}{M+2} \tag{5}$$

For instance, a growing level of Blood Sugar level during a certain period, will increase the Hunger drive. This implies a change on the body state (see Fig. 3), and consequent effect on other neural process (e.g. decision making), since they share the same neural network.

As defined in Sec. II, changes in the body state are caused by interaction with objects. But, as shown in Table III, the environment also changes the body of the agent indirectly because of its metabolism. Agent's ongoing tasks (when not interacting with objects) change its internal physiological data; i.e., corresponding to a decrease/increase in a physiological variable according to the metabolism (decrease blood sugar, increase pain, etc.). At each iteration, each Drive is feed and propagated into the NN together with retina signals.

To express its desire to act in the environment, the agent possesses a set of Motivations. These correspond to the level of will to adopt a certain behaviour (Eat, Drink, etc.). The Motivational System is controlled by the neural process. One action is chosen from the Motivations set (neural network output layer), according to a *roulette* algorithm: Motivations with higher value (higher output neurons activation), have more probability of being chosen (see Fig. 3).

F. *Background Emotions*

The agent's emotional state is processed in parallel and is mirrored into a set Background Emotions (see Sec. I-C). Background Emotions (see Table V) are obtained from the analysis of the Goal System (See Table VI), and the body. The goal system corresponds only to self-survival tasks, related with body state evolution. They reflect the success or failure of a certain self-survival task or behaviour.

Background Emotion	Affected by
wellness/malaise	survivalGoal
relaxation/tension	pain, survivalGoal
fatigue/excitement	energy, ongoingGoal

TABLE V

BACKGROUND EMOTIONS.

Goals	Description
survivalGoal	survival status (0%-100%, low fitness-high fitness)
ongoingGoal	successfully achieved tasks

TABLE VI

GOALS.

G. *Reward and Punishment: "feeling" the interaction*

Learning is performed by means of an algorithm inspired by the TD-Learning technique, a type of reinforcement learning algorithm [31]. One characteristic of this algorithm is that it associates a Q-value (the predicted reward) with each output continuously, corresponding to the desirability of choosing that behaviour. The reward received in the future (when the task finishes, successfully or not) is used to update the weights that activated the chosen outputs by means of a back-propagation algorithm.

As introduced in Sec. I-C, Emotions are usually associated with either pleasant or unpleasant feelings that can act as a reinforcement [32][28]. For that we created a different reward scheme. The outputs (see Fig. 3) do not have an associated Q-value. Rewards depend on the agent's actions: they are proportional to their effect on the agent's well-being, and their valence (positive or negative) depends on the pleasantness of the new body state. These rewards are received after interacting with the world, reflecting the consequences of the action performed.

There are two types of rewards: one for the movements and another for the chosen motivation. They are used to update the weights of the NN using a back-propagation algorithm. The agent's internal representation of the objects is an important aspect of the model. The learning process enables the agent to attribute meanings to the objects. They don't have any internal explicit representation.

The following steps are taken in a complete cycle of the system : the new body states are calculated according to the interactions (objects and metabolism), new body state is compared with the previous body state (e.g. pain increase), Goals and Background Emotions are updated, reward is calculated according to the arousal and valence of the interaction (huge pain augment implies negative reward - high arousal, negative valence), the neural network inputs (retina and drives) are refreshed, and finally the neural network outputs are calculated (and new Motivation and movement chosen).

IV. SIMULATION RESULTS

With this framework we aim, at this point, to test three main hypothesis:

1) An emotional system can emerge from the interaction of self-regulatory Homeostatic Processes and the Environment;
2) The regulation of the Homeostatic Processes influences world categorization and decision making by attributing emotional meanings to objects, and by affecting cognitive processes (e.g. driving attention);
3) Emotions act as a system of internal rewards, that preserve the system, and permit continuous adaptation process in self-survival tasks, by signalling and scaling pleasant or unpleasant interactions/stimuli.

We analyzed several simulations. Each simulation ran with different initial weights of the NN, which were randomly generated. One agent was inserted in a world populated with the objects as referred in Sec.II. Each simulation ran for 40000 cycles. (Each cycle corresponds to an agent's time step to update internal variables, apply Reinforcement Learning, receive and process stimuli, propagate data through the NN, and choose the next action). The following data corresponds to a representative set from our experiments.

A. Adaptation and Self-survival

This section analyzes the agent's ability to regulate its Homeostasis. We assessed the degree of adaptation (Fitness) of the agent, through a Fitness[3] function that expresses the body state of the agent: the agent's *health coefficient*.

$$fitness = 1 - \left(\frac{1}{n * DriveMaxLevel}\right) \cdot \sum_{k=1}^{n} \cdot |drives_i| \tag{6}$$

[3]We use the Fitness concept due to the fact that we are already using Genetic Algorithms in our ongoing work.

DriveMaxLevel stands for the absolute maximum level that Drives can have (10, in the current version), while *n* corresponds to the current number of Drives (five) and $drives_i$ to the value of each drive (numbered from one to five).

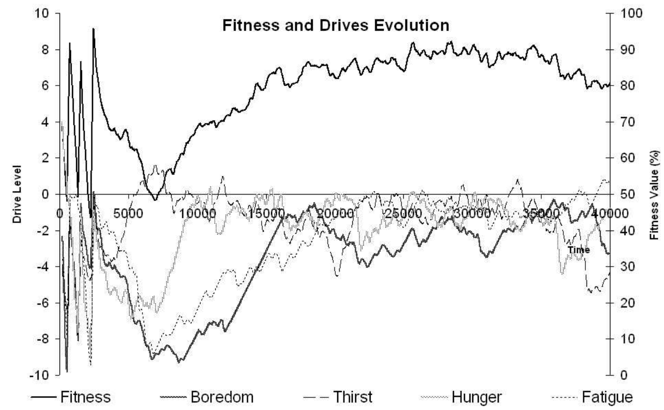

Fig. 4. Fitness and Drives evolution in time: representative simulation 1

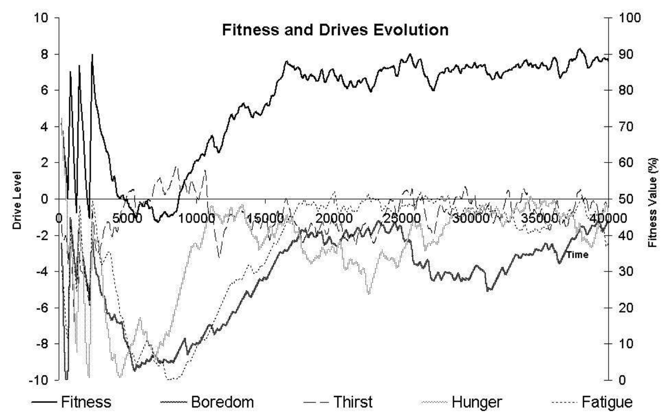

Fig. 5. Fitness and Drives evolution in time: representative simulation 2

Figs. 4 and 5 show the relation between the Fitness function and the evolution of Drives for two representative simulations.

The evolution of the Fitness value in time shows an overall increase of the agent's ability to regulate its body state by interacting with the world. In fact, it can be seen in both charts that after an initial unstable phase the agents were capable of associating the resources in the world with their own internal needs, and use these resources as they needed. Another interesting phenomena can be seen by analyzing the Drives variation in time: when learning allows the agent to reach a stable situation, the Drives variation is maintained within a range of values near to the optimal value (i.e., 0). The agent is not only capable of increasing its Fitness, but it does so maintaining a "healthy behaviour". Extreme body states are avoided, showing the ability of the agent to regulate its own body status, by coping with its metabolism and managing competitive internal stimuli. Note that, as an initial help for the system to learn, when the fitness value is below 40%, the agent's physiological data are reset to their initial values. This explains the initial picks in the first iterations on the chart.

These results are coherent with our hypothesis. In fact, the properties of an emotional system, can emerge from the interaction between an organism self-regulatory Homeostatic Processes and its Environment (the fundamental role of the body), through the learning process used. The attribution of emotional meanings to objects, through Associative Learning driven by the body, proved to be effective and fundamental to adaptation process.

B. Categorization

We analysed the system further in order to better understand the dynamics of the NN and the learning process. Specially, we wanted to study the effect of the reward system. We suggested previously that an agent would be able to categorize objects in the external world by giving meanings to objects in relation to their body state: the emotional categorization of objects. For these tests we analysed the hidden layer activations of the agent presented in Fig. 4, using Principal Components Analysis (PCA).

To test the NN categorization process, we presented the agent one object at a time. For each object we activated all Drives to their maximum level (also one at the time, see Table VII). For instance, in a state of Hunger, all five objects in the environment were perceived individually. The clusters seen on the PCA chart (Fig. 6) group the stimuli for each object presented to the agent in the tests phase.

Input Number	Object
1-5	Food (Red)
6-10	Bed (Green)
11-15	Obstacle (Blue)
16-20	Water (White)
21-25	Toy (Purple)

TABLE VII
NN OBJECTS STIMULI.

It can be seen that the agent was able categorize the world. In fact, identical external stimuli (objects) are represented internally in a specific and dedicated way.

But how does the agent contextualize the object with its body state? When does it decide to interact with objects in order to survive? Taking a deeper look at these clusters, we can find patterns that are identical to each other. Our hypothesis is that they may represent a second categorization level. A new test scenario was created to analyze these important aspects: in the presence of related object, we varied each of the agent's drives from its minimum value (-10) to its maximum value (+10), considering steps of 2 units (-10, -8, ..., 8, 10). See Table VIII. In Fig. 7 we plotted the PCA analysis for the 1st and 2nd Principal Components of this test case, using the object Food, and the drive Hunger.

There is a clear definition of the different drive levels: starting from the extreme need of food (measures 1-4), passing through the absence of the hunger stimulus (measure 6), to the representation of excess of blood sugar (measure 8-11). The agent can identify its own body needs and attribute dynamical meanings to the objects by a 2nd level categorization. It is evident by the sequence the complete separation of the different states of well-being (over-stimulated, homeostatic level, under-stimulated). These results are aligned with our Hypothesis (3): the signalling and scaling of pleasant or

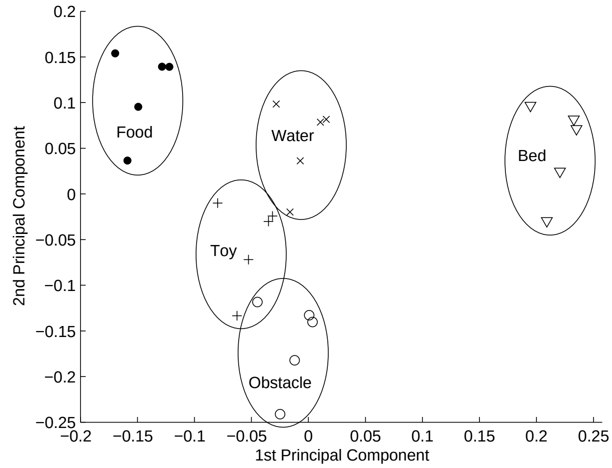

Fig. 6. PCA: Categorization Process

Input Number	Active Drive
1, 6, 11, 16, 21	Hunger
2, 7, 12, 17, 22	Thirst
3, 8, 13, 18, 23	Boredom
4, 9, 14, 19, 24	Fatigue
5, 10, 15, 20, 25	Withdraw

TABLE VIII
NN DRIVES STIMULI.

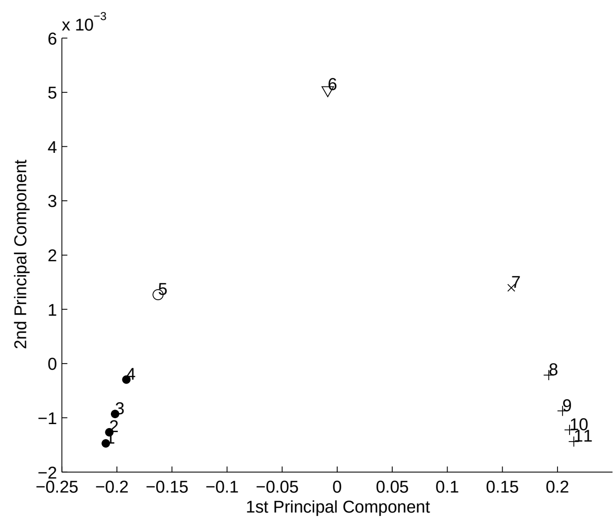

Fig. 7. PCA: variable Hunger level internal representations.

unpleasant interactions/stimuli .

C. The Role of the Body

Next, we tested the detection of "emotional-competent-stimulus" [1], as defined by Damasio. These would be objects or situations (present or remembered) that would lead to a specific emotional state, which could be observable in a stable emotional system.

We considered 3 test cases:

1) No body stimuli (only visual stimuli);
2) No visual stimuli (only body stimuli);
3) Both.

In Fig. 8 drives were kept at zero level (Homeostatic Regime) and we presented each type of object to the agent (no body stimuli) - test case 1. Then, each drive was activated at its maximum level, and the agent was isolated from the environment (no visual stimuli) - test case 2.

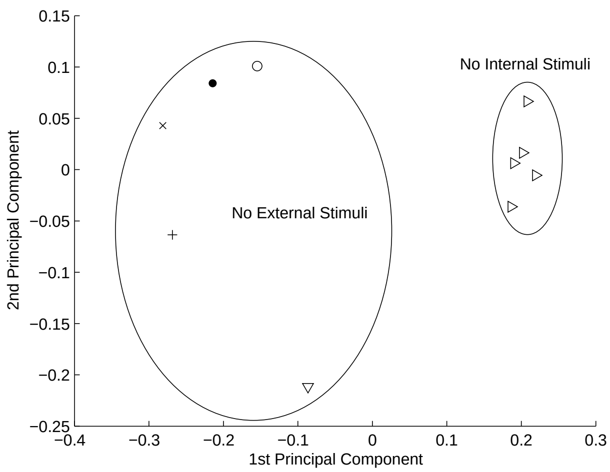

Fig. 8. PCA: test cases.

In Fig. 9 we plot the previous test plus additional more test cases (11 to 15 in the chart): we activated each drive to its maximum level and presented the object that would satiate that need of the agent (e.g. high hunger level in the presence of food) - test case 3.

From both figures, it can be seen that when the agent was situated in its Homeostatic Regime (all drives at level 0, test case 1), objects were categorized within an emotional meaning, not showing special distinction between them. The variance values for each test case can be seen in Table IX [4]. By comparison with the other test cases, test case 1 variance, can be considered very low. This seems coherent with our expectancies, taking into account that the objects have a meaning when related with the body. Even though a discrimination among objects can be seen: probably an influence from the new neural predisposition (after interacting and learning with the experience).

[4]The variance was calculated for the different test cases using the first 3 Principal Components. The presented values for the variance are separated by dimension.

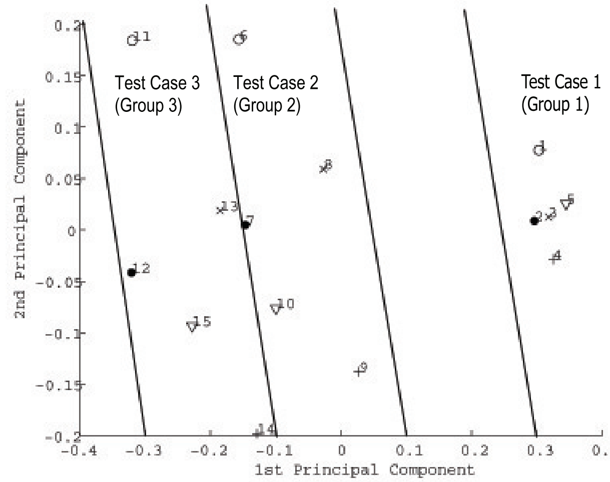

Fig. 9. PCA: test cases.

Test Case	Component 1 (x)	Component 2 (y)	Component 3 (z)
1	0.0004	0.0015	0.0026
2	0.0062	0.0156	0.0144
3	0.0071	0.0201	0.0127

TABLE IX
VARIANCE VALUES FOR THE FIRST 3 PRINCIPAL COMPONENTS (DIMENSIONS).

In the absence of external stimuli (test case 2) the agent identified clearly its body state, and its body needs trough the creation of an implicit body map (i.e., a internal representation of the body state). This fact becomes even more evident in test case 3, when the object to satiate the body need is present (Fig. 9): objects and drives are strongly associated, showing that the agent acquired specific ways to respond to specific internal and external events (similar symbols refer to the same Drive).

Distance	Value
d_{31}	0.4092
d_{32}	0.0365
d_{21}	0.3754

TABLE X
DISTANCES BETWEEN CLUSTERS' ATOMIC POINTS.

Summarizing, several facts can be observed: the variance in test case 1 ("*no-internal-stimuli*") is lower than in both other test cases; test case 3 results are closer to test case 2 results ("*no-external-stimuli*"), than to test case 1 (see Table X): $d_{31} = 0.4092$ (distance from groups 3 to 1), and $d_{32} = 0.0365$ (distance from group 3 to 2); group 1 presents a similar pattern to the other groups, an influence in the categorization process.

These observations indicate a great influence of the body on the cognitive processes, in the case related with the internal representation of a perceived object. Indicates also the preferential perceptual processing regarding the pleasant or unpleasant “meaning” of objects, influencing the accuracy of object representation during the perceptual process. There is a scaling factor for the object’s internal representation (as seen in the previous section). These results are strongly coherent with Damasio’s theory [1].

V. Conclusion and Future Work

Damasio refers to the importance of Emotions in assisting an individual to maintain its survival because they seem to be an important mechanism for adaptation and decision making in dynamical systems [1], [16], [17]. In this phase of our work we focused on the basic foundations of Emotions from an evolutionary perspective: we assumed the existence of neural pathways that facilitate survival. Moreover we use the dimensional approach (arousal/valence), together with an Associative Learning process [28], to drive adaptation contingencies, using the body to drive such process.

We addressed the notion of the emergence of a stable emotional system by means of self-regulatory Homeostatic Processes. In the previous section we demonstrated that it is possible to model such phenomenon. As suggested by Damasio [1], environmental events of value should be susceptible to preferential perceptual processing regarding their pleasant or unpleasant meaning. We believe that the architecture and specially the reward system (the agent’s appetite for well-being) were responsible for the emergence of stable emotional systems in our simulations. Furthermore, the results are coherent with Damasio’s convincing theories about the existence of a background emotional system [1]. We demonstrated that phenomena such as body/world categorization and existence of a body map can evolve from a simple rule: self-survival. As already discussed in the previous sections, we were able to evaluate our hypothesis.

Our model also demonstrated that physical restrictions (even with a very simple artificial embodiment) can play an important role in the adaptation of the agent to its environment. The use of a learning algorithm based on the environment and embodiment allows for the agent’s “brain” to dynamically categorize the world regarding bodily, environmental and individual aspects (metabolism). Agent and environment are strongly coupled in learning and living. The emergence of a stable emotional system (albeit in low level tasks), potentiated dynamical categorization of objects due to their emotional context, proving to be effective and versatile enough to allow the agent to adapt to an unknown environment.

Currently, we are looking at more complex tasks to be performed on top of our background emotional model. We are in the process of defining a system of foreground emotional states, and developing the current one. A more close investigation about the changes in the body state due to an induced emotion, is also an interesting perspective. At this stage we will then be able to develop our investigations on the role of music in emotional states, and on the possible existence of co-evolutionary mechanisms reinforcing the relation between Emotions and Music.

On the long run, we hope to apply our model to decision making tasks (e.g. music composition), as it allows to reduce the space state of choices, through an emotional categorization. Another interesting perspective comes from recent claims, specially in Robotics, more specifically in a new field: Internal Robotics [33].

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