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The Psikharpax project: towards building an artificial rat

Jean-Arcady Meyer[a,*], Agnès Guillot[a], Benoît Girard[a,c], Mehdi Khamassi[a,c], Patrick Pirim[b], Alain Berthoz[c]

[a] *AnimatLab/LIP6, Université Paris 6, CNRS, France*
[b] *BEV, France*
[c] *LPPA, CNRS, Collège de France, France*

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Abstract

Drawing inspiration from biology, the Psikharpax project aims at endowing a robot with a sensory-motor equipment and a neural control architecture that will afford some of the capacities of autonomy and adaptation that are exhibited by real rats. The paper summarizes the current state of achievement of the project. It successively describes the robot's future sensors and actuators, and several biomimetic models of the anatomy and physiology of structures in the rat's brain, like the hippocampus and the basal ganglia, which have already been at work on various robots, and that make navigation and action selection possible. Preliminary results on the implementation of learning mechanisms in these structures are also presented. Finally, the article discusses the potential benefits that a biologically inspired approach affords to traditional autonomous robotics.

Keywords: Artificial rat; Navigation; Action selection; Learning

1. Introduction

Since the 2-month workshop in Dartmouth College that founded the field of artificial intelligence in 1956, and since the enthusiastic comments on the prospects of the discipline that this event triggered [47,19], serious doubts have been raised (e.g., [16,17]) about the chances that an artificial system might compete in the near future with the amazing capacities exhibited by the human brain. In particular, several researchers consider that it is quite premature trying to understand and reproduce human intelligence – whatever this expression really means – and that one should first try to understand and reproduce the probable roots of this intelligence, i.e., the basic adaptive capacities of animals [8,9]. In other words, before attempting to reproduce unique capacities that characterize man, like logical reasoning or natural language understanding, it might be wise to concentrate first on simpler abilities that human beings share with other animals, like navigating, seeking food and avoiding dangers. In this

* Corresponding author.
E-mail address: jean-arcady.meyer@lip6.fr (J.-A. Meyer).

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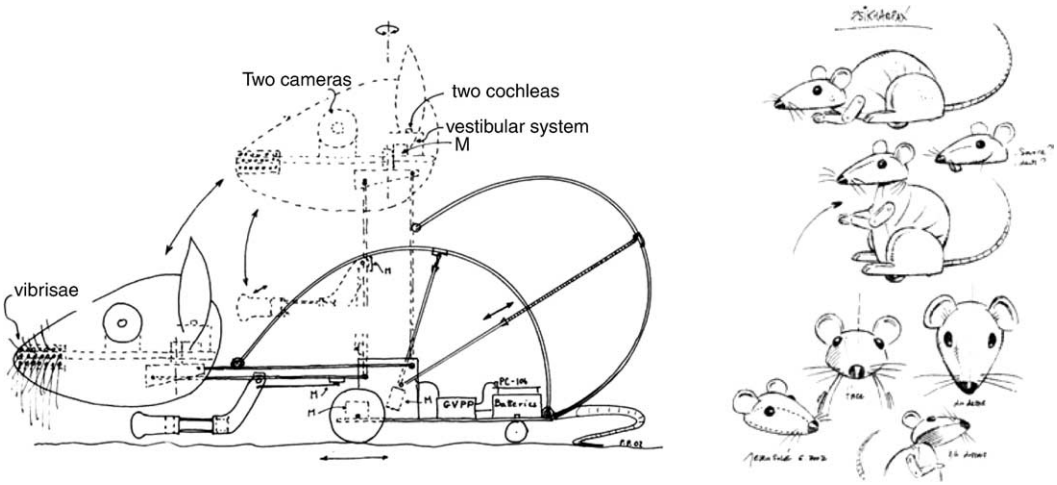

Fig. 1. The overall design of Psikharpax.

spirit, several research efforts are devoted to the design of so-called *animats*, i.e., simulated animals or real robots whose sensors, actuators and control architectures are as closely inspired from those of animals as possible, and that are able to "survive" or fulfill their mission in changing and unpredictable environments [38,39,30].

This article describes one such endeavor, the *Psikharpax*[1] *project*, which aims at designing an artificial rat that will exhibit at least some of the capacities of autonomy and adaptation that characterize its natural counterpart—the living creature for which the product (brain complexity) × (biological knowledge) is the highest. In particular, this robot will be endowed with internal needs – such as hunger, rest, or curiosity – which it will try to satisfy in order to survive within the challenging environment of a laboratory populated with humans and, possibly, other robots. To this end, it will sense and act on its environment in pursuit of its own goals and in the service of its needs, without help or interpretation from outside the system.

This article summarizes the current state of this project. In particular, it describes the robot's future sensory-motor equipment and the major modules of its control architecture. It also describes the behaviors that the robot Psikharpax already exhibits in simulation.

2. Sensory-motor equipment

Psikharpax will be a 50 cm long robot (Fig. 1) equipped with three sets of allothetic sensors: a two-eyed visual system, an auditory system calling upon two electronic cochleas, and a haptic system made of 32 whiskers on each side of its head. Sensor fusion will be realized through the use of Generic Visual Perception Processor (GVPP), a biomimetic chip dedicated to low-level real-time signal processing that already serves robot vision [28].

Psikharpax will also be endowed with three sets of idiothetic sensors: a vestibular system reacting to linear and angular accelerations of its head, an odometry system monitoring the length and direction of its displacements, and capacities to assess its current energy level.

Psikharpax will be equipped with several motors and actuators. In particular – despite the fact that such a device is not really biomimetic – two wheels will allow the robot to move at a maximum speed of 0.3 m/s. Although it will usually lie flat on the ground, it will also have the possibility of rearing, as well as of seizing objects with two forelegs. Likewise, its head will be

[1] Psikharpax was the king of the rats – i.e., an intelligent and adaptive character – in the Batrachomyomachy, a parody of Iliad written in Greek verses and (falsely) attributed to Homer. The name means "crumb robber".

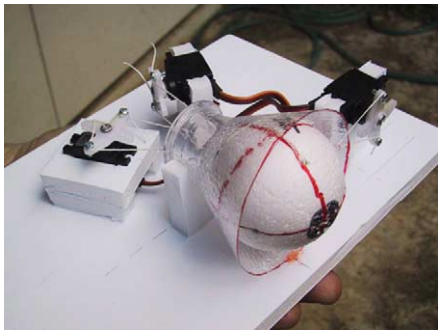

Fig. 2. An eye equipped with a camera and a log-polar sensor, which is actuated by three motors.

able to rotate, and three pairs of motors will actuate each of its eyes (Fig. 2).

Several low-level reflexes will connect Psikharpax's sensors to its actuators, thus making it possible, for instance, to keep looking at an object even when its head is moving, and to avoid an obstacle detected by its whiskers or by its visual or auditory systems.

3. Control architecture

Likewise, several models of nervous circuits that contribute to the adaptive capacities of the rat are currently simulated or tested on real robots, and will be implemented in the final control architecture of Psikharpax. In particular, this artificial rat will be endowed with the capacity of effecting visual or auditory saccades towards salient objects, of relying on optical flow to determine whether a given landmark is close or distant, of merging visual and vestibular information to permanently monitor its own orientation. Among such circuits, those that afford capacities for navigation and action selection have already been validated on preliminary versions of the future Psikharpax. The corresponding realizations will now be briefly described.

3.1. Navigation

Many simulation models – see [51] for a review – call upon so-called *place cells* and *head direction cells* to implement navigation systems that are inspired from the anatomy and physiology of dedicated structures in the rat's brain, like the *hippocampus* and the *postsubiculum*. The model described here implements a

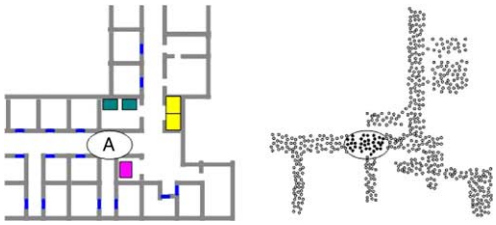

Fig. 3. While exploring the environment shown on the left, the robot built the cognitive map shown on the right. This map is made of interconnected neurons (the corresponding links are not shown) whose activation level depends upon what the robot perceives in its surroundings. Thus, when the robot is situated in zone A of its environment, according to the various landmarks it perceives from this place, some neurons in its map become more activated than others, thus affording the robot the capacity of locating itself.

multiple-hypothesis tracking navigation strategy, maintaining a set of hypotheses about the robot's position that are all updated in parallel [21,40]. It serves to build a dense topological map [20], in which nodes store the allothetic data that the robot can perceive at the corresponding places in the environment. A link between two nodes memorizes how far off and in what direction the corresponding places are positioned relatively to each other, as measured by the robot's idiothetic sensors. The robot's position is represented by an activity distribution over the nodes, the activity level of a given node representing the probability that the robot is currently located at the corresponding position (Fig. 3).

As the robot moves in its environment, the activity level of neurons in the map changes accordingly. Not only is this activity propagation within the map coher-

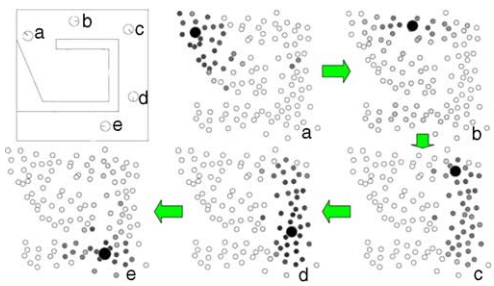

Fig. 4. Activity updates within the map as the robot moves to successive places in its environment. Labels a, b, . . ., e indicate both the actual position of the robot and the corresponding map activity. The grey level of each small node in a map indicates its activity, ranging from 0 for white nodes to 1 for black nodes. Larger black dots indicate the robot's most probable current localization.

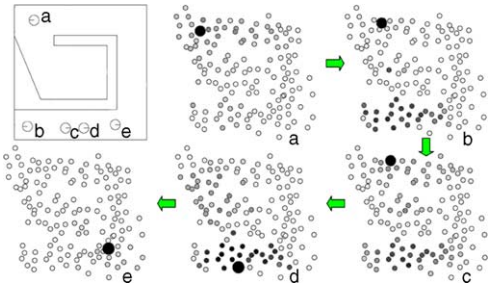

Fig. 5. Activity updates within the map after a translocation process during which the robot has been moved passively from place a to place b in the environment. After a few mistakenly recognized positions (b–d), the robot correctly recognizes its actual position (e).

ent with the robot's actual moves (Fig. 4), but it also affords useful relocalization capacities when the robot is passively moved from one place to the other (Fig. 5).

In [20,22], this navigation model has been implemented on a Pioneer 2 mobile robot and proved to be efficient in the unprepared environment of an ordinary laboratory, notably for detour planning.

3.2. Action selection

To survive, the rat must be able to solve the so-called *action selection problem*, i.e., it must be able to decide at every moment what to do next in the service of its needs. Some of the circuits involved in this task are known to be located in *basal ganglia–thalamus–cortex* loops and have inspired the *GPR model* designed by Gurney et al. [31]. Basically, this model is implemented as a network of leaky-integrator neurons, and assumes that the numerous segregated channels observed in each nuclei of the basal ganglia each correspond to a discrete motor action (the granularity of which has still not been deciphered) that is inhibited by default and thus prevented from being executed (Fig. 6). Inputs to these channels are so-called *saliences* that take into account both internal and external perceptions to assess the relevance of each action with respect to the robot's needs. A positive feedback loop involving the thalamus serves to introduce some persistence in such assessments. Two parallel *selection* and *control* circuits within the basal ganglia act to modulate interactions between channels.

Finally, at the output of these circuits, the action that is the least inhibited by others is selected and allowed to be executed by the motor system.

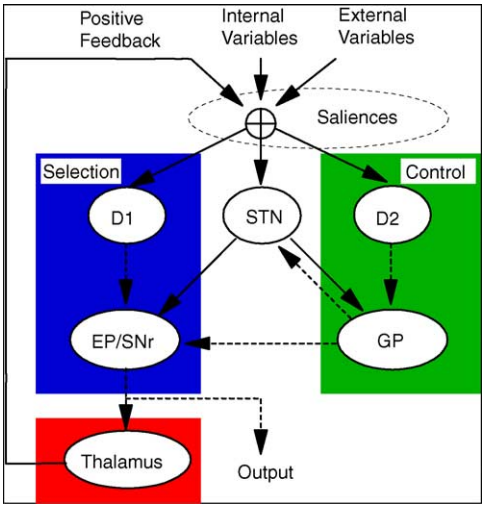

Fig. 6. A single channel within the basal ganglia in the GPR model. D1 and D2: striatal neurons with different dopamine receptors; STN: sub-thalamic nucleus; EP/SNr: entopeduncular nucleus and substantia nigra reticula; GP: globus pallidus. Solid arrows represent excitatory connections, dotted arrows represent inhibitory connections.

This model has been implemented in a Lego robot whose task was to select efficiently between four actions – wandering, avoiding obstacles, "feeding" and "resting" – in order to "survive" in an environment where it could find "food" and "rest" places [25,26] (Fig. 7).

Experimental results demonstrate the model's ability to promote survival, in the sense that it permanently keeps two *essential variables* [4] above lethal levels: *Potential Energy* (obtained via "feeding") and *Energy* (converted from Potential Energy via "resting"). Moreover, the model ensures clean and efficient switching between actions and, because it adds a *persistence loop* to a classical winner-takes-all (WTA) architecture, it maintains the *Potential Energy* level at its maximum charge more often (25% of the time) than in the absence of such loop (less than 10% of the time) (Fig. 8).

However, the robot's survival depends on its chances of getting to the right place at the right moment, i.e., to a food place when its *Potential Energy* level is low, or to a rest place when it lacks *Energy*. Obviously, additional adaptive capacities would depend on the robot's aptitude to record the position of such places on its map and to use this map to reach such places when needed. This

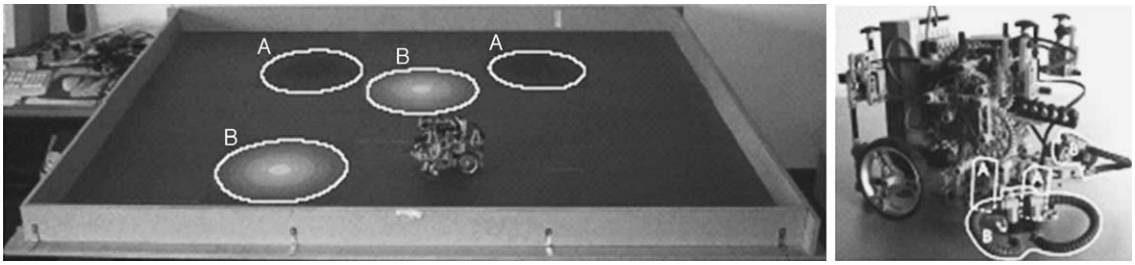

Fig. 7. Left: The environment showing "food" (A) and "rest" (B) places. Right: A Lego robot equipped with light sensors (A) and bumpers (B).

has been made possible thanks to a model combining navigation and action selection capacities.

3.3. Navigation and action selection

The connection of the previously described navigation and action selection models and their implementation on a simulated robot were inspired by recent hypotheses concerning the role of dedicated structures within the basal ganglia – the *nucleus accumbens* in particular – and the interaction of *basal ganglia–thalamus–cortex* loops in the rat's brain [24,27]. The corresponding model (Fig. 9) basically involves two such loops: a *ventral loop* that selects locomotor actions, like moving north or east, and a *dorsal loop* that selects non-locomotor actions, like feeding or resting. Each of these loops has been modeled as a GPR system like the one shown on Fig. 6. The STN of the dorsal loop provides the interconnection between them because it sends excitatory projections to the output of the ventral loop. Consequently, when the dorsal loop is active and triggers some non-locomotor action, the excitatory signal that is sent towards the ventral loop raises the inhibition level of every locomotor action and prevents it from being selected. Hence the robot cannot move and eat at the same time.

As usual, saliences in both loops depend upon both internal and external perceptions. However, saliences in the ventral loop also depend upon four direction profiles (Fig. 10) that are generated by two different navigation strategies, i.e., a simple *guidance* (or *taxon*) strategy, and a more elaborate *topological navigation* strategy [51]. This allows the robot to be attracted either by an object that it directly perceives (guidance profile) or to move towards a region where such an object is located in its map (planning profile). The latter possibility puts some constraints on action selection because the robot is committed to regularly returning to previously mapped areas in its environment in order to check the accuracy of the current map (homing profile). This need

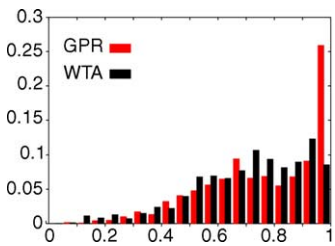

Fig. 8. Histogram showing the percentage of overall time during which Potential Energy is reloaded at the values shown on the abscissa.

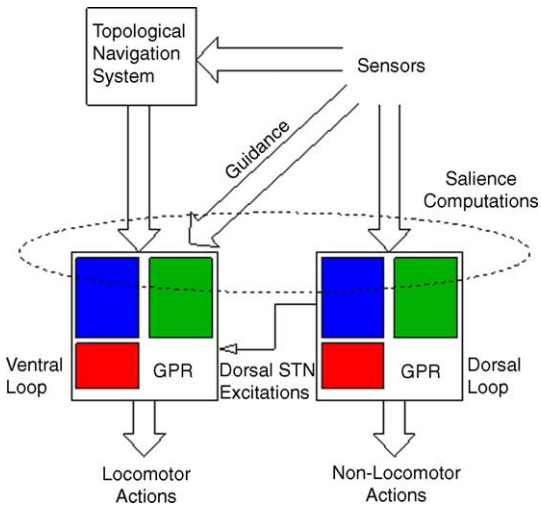

Fig. 9. Interconnection of the ventral and dorsal loops in the basal ganglia. The ventral loop selects locomotor actions, the dorsal loop selects non-locomotor actions. The latter subsumes the former.

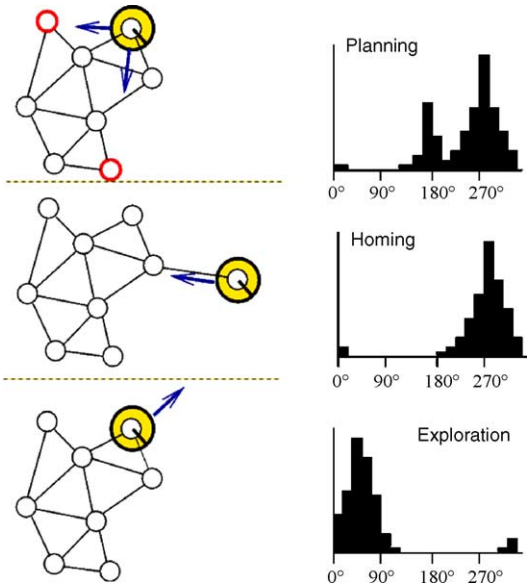

Fig. 10. Three direction profiles (right) — out of the four used by the model — that call upon the current map of the environment (left). According to the planning profile, the robot is motivated to move in two broad directions that correspond to two resources recorded in its map. According to the homing profile, the robot is motivated to return to already explored regions of the environment. According to the exploration profile, the robot is motivated to wander in as yet unexplored regions of its environment.

is expressed by a *Disorientation* variable managed by the model, which increases when the robot enters unexplored areas, and decreases when it returns to known areas. When this variable is not too high, the robot is motivated to explore its environment (exploration profile). This model has been implemented in a version that manages 36 locomotor actions, i.e., moving in each of 36 possible directions, and two non-locomotor actions, i.e., reloading actions on food and rest places that change the robot's *Energy* and *Potential Energy* levels.

In the simplified example described by Fig. 11, only locomotor actions are selected because external perceptions are not strong enough to suppress the inhibition of reloading actions on resource spots A or B. Because the level of the B battery is the lowest, the robot's main motivation is to move north, according to one of the directions advocated by the current planning profile. In all probability, the robot following this navigation strategy will later turn east, then south. When it gets close to the B object, this fact will be detected by its sensors, a refueling action will be triggered, and an excitatory signal will be sent to the ventral loop in order to inhibit locomotor actions during this period.

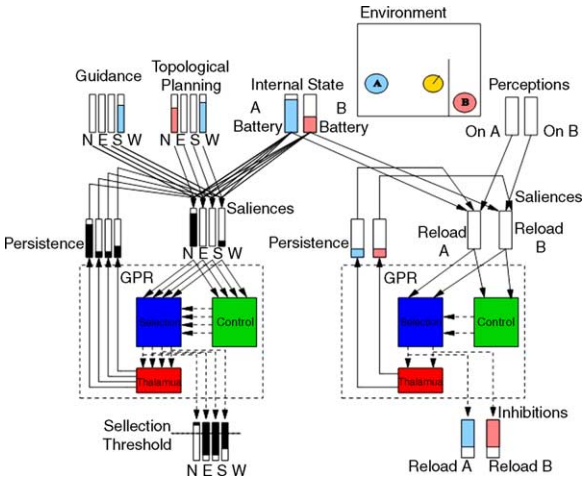

Fig. 11. The model integrating navigation and action selection calls upon two basal ganglia–thalamus–cortex loops. Each loop is managed by a GPR model, and the coordination between loops is provided by the subthalamic nucleus of the dorsal loop, which is connected to the ventral loop (connection not shown here). The dorsal loop selects one of the two possible reloading actions, the ventral loop selects one of the 36 directions of motion (simplified here to four cardinal directions, whereas the homing and exploration input profiles are not shown). Inhibitory connections are represented by dotted arrows, excitatory connections by solid arrows.

Several experiments have been performed to test the capacities of this control architecture to ensure survival by maintaining the robot's essential variables above lethal levels. In particular, it has been shown that, in the environment on the left of Fig. 12, a robot (robot A) calling upon both topological navigation and guidance strategies survived longer than another (robot B)

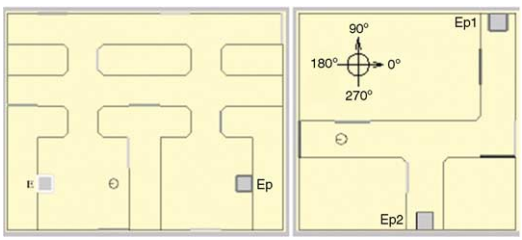

Fig. 12. Two environments used to test the connection of navigation and action selection models. E: "rest" place, Ep: "food" place. Left: In this environment, it is impossible to see one resource place from the other. Right: The resource at Ep2 is not present during the elaboration of the map.

Table 1
Statistical comparison of survival times measured along 10 runs for two robots tested in the environment on the left of Fig. 12 over a 6-h interval

	Survival times (s)	
	Median	Range
Robot A	14431.5	2531:17274
Robot B	4908.0	2518:8831
U Mann–Whitney	$U = 15$	$P < 0.01$

relying on guidance only (Table 1). Hence, being able to build a map of an unknown environment and to use this map to navigate between places *E* and *Ep* where *Energy* and *Potential Energy* could be acquired enhanced the robot's survival. A new action being selected every 0.87 s as a mean, survival times equal to 4 h – the maximum simulation length – were attained. However, in some occasions, premature deaths occurred because of the difficulty of elaborating a map from scratch that was precise enough to help the robot reach the right resource before exhaustion.

Likewise, in the environment on the right of Fig. 12, it has been shown that, if place *Ep1* is the only one previously encountered by the robot and recorded on its map, the robot may decide to move towards that place to reload its *Potential Energy*. However, if on its way it detects the proximity of another food place like *Ep2*, it will occasionally give up navigating towards *Ep1* and opportunistically divert via *Ep2*. Then, having consumed the corresponding resource, it will register the position of *Ep2* on its map. Thus, next time it needs to reload its *Potential Energy*, it will have the choice of navigating towards *Ep1* or *Ep2*. Table 2 shows that such opportunistic behavior depends upon the respective weights that were assigned to topological navigation and guidance profiles and that served to compute

Table 2
Number of opportunistic detours towards Ep2 out of 15 runs in the environment on the right of Fig. 12

Number of Ep sources	Weight of topological navigation	Weight of guidance	Opportunistic detours towards Ep2
1	0.65	0.55	0/15
2	0.65	0.55	2/15
2	0.55	0.55	8/15
2	0.45	0.55	13/15

These numbers increase when greater weights are given to guidance than to topological navigation.

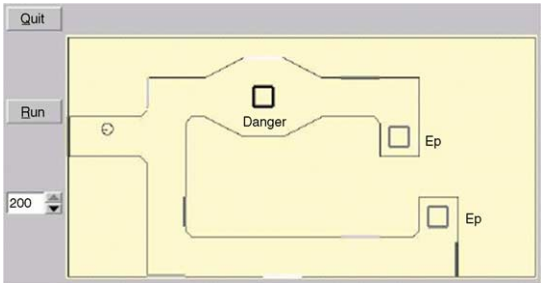

Fig. 13. Two trajectories leading to "food" places (Ep). One is shorter than the other, but entails passing through a dangerous place (Danger).

saliences, i.e., upon the respective attractiveness of a resource perceived directly and one whose location is recorded on the map.

In the environment on Fig. 13, the robot has the choice between two trajectories leading to a "food" place. The first one is shorter but entails passing through a "dangerous" place. The second one is longer, but safer. Experience shows that the robot is able to decide to navigate via the longer path when its *Potential Energy* level is not so low that a long journey would compromise its survival, but that otherwise it chooses the shorter path risking having to face the potential danger recorded on its map. Path choice depends on the respective weights of two internal states respectively related to the need of *Potential Energy* and to *Fear* (Table 3).

Finally, in the complex and challenging environment of Fig. 14, in which several possibilities exist of getting lost, of encountering dangers, of discovering newly created resources, and of reaching places in which a given resource is no longer available, experience shows that the robot survives autonomously for long periods, thanks to the many adaptive mechanisms and behaviors that have just been described [24].

Table 3
Number of trips via the short and long paths out of 20 runs in the Fig. 13 environment

Fear level	Potential Energy level	Short path	Long path
0.2	0.1	13	7
0.2	0.5	2	18

The greater the need for Potential Energy, the more often the short path is preferred.

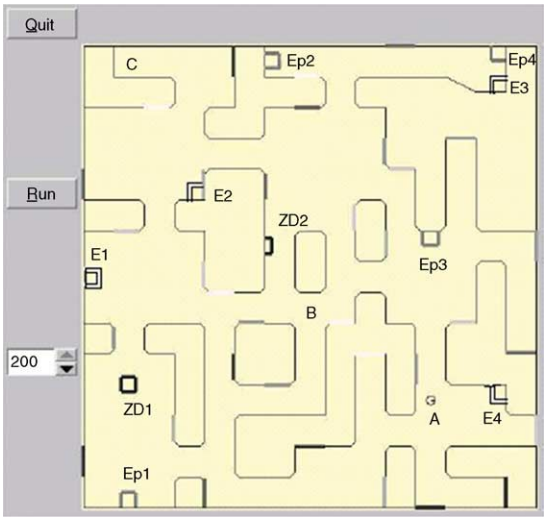

Fig. 14. A complex environment with four "rest" places (E), four "food" places (Ep) and two dangerous places (ZD). Resource E1 appears and disappears every 30 min.

The longest survival time thus obtained was 21 h of simulated time. In this case, the major cause preventing indefinite survival does not seem to be the navigational issues mentioned above, but rather an intrinsic drawback in the GPR model, which gets locked in particular circumstances, with no action being disinhibited enough to be selected. Current work aims at suppressing such limitations and at further enhancing the robot's lifetime.

3.4. Learning

In an unknown environment, a rat is able to explore it and to incrementally build a map that describes its topology. Such *associative learning*, which combines both allothetic and idiothetic data, was implemented in the navigation model described above.

However, a rat is also able to improve its behavior over time through *reinforcement learning*, i.e., thanks to adaptive mechanisms that increase its chances of exhibiting behaviors leading to rewards and that lower those of behaviors leading to punishments. Concerning action selection, a recently debated hypothesis [6,34,46] postulates that such mechanisms could be mediated by dopamine signals within so-called *actor-critic* architectures. According to this hypothesis, a GPR module could play the role of an actor, while a critic module could call upon a dopamine reinforcement signal $\check{r}_t$ that is assumed to evaluate both the episodic primary reward signal r_t occasionally generated by the robot's actions, and a secondary signal computed as the difference $gP_t - P_{t-1}$ between currently expected and future rewards (g being a discount factor which determines how far in the future expected rewards are taken into account). This reinforcement signal would be used in the GPR module to adapt the way saliences are computed in order to select the most appropriate action, i.e., the action the most likely to maximize the reward it will lead to (Fig. 15).

Several variants of this learning architecture [36] have been implemented in a simulated robot that must learn in a plus-maze, and through successive trials, which action to perform in order to get to the end of a corridor where a door may provide access to a reward

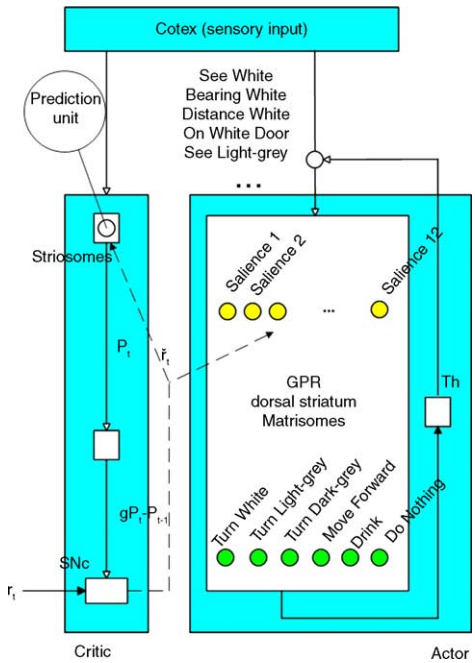

Fig. 15. An actor-critic model of reinforcement learning. In this version, the actor module is a GPR model (involving matrisomes in the dorsal striatum) that is segregated into different channels, with saliences as inputs and actions as outputs. The critic module (involving striosomes in the dorsal striatum) propagates towards the actor module an estimate ř of the instantaneous reinforcement triggered by the selected action. Th: Thalamus; SNc: substantia nigra compacta.

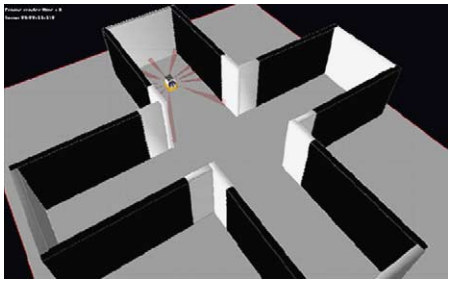

Fig. 16. The plus-maze in which the robot has to learn which action to perform in order to reach a rewarding resource that is delivered at a given end. The doors at three such ends are colored dark-grey and do not deliver any reward, whereas the fourth one is colored white and leads to the resource. The center of the maze is characterized by light-grey walls, corridors by black ones. The position of the rewarding extremity is chosen at random at the beginning of each new trial, when the robot succeeds in returning to its starting point, i.e., at the intersection of the four corridors. The robot is equipped with a visual system that serves to detect the colors, bearings and distances of walls and doors, and with infrared sensors that trigger low-level obstacle-avoidance reflexes.

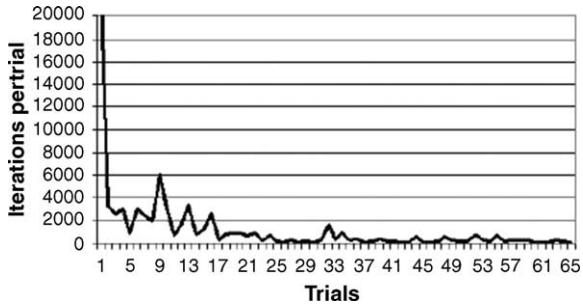

Fig. 17. Evolution over successive trials of the number of actions that the robot triggers before getting to the reward.

(Fig. 16). This setting reproduces an experiment performed with real rats [1] that must learn to reach the center of the maze, to seek which door gets lighted by an overhanging lamp, to move to that door and gain access to a water dispenser, to return to the center, and so on.

To learn this task, 12 variables describing the robot's visual input were used by the GPR to select among six possible actions (*drink*, *move forward*, *turn to white*, *turn to light-grey*, *turn to dark-grey*, *do nothing*—see Fig. 15). Hence, instead of being hand-crafted as in the experiments described in Sections 3.2 and 3.3, the saliences of the action selection module were self-adapted so as to maximize the incoming rewards.

Experimental results demonstrate that the most effective learning architecture is obtained when the whole maze is arbitrarily partitioned in several zones, and when a specific actor-critic pair learns the right action to be accomplished in each zone. This architecture, inspired by [48] and [14], yielded the learning curve shown in Fig. 17, which compares favorably with the best hand-crafted action selection module that has been able to be designed. As expected, after learning, the *turn to dark-grey* and *do nothing* actions were never selected. Future work will aim at self-adapting the arbitrary partition that has been used here.

4. Discussion

It is clear from recent reviews [5,33,52] that, although many research efforts have been devoted to the design of biomimetic sensors or effectors for robots, relatively little work has been done on control system architectures, and what has been done has focused primarily on invertebrate models. Only a few groups are currently building biomimetic robot control architectures modeled on mammalian nervous systems and, moreover, their efforts are often centered on isolated behaviors, like locomotion in cats [44] or feeding in mice [29], which are not dealt with in an integrated perspective. To the best of our knowledge, the scope of the Psikharpax project is unique. First, it draws inspiration from a vertebrate instead of an invertebrate. Second, it aims at designing both biomimetic sensors and control architectures. Third, because it capitalizes on a dedicated robotic platform, it will integrate a variety of sensors, actuators and control systems making it possible to assess its adaptive capacities in much more challenging circumstances than those that characterize seemingly comparable biomimetic robotic approaches [11,23,32,41,49].

However, from the point of view of biological realism, several improvements could be made to the models just described. In particular, the current navigation model could be replaced by a version reproducing more faithfully the anatomy and physiology of the hippocampus and related areas (e.g., [50,3]), or several hypotheses about the way cortical columns are connected to these areas and afford planning capacities (e.g., [10,37]) could be explored. Likewise, other hypotheses about how the navigation and action

selection models could be connected should be implemented and compared to the control architecture described herein. For instance, instead of selecting mere locomotor actions from the saliences of several direction profiles, the ventral loop in the basal ganglia might play a higher-level role and use current internal and external perceptions to select the most appropriate among the possible navigation strategies [43]. Finally, there are many possibilities for extending the results obtained so far on learning. Actor-critic models calling upon dopaminergic neurons should be compared to concurrent hypotheses involving the role of glutamate [45] in reinforcement learning. Also, useful distinctions are probably to be made between habit learning and goal-directed learning [12]. Finally, the role of neuromodulators in the setting of learning metaparameters should be investigated, as suggested in [15].

From an engineering point of view, the system described above raises several important issues. Considering that living systems are the product of roughly 3.5 billions years of evolutionary tinkering [35], one may wonder if there is the slightest chance that artificial systems exhibiting adaptive behaviors of a comparable efficiency might call upon simplistic neurons (e.g., threshold-gate models) and homogeneous architectures (e.g., perceptrons). In other words, if nature has invented the highly complex and still imperfectly understood processes at work in real neurons and, if it has connected them in highly heterogeneous networks, it is probably for good reasons, worth deciphering. Likewise, there are certainly good reasons why the output neurons of so many structures in the brain (e.g., the cerebellum, the frontal and prefrontal cortex, the basal ganglia, the striatum, etc.) play an inhibitory role. As described by Berthoz, decision in the brain is often the selective suppression of actions that are irrelevant with respect to the goal, to the context, to past experience. “I think, therefore I inhibit. [. . .] Whereas engineers tend to formalize the problem of action selection in terms of probabilities of winning more than loosing, nature’s solution is in terms of excitation/inhibition. Underlying such competition, there is a wealth of possibilities that we are a long way from understanding, but that far transcends the cold estimate of probability calculus, how Bayesian it may be. A new neurocognitive theory of decision remains to be elaborated” [7]. Again, such considerations lead to the question of understanding which solution, the natural or the artificial, is better adapted to which decision problem.

From the point of view of robotics, the Psikharpax project substantially extends the scope of traditional approaches to robot control because it will involve a wide variety of behaviors, because it will implement different learning mechanisms, and because it is not exclusively devoted to tasks that serve humans. As noted in [2], the majority of research conducted so far on autonomous mobile robots has concentrated on developing vehicles that exhibit a single type of behavior supporting the specific task of moving between two positions in the environment while avoiding collisions with obstacles. Clearly such limited capacities may not afford the degree of autonomy required in situations where human intervention is undesirable or impossible, and raises the question of how the concept of “self-autonomy”, i.e., behavior which may be characterized as supporting self survival differs from that of “imposed autonomy”, i.e., behavior which does not benefit the robot but fulfils some desired task which we impose upon the system. In this perspective, being able to integrate the past (through its recorded map), the present (through its sensors) and the future (through its planning capacities), Psikharpax will represent an embodied example of a *motivationally autonomous animat* whose control complexity may well challenge the possibilities of external control and, hence, its capacities to withstand any imposed autonomy [18]. Conversely, following Moravec [42], one may hope that its mobility, its sensor equipment, and its ability to carry out survival-related tasks in a dynamic environment will provide a necessary basis for surpassing the current “reptile-stage” of robots and eventually reaching the general competence and “true” intelligence of human beings.

5. Conclusion

The Psikharpax project aims at designing an artificial rat able to “survive” in a laboratory populated by humans and other robots. It has two main objectives: better understand the control mechanisms of rats, improve the autonomy of robots. The robot Psikharpax will be endowed with many sensors and motors that are currently under development and that will serve to implement various reflexes. Its control architecture

has already been tested in simulation and implemented on simpler versions of the future robot. In particular, models for navigation and action selection – which afford capacities of associative and reinforcement learning – have been successfully tested. It thus appears that Psikharpax will be able to explore an unknown environment, to build a topological map of it, and to plan trajectories to places where it will fulfill various internal needs, like "eating", "resting", "exploring" or "avoiding danger". The first version of such an efficient robot is expected to be available at the end of year 2005: still a long way to the "whole rat" that Dennett might have advocated [13]. Even a longer way to the intelligence of man.

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Jean-Arcady Meyer is Research Director at CNRS and heads the AnimatLab within the Laboratoire d'Informatique de Paris 6 (LIP6) in Paris. He trained as an engineer, he graduated in Human and Animal Psychology, and received his PhD in Biology. He is the founder of the journal Adaptive Behavior and a former Director of the International Society for Adaptive Behavior. His primary scientific interests are in adaptive behaviors in natural and artificial systems. He is the main coordinator of the Psikharpax project.

Agnès Guillot is Associate Professor of Psychophysiology at Paris X University. She graduated in Human and Animal Psychology, and holds PhDs in Psychophysiology and Biomathematics. Her main scientific interests are in action selection in animals and robots. She coordinates the biomimetic modelling of Psikharpax.

Benoît Girard is a Postdoctoral Fellow at the Laboratoire de Physiologie de la Perception et de l'Action (LPPA) at the Collège de France. He trained as an engineer and received his PhD in Computer Science from the University of Paris 6. His current research interests are focussed on computational models of action selection in the rat brain, and notably in the control of oculomotor saccades.

Mehdi Khamassi is working both at the AnimatLab and at the LPPA as a PhD student. He trained as an engineer and received a Master Science degree in Cognitive Science from the University of Paris 6. His current research interests include electrophysiology experiments and computational modelling of learning processes in the rat brain.

Patrick Pirim trained as an engineer. He founded BEV, a company that brings fully developed new technologies to the marketplace. He invented the GVPP chip that is dedicated to low-level real-time signal processing. He coordinates the sensory-motor design of Psikharpax.

Alain Berthoz trained as an engineer. He graduated in Human Psychology and received his PhD in Biology. He is Professor at the Collège de France, where he heads the Laboratoire de Physiologie de la Perception et de l' Action (LPPA). He is a member of many academic societies, an expert sitting on several international committees, and he has been awarded many prizes. His main scientific interests are in the multisensory control of gaze, of equilibrium, of locomotion and of spatial memory. He coordinates the neurophysiological experiments that inspire the Psikharpax project.