

Integration of a visual system with the control architecture of Psikharpax

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Abstract. The aim of this paper is to develop an artificial bio-inspired architecture of a rat ensuring its autonomy. It introduces different artificial control modules and presents a complete implementation with experimental results. The paper also introduces a new visual system module that is one of the main contributions. It relies on an optimal recursive sampling of images into sub-images that remains stable under translation. The visual system ensures both the visual characterization of locations and object recognition.

Key words: Animat approach, Action selection, Navigation and mapping internal models and representation, Autonomous robotics

1 Introduction

The issue of ensuring autonomy and adaptation of robots to changing environment without any human help relies on the development of two kinds of autonomy. The first one is related to energy that robots must be able to find alone. Several experiments have been carried out using different approaches like solar energy [17], ingestion of living gastropods [5] and even virtual energy [4]. The second is functional autonomy that allows the robot to fulfill the task it has been created for. Several applications can be found in [13, 15]. This paper contributes to the Psikharpax project [11] that aims at tackling these autonomy issues by building an artificial rat integrating sensory-motor equipments and a control architecture inspired from the rat itself. Psikharpax is following the animat approach [12] to ensure behaviors that allow the robot to survive within its environment. These include tasks like obstacle avoidance, energetic autonomy and navigation in real or virtual environments using neural controllers models [4, 7, 8]. The aim of the work as will be shown through the paper is to integrate on a robotic platform a complete implementation of the autonomy functionalities in real environment that have been previously tested in simulation only [4]. The paper also introduces a new visual system module that is one of its main contributions. It allows a robust and efficient perception of scenes using an optimal

sampling of images. The visual system makes visual characterization of locations and object recognition both possible. The paper is organized as follows, section two introduces the visual system. Section three will briefly present the action-selection loops and their influence on navigation. Finally a complete set of experimental results will be shown in section four.

2 The visual system

Visual systems that allow navigation and scene recognition can be sorted into two categories. Local approaches relying on features points like SIFT and Harris [6], and global approaches that consider the whole content of the image like histograms [16]. Quad-tree algorithms cut images into sub images recursively. Starting from an initial image, each sub-image is cut into four equal sub-images (Fig.1(b)). The idea of the optimal sampling is to use the same principle, but on the contrary of the regular approach, the division of sub-images is driven by an entropy measure. The idea is to cut at the location where the difference of the quantity of information between possible sub-images is minimal. All sub-images have the same probability to contain interesting and valuable information (Fig.1(a)). Information can be chosen according to the application needed (color, texture,...) , in this work it is set as the mean value of the patches. A complete description of the algorithm can be found in [9]. The quadtree decomposition

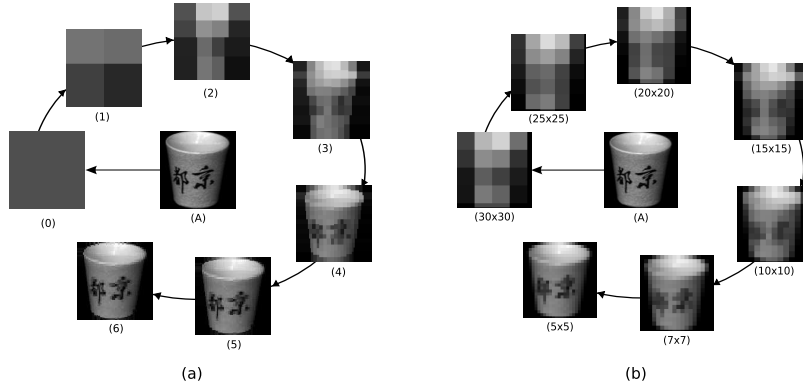


Fig. 1. (a) Optimal sampling of an object (A). using 7 levels of recursion.(b) Static Sampling of an object (A) with different size of square. The optimal sampling produces a sharper decomposition of the image as it preserves information.

is not stable under translation, which means that if an object or a location are seen from a slightly translated point of view, it will produce different patches and thus will not be recognized. On the contrary, the optimal sampling has a strong stability of the decomposition as shown by Fig.2(a). It can be noticed

that in both cases patches cover the same zones despite the important translation of the considered object. This decomposition is also robust even in case of complex backgrounds [9]. The optimal sampling is also applicable on catadioptric

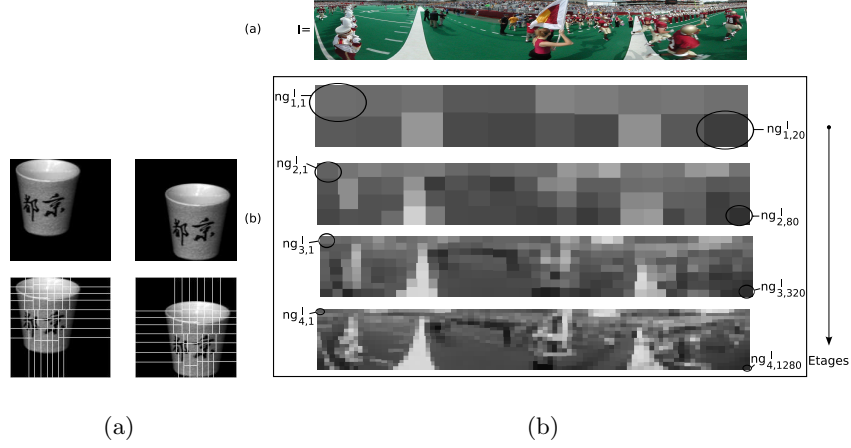


Fig. 2. (a) Optimal generation of patches for a translated object. The object is covered with the same patches, covering the same areas and providing an equal decomposition of the image.(b) Starting from a omnidirectional image, the optimal sampling using 4 steps gives 4 patches sets.

omnidirectional images, Fig.2(b) shows a decomposition an image as performed by the robot. The comparison between locations is computed using the distance between the mean color of each patch. If ng is set to be the mean color of a patch, then the similarity measure between two image locations I_i et I_j is given by :

$$d(I_i, I_j) = \sum_{m=1}^{Nb_{levels}} \sum_{n=1}^{4^m} \|ng_{m,n}^i - ng_{m,n}^j\|$$

with $ng_{a,b}^k$ the mean color of patch I_k , at the level a , placed at the location b . The positions of the different ng are given by Fig. 2(b).

3 Control Architecture

The general architecture of Psikharpax (Fig. 3) includes a navigation system (Fig. 3(b)), that allows a robot to build a "cognitive map" that authorizing self-localization and the recording of salient places where resources or potential dangers may be encountered. It also holds an action selection module (Fig. 3(b)) that selects at every time step the most adapted action ensuring the survival of the artificial rat within its environment.

3.1 Navigation System

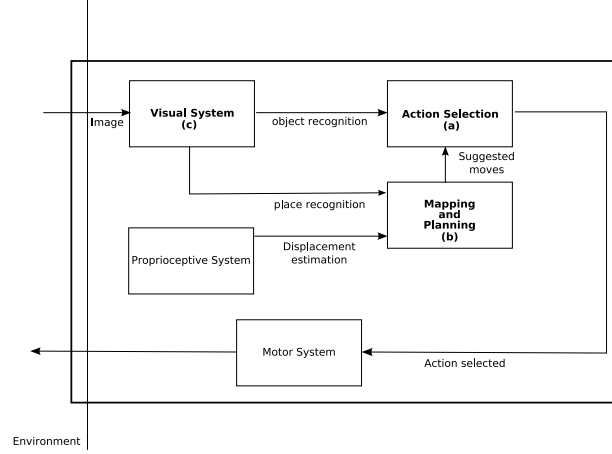


Fig. 3. The perception and control architecture of Psikharpx. The Action Selection module decides which action to execute, according to information provided, on the one side, by the Mapping and Planning module - which may suggest a move towards a given place in the robot's cognitive map - and, on the other side, by the Visual System - which may suggest moving towards a perceived object.

The navigation system [2] affords two main complementary functionalities : map generation and localization.

Map generation The system creates and updates a dense topological map relying on a graph where nodes represent locations, with arcs linking each pair of adjacent nodes. Each node stores the optimal decomposition of the image taken at that location, whereas each arc contains the odometric distances and orientation between two adjacent nodes as shown by Fig. 4. **Localization** The system computes a probabilistic measure of its current location, using the activities of existing nodes combined with the information given by the visual system and the odometric data. Fig. 4 shows the activity of each node in the map according to the position of the robot. Similarity is expressed using grey levels.

3.2 Action Selection

To survive, a rat must be able to solve the action-selection problem i.e., that of deciding which action to perform to fulfill its needs. Likewise, the robot is innately endowed with an artificial metabolism that imposes it to occasionally find sources of food and to return to its nest. [4].

The artificial metabolism Two essential variables [1] are dealt with in the following experiment,, the energy (E) and the potential energy (E_p). Each action

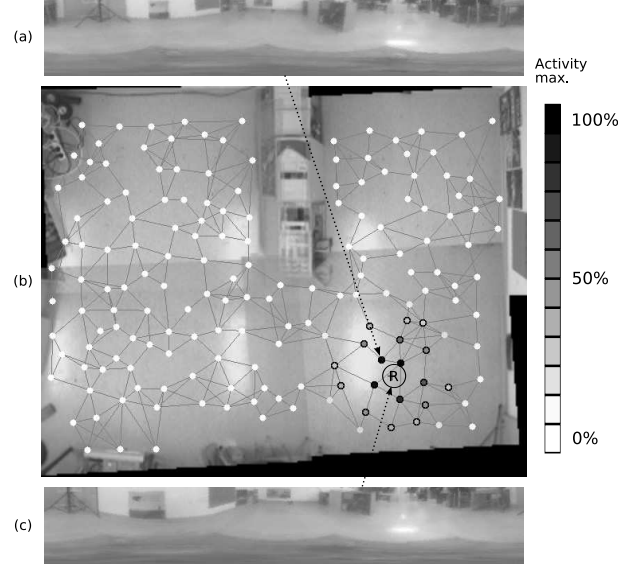


Fig. 4. Example of a cognitive map generated by the robot after exploring its environment (b). A blob of activity in this map indicates the current position of the robot. Two panoramas are shown that respectively correspond to what the robot sees in its current location (c) and to what it previously saw in a nearby location (a).

consumes a certain amount of E . When close to its nest, the robot can transform part of its E_p in E . To reload E_p , the robot must find in its environment a source of food. Survival fails if E falls to 0. To solve constraints imposed by its metabolism, the action-selection system uses the GPR computational model of basal ganglia described in [3].

Selection action without Navigation This model (figure 5(a)) is implemented as a network of leaky-integrator neurons, and assumes that the numerous segregated channels observed in 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. 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 robots needs. 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. In the first series of experiments, the model uses 5 different behaviors : DIGEST-IN-NEST (E_p becomes E), EAT (increases E_p), RANDOM-EXPLORATION, GO-TO-NEST (if visible), GO-TO-FOOD (if visible).

Action Selection with Navigation 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 ded-

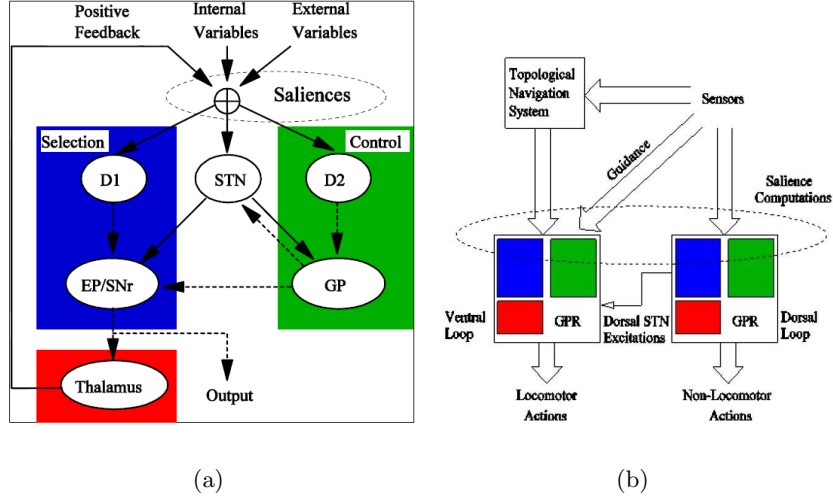


Fig. 5. (a) A single channel within the basal ganglia in the GPR model. D1 and D2: striatal neurons with different dopamine receptors; STN: sub-thalamic nucleus; EP/SNr: entopeduncular nucleus and substantia nigra reticula; GP: globus pallidus. Solid arrows represent excitatory connections, dotted arrows represent inhibitory connections. (b) 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 via STN connexions.

icated structures within the basal ganglia the nucleus accumbens in particular and the interaction of basal ganglia-thalamus-cortex loops in the rats brain. The corresponding model is described in [4] and basically involves two such loops (figure 5(b)): 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. In the following experiments, the ventral loop, has 36 channels each corresponding to a displacement sorted using orientation (from 0 a 360° with a step of 10°). The dorsal loop is made of 2 channels, one for each type of recharge (E or E_p).

4 Experiments

The capacity of both the visual system and the control architecture described above to afford the robot with survival abilities - according to which it will be able to find food in its environment and digest it in its nest - has been tested in a series of experiments. The robot was equipped with an omnidirectional catadioptric sensor in an arena observed by four camera ceiling mounted. This system allows an accurate monitoring of the positions of the robot that may be recognized according to colored marks on its roof, as shown in Fig 6(a) shows an on-line reconstruction of the scene, when the four camera views are merged

in a single one. Fig 6 (b) shows the robot. A first series of experiments served

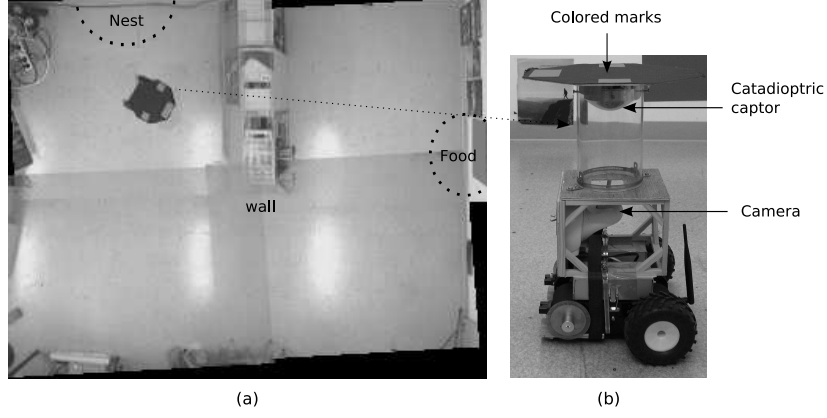


Fig. 6. Upper view of the monitored arena observed by four camera mounted in the ceiling (a). Close view of the robot (b). The colored marks on the roof serve to monitor the robot's orientation and position.

to assess the robustness and precision of the visual system in localization tasks. A second series were targeted at assessing the robot's survival capacities.

Visual system : The visual localization using the sampling procedure is compared with SIFT [10] and with a method relying on image histograms. In order to check the robustness of the method, and to study the precision of the localization, series of tests with additive noises are carried out. The acquired images are transformed into cylindrical images of size 1400×140 pixels. In order to test different scenarios, the content of acquired omnidirectional images is modified in the following manner:

- Virtual occlusions are added (from 1 to 10 squares) at random positions, their individual size never exceeding 10% of the size of the original image.
- Independent white noise is added having a uniform distribution between 0 and 255 concerning 10% of the maximum number of pixels.
- Change of illumination: additive noise with modification up to 40% of the value of pixels.

The corresponding localization rates are given by table 1. We can easily check that the optimal sampling leads to the most stable and accurate results, except for the change of illumination which is an expected result as the method is relying on the mean value of patches. To overcome this limitation the method could rely texture to get more stable results, but this approach is likely to be slightly more time-consuming (see [9] for details). The performance of the visual system in case

Localization rate				
	Original images	White noise	Illumination	Occlusions
SIFT	0.586	0.591	0.578	0.558
Histogram	0.395	0.398	0.146	0.326
Optimal (5 étages)	0.758	0.781	0.223	0.746

Table 1. Localization rates using three localization methods inside the experimental monitored arena.

of orientation errors has also been assessed. As the optimal sampling procedure uses omnidirectional images that are resampled and transformed into cylindric images according to the estimated orientation, accurately estimating orientations is a crucial issue. Several tests were made, in which various orientation errors were introduced. The corresponding results are given in table 2, and turn out to be very stable even in case of large errors. Finally the performance of the visual

Robustness of localization					
angles errors	0° (no noise)	5°	10°	15°	20°
Localization rates	0.7261	0.6546	0.533	0.4496	0.4182

Table 2. Effect of the accuracy of orientation on localization.

system is assessed in a complete navigation task, where the robot explores and unknown environment and builds a cognitive map that makes an accurate self-localization possible (Fig. 7).

Autonomy: To assess the robot’s survival capacities, two experiments have been done that reproduce in reality the simulation settings of [3, 4]. In both conditions, the robot must manage its E and E_p levels to avoid dying from starvation but, in the first case, it relies on mere chance to find food - because it doesn’t use any map - whereas, in the second case, it may build such a map to increase its chances of surviving. The corresponding results are given in Fig. 8. It can be clearly seen that energy is managed in a better way in (b) as it is always charged to its maximum each time its possible at the contrary of (a). During the 6 experiments using the selection-action loops without use of the map the robot survived an average of 848 time steps, while the full system easily goes beyond 1800 time steps.

5 Discussion

The catadioptric system that has been used here proved to be robust and allowed better results than SIFT and the histogram approaches. This is due to the optimal sampling procedure that has two major effects. It uses the whole

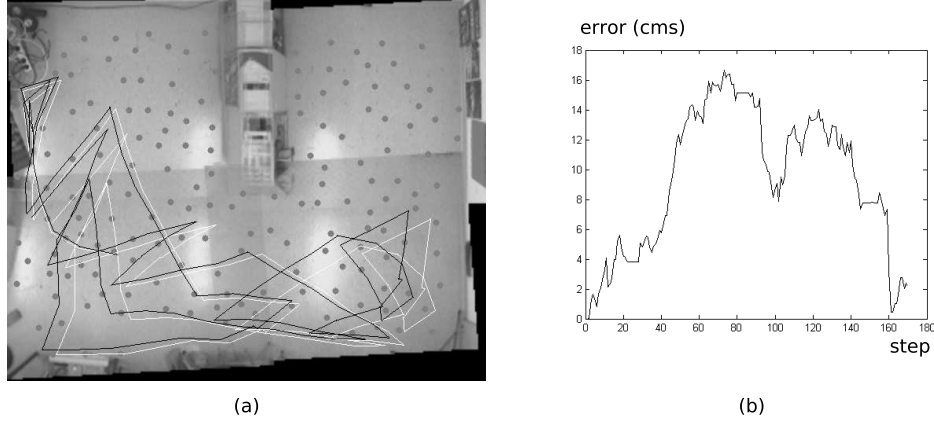


Fig. 7. (a) Upper view of the arena showing the estimated trajectory (white) of the robot using its generated map (white) and its real trajectory (black). (b) The error between the real and estimated position.

image to extract information contrary to local approaches like SIFT, and it can be easily applied to catadioptric images that ensure high robustness to changes in orientation. Catadioptric images also introduce a major difficulty due to the non linearity of the resolution of the image they provide. Most of the important features needed for localization are located at the periphery of the image where the resolution is at its lowest, existing techniques relying on feature point like SIFT can then only fail. One additional property of the optimal sampling is its low time consuming compared to SIFT in a non optimized programming around 5-10 frames/sec on a P4M 2:20GHz/512Mb. The full integration of the robot functionalities shows that a robust generation of accurate maps is a crucial step towards decisional autonomy. The results that have been obtained here may certainly be improved using additional perceptual modalities that are currently implemented on the Psikharpax platform, i.e., 2 moving ears, 2 moving eyes, a more accurate odometry system and an accelerometer generating vestibular data. In particular, the binocular system that will replace the omnidirectional camera that has been used here will provide the additional capacity of providing depth information. Likewise, the auditive stereo perception should also introduce more accuracy in localization and new interactions with the environment.

6 Conclusions

This work described the full integration of a control architecture on a robotic platform that demonstrates robust decisional autonomy capacities in a real environment. The paper introduced a new visual module that is one of the main contributions of the paper and ensures a robust perception of scenes based on an optimal sampling of images. Results obtained so far are likely to be improves

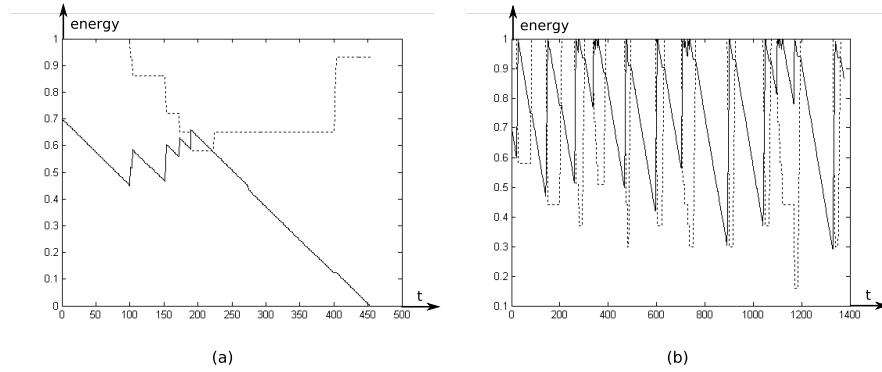


Fig. 8. Illustration of the energy management using two series of experiments. In (a) the first series using only the selection-action loop, while (b) uses the complete functionalities of the robot. The full line represents energy E , while the dashed line is relative to the potential energy E_p .

when new sensors and new controllers will be implemented on the current platform.

7 Acknowledgement

This research was granted by the EC FP6 integrated Project ICEA (Integrating Emotion, Cognition and Autonomy). The authors would like to thank David Filliat and Benoit Girard for their permission to capitalize on their previous contribution to the Psikharpx project.

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