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Interest of spatial context for a place cell based navigation model

N. Cuperlier², P. Gaussier^{1,2}, M. Quoy²

¹ Member of the Institut Universitaire de France,
²Neuro-cybernetic team, Image and Signal processing Lab.,
Cergy Pontoise University / CNRS UMR 8051 / ENSEA

Abstract: After a short review of properties of biological place cells, mainly found in the hippocampal region of rodents, and a brief presentation of a biologically inspired navigation architecture relying on these cells, we will show how contextual information could facilitate scale changes to large environments. We thus present a simple model of spatial context allowing to both reduce noise effects on place cells (in biological model) and increase its computational performance.

1 Introduction

The startling discovery by O’Keefe & Dostrovsky [15] of the spatial correlates of neural activity in the hippocampal system of rodents was a first step to understand the mechanisms by which the brain processes spatial information. This pioneer work has stimulated a substantial body of computational models to understand the role of these place sensitive cells in spatial representation and navigation. These cells exhibit the property to fire selectively in different regions of an environment and were named place cells (PC). PC regions of high activity are termed place fields. Later, PC like property neurons have been detected in other structures near the rodent hippocampus. Indeed, neurons of these regions also show significant activity in localized regions of spatial environments while performing spatial tasks: the superficial [16, 17] and deep [7] entorhinal cortex (EC), the dentrate gyrus (DG) [11] and the subiculum (SUB) [18] where also grid cells are found [10, 8].

Thus, ensembles of PC are thought to form spatial representations that can be used in navigation and numerous models have been proposed, see [4] for a short review of navigational model based on PC.

In previous papers [3, 5, 4], we had proposed a control architecture based on transition cells and a cognitive map for planned navigation tasks (see figure 1). Whereas our model relies on transition cells to navigate, place cells are still a key element of the system, since PC are constitutive elements of transition cells and successful spatial task performance is associated with stable place fields (like in rodents). Without describing here the whole model in detail, we just mention that this architecture has been already successfully tested on a robot with a panoramic camera in several indoor environments (one room, two rooms and a corridors).

Instead of describing the global architecture, we will focus in this paper on its two main scaling problems impairing navigation in large environments which have been shown by our last robotics experiments:

1. The computational cost of the PC layer is linear in the number of learned place cells, which itself increases with the number of environments explored. Moreover this growing number of place cells involved in the competitions increases the noise level.
2. In our architecture, planning relies on a single cognitive map. Problems appear when one wants to code several different maps coding for different environments or subsets of a big environment.

A contextual information could overcome these difficulties for large scale navigation:

- First, contextual information could increase the reliability of PC response by selecting only a subset of the PC population. Appropriate context activity and connectivity reduce the number of place cells in competition and thus avoid false detection. Furthermore, from a computational point of view, we can also use this contextual information to increase the simulation speed (reducing the number of place cells that have to be computed).
- Second, each map could be linked with a kind of context signal (linked for instance to the global recognition of a room) that should be able to ”reload” the previous learned map (or a part of it) into the different neural structures used here.

Place fields of rodent hippocampal place cells are strongly determined by the local geometry of the environment. Thus spatial representations in the hippocampus proper are highly context-specific. It is well established that modifications in environment change the spatial ring properties of PC, a phenomenon also known as remapping. The dependencies of the place code on geometric information (visual cues) have been investigated

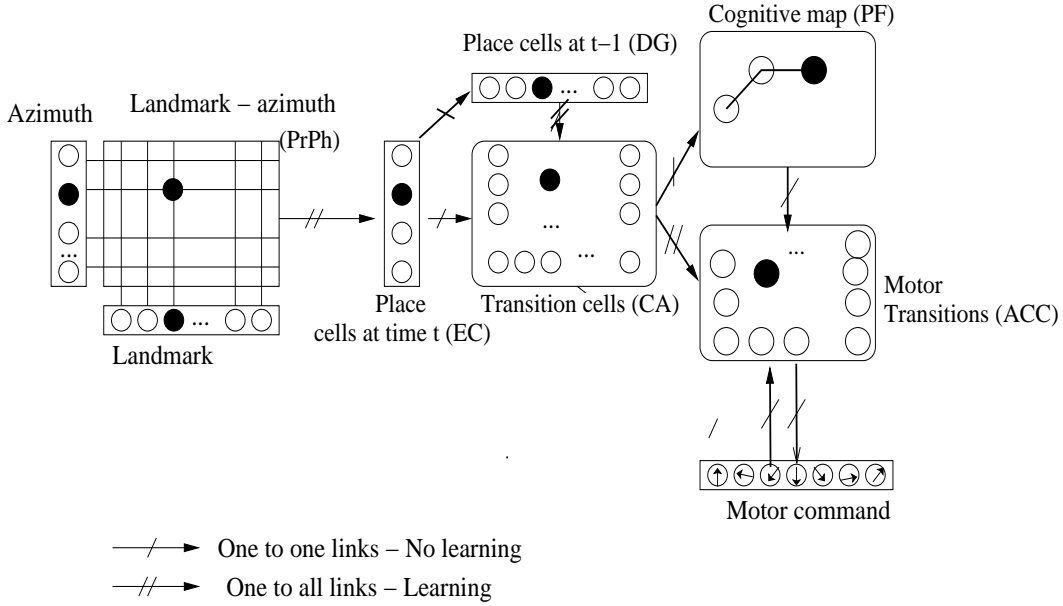


Fig. 1. Control architecture for planned navigation involving a simplified view of the loop between the hippocampus, the prefrontal cortex and the basal ganglia (here limited to ACC).

extensively [13, 14]. However, place representations also exhibit strong dependence on nongeometric information such as sounds, odors, somatosensory stimuli and behavioral context [1, 6]. This suggests the existence of a context-representation system which biases the hippocampal representations. We have chosen to begin our study by focusing on the geometric information since they seem to be of importance for this context code [12]. Nevertheless, we still have in mind that context doesn't rely exclusively on this sole information [1]. Future works will try to integrate nongeometric information in the model (see section 4).

In the next sections, we will show how a simple mechanism, based on a PC system with several resolution scales, could be a first step toward the constitution of this contextual information. We will show some experiments enlightening the interest of this model. Finally, we will discuss the results and the future extensions of the model.

2 Model

We present a model of modulation between two levels of PC (context and EC_s). We show how such a modulation could be modified by experience in a Hebbian manner, thus explaining the context specificity of PC.

In order to capture and learn geometric contextual information, context neurons are modelled by a specific PC layer. We name context neurons ($X^{Context}$), see figure 2. This new layer takes its inputs from a network (PrPh) merging recognized landmarks and azimuths in a product space. One can refer to [4] for more details on this process.

Activity of the the j^{th} context neuron is expressed with the same equation than in our previous work, as follows:

$$X_j^{Context}(t) = \frac{1}{W_j} \left(\sum_{kl}^{N_{PrPh}} W_{j,kl}^{PrPh-Context} \cdot X_{kl}^{PrPh}(t) \right) \quad (1)$$

with $W_j = \sum_{kl}^{N_{PrPh}} W_{j,kl}^{PrPh-Context}$, $X_{kl}^{PrPh}(t)$ the activity of the kl^{th} neuron in the product space (PrPh) merging landmark recognition and their azimuth. The learning of context neurons follows a Hebbian like rule:

$$\frac{dW_{j,kl}^{PrPh-Context}(t)}{dt} = -\lambda_1 \cdot W_{j,kl}^{PrPh-Context}(t) \cdot X_{kl}^{PrPh}(t) + \lambda_2 \cdot \left(1 - \sum_{kl \in N_{PrPh}} W_{j,kl}^{PrPh-Context}(t) \right) \cdot X_{kl}^{PrPh}(t) \cdot X_j^{Context}(t) \quad (2)$$

With λ_1 a decay term and λ_2 a learning constant.

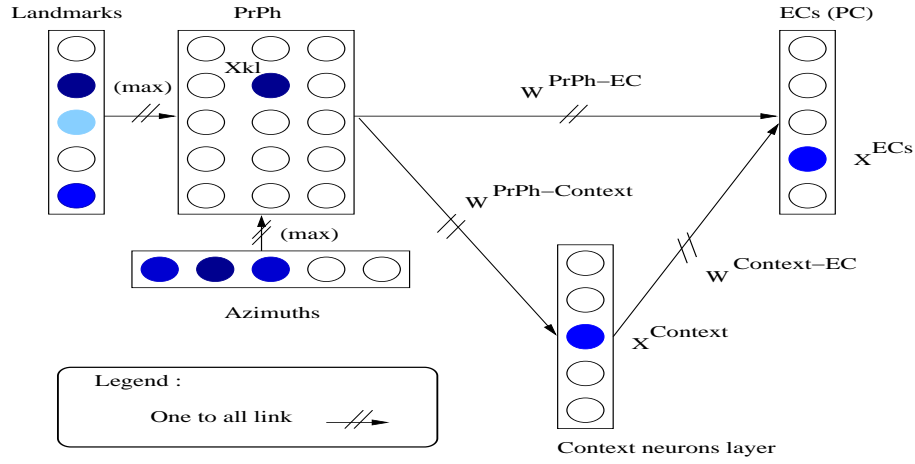


Fig. 2. Our model with a PC layer linked to the context layer. Context neurons also exhibit PC properties but with a larger firing field.

The recruitment of a new neuron for encoding a new location occurs during the exploration of an unknown environment. This mechanism is performed autonomously, without any external signal, relying only on the PC population activity. If the activity of any previously learned place cell is below a *fixed* recognition threshold (RT), then a new neuron is recruited for coding this new location. We need PCs of the Context layer with bigger place field than PCs on EC_s . Place field size of the winning PC (or generalization) can be set by adjusting this RT parameter. We thus choose a RT for the context population lower than the one chosen for the EC_s population (see section 3). If at a given place, several PC respond with an activity greater than the recognition threshold, a competition takes place so that the most activated cell wins and codes the current location. However, place fields are overlapping.

The PC population previously identified in our model as cells in the enthorinal cortex (EC_s) still also receive inputs from PrPh. But EC_s has now another input from the context layer (possibly located in a cortical area). PCs are linked to contextual PC with a weigth equal to one. Hence, at the beginning, each PC can receive an activity from all the context neurons. This choice has been ruled by the following modification of the activity equation on the EC_s layer: activity of a neuron X_i^{EC} is modulated by active context neurons. Thus in the beginning, since all weigths $W_{i,j}^{Context-EC_s}$ are equal to 1, any PC on EC_s can be activated and recruited. The context modulation operates under a multiplicative form, according to the following equation:

$$X_j^{EC_s}(t) = \left(\sum_i^{N_{Context}} W_{j,i}^{Context-EC_s} \cdot X_i^{Context}(t) \right) \cdot \frac{1}{W_j} \left(\sum_{kl}^{N_{PrPh}} W_{j,kl}^{PrPh-EC_s} \cdot X_{kl}^{PrPh}(t) \right) \quad (3)$$

At this state, since there is always at least one context neuron activated (a large PC), the activity of the PCs on EC_s remains the same as without the context layer. But we want that each PC belongs only to coactivated contexts and not to the others. This specialization process occurs online via the learning of links $W_{i,j}^{Context-EC_s}$ following a hebbian learning rule. Coactivation of a context neuron and a PC is detected and memorized (*coact*). This information modulates the modification applied to the corresponding synaptic weight:

$$W_{j,i}^{Context-EC_s}(t) = (W_{j,i}^{Context-EC_s}(t-1) + (X_j^{Context} * X_i^{EC} * c)) - \alpha \cdot (1 - coact) \quad (4)$$

with α a penalty term. If a coactivation has been already detected ($c = 1$) and both input (context) and PC are activated, the weight is increased otherwise the weight remains unchanged. Otherwise, if no coactivation has been yet detected ($c = 0$), the weight is decreased.

After some time exploring the environment, the PC only keep connections ($W^{Context-EC_s} > 0$) with very few context neurons. A majority of PC are linked with one context neurons. We thus has constructed a two resolutions PC system. Context neurons code for a broad and large zone of the environment, whereas EC_s can have a much better resolution. Only two levels of hierarchy have been used, but this could be generalized to other level (for instance the landmark recognition, or a more generalcontext for PCs)...

3 Experiments

As our context neurons are themselves place cells, they are sensible to the same parameters: proximity of landmarks (closer landmarks have greater angular displacement when moving) and the complexity of the environment (number of room, gates etc...). Actually, more locations are learned near walls or doors due to the fast changes in the angular position that can occur near landmarks, or in the (dis)appearance of landmarks caused by these obstacles.

We have thus performed several experiments on different large simulated environments (one room, three rooms and nine rooms) with several RT for the context neurons see fig 3.

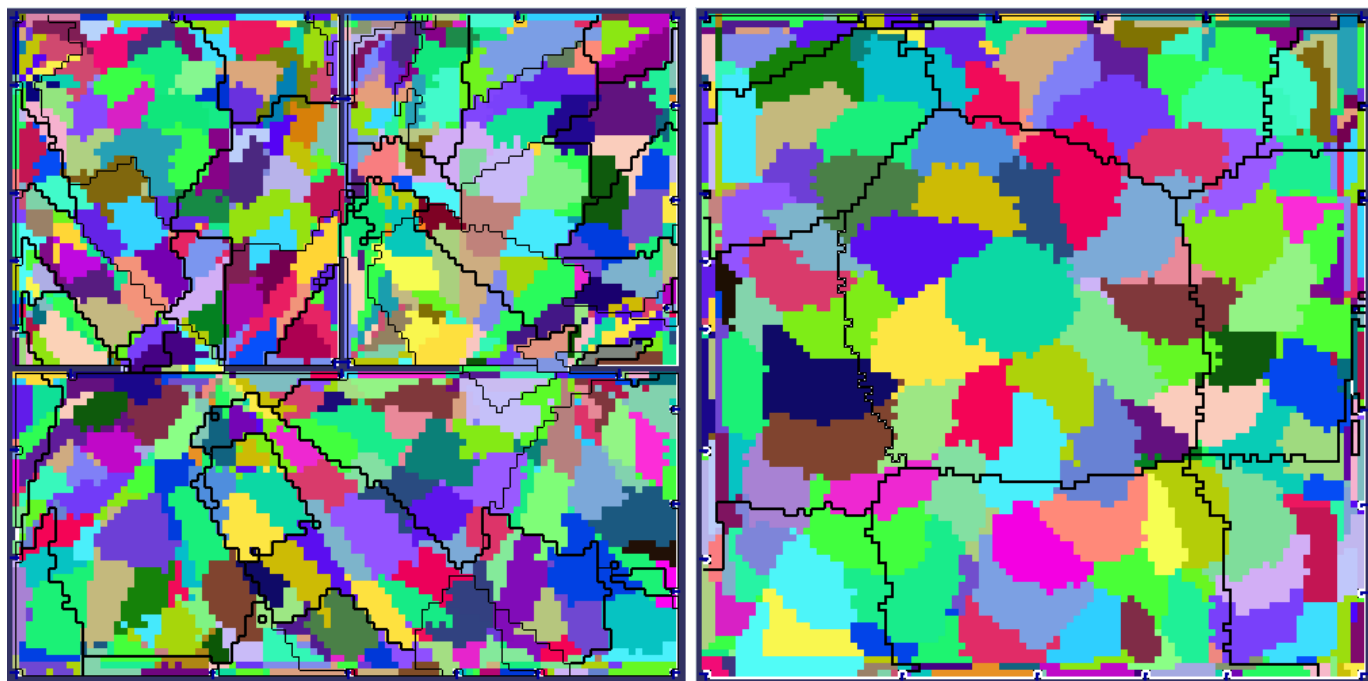


Fig. 3. Example of two environments. Blue crosses are landmarks. Each colored region represents the place field of a particular place cell. After a complete exploration of the environment, the entire environment is covered by the place cell population. Context place fields are delimited in black.

For each one, we measure the number of PC linked to each context neuron and the number of context neuron linked to each PC.

This preliminary statistical study implies very long experiment that can't be easily performed on a real robot. We thus use simulation performed over more than 400000 simulation step (around 56h on bi-core bi-processor PC with 4Gb of ram). Simulation is always different from real robot experiment; nevertheless simulations are based on the results of real robotics experiments and some previous simulations were confirmed by real experiments. Moreover real data experiment are currently performed on an image data base > 100 giga octets corresponding to a loop of more than 30km and robotic tests will be performed to definitively validate this approach. We use in our simulation a fixed RT_{PC} since we already have studied the impact of this parameter over a population of PC [4].

Table 1 show the mean number of cells recruited over several tries with ($\alpha = 1$, $RT_{PC} = 0.966$):

These results confirm several expectations:

- the number of PC associated to a given context increases when the context RT decreases (Context PCs have larger place field)
- this number of PC associated to a given context decreases with the number of rooms. This was expected since PC are sensible to the complexity induced by obstacle (hiding landmarks). Moreover the global size of the whole environment remain unchanged for all the environments. Hence, combining the fact that rooms

Context R.T=0.65	1 room	3 rooms	9 rooms
PC recruited on ECs	243	525	647
Context neurons recruited	8	26	61
PC over context neurons	43.87	26.38	23.87
Context R.T=0.75	1 room	3 rooms	9 rooms
PC recruited on ECs	238	531	760
Context neurons recruited	13	51	101
PC over context neurons	43.87	26.38	23.8689
Context R.T=0.85	1 room	3 rooms	9 rooms
PC recruited on ECs	212	501	720
Context neurons recruited	29	106	244
PC over context neurons	17.51	12.38	10.36

Table 1. Mean results for different values of context R.T. and several environments. (See text for an explanation.)

in the three (and nine) rooms environment are much smaller and that landmarks are placed along the wall leads to an increase of context and place cell neurons.

This last point can balance the apparently medium result found in the three and nine rooms environments, since we know that, for a given RT, our PC place fields are homothetic: bigger in a large environment than in a smaller one [9].

Figure 4 shows detailed histograms for the number of PC linked to each context neuron and for the number of context neuron linked to each PC in two given experiments (one and three rooms environment). RT for the context layer has been fixed to 0.75 in these simulations.

Finally, we analysed the impact of this contextual bias on the computational cost of the PC activity update. Without contextual information, this cost is linear to the number of PC recruited in the whole environment. Exploiting a contextual information allows us to only update PCs (compute the equation) linked with the activated context neurons, since we know the other ones will have a very low activity. Figure 5 shows the number of place cells updated at each iteration over a periode of 400000 iterations. This result shows an interesting decrease of the updating process cost. After, the exploration of the entire environment (iteration 0.510^5), this cost is really reduce, divided by two compared to the number of recruited PC (500).

4 Conclusion

The results described in this paper confirm the validity and the computational interest of our model of the interaction between place cells and contextual cells. However, this work is a very first step toward the constitution of a context. The model still need to be enhanced, for example by adding other information (like idiothetic information, other geometric or nongeometric information like sound). Nethertheless, even at this preliminary stage, this first model leads to several interesting properties, since contextual PCs can:

- increase the reliability of the PC code by limiting the range of the neurons competing for a given place. For example, a place cell a learned in a part of the environment coded by context neuron A can not perturbate the competition taking place in another location belonging to a context neuron B if no link exist between PC a and context neuron B .
- decrease the computatinal cost of the PC update process of the activity .
- provide a multiresolution localisation system to a more general navigation model.

We currently work on experimatal data (images and azimuth) acquired while a car performed a loop in the city near over 30km. We will certainly have to introduce path integration information and to introduce grid cell activity in order to discriminate ambiguous visual places when visual stimuli are ambiguous (long corridor for instance). We will also perform experiments on a real robot over a whole floor to validate these first findings.

We also plan to modify the context layer to obtain a distributed code of context, whereby context information is shared across a population of neurons. We think this kind of coding could take care of the remapping phenomenon observed in rodent hippocampus as recent finding suggest it [2]. Furthermore, this code could reduce the number of both needed PC and context neurons.

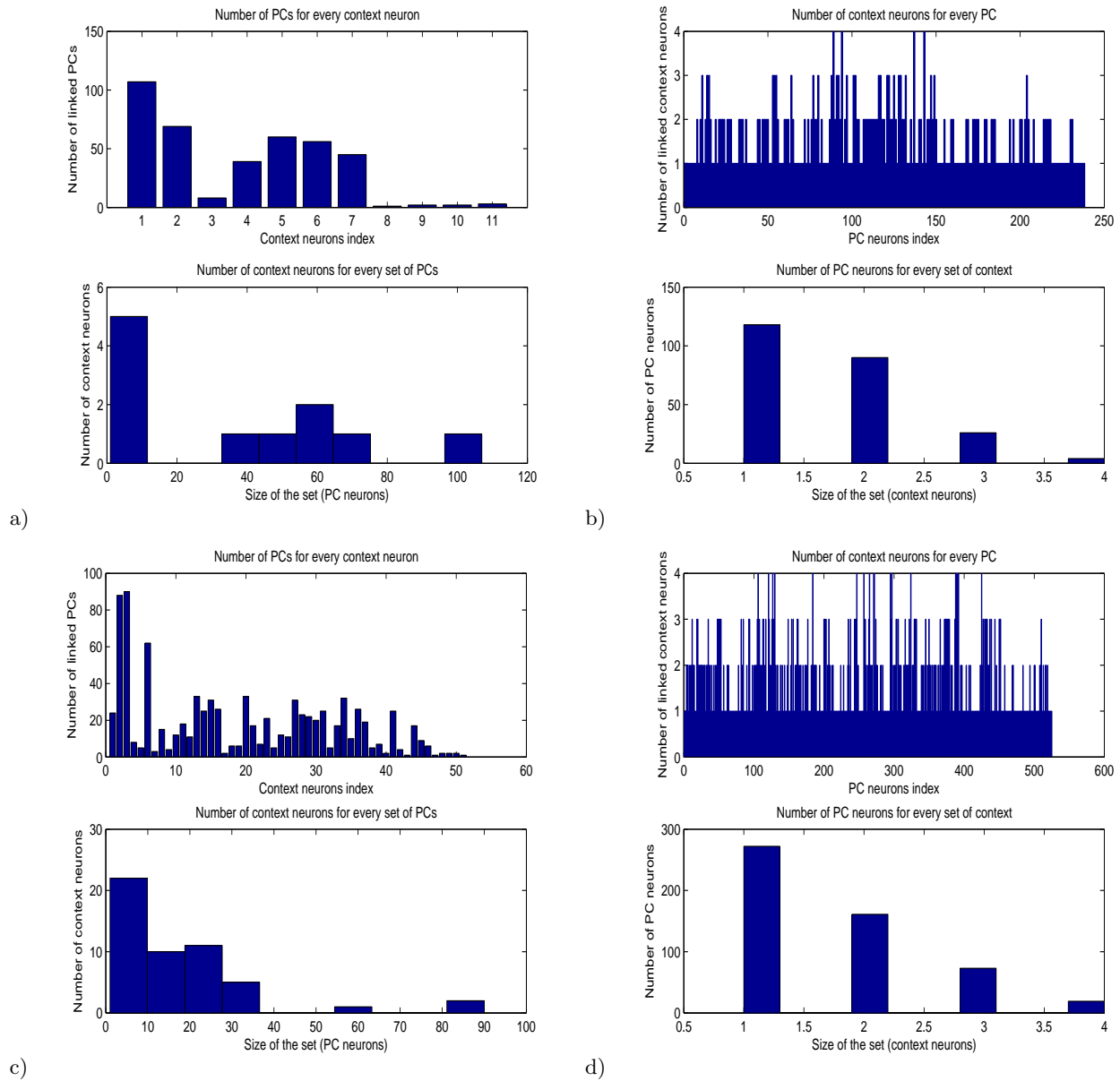


Fig. 4. Histograms of the number of PCs linked to each context neuron and of the number of context neurons linked to each PC respectively a) and b) for a given one room environment and c) and d) for a given three rooms environment. R.T. for the context neurons have been set to 0.75. Histogram c) and d) show how are distributed PCs according to context neurons. For the one room environment, the first two cells are linked with around half of the PC population size. In the three room environment, more context neurons are recruited and consequently the distribution is more equally dispatched, but there are still three major context neurons. Histograms b) and d) show that the majority of PCs are linked with at most 2 context neurons.

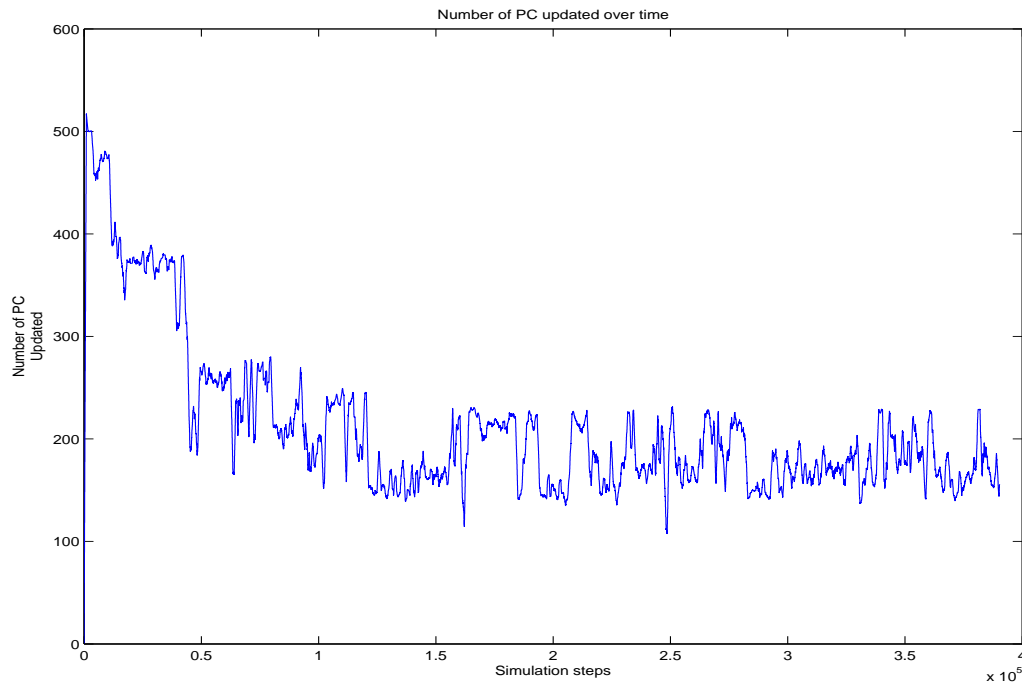


Fig. 5. Measure of the computational cost of the PC updating process for a three rooms environment. The computational cost is, in mean, reduced by a factor of two after the entire exploration of the environment (iteration 0.510^5).

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