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Cognitive map plasticity and imitation strategies to improve individual and social behaviors of autonomous agents

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Abstract

Starting from neurobiological hypotheses on the existence of place cells (PC) in the brain, the aim of this article is to show how little assumptions at both individual and social levels can lead to the emergence of non-trivial global behaviors in a multi-agent system (MAS). In particular, we show that adding a simple, hebbian learning mechanism on a cognitive map allows autonomous, situated agents to adapt themselves in a dynamically changing environment, and that even using simple agent-following strategies (driven either by similarities in the agent movement, or by individual marks - "signatures" - in agents) can dramatically improve the global performance of the MAS, in terms of survival rate of the agents. Moreover, we show that analogies can be made between such a MAS and the emergence of certain social behaviors.

Keywords

embodied intelligence · biomimetic autonomous systems · cognitive maps · imitation · social intelligence · collective learning

1. Introduction

Swarm-based systems [1] are a classical approach to deal with collective intelligence problems. In such approaches, newly gathered information is represented by physical traces (pheromones) let by agents in the environment. We develop an alternative approach in which information is stored internally in agents, with no marking of the environment but with will to get similar emergent behaviors. Several works [2–4] relate the possible use of special cells in the rat's hippocampus that fire when the animal is at a precise location. These neurons have been called "place cells". Starting from those neurobiological hypotheses on the existence of place cells (PC) in the brain, we show how agents can continuously learn during the exploration of their environment, and how they can share the information they have using a simple agent-following mechanism, seen as a low-level kind of imitation. Imitation processes are usually divided in two levels: the *action level* of imitation [5, 6] is related to the mechanisms involved when reproducing a simple action, often an elementary movement. In what follows, we refer to this agent following capacity as "imitation". The *program-level* refers to imitation of more complex actions while preserving their organizational level. The work presented in this paper mainly focuses on the first of those two levels. It lies at the intersection between several domains: we use a multi-agent system (MAS) to test hypotheses on both individual cognitive processes in simple agents and the emergence of non-trivial collective behaviors in some (sub-)groups of those agents. At the individual level, agents can rely on an on-line, continuous building of a cognitive map [2, 7–11] whose structure depends on their own experience and discovery of the environment in which they live. At the global, population level, they can take advantage of the ability to imitate one another using simple agent-following strategies to transmit parts of one agent's cognitive map to another's, leading to some kind of natural distributed knowledge, similar to what can be achieved in swarm-intelligence systems, except that shared knowledge does not use the physical space as repository (as is the case for pheromones) but individual cognitive maps instead. Those maps are a subclass of topological maps, used in several context, from navigation [12–14] to image processing [15] and others. This process, though mainly illustrated here in navigation tasks, can thus be reused for a wide range of action selection problems.

Some of our previous papers [16–19] showed how to use a cognitive map to solve non-trivial, possibly contradictory goals at an individual level and to let social behavior emerge from a group of situated agents launched in a previously unknown environment. Similar works [20, 21] use sensorimotor maps together with an additional field to distinguish between information about position and activity spreading mechanism on a cognitive map. These two fields play a similar role as the sensorimotor and planning maps in our architecture. The navigation and planning aspects described here are meant as parts of a more global and complex autonomous system, which in time aims at recognizing objects [22], imitating [23–26] and communicating information among them. Other experiments in our lab showed that our model can successfully be used on actual robots navigating in the outside [27], but

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also learning sequences of actions, either from a human being or from another robot [25, 26].

In social sciences, and more precisely in the economics field, MAS are used to "formalize complex situations with various, spatial, temporal or organisational scales and heterogeneous agents engaged in social activities" [28]. Previous works on the formalization of bottom up processes and rooted in the Santa Fe Institute, "Simulating Societies" [29], "Artificial societies" [30] then "Growing up societies" [31] have arisen the interest of the application of MAS in economics and more generally, MAS can be seen as a tool to model macro and micro relationships such as the artificial stock market in Santa Fe [32], the complexity of exchange and market mechanisms [33] or the strategic behavior of agents [34]. In those contexts, agents are purely rational: they try to optimize a hardwired satisfaction function. Moreover, we know that individual behaviors are able to produce social and spatial phenomena unexpected in theory [35]. In social science, the Schelling segregation model is doubtlessly one of the first models of a dynamical system capable of self-organization. It shows that a small preference for one's neighbors to be of the same color can lead to a spatial segregation. MAS also exhibit the emergence of urban patterns such as urban hierarchy [36], resilience and the persistence of urban settlement structures and emergence of polynucleated urban landscapes [37]. Whereas the process is quite similar (except that agents are immobile geographical entities in [36]), spatial organization and clusters emerge from the definition of different categories of agents: population size, activity, urban functions and range in [36], color in [38], ethnic specification in [39] or income level in [40], and spatial marks (such as ants in [37]). It remains that, in human geography too, agents are truly rational. The choice criterion is only making the difference: as an example, agents locate their home with regard to income and job accessibility [40], a convenient cultural environment [39], a mild preference for having neighbors of their own color 1 [38]; towns trade with regard to surplus and the creation of new functions [36] and agents, following the tradition of swarm-based systems, leave physical traces in the environment that enable learning to occur and routines to emerge [37]. The spatial dimension is the consequence of the definition of agents' basic characteristics and location or moving processes on a lattice. If human geography has engaged successfully with applications in agent-based systems, it has surprisingly omitted to integrate cognitive maps. Indeed, the definition of cognitive and mental maps processes come from the geography and psychology and previous works by Lynch [41] have shown that space is of fundamental interest to understand individual routes, spatial routines or the geography of places. Renewed in the nineties, partly by the development of computer sciences and interdisciplinary approaches [42], authors were expecting a better understanding of individual spatial behavior that could replace the simplistic homoeconomicus hypothesis [43]. Using cognitive maps to model economic agents enables us to live up to this expectation and to deal with limited and situated rationality. Our systems deal with two kinds of agents, reactive and cognitive [17]. Reactive agents are "naturally" rational in simple environments (where visual continuity allows for the success of simple gradient following strategies), but fail as soon as those hypotheses are not met. Cognitive agents are not rational initially, but tend to become rational when their knowledge of the environment increases. Our aim is to show that this last kind of agents, dotted with a cognitive map, though only partially rational, can help to model complex social patterns in which simple reactive agents are of no - or few - help.

Next section is devoted to the description of our model of place cells (and transition cells [44], see 2), and to that of the agents. In particular, we show that using transition cells (TC) solves the important problem of unambiguously linking actions to places in the environment. The term has been proposed by our lab, initially without actual biological justification, even if several recent biological recordings [45, 46] can be interpreted as coming from such transition cells. Section 3 depicts the structure, role and construction of a cognitive map, then shows that adding a hebbian learning rule on the weights of the connections in the cognitive map can help the agents adapt themselves to a dynamically changing environment. Using such a map can allow non-trivial behaviors, such as the ability to deal with contradictory goals [16]. Section 4 focuses on two agent-following strategies that can help to transmit information from an agent to others. We describe a signature-based mechanism to distinguish agents from one another, then compare a "blind" following strategy to the strategy based on the agents' signature. We show that in both cases, simulations lead to the formation of subgroups, though not identical in their structure and stability. As a consequence, the analysis of such subgroups may question spatial economic analysis. Section 5 discusses how to implement such a model in the spatial economic field which main purpose is to study the importance of space in both individual and collective economics processes.

2. Model, material and method

In our experiments, software agents - or *animats* [47] - are launched in an unknown environment. They are motivated by the simulation of three types of needs (hunger, thirst and stress) that can be contradictory. Each need can be satisfied by a (pool of) corresponding resource(s), namely food, water and nest, that can be found in the environment. The level of each type of need is internally represented by an *essential variable* [48], $e_i(t)$ whose value is in $[0, 1]$ and varies with time as in Equation 1, except when the agent reaches the resource and the variable level is reset to 1.

$$\frac{de_i}{dt} = -\alpha_n e_i(t) \tag{1}$$

In the equation, α_n represents the decreasing rate of the i^{th} essential variable. When $e_i(t)$ falls under a given threshold, a planning behavior is triggered to go back to the (known) resource. Thus, changing its value has an impact on the frequency of the visits to the resource: the higher α_n, the more frequent the visits. If no resource of the corresponding type has been found by the agent, the level decreases until 0 and the agent dies.

The environment is gradually discovered by the agent during random exploration phases. Each time-step, the agent receives information about the visible portion of its surrounding environment. This information is made of couples of "what" and "where" information. "What" relates to the recognition of a local view centered around a point of interest (corner, end of line, etc.). "Where" represents the azimuth (angle) under which each point is seen by the agent, compared to the North. The perceivable points of interest are as follows:

- landmarks: fixed remarkable points (thus a particular location is given by a set of landmark/azimuth pairs). Those points are defined during the design of the environment and are not subject to changed during an experiment;
- obstacles: locations that the agent cannot cross, and which prevent it from seeing what is beyond;
- resources;
- other agents.

Landmarks may be seen from anywhere unless occluded by an obstacle. All other elements are only detected within a given detection range.

Table 2. Influence of the imitation strategy on the survival rate of the populations. Average number (and standard deviation) of surviving agents. The much higher standard deviation for signature-based imitation is due to some global group disappearance.

# agents	random	azimuth	signature
40	14.2 +/- 1.5	15.0 +/- 1.5	18.4 +/- 2.4
50	15.5 +/- 3.1	16.3 +/- 3.1	17.6 +/- 4.9
70	26.4 +/- 4.5	27 +/- 4.8	31.1 +/- 8.3
average	34.73%	36.22%	41.87%

village is close enough to existing villages (say nc villages), it is likely that subgroups can emerge, oscillating between the new village and one of the nc closest neighbors. That leads to a new couple (nv', ns') where $nv' = nv+1$ and $ns' = ns+1+i, i \in \{0, ..., nc\}$: clearly we still have $ns' \geq nv'$. Figure 11 shows an experiment with 4 villages, where 5 stable subgroups appear. The fact that the number of subgroups is not that high when agents imitate on the azimuth is due to the lower stability of subgroups in that case: agents arriving in a village are likely to follow other agents that stick to the village (same probability as to continue their oscillation), so oscillating subgroups are unstable over time.

To study the influence of the imitation strategy on the survival rate of the populations, we used the same environment and successively launched 40, 50, then 70 agents, for both of the imitation strategies, and counted the number of agents that survived, or died for not having found all of the three types of resource. Each of the experiments has been conducted 7 times, and the results are summarized in Table 2. Average number of surviving agents is almost always greater with signature-based imitation strategy. This result is linked to the greater stability of the groups in such a strategy. If one of a group member has found the three resource types, the probability for the entire group members found to find the three resources is higher (indeed the probability each agent of the group imitates another is greater). What can seem more curious is that the standard deviation is significantly higher. Observing what happens during those simulations, we saw that this was due to some subgroups creation around one or two agents that *did not find the three resource types* at the time the group emerged. Consequently, since the chance for an agent to follow its peers is high, the result is of type "all or nothing": either the resources are discovered by one of the group members, and the whole group survives, or they are not and the whole group disappears.

5. Discussion

The kind of complex behaviors illustrated in this article explains the interest for cognitive maps and imitation in social sciences, and more precisely in the spatial economics field.

Concerning the agents imitation ability, the group behavior observed in Table 2 is related to a process observed in the spatial economics field, known as "unemployment traps": they are well-defined portions of urban territories in which the unemployment rate is significantly higher than anywhere around [60]. Although it might be possible for people living there to find a job a few kilometers ahead, things are like if people could not - or didn't try to - move outside this small region. In our simulations, although the needed resource is in the reach of the group, it is only seldom discovered because of the strength of the intra-group link.

Using a cognitive map is a way to store information internally in agents and, together with the ability to imitate, to get similar emergent behaviors as in swarm-based systems. It questions the analysis of the resilience of urban systems and the complexity of cities [37, 61]. The results presented here show that the cognitive map is a way to envisage broad-minded agents that enable us to deal with series of spatial economics issues. They question spatial economists as the issue is not only the analysis of collective spatial dynamics but also a better understanding of the agents' behavior. If classical economics generally considers agents as rational, the cognitive maps raise the interest to work with cognitive agents instead. As an example, in spatial economics, the interest is to minimize distances or costs to one or several objectives that are previously known by the agent. As a consequence, when maximizing an objective function, agents are considered having a substantive rationality. In most cases, this optimization is incompatible with the limited cognitive capacities of the agents. Agents do not have complete and perfect information: they have a bounded rationality [62], a procedural knowledge that enables them to discover new places, new objectives locations and learn new paths to reach a known objective or to satisfy a multi-objective function. In this respect, spatial economics suppose that the question of the knowledge of places, of objectives location, paths and obstacles can be thought of as a matter of geography and regional planning. Indeed, classical economics generally considers that space is an additional index we add on economical variables, so space is not considered as an important variable in individual and collective analysis: the spatial configuration of places or roads would only imply a marginal modification of the agents' rational strategies.

Works in cognitive science show that spatial cognition – and cognitive maps – take part directly in the effectiveness of individual strategies. Environmental psychologists and researchers in human geography had the intuition of this result. Quoting from Portugali's paper [43], "mental maps studies would provide a deeper understanding of human spatial behavior and as such would replace the simplistic assumption of a rational 'economic man' which underpinned the theory of location and spatial analysis". Indeed, works in cognitive science teach us that each agent has its own procedural knowledge of space, places, objectives and possible paths to reach a previously learn objective. Each agent is equipped with a cognitive map, that its experience or its past discovery and learning of places and paths has enlarged with time. As a consequence, simulations of cognitive maps are a way to show the importance of space in individual and collective intelligence processes.

A main result of cognitive map models in economics field is to explain how the learning process is functioning and so on, how this procedural knowledge is constructed. Following Bourgine's paper [34], it's important to note the "remarkable property of neuronal plasticity that make adaptation possible in complex situations". Here, we mobilize tools of simulation and modeling from robotics and computer science: the cognitive map is referring to two levels of neural networks (the first one intended to learn and recognize distinct places; the second one to memorize the paths most frequently used by the agent to achieve a goal, see 3). As a consequence, agents inherit adaptability in complex environment. In such a context, they have to locate according to a set of visible landmarks likely to change (landmarks could be hidden by a wall, houses...) and they are able to benefit from a former exploration of space: they will find different ways through intermediary goals set on their cognitive maps. Hence, economic agents are in a situation of limited rationality: they can see and discover their environment (see 2), they can learn and plan optimal paths (see 3), solve multi-objective problems according to their experience and to their discovery of the environment (see 4).

Another result is the interest to work with cognitive agents compared to purely reactive agents when faced with increasingly complex spatial environments. When the environment is complex (made of obstacles, vanishing or non-renewable resources as example), the cognitive agents are more effective than the reactive ones (which is not the case with simple, obstacle-free environments): in such a situation, the masking of landmarks leads to important distortions, and the agents may have difficulties to locate or to find an effective path because they will find their way through intermediary goals set on their cognitive maps. Moreover, when multiple solutions exist, such cognitive agents will naturally “spread” on the different solutions instead of sticking to the apparently best one (that with the maximum average value of essential variables level for instance). That can lead to a better global solution: in the case where resources are limited and can only renew with time, purely rational economic agents would all stick to the nearest village, exhaust its resources and die if too far from the next village; cognitive agents, by spreading on all the solutions, can exhibit a better global behavior (in term of surviving agents ratio for instance) in this situation. On the other hand, if the environment is simple, reactive agents are more effective than cognitive ones because they do not refer to previous paths and go straight to the objectives. It seems that the collective intelligence processes have inherited from these results. Following classical economics fields, as in a simple environment, natural resources have been over-exploited or exhausted whereas in a complex environment, the agent exhibits complex dynamics such as adaptability or survival when resources exhausted and it will be interesting to analyse the agents capabilities to manage existing stocks of resources. In the first case, we consider that natural resources, that have been discovered, are exploited independently of their location. Prices (including transportation costs) and available quantities are the single limits to resources exploitation. In that case, environment is quite simple, routes are known and the economics question is to preserve resources controlling prices or quantities. In the second case, we have to deal with the complexity of the environment: resources can become exhausted, new ones are discovered and agents are simultaneously interested in different types of resources. Pressures to resources are unequal and are not systematically a function of the transportation costs of agents. The complexity of the environment is also questioning local unemployment contexts: finding vacant jobs asks for an ability to move, to know the location of firms, skills and vacancies to avoid spatial mismatch. Urban economics encounters spatial mismatch cases without taking into account the spatial strategies of unemployed people. It supposes that the standard characteristics of agents (gender, age, qualification, car ownership, distance from home to potential jobs, incomefl) or of local policies (collective transportation system, unemployment agenciesfl) and labor market functioning (internal market, adequacy between supply and demandfl) are the main variables to understand spatial mismatch. Agents may have spatial habits or routines that constrain their use of space whereas the economics analysis is always developed in a simple environment. It argues as if unemployed people have all information on firms, jobs and road to apply when individual strategies and contexts are complex. Cognitive maps enable to catch this phenomenon. Nevertheless, it requires adequate tools to identify, test and calibrate different groups and spatial configurations.

Schelling's work [38] is a fundamental example of the analysis of spatial configurations in economics: “The demographic map of almost any American metropolitan area suggests that it is easy to find residential areas that are all white or nearly so and areas that are all black or nearly so but hard to find localities in which neither whites nor nonwhites are more than, say, three-quarters of the total”. The main question is to identify why such a non-organized segregation exists. To mimic the distribution of ethnic groups in an urban area, Schelling sets up the following hypothesis: residents of a given area are happy as long as the majority of their neighbors are the same color as themselves. If the residents are “unhappy” they move to a new area. On the basis of such an hypothesis he showed that even if all agents have a preference for integration, the model dynamics leads to segregation. The main criticisms consist of an *a priori* definition of the origin of segregation (the color) and the dynamics rule that inevitably leads to “tipping point” and segregation. The use of cognitive maps together with the ability to imitate show that it is possible to define “villages” as in Figure 11 and segregation outlines: the signatures of agents are a way to differentiate them and to define the nature of the groups, whereas the collective intelligence process is running on the base of space discovery and known essential resources reaching. It is a way to deepen the analysis of collective dynamics [31, 61] to better understand the part that space is playing.

An important question is now to characterize the set of spatial collective dynamics which can be obtained according to the level of complexity of the model of agents, their environment and their interactions with the environment and other agents. If limited rationality is now an operational concept, it's in the interest of economists to recognize the importance of space in some basic economics question. When considering a complex environment, space is essential to the analysis of collective intelligence processes.

In conclusion, we showed that our model and system allow to to solve non trivial planning and optimization problems, with only very little assumptions on the initial knowledge of the agents. They can adapt themselves to a changing environment, share a partial knowledge of the problem with each other, handle multiple, contradictory goals and find different solutions to the problem when multiple solutions exist.

It should now be possible to see how the optimization can be pushed one step further, by making agents able to act on their environment instead of just adapting themselves to it: for instance, letting agents specialize in a given task [63], or letting them carry some resource from “natural” sources to locations near important paths could dramatically enhance the performance of the global system, as far as the average “satisfaction” level of the agents (the average of an agent's essential variables values) is concerned.

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