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Research Article

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Studying the Development of Spatial Cognition with Evolving Neuro-Agents

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Abstract

This paper describes an evolutionary robotics approach to study spatial cognition. Through the analysis of evolving neuroagents, run on behavioral, computational and evolutionary/development level, we show how relevant is considering the dynamic perspective in the observed phenomenon genesis and how useful can be using the evolutionary robotics methodology to address this issue. The experiments described in this short paper use simulated agents led by an artificial neural network and evolved through artificial selection to accomplish some spatial tasks commonly used in animal psychology. Results indicate that behaviors, especially biases, can be understood only taking into account the evolutionary/development pathway of each agent.

Keywords

Spatial cognition; Neuro-agents; Artificial life techniques; Neural control system

Introduction

Vertebrate species use geometric information and nongeometric or featural cues to orient that Gallistel [1] defines in the non-geometric property is any property that cannot be described by relative position alone. When both sources of information are present at the same time different behavioral patterns are observed:

1. Geometric information overwhelms non-geometric cues (geometric primacy);
2. Non-geometric cues prevail over geometric ones (non-geometric primacy);
3. Integration of both cues.

When the first case was observed for the first time in rats studied by Cheng [2] and Margules and Gallistel [3], geometric primacy was explained postulating the existence of a geometric module: geometric and non-geometric information are processed separately, with the geometry module playing a dominant role. Non-geometric primacy and integration of cues do not support the modular hypothesis, that for some years have been critiqued (consider for example, Twyman and Newcombe, [4]). In this debate, some interesting hints come from the studies on humans. Hermer and Spelke's [5] and Gouteux and Spelke' studies [6] have tested adults that proved to be able to use both kinds of cues. In children a particular responses pattern emerges: in the experiments with children of about 2 years, the subjects could use the geometric information in almost every condition, but could use the non-geometric information only in some conditions [7-10]. When children grow older, at about 6 ages, the primacy of geometric information is overcome and they can use the non-geometric information consistently [11]. The children strange case is paradigmatic in indicating that the dynamic perspective fundamental role must not be neglected. To understand some relevant phenomena observed in natural organisms it is necessary to take into account the evolutionary/developmental perspective. Artificial Life techniques are a precious tool that can be employed to approach this issue. In this short paper we will show an example of how using evolutionary robotics methodology can help clarifying the evolutionary/development pathways that lead to a specific behavior and the corresponding computational/neural organization.

Materials and Method

The agent and its neural control system

We used a simulated agent, a round, 30 mm tall agent with a diameter of 55 mm. eight simulated proximity sensors are positioned around the agent's circumference at a mid-height. Sensors can detect obstacles within a range of 3 cm. The agent is also provided with a visual sensory system with a visual field of 270 degrees wide and 1 m long, similar to the visual field of fish (private communication from Sovrano [12]). The perceived objects in the environment tending towards white were coded with a value of '0' and the ones tending towards blue received a code of 1. The agent moves using two wheels located on either side of its simulated body, each controlled by a motor. The agent is also provided with a localization unit whose activation determines the agent stop. In our own experiment, we used a modified version of the "Evorobot*" simulator developed by Nolfi and Gigliotta [13], an environment created specifically for experiments with simulated populations of agents. The robot control system consists of an Artificial Neural Network with 16 input units, 7 hidden units and three output units. The input layer consists of eight detectors for proximal stimuli and eight detectors for distal stimuli. The output layer consists of two motor units and one localization unit; agent behavior is determined by the activation of these units. The third output unit (the localization unit) temporarily halts the agent whenever its level of activation is higher than 0.5. In other words, the localization unit signals that the agent has identified a specific location, indicating a place recognition behavior.

Experimental Setting

The experimental setting for our study was similar to the setting in which Sovrano [12] conducted their work. Each experiment took place in an arena with a "reward area" in one corner. The first environment we used is the complete "geometric plus non-geometric arena" in which, the long side opposite to the reward corner, as well as the corners were colored blue: in the arena where both geometric and nongeometric cues are available, if an organism uses no information but the shape of the box, the agent will commit a rotational error. If it merges geometry and color information, it will choose the correct corner. Removing the blue wall from the complete arena, we obtain

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the "geometric arena" which is rectangular with four white walls and angular landmarks. Instead removing the geometric information from the complete arena that is the rectangular shape of the arena and the angular landmarks, we obtain a "non-geometric arena", square-shaped and with a blue wall. Square arenas were also used by Huttenlocher and Lourenco [14] in their experiments with toddlers. The square arena does not have resolutive geometric information so it is a good non-geometric.

Both rectangular environments were 56.8 × 25.6 × 20.0 (height) cm, while the square one was 56.8 × 56.8 × 20.0 (height) cm. In all environments, a circular reward sector was located in the bottom-left corner with a radius of 8 cm. In the "geometric arena", the only available information is geometry, according to which we expect agent to choose the correct corner as well as the rotationally equivalent corner. In the "non-geometric arena", the blue wall disambiguates the task, so we expect the agent to choose the correct corner.

The evolutionary/adaptive process

We evolve the agents using a Genetic Algorithm with the first generation made up of 100 simulated agents, controlled by a feed-forward neural network with random connection weights. We then test the ability of each agent to localize the reward area for 100 trials. At the beginning of each trial, the agent is positioned in the centre of the arena, facing in a random direction. We then allow the agent to move for 1,500 computation cycles. Every time the agent "identifies" the target area (activation of the localization unit greater than 0.5) it stops for 5 computation cycles and receives one "reward point". The agent's final score is the total of reward points received during trials. After all agents have been tested, the best 20 agents are chosen to "survive" and "reproduce". The neural system for each selected agent is cloned five times.

During cloning, 35% of connection weights are mutated. The testing/selection/reproduction cycle is iterated for 100 generations. To investigate how the evolutionary/development pathway can have effects on the behavior of a agents and their neural structure we analyzed the effects of differing frequencies of exposure to different classes of spatial information, performing 11 experiments with different exposure to the arenas. On each experiment, we increase the proportion of trials conducted in the geometric arena (the exposure balance), beginning with 0% and increasing by 10% on each experiment. We replicate each experiment 20 times using different initial weights in each replication.

Results and Discussion

Agents' behavior

Results show a clear interdependency between exposure balance and reward scores. The agents with the strongest ability to integrate geometric and non-geometric information are those that evolve for 50% of trials in the geometric and for 50% in the non-geometric arena. Agents whose main exposure is to the non-geometric environment, agents who receive balanced exposure to both environments and agents whose main exposure is to the geometric environment display significantly different levels of reward scores (ANOVA: F(2,217)=12.191 P<0.001). To gain further insights into agent behavior (Figure 1), we group them according to their "skill". Disoriented agents that fail to achieve a minimum level of acceptable

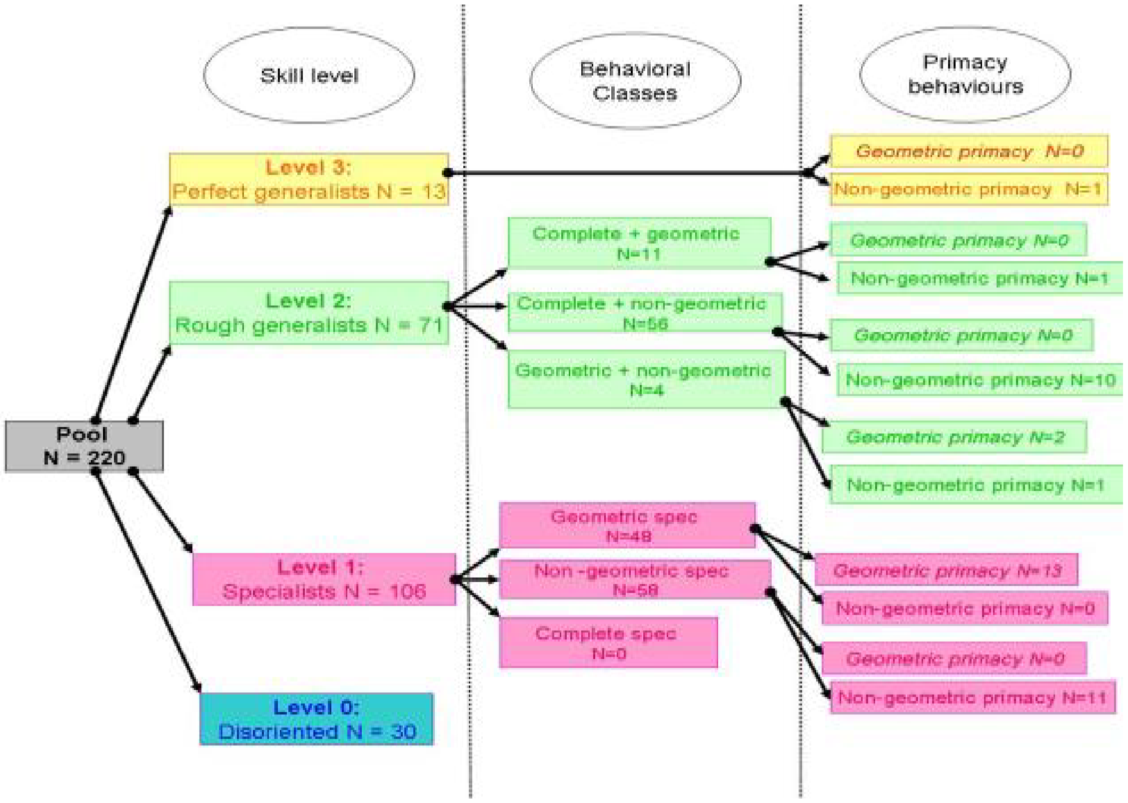

Figure 1: Skill level, behavior classes and primacy behaviors in a pool of 220 agents (the agents with the highest level of reward scores in the last generation of each trial).

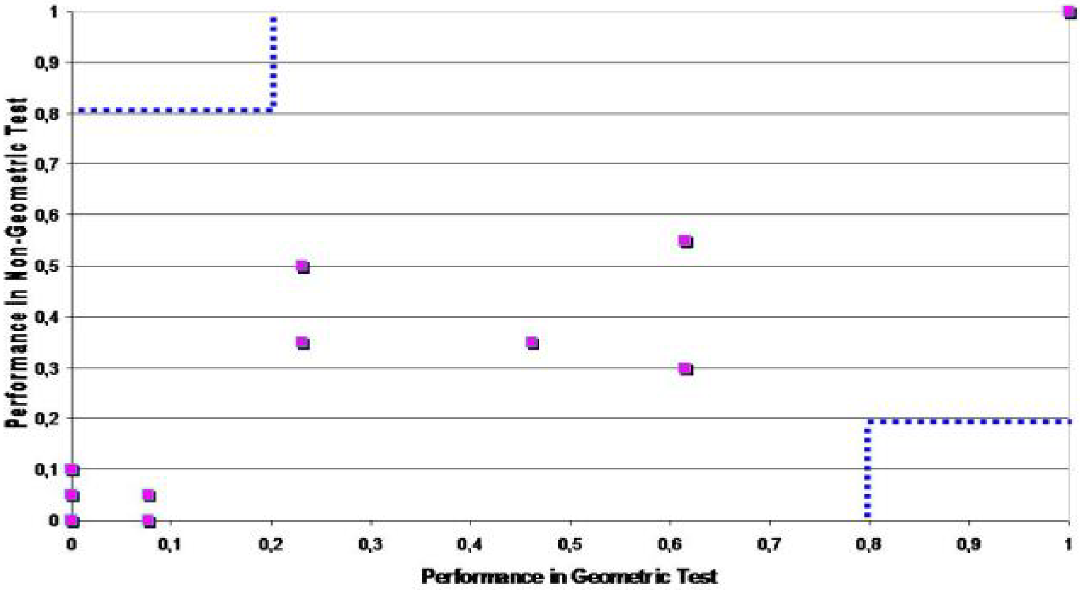

Figure 2: Performances of lesioned perfect generalists on the geometric and nongeometric task.

performance in any of the environments (30 agents, 13.63% of the pool) are classified as level 0.

Specialists (106 agents, 48.18% of the pool) that achieve acceptable performance in just one of the environments are classified as level 1. This class includes 48 geometric specialists (21.81% of the pool) that are unable to orient correctly in the non-geometric environment and 58 nongeometric specialists (26.36% of the pool). Rough generalists that perform well in two out of three environments (71 agents, 32.27 % of the pool) are classified as level 2. Perfect generalists that achieve above threshold performance in all three environments (13 agents, 5.9% of the pool) are classified as level 3. If we look over these skill levels, we will find different behavioral classes, depending on agents' ability to localize the reward sector in the arenas. For level 0 and level 3, we just have one behavioral class, as no permutation is possible. Instead, on level 1, we have three kinds of specialists: geometric specialist that orient only in geometric arena (48 agents, 21.81%) and non-geometric specialists (58 agents, 26.36%) that orient only in non-geometric arena. Complete specialists that can orient in the "geometric plus non-geometric" arena only did not emerge in this pool. On level 2, we observe three kinds of rough generalists, agents that orient correctly in two of three environments: "complete plus geometric" generalists (11 agents, 5%), "complete plus non-geometric" generalists (56 agents, 25.45%) and "geometric plus non-geometric" generalists (4 agents, 1.81%).

Does exposure balance determine this distribution? In other words: does agents' evolutionary/development history determines their behavior? Yes, it does! Agents showing a specific kind of behavior emerge most frequently in environments where this kind of behavior gives them a selective advantage. Generalists emerge when the number of trials in the "geometric arena" and the "non geometric arena" is roughly balanced. In fact, if we compare the frequency of generalists in the three aggregated groups: unbalanced exposure to non-geometric environment, balanced exposure and unbalanced exposure to geometric environment, the chi 2 test is significant for non-geometric specialists: chi 2=8, p=0.0183. By contrast, specialists emerge more frequently when agents are mainly exposed to just one of the two environments. Comparing the frequency of specialists in the three aggregated groups (unbalanced exposure to nongeometric environment, balanced exposure and unbalanced exposure to geometric environment) the chi 2 test is significant for non-geometric specialists: chi 2=32.14, p<0.001, as well as geometric specialists: chi 2=38.62, p<0.001.

Agents' neural organization

To understand agents' neural organization we have systematically lesioned agents' neural networks, in particular to the healthy subjects that, in our pool, are the perfect generalists. The neural encoding underlying various spatial information patterns has been determined by the whole data set about perfect generalists. The chart shows that there is no dissociation between the processing of geometric and non-geometric cues. In the huge majority of cases (118 out of 128), lesions produce a general loss of performance that affects the ability to perform either task. In not one case, do we observe a loss of the ability to perform one task and the conservation of the ability to perform the other task. This implies that it is possible to evolve geometric and non-geometric primacy in the absence of specific modules performing these functions: a modular neural organization in not necessary.

Conclusion

The experiments described in this paper show clearly that it is fundamental to take into account the evolutionary/development history to understand a present behavior. As shown in the present paper, the biases in spatial behavior can be understood only in a dynamic perspective; data pictured in a single moment do not shed light on this kind of problems. In the present paper, the exposition to specific environment cues during the evolutionary process determines the behavior observed at the end. The evolutionary/ development perspective helps understanding those phenomena and evolutionary robotics techniques helps studying the evolutionary/

development perspective. Indeed evolutionary robotics techniques allow to effectively following this approach, not easily feasible with natural organisms, because it is virtually impossible to control all the potential error sources (i.e. exposition to other cues during evolution).

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