A study on the origin of anticipation by guidance for artificial dynamic cognition

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1 Introduction

Our work falls within the scope of the *enactive artificial intelligence* theoretical framework [FZ08]. The guiding idea of this area is to take the biological roots of cognition [MV80,VTR93], as a starting point to create artifical entities endowed with agency and allowing the study of some cognitive sciences hypothesis. These entities are self-organized complex systems which can be disturbed by their environment. If the dynamics of the system compensate these disturbances, the system is viable and the environment makes sense to it [ID07]. The concept of representation of the environment is then replaced by the concept of sensorimotor invariants that the autonomous entity must learn. At the neural level, these considerations lead to the dynamic cognition concept [Bee00]. According to this concept, evolutionary robotics uses Continuous Time Recurrent Neural Networks (CTRNN) because they have properties of complex systems [FN93] (chaos, attractors, emergence). Using this networks, one can create robots able to adapt to environments for which they have no symbolic representations [BG92]. To fit within the enactive perspective, [DP00] proposes to provide these networks with a plasticity mechanism, based on the ultrastability concept [Ash60]: If the system enters functioning areas defined as unviable, its functioning is modified. These approaches are greatly relevant to show astonishing self-adapting behaviors such as, for example, the imitation of experiments made on human perception in psychology [DP00,WDP07]. More importantly, however they investigate the field of artificial sense-making. The problem is to evaluate whether or not such absence of symbolic representations is compatible with the notion of anticipation, which is crucial to obtain effective behavior [Pez08].

Consequently, our concern is to establish experiments which will enable us to move from the status of self-adaptation to that of anticipation induced by training, while preserving the use of an artificial dynamical cognition approach. We ask the following questions:

- Is an artificial dynamic cognition model capable of anticipation ?

– If so, is it possible to use something like reinforcement learning to obtain such anticipation ?
– How might we extract the dynamic principles from this anticipation and this training ?

The expression of such generative principles concerns what [FZ08] call the *hard problem of the enactive artificial intelligence* because it is necessary to associate phylogenetic mechanisms with the clarification of ontogenetic principles.
Here, we fall under a Vygotskian prospect according to which training constitutes a systematic enterprise which fundamentally restructures all of the behavioral functions; it can be defined as the artificial control of the natural development process [Vyg86]. All of these elements lead us to present an evolutionary robotics experiment highlighting a training phenomenon by means of guidance which implies an anticipation phenomenon.

2 Experiment

The behavior of the considered entity is conditioned by particular environment stimuli. Another environmental stimuli might have no influence on the initial behavior of the entity. The challenge is to make a new behavior emerge because of this second stimulation, so that the first is not longer necessary. The entity then enacts and anticipates the occurrence of initial stimulation starting from the secondary stimulation. In concrete terms, let us consider an entity equipped with sensors functionally comparable to "eyes and ears". Its "ear" detects signals that make it change its orientation (right/left). Each "eye" detects the presence of one kind of light (A) or (B), but it initially does not display any particular behavior in presence of these lights. The idea is that the signal sent to the ear will act as a guidance, so that an association between the signal received by the eyes and the one received by the ears is carried out dynamically in the interaction. In order to do so, we associate the presence of a light with a guidance moderated according to the effective behavior (for example: send signal turn to the right when light (A) is present and the entity is not turning to the right and turn to the left if it is light (B) and the entity is not turning to the left). The goal is that this guidance can attenuate gradually and that in the long term will no longer be necessary. Contrary to reinforcement learning, the question here is not to associate weights in states or in perceived symbols with a preset strategy of action selection; the question is rather to evolve a dynamic system which does not use any pre-given representation of the concepts of action and environment.

Our contribution will describe in detail the simulation, the models and the parameters associated with such an experiment. To summarize, the entity is equipped with the sensors mentioned previously and with engines allowing movements by using a CTRNN of variable size (we carried out various tests). A genetic algorithm is used to establish networks able to associate a movement of the entity with a signal corresponding to guidance. We will show the difference in behaviors obtained by using a nonplastic network compared to the use of a

Hebbian plasticity which is more powerful. We will support the idea that this kind of plasticity seems more relevant to us in the context of training whereas ultra-stability would be more adapted to self-adaptation. A second phase of the genetic algorithm selects entities resulting from the first phase which are also capable of *progress* in the presence of the light signals. Progess is measured by checking that the entity is not initially capable of associating sight with movement, and that it will gradually learn to do so. The algorithm then selects entities able to learn two different associations.

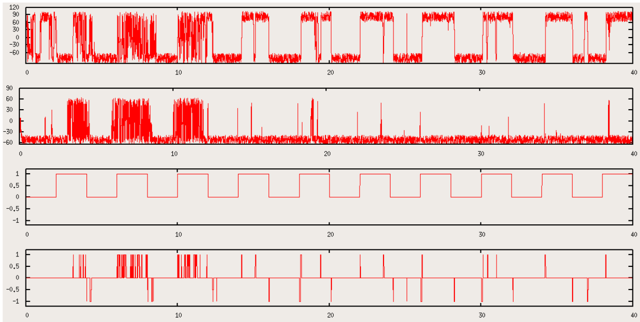

Fig. 1. Plastic network. The two first graphs plot the motor neurons activity, the third graph plots the alternance light (A)/light (B) activity and the fourth graph plots the guidance neuron activity.

3 Results

Figure 1 shows an example of the progress of an entity equipped with 7 neurons and which can already associate movement with sound guidance. The entity is here in the presence of visual signals. One seeks to make the entity associate movements with these signals by using guidance. The most important graph to observe is the forth starting from the top. It shows the progressive reduction in guidance required in the association between light and movement. Though it is not actually the case, one of our objectives is to show the possibility that starting from the same initial state, one entity can be receptive to two different sight/motion associations. Such behavior will enable us to consider that an anticipation and an enaction of the guiding signal are caused by the light signal and that this anticipation has been learned by guidance. By analyzing the various signals at key moments during the entity's evolution, we hope to identify the ontogenetic principles from which training and anticipation originate.

4 Prospects

Now, we plan to study the internal dynamics of these network. We are particulary interested in comparing such principles with works on reinforcement learning on other recurrent neural networks [DQC+98]. Obviously, the task presented here is voluntarily very simple because the objective is to study the origin of the training and of the anticipation. That experiment could be comparable with Pavlovian conditioning. However, our objective is to study the possibility of using active guidance in order to make the entity learn a sensorimotor dynamics. To treat more complex tasks, it will be necessary to increase the sensorimotor capacities of the entity. For example, the design of the entity will then require consideration of the entity's shape [PI05], the evolvability of the morphology of the neural network [Gru94] and the imagination of slight variations of the complexity of the task.

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