A neuronal structure for learning by imitation

Sorin Moga and Philippe Gaussier

ETIS / CNRS 2235, Groupe Neurocybernetique,
ENSEA, 6, avenue du Ponceau,
F-95014, Cergy-Pontoise cedex, France
{moga, gaussier}@ensea.fr
http://www-etis.ensea.fr

Abstract. In this paper [1], we present a neural architecture for a mobile robot in order to learn how to imitate a sequence of actions. We show that the use of a representation of the information in a continuous and dynamic way is necessary and the use of the neural fields can be a good solution to control the dynamic of several degrees of freedom with a single internal representation.

1 Introduction

Until now, our work has been mainly focused on the design of a neural network architecture (named PerAc: Perception-Action) for the control of a visually guided autonomous robot. However, the PerAc architecture does not help to solve problems which have an intrinsic high dimension. Therefore imitation of already learned behaviors or subparts of a behavior not completely discovered is certainly one way to allow a population of animals or robots to learn and to find solutions by themselves. Learning by imitation is already used in a few projects of Artificial Intelligence (see [2, 3, 5]). In our previous work [6], we proposed a neural architecture for imitation based on visual information and we shown how to use it to teach the robot to perform a particular sequence of movements (to make a zigzag trajectory, a square ...). In this paper we try to put together 2 ideas: how a PerAc architecture can be used for learning by imitation and how the properties of the neural fields can be used to improve the motor control.

2 Neural network for sequence imitation

For the imitation behavior, we start with the assumption that proto imitation (not intentioned imitation) is triggered by a perception error (see [6] for details) and in Fig. 1 we present an overview of a general PerAc architecture using this principle. The reflex path of PerAc works as a movement tracking mechanism which consists in going towards any perceived movement. The second level

[1] In D. Floreano, J.-D. Nicoud, and F. Mondada, editors, *Lecture Notes in Artificial Intelligence - European Conference on Artificial Life ECAL99*, pages 314–318, Lausanne, September 1999.

of the architecture learns the temporal interval between the successive robot orientations (i. e. a sequence of movements), and associates it to a particular motivation.

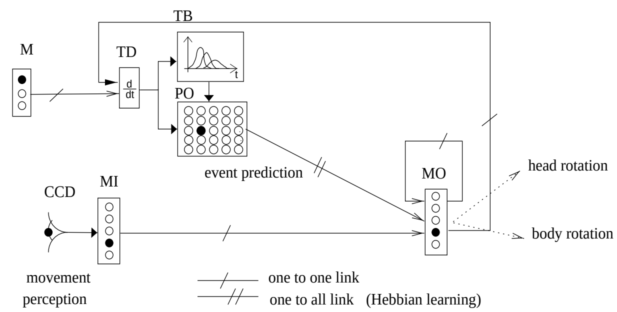

Fig. 1. A general diagram of the PerAc architecture use for learning the temporal aspects of a trajectory. CCD - CCD camera, M - Motivations, MI - Movement Input, MO - Motor Output, TD - Time Derivator, TB - time battery, PO - Prediction Output

A frame-grabber is used to take a sequence of images. In one of our simplest implementation, a "movement image" is the difference between 2 different time integrated images of the above sequence. The perceived movement orientation is computed from the "movement image". The result is one-to-one "projected" on a map of analog formal neurons, the Motor Input (MI) group in Fig. 1. To avoid the perception errors in the tracking mechanism, we allow the robot camera (robot head) to rotate. In this way, the head tries to pursuit the teacher at any time by centering it in its visual field. The robot body turns only if the teacher movement is observed under the same angle for a given time interval. The independent rotation of the robot head and its body can be viewed as a simple two degrees of freedom system. The functioning of the motor group (MO) is quite simple. At each step, a WTA mechanism chooses the most activated neuron, performs the rotation corresponding to this neuron and finishes with a fixed translation. The MO group uses the same information representation as the MI group. It receives the information from both reflex level and event prediction level.

In order to learn a sequence, the student robot detects and learns the transitions in its own body orientation and to be able to reproduce them. The movement rotations characterized by OFF-ON transitions (Time Derivative TD group) of MO neurons are used as input information for a bank of spectral neurons (TB in Fig. 1). Time filter batteries (TB) act as delay neurons endowed with different time constants. As such, they perform a spectral decomposition of the signal that will allow the neurons in the Prediction Output group (PO) to store the transition patterns between two events in the sequence. Finally, the PO group is linked with the MO group via one-to-all modifiable links.

3 An neural dynamics of the motor system

The first limitation in our architecture is the poor stability of the tracking behavior. Even if the temporal integration allows a memory effect, any new input stimulus can generate an immediate change of the head orientation (a classical WTA decision). A second major limitation is the input discrimination. Two or more movement zones can be interpreted as different targets or as the same target due to perception error. In the present system, no interpretation of the perceived movement is performed in order to avoid a misinterpretation. The motor group has to be a topological map of neurons using a dynamical integration of the input information to avoid forgetting the previously tracked target. A dynamical competition has also to be used to avoid intermittent switchings from a given target to another.

We will use the simplified formulation of the neural field proposed and studied by Amari [1].

$$\tau \cdot \frac{f\,(x,t)}{dt} = -f\,(x,t) + I\,(x,t) + h + \int_{z \in V_x} w(z) \cdot g\,(f(x-z,t))\,dz \qquad (1)$$

Without inputs, the homogeneous pattern of the neural field, $f\,(x,t) = h$, is stable. The inputs of the system, $I\,(x,t)$, represent the stimuli information which excite the different regions of the neural field and τ is the relaxation rate of the system. $w(z)$ is the interaction kernel in the neural field activation. These lateral interactions ("excitatory" and "inhibitory") are modeled by a DOG function. V_x is the lateral interaction interval. $g\,(f\,(x,t))$ is the activity of the neuron x according to its potential $f\,(x,t)$. We use a classic ramp function.

G. Schöner [7, 4] has proposed to use the properties of the neural field for motor control problems. The "read-out" mechanism consists in the use of the derivate of the neural field activation to compute the motor command. The orientation of the robot head, ϕ_{rob}, relative to a fixed reference is used in the system as a behavioral variable. The state of the system is expressed as a value of this variable. The local maxima of the neural field are named attractors. If the target orientation is ϕ_{tar} (see Fig. 2, a), it erects an attractor in the neural field (see Fig. 2, b) and the robot rotation speed will be $\omega = \dot{\phi} = F\,(\phi_{rob})$. $\dot{\phi}$ is a function of the current robot orientation, ϕ_{rob}. It sets the dynamics of our robot.

Taken separately, each input erects an attractor in the neural field. The Amari's equation allows the cooperation for coherent inputs associated with different goals (spatially separated targets). For closely spaced input information, the dynamic has a single attractor corresponding to the average of the input information. For a critical distance between inputs, a bifurcation point appears and the previous attractor becomes a repellor and 2 new attractors emerge. Depending on the initial state, the robot switches to one of the 2 new fixed points. This mechanism of input competition / cooperation has an hysteresis properties which avoids oscillations between the two possible behaviors. Another feature of

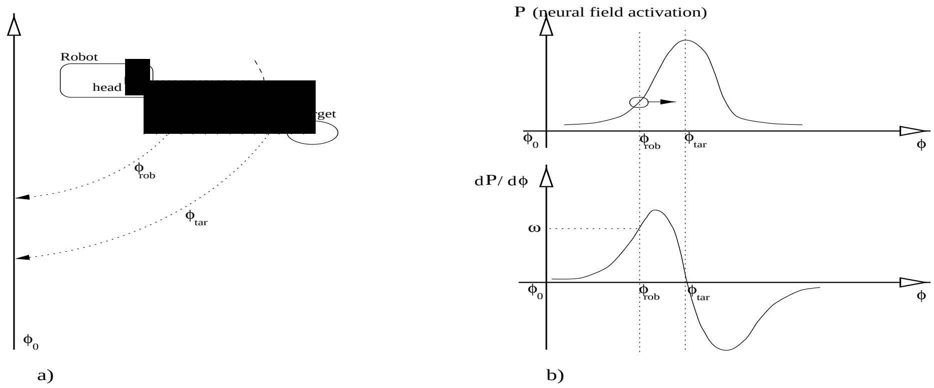

Fig. 2. a) The robot and the target coordinates are represented in the same reference. The reference orientation, ϕ_0 is used to compute ϕ_{rob} and ϕ_{tar}. b) The target position erects an attractor at ϕ_{tar}. The "read-out" mechanism allows to compute the rotation speed ω using the derivate of the neural field activation.

the neural field is the memory. If the parameter h in Eq. (1) has a sufficiently negative value then the neural field operates with a memory effect in which a peak of an attractor has been maintained for a short time interval. A large positive value of h determines a supra-threshold in the neural field activation. We use the inputs of the actual system to drive a motor command using a neural field without any modification. Replacing the MO group by a neural field is the sole modification in the architecture (see Fig. 1). All above properties of the neural field come into the general architecture, eliminating the input segmentation and the stability problem of the initial architecture.

4 Experimental results and discussion

At first, we have implemented the tracking reflex using only one degree of freedom, i. e. the robot moves only its head. In order to demonstrate the capabilities of neural field to control several degrees of freedom we take a simple example. The robot follows a "teacher" and learns a sequence of movements ABC. The sequence starts with the activation of the state A (orientation) corresponding neuron. The input in the neural field generates an attractor at the the ϕ_A orientation (see Fig. 3).

At τ moment, the ϕ_B neuron will be activated by the PO group. This activation shifts the attractor to ϕ_B in the neural field. Using the "read-out" mechanisms, we obtain 2 rates of orientation change (due to differences inertia): one for the head orientation and another one for the robot body orientation. In the top of the Fig. 3, we show the variation of head and body orientation as a function of time. According to neural field dynamics, the change of the orientation is continuous. For an external observer, the head orientation anticipates the body orientation (i.e. the inertia of the robot is learned too).

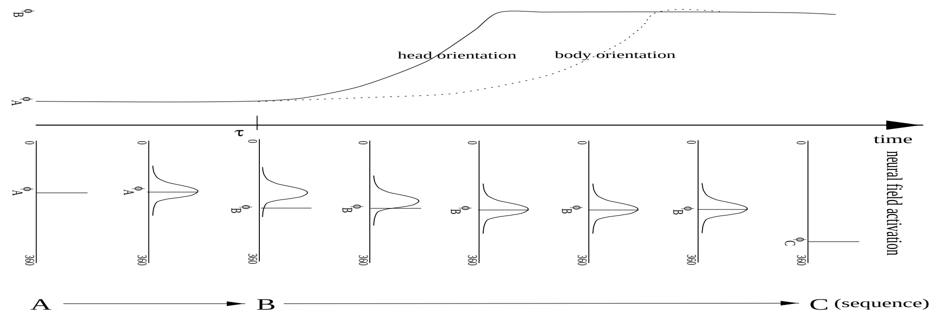

Fig. 3. Top: the temporal variation of the head and of the body orientation. Bottom: the neural field activation for an ABC sequence. The bar represents the predicted movement.

This work is at its beginning. Its interest is in its use of the neural field concept in a PerAc architecture. We show that we can learn the temporal sequence of movements by imitation using a PerAc architecture. The tracking mechanism in the reflex path of PerAc permits the temporal "segmentation" of the "teacher" movements without learning to visualize what the teacher is doing or not. The use of the neural field improves the stability of the proto imitation process and permit the discrimination of moving objets in the visual perception field.

References

1. S. Amari. Dynamics of pattern formation in lateral-inhibition type neural fields. *Biological Cybernetics*, 27:77–87, 1977.
2. P. Bakker and Y. Kuniyoshi. Robot see, robot do : An overview of robot imitation. In *AISB Workshop on Learning in Robots and Animals*, Brighton, UK, 1996.
3. L. Berthouze and Y. Kuniyoshi. Emergence and categorization of coordinated visual behavior through embodied interaction. *Machine Learning*, 31(1/2/3):187–200, 1998.
4. E. Bicho and G. Schoner. The dynamic approach to autonomous robotics demonstrated on a low-level vehicle platform. *Robotics and Autonomous Systems*, 21:23–35, 1997.
5. John Demiris and Gillian Hayes. Imitative learning mechanisms in robots and humans. In *Proceedings of the 5th European Workshop on Learning Robots*, Bari, Italy, July 1996. 1996.
6. P. Gaussier, S. Moga, M. Quoy, and J.P. Banquet. From perception-action loops to imitation processes: a bottom-up approach of learning by imitation. *Applied Artificial Intelligence*, 12(7-8):701–727, Oct-Dec 1998.
7. G. Schöner, M. Dose, and C. Engels. Dynamics of behavior: theory and applications for autonomous robot architectures. *Robotics and Autonomous System*, 16(2-4):213–245, December 1995.