

Autonomous learning and reproduction of complex sequences: a multimodal architecture for bootstrapping imitation games

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Abstract

This paper introduces a control architecture for the learning of complex sequence of gestures applied to autonomous robots. The architecture is designed to exploit the robot internal sensory-motor dynamics generated by visual, proprioceptive, and predictive informations in order to provide intuitive behaviors in the purpose of natural interactions with humans.

1. Introduction

Discriminating and learning sequences is a crucial mechanism in our efforts to device robots that can learn from imitation. Previous techniques have included using symbolic approaches and frequently they clearly separated the demonstration and reproduction phases (see from (Kuniyoshi, 1994) to (Tani, 2002) and a complete review about sequence learning architectures in (Tijsseling and Berthouze, 2003)). Our architecture, taking inspiration from experiments with pre-verbal children removes both these assumptions. Indeed, addressing the problem of learning sequences of gestures with an autonomous and developing system arises important and very interesting remarks. First, we can argue that at a given level of its "developmental course" our system has no access to any explicit nor symbolic informations. Nevertheless, if we take a look at pre-verbal children, or even young babies, learning sequences of action seems to be possible, on the basis of, for example, imitation games or/with simple sensory-motors interactions (see (Uzgiris, 1999, Nadel, 2000) for a selective review on infant imitation). Learning something new from a gestural interaction, as a new arrangement made of motor primitives of self but showed by the other, constitutes an interesting building block of "pre-verbal" communication. In this sense, our

problem arises the exciting question of how can sense and high level categorization emerge in a basic sensory-motor system from gestural interactions and from the building of shared representations? For the autonomous system designer interested in modeling this course of development, it obviously means that he can not constrain the environment nor the demonstration phase in order to fit with previously determined inputs or sensors. It also means that the robot is a part of an interaction whose dynamics may be constituted of actions of the demonstrator and actions of the robot, and, unless the robot has autonomously learned how to take turn or switch role, actions of both actors could happen at any time. Demonstration and/or reproduction phases can occur at the same time, with the consequence that the system will have to extract by itself the relevant information from its perception. Consequently, the sequence learning and recognition tasks appear to be components of the same issue that can difficultly be stated as independent problems. This paper present a neural architecture that fuses the demonstration and reproduction stages, which correspond to two different dynamics of the same perception action architecture: learning correspond to a situation where the different input informations are not at the equilibrium, and reproduction can be done when this system is able to predict learned sequences. Interestingly we will link these results with what has been the drive of the development of our architecture from scratch, the homeostatic behavior, that has led the system to learn its first visuo-motor repertory, and that triggered imitative behaviors and first gestures imitations. Finally we will discuss that our perception/action system in the perspective of turn-taking : how different modalities can determine the behavior of the system.

2. Homeostasis and development

Lets suppose a simple perception action architecture using vision as main source of information, and a

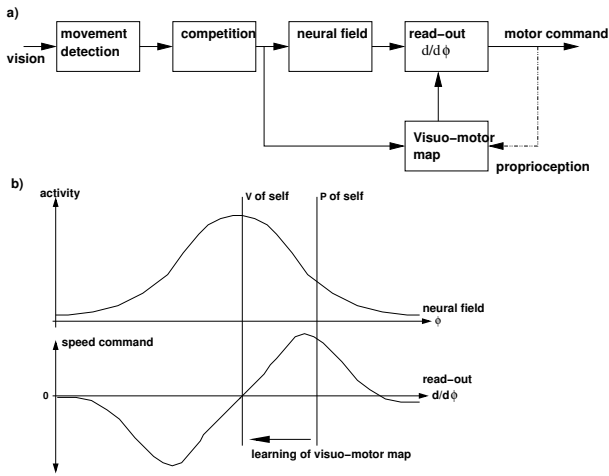


Figure 1: a). Simplified architecture for self visuo-motor coordination and immediate imitation. The Visuo-motor map allows to compare visual (V) and proprioceptive (P) information on the same space. Visual information triggers dynamical attractors on the neural field. b). Initially, (V) and (P) of the same end point of self do not have the same value (random initialization). This error induce the change of the Visuo-motor weights, and the step by step equilibrium of (P) and (V) during random movements. Immediate imitation is obtained the same way, if Vision of others is confused with vision of self.

device (of a given complexity) to perform its actions. Such a system has to deal with at least 2 different informations:

- Visual information (V), about the external environment. It can concern useful information, such as the movements of others, an object being grasped or self movements. This information is often two-dimensional, related to the pixel space.
- Proprioception information (P), i.e information about self movements that are being done (angle of joints $\phi_1, \phi_2, \dots, \phi_n$, speed of the joints $\frac{d}{dt}\phi$, etc.);

In previous works (Andry et al., 2004), we have implemented a model relying on dynamical neural fields (see S. Amari's equations (Amari, 1977)) allowing a control architecture to behave like an homeostatic machine. It tries to minimize differences between P and V. We have shown that this homeostatic behavior was enough to drive, in the order:

1. Visuo-motor learning of associations between P and V about self devices. For example, an eye-arm system during a babbling phase produce random arm movements in order to learn to equilibrate input V and P information projected on an internal Visuo-motor map. The result is a system that is able to transform Motor information ($\phi_1, \phi_2, \dots, \phi_n$) into a simpler 2D space corresponding to the visual one. As a result, movements to

reach visual goals can then be more easily computed on this visual space.

2. Because the system perception is ambiguous, V information about movements of other are confused with movements of self. We have shown that The homeostatic behavior and this perception ambiguity triggers for free an immediate and systematic imitation behavior.

Now we propose that the same simple homeostasis principle can still be applied to this same system in order to switch from a phase of immediate systematic imitation of simple gestures, to the learning of more complex sequences of these gestures in order to be able to reproduce them later. To do this, we introduce a new structure that tries to predict the next sensory-motor activity. This structure tries to keep an equilibrium between its predictions (Pred) and the sensory-motor activity of the system. Moreover, most sequences that are used for natural gesture interactions turn to be complex, and a reliable system need to use hidden states to code them in the case of the involvement of the same state in different transitions (for example A-B-A-C-A-B, etc.). We describe in the following section the system that learn and predicts such complex sequences of actions.

3. Learning complex sequences

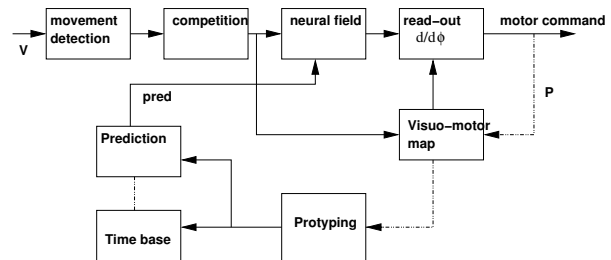


Figure 2: The architecture for on line sequence learning. Dashed lines correspond to learned connections. See text for details.

Our system does not directly takes the visual input as the model of the sequence to learn. Instead, immediate imitation plays a crucial role in the learning mechanism. Movements of the robot are a filtered response of visual inputs, and the proprioception information is therefore more continuous, less noisy and still contain the dynamics of the demonstrated sequence. Hence, using the output of the visuo-motor map provide a simpler and more reliable signal of the demonstrated trajectory. An integration and derivation mechanism of this visuo-motor information allows to detect changes in the trajectory. These detected points form a temporal succession of relevant positions (in the visuo-motor space). In real conditions, a sequence of gestures demonstrated by a

human will not be exactly the same. In a gestural game, for example, repetitions of the same sequence turn to be different with numerous demonstrations. In this case, detection of “via points” in a simple sequence become quickly unstable from an iteration to the other. To build a stable sequence, we introduce a Prototyping group (see fig. 2) that learns the spatial characteristic (in the visual space) of the relevant points of the sequence, and exhibits robustness to changes from iterations of the same sequence.

The neurons are activated as follow (Hersch, 2004), eq. 1:

$$P(S_j^t|x) = \frac{P(x|S_j^t) \cdot \sum_i P(S_j^t|S_i^{t-1})P(S_i^{t-1})}{\sum_j P(x|S_j^t) \cdot \sum_i P(S_j^t|S_i^{t-1})P(S_i^{t-1})} \quad (1)$$

Moreover, this law combines properties of HMM and Self Organizing Maps algorithms, where hidden states can be used to code complex sequences. Neurons (S_j , with activity $P(S_j^t|x)$ at time t) of this group have one to all connections (W_{ij}) whose weights are modified in order to learn transitions between states :

$$\delta w_{ij} = \epsilon_w P(S_j^t|x) \cdot P(S_i^t - 1|x)(1 - w_{ij}) \quad (2)$$

The main advantage is that computation can be done on line, and the weight update is made according to the previous activated state ($P(S_i^{t-1}|x)$, a kind of contextual activity at $t - 1$). The neurons of the Prediction group learn to predict the timing of the transitions between activated neurons of the prototyping group. Equations of activation of Prediction and Time Basis neurons can be found in (Andry et al., 2001). The rule learning the timing k of the transition between neurons i and j of the prototyping group, using time trace of the Time Basis (TB) groups is the following :

$$\Delta w_{k-ij} = \epsilon \cdot TB_{ik} \cdot (Prototyping_j - Pred_{ij}) \quad (3)$$

where ϵ is the learning rate. The sequence learning mechanism generates step by step predictions of sensory-motor information used to recall the sequence in order to play back a learned sequence.

4. Experiments and results

Experiments were made with a 2 degrees of freedom eye-neck device. Initially, the architecture was planned to be tested with the 5 DOF robotic arm used in previous works, but a mechanical fault has delayed the tests ¹. The main point is that the architecture remains unchanged for the 2 DOF device application, and that the transformation of complex device information into the 2

¹A new robotic arm is under construction in order to validate the present work

dimensional visuo-motor space was demonstrated in (Andry et al., 2004). During the experiment, the experimenter demonstrates repetitively the same sequence in front of the robot, adapting the speed of its movements to the robot dynamics (but the demonstration remains very close from natural movements). The robot learns the sequence online. First, the progressive learning of the sequence induces a low prediction activity. This activity is not strong enough to trigger the activity of the neural field. As a result, the robot’s behavior is only triggered by V information, that “drives” the motor command: while the system is not able to process strong predictions, it keeps an imitative behavior. After several demonstrations, the Prediction information reaches a level strong enough to activate the neural field: Pred “drives” the system movements and allow the reproduction of the learned sequence: the system switch from imitation to the demonstration of the learned sequence. Of course, proper reproduction is only possible if the experimenter stops the demonstrations when the system starts to predict, otherwise V and Pred information will be in competition to drive the movements (imitation or reproduction ?). Figs: 3 and 4 shows the internal activities of the main groups of neurons of the architecture during learning and reproduction.

5. Discussion

According to the purpose of this work, the main question we can ask now is “is the robot behavior autonomous ?”. The tested scenario was the following: the robot imitates the experimenter gestures with the consequence that V information is filtered by self movements in a more continuous visuo-motor information. The sequence of visuo-motor activities is then learned by changing the weights of the Prediction (time) and the prototyping (space) groups. Moreover, taking into account hidden states (algorithm of the prototyping group) allow the experimenter to repeat during its interaction with the robot the same sequence many times, until the prediction information arises. But at this point, the interaction stops to be intuitive and autonomous, in the sense that a complete reproduction of the learned sequence implies that the experimenter control the system: First, when the prediction arises, the robot reproduction can only be done if the experimenter stops moving, otherwise V and prediction informations will compete, inducing an unstable behavior : at any time, vision of the other moving can change the system dynamics and confuse the reproduction of the sequence. Second, to stop moving, the experimenter has to monitor the systems predictions in order to see when the prediction information will overshoot a given threshold and activate the neural field activity. To sum up, such a system is not

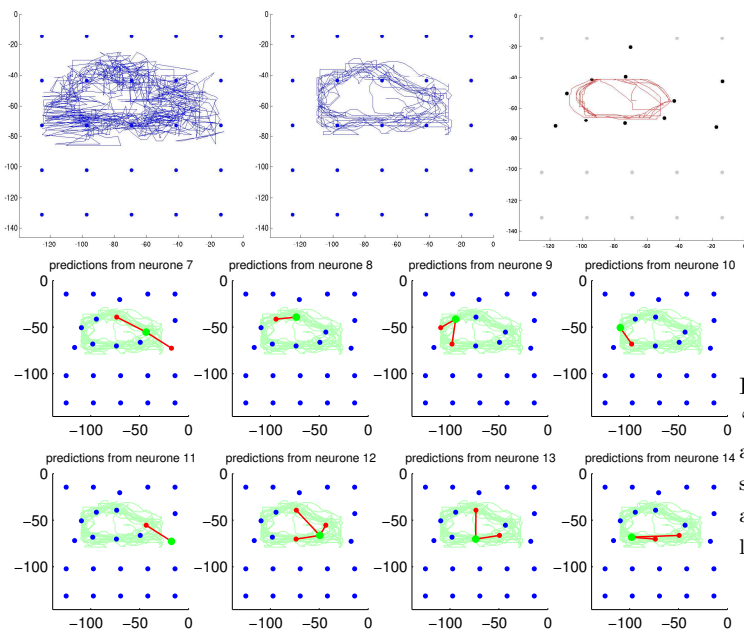


Figure 3: Learning and reproducing a circle. Up : representation in the visual space. Left: Input activity (competition of movement detection). Middle : Visuo-motor map activity (filtered response) during immediate imitation. Right : Visuo-motor map activity during the reproduction of the sequence; this figure also show in black the neurons of the prototyping sequence that have learn. Bottom: Activity showing the transitions learned by the Prediction group during a reproduction of the sequence. The step by step recall of the transitions allow to trigger the neural field activity and the motor command to reproduce the sequence.

able to know how to switch back from reproduction to learning. If our system is able to build two different sensory-motor dynamics, immediate imitation and learning vs reproduction of a learned sequence, it is not able to cope between these two dynamics. In future works, we plan to adapt on going research (Andry et al., 2001) about the dynamics of turn taking of simple perception action systems to see if minimal changes can be applied to the architecture in order to cope learning and reproduction dynamics for stable interactions, in the manner of (Ito and tani, 2004) with the learning of sequences of increasing complexity.

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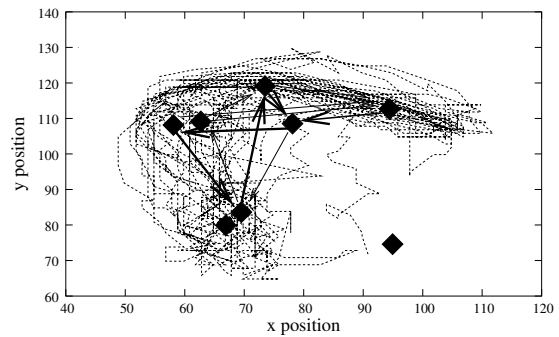


Figure 4: A more complex trajectory with ambiguous states: “start-up-right-left-down-stop”. The sequence was repeated about 20 times. Result with the prototyping group, arrows showing transitions between the learned points. The “goes and back” characteristic of the sequence has been properly learned.

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