Development of the First Sensory-Motor Stages: A Contribution to Imitation.

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Abstract

We present the first stages of the developmental course of a robot using vision and a 5 degree of freedom robotic arm. During an exploratory behavior, the robot learns autonomously the visuo-motor control of its mechanical arm. We show how a neural network architecture, combining elementary vision, a self-organized algorithm, and dynamical Neural Fields is able to learn and use proper associations between vision and arm movements, even if the problem is ill posed. We show as a robotic result that the architecture can be used as a basis for simple gestural imitations.

1. Introduction

Far from complex recognition systems, we propose a neural network architecture able to learn and store association between 2-D elementary vision and the 3-D working space of a robot's arm. We show how the use of a new type of associative coding neurons coupled with dynamical equations solves the reaching of visual parts of the working space, independently of the number of degrees of freedom of the arm (and their potential redundancy). We will also emphasize the importance of the on-line learning process, where the robot performs sensory-motor associations thru a random exploration of its own motor dynamics and physics. As a robotic validation, we will present how dynamic and perceptive properties of such a generic architecture allow to exhibit real time imitations gestures.

2. A Neural network architecture for Visuo-Motor development

With complex arms (such as the one we use), the same position of the extremity corresponds to multiples vector positions of the joints. To allow the association of multiples proprioceptive vectors with a single visual perception, we use a new kind of sensory-motor map, composed of *clusters* of neurons (fig 1). Each cluster associates a single connection from one neuron of the visual map with

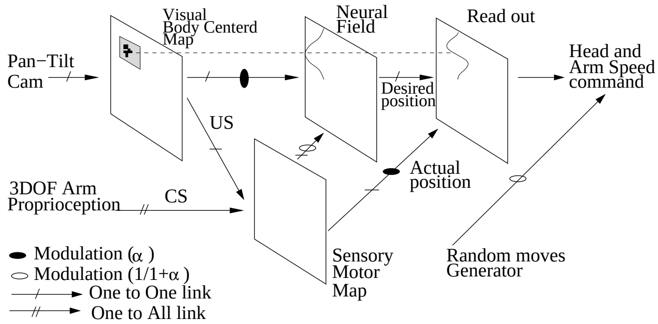

Figure 1: The simplified architecture.

multiples connections from the arm's proprioception. Visual information is considered as a 2-D Unconditional Stimuli (US) that controls the learning of particular pattern of a 3-D proprioceptive input(Conditional Stimuli -CS). Thus, this sensory-motor map has the same global topology as the visual map. A cluster i is composed of (fig 2): *(1)*one input neuron X_i linked the visual map. This neuron responds to the US and triggers learning. *(2)*A small topological *submap* of Y_i^k neurons ($k \in [1,n]$) which learn the association between proprioceptive vectors and a given visual position. *(3)* One output Z_i neuron, merging information from X_i and $submap_i$. The winner neuron Z will represent the "visual' response associated to the proprioceptive input presented. Thus, many proprioceptive configurations are able to activate the same "visual feeling", while close visual responses can be induced by very different proprioceptions (thanks to the independence between each cluster). The learning phase is performed during an exploratory behavior. Both head and arm are controlled by the sensory-motor map, providing random excitations at the begining of the learning phase. During the learning process, visuo-motor associations are slowly learned, inducing progressively a coherent control of the head and arm.

A 2D dynamic for 3D arm movements

To reach a perceived target, the error between the desired position (the visual position of the target) and the current position of the device has to be minimized. The error has to be converted in an appropriate movement

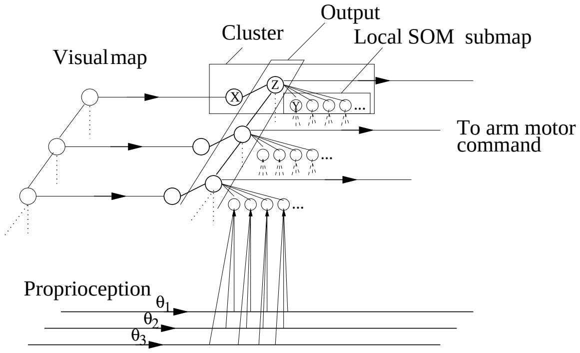

Figure 2: Organization of the sensory-motor map. The activity of one neuron of the vision map will trigger the learning of the corresponding cluster (one to one links).

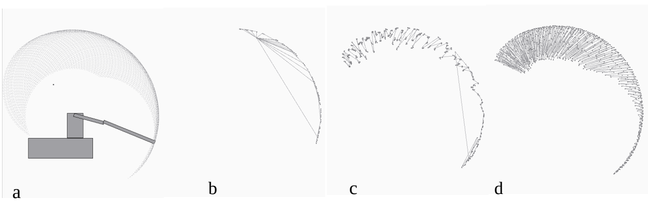

Figure 3: A sensory-motor vector of 146 clusters learning vertical movements (redundancy between θ_2 and θ_3 joints). Each cluster is composed of a submap of 6 Y neurons. A point represent the values of the Y neuron's weights learning the θ_2 and θ_3 values. a): theoretical positions. b,c,d): Progressive dissociation of Y neurons.

vector to move each device's joint toward the target. This process is done by computing a dynamical attractor centered on the target stimuli. The computation is made on maps of neurons having the same topology that the visual map, using neural field equations (eq 1, (Amari, 1977)):

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

The spatial derivate of the NF activity is interpreted as two 1-D desired speed vectors (horizontal and vertical), to reach the attractor target (*read-out* mechanism (Gaussier et al., 1998)). Thus each joint will then contribute simultaneously to the global move of the arm toward the visual objective, the shape of the NF activity on the target ensuring convergent moves. The robot behavior appears as a minimization between visual and proprioceptive representations (homeostatic principle).

A Contribution to imitation behaviors

An elementary imitative behavior can be triggered by exploiting the *ambiguity* of the perception. Using only movement detection, the system can't differentiate it's extremity from another moving target, such as a moving hand. The generated error will induce movements of the robotic arm, reproducing the moving path of the human hand: an imitative behavior emerges. The experimenter was naturally moving its arm in front of the robot. The camera rapidly tracked the hand (the most moving part of the scene) and the arm, reproduced in real time the hand's perceived trajectory. The use of neural fields ensures a reliable filtering of movements and a stable, continuous tracking of the target by the head and the arm of the robot.

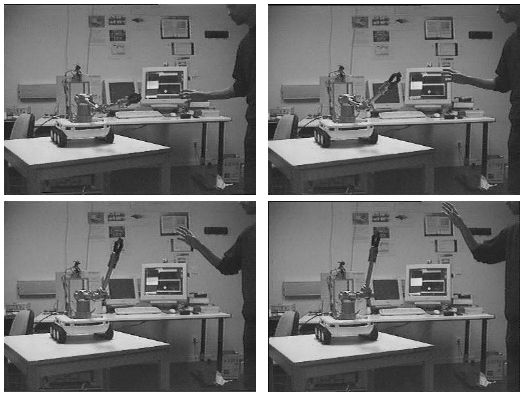

Figure 4: Real time imitation of simple vertical gesture.

3. Conclusion

Far from building a control architecture dedicated to imitation tasks, we showed how a generic system with learning capabilities and dynamical properties, can easily exhibit low-level imitations. These imitations of arm movements are performed without any internal model of the human arm, and can easily be transposed to imitation of robotic arm movement, whatever the morphology of the arm is. We have also shown how a very simple vision system, only built on movement recognition, gets for free end point tracking, without the use of any recognition system of the hand. The "low-level" characteristic of the imitative behavior is here related to the basic sensory-motor repertory whose accuracy is dependant of the duration of the learning proces. But independently of the accuracy of the sensory-motor associations, we have shown how the use of dynamical equations ensures stable and coherent behavior.

References

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