# A Developmental Approach for low-level Imitations

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## 1. Introduction

Historically, a lot of authors in psychology and in robotics tend to separate "true imitation" and its related high-level mechanisms which seem to be exclusive to human adult, from low-level imitations or "mimicries" observed on babies or primates. Closely, classical researches suppose that an imitative artificial system must be able to build a model of the demonstrator's geometry, in order to reproduce finely the movements on each joints. Conversely, we will advocate that if imitation is viewed as a part of a developmental course, then (1) an artificial developing system does not need to build any internal model of the other, to perform real-time and low-level imitations of human movements despite the related correspondence problem between man and robot and, (2) a simple sensory-motor loop could be at the basis of multiples heterogeneous imitative behaviors often explained in the literature by different models.

## 2. Architecture

The robot system is a Koala mobile platform equipped with one pan-tilt CCD camera and a 3 degrees of freedom (DOF) Katana arm. The arm can pivot around its base ($\theta_1$), and the other two joints allow the arm to rotate in a vertical plane ($\theta_2$,$\theta_3$). With such a system, the control of the arm from the sole visual information is an ill posed problem, since the 3-D position of a target cannot be completely defined from the sole 2-D visual information. To solve this problem, our architecture has to learn the associations between vision and proprioception information about the end point of its arm. The neural network architecture is designed as an *homeostatic* perception-action control loop. The system tend to maintain the equilibrium between its visual and proprioceptive information. If a difference is perceived, then the system tries to act in order to reach an equilibrium state. Inspired from the self-organizing properties of the Kohonen net, our architecture relies on two principles. First, our solution to the end point positioning problem is inspired by the micro-columns of the brain: A *sensory-motor* map which consists in a 2-D arrangement of neural functional units, the *clusters*. Each cluster learns many (proprioceptive)-to-one (visual) associations (Fig. 1), in the manner of a small Kohonen net. Second, instead of controlling the movements in the motor space (matching or comparing motor position of the joints), our solution is to control the movements in the visual space. Therefore, the positioning (or further and more complex tasks) of the end point will be dependent of the 2-D visual space instead of the joint space. This choice limits the complexity of the computations related to the arm, to the visual space. The topology of the map is the same as the *visual map* (movement detection on the visual CCD flow), and each cluster associates a single connection from one neuron of the visual map with multiple connections from the arm's proprioception. Movements can then be computed in the visual space and benefits from the intrinsic properties of fields of neurons used for motor control (Amari, 1977). The activity of the neural field is used for a speed control of devices. The advantage of the speed control relies in its intrinsic stability. A spatial derivative of the field is performed. The value of the derivative at the position associated to the joint proprioception is used to set the joint speed rotation. Hence, the joint will rotate in the direction of the nearest local maximum of the neural field activity and not in the direction of the global maximum. Lateral interaction will allow the most active goals to override/inhibit the smaller activity bubbles and will induce smooth joint movements from one goal to the next one.

## 3. Exploiting imitation to learn sequence of movements

During the learning phase, random arm and head movements allow the robot to progressively learn the visuo-motor associations about its end point position. Then, if an experimenter comes and start to move its hand in front of the robot camera, it will generate new perceptive information that the robot will mistake for the position of its own mechanical arm (perception ambiguity). Because the robot acts as an homeostat, it will tend to reduce the perceptive error by moving its end point with the same dynamic as the experimenter's hand. It will then perform low-level imitative behaviors, and reproduce a wide variety of simple arm movements (for example simple vertical and horizontal movements). Moreover, complete trajectories of the demonstrator arm can be learned in a simple way thanks to the choice of rep-

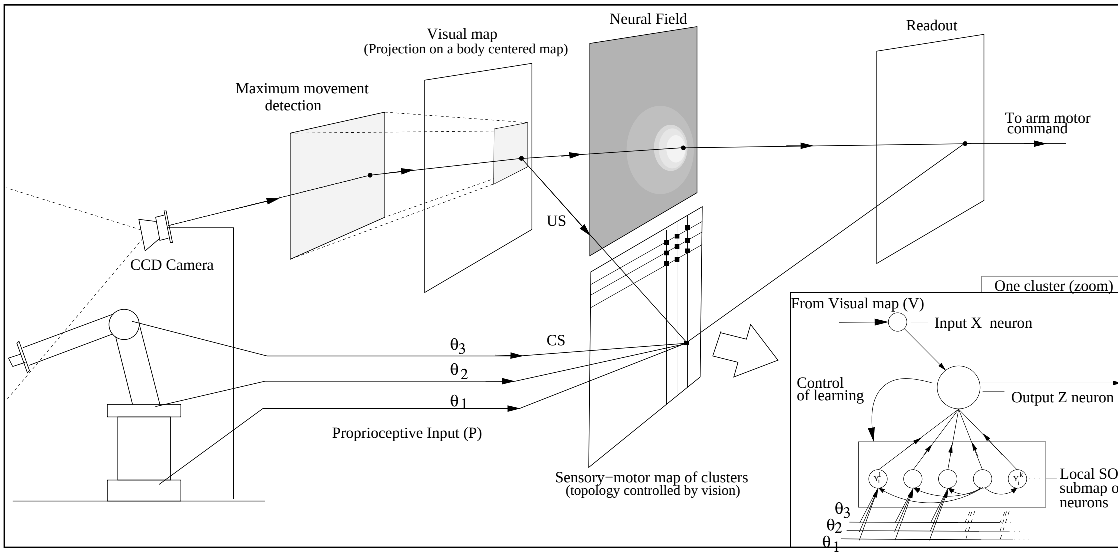


Figure 1: The neural network controller for arm movements (simplified architecture). This controller learns visuo-motor associations about the end point position of the arm. Learning is made by the sensory-motor map of clusters. The activity of one neuron of the visual map will trigger the learning of the corresponding cluster of the sensory-motor map (one-to-one links,US). The resulting Activation of $X$ triggers the learning of its associated *submap* (Right corner). Learning consists in a self-organization of the $Y_i^k$ neurons linked to the values of the joints ($\theta_1$, $\theta_2$, $\theta_3$, CS)

resenting proprioception in the visual space of the robot. To do this we use a modular "sequence learning" neural network (inspired form the cerebellum and hippocampus properties (Banquet et al., 1998)) able to perform a one-shot learning and prediction of sequence of items. The trajectory is coded as a sequence of attractors triggered on the neural field. The resulting activity is directly available as a speed command for any device of the system, and can be used to control even devices that where not involved in the learning process.

## 4. Discussion

If our architecture is already able to exhibit imitative behaviors of different levels of complexity, we believe that it can also be in further works a good model for more heterogeneous and apparently complex imitative behaviors. We assume that the coding and representation of motor action in the visual space, which allow the independence of the device executing an action, can also represent the core principle of a perception-action model unifying immediate and deferred imitation. Traditional studies in psychology often separated immediate imitation of the baby (a "mimic" exhibited during the first month of life) from apparently more complex deferred imitation. Deferred imitation consists in the reproduction of a previously observed action in different spatio-temporal modalities from the observation. Indeed, we showed that our architecture is able to learn a succession of movements whatever the robotic device is. For example, a trajectory could be learned only by using the movements of the head, the tracking activity inducing a sequence of internal attractors on the NF activity. Because the internal representation of the trajectory is not anchored in the visual environment, and because our system does not need any information about the demonstrator, such a robot is not dependent of the spatial modality of the demonstration. It can reproduce the trajectory anywhere. If we now suppose that our system possesses an inhibition mechanism allowing to freeze/free the movements of its arm, our robot would be no more dependent from the temporal modality. It would be able to reproduce the trajectory at any time after the observation. It could therefore learn a trajectory using only the movement of its eye or head in the visual space, and then reproduce it with its arm, performing what could be called a "deferred imitation" of the trajectory. From a theoretical point of view, the architecture could represent the first step of a sensory-motor model unifying two imitative behaviors often viewed as separated. Obviously, our objective is not to add an ad-hoc inhibition mechanism, but to study how an inhibition loop could be learned to control the action selection from the development of the architecture. This perspective imposes to restart the whole development process with consideration of the loop constituted of the imitators and the imitated agents and the turn-taking related issue.

## References

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