Learning invariant sensori-motor behaviors:
A developmental approach of imitation mechanisms

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Abstract— **In this paper, a model linking together the development of sensori-motor and imitation capabilities is proposed. The model has been tested on a mobile robot doted of a pan/tilt vision system and a 5 degrees of freedom robotic arm. The proposed Neural Network architecture allows to learn and use proper associations between vision and arm movements, even if the problem is ill posed (mapping problems between the visual space and the robot arm space). The central part of the model is a visuo-motor map allowing to store motor behaviors in a space invariant from the arm and body configuration (posture). This very simple multi-modal or a-modal representation can control the whole system dynamics of our robot. The use of dynamical neural field equations at the different stages of our model allows to explain how apparent complex motor dynamics can be generated and controlled from very simple internal dynamics simplifying at the same time the learning problems. Highlighting the generic aspect of our architecture, we show that our robot can autonomously imitate and learn simple gestures after the on-line learning of the visual and proprioceptive control of its hand extremity (without any change in the NN architecture). Finally, we defend the idea of a co-development of imitative and sensori-motor capabilities, allowing the acquisition and the structuration of increasingly complex behavioral capabilities.**

I. INTRODUCTION

In Artificial Intelligence and cognitive psychology, learning is often seen as a set of individualized and successive phases allowing to build more and more complex categories in a hierarchical way. According to this perspective, acquisition of higher cognitive functions implies the stabilization of some lower functions, as otherwise the meaning of the higher levels would change when modifications at the low level occur (learning instability). Specialists in learning theory have then proposed the idea of shaping techniques [Thrun and Mitchell, 1995], [Kaelbling et al., 1996] in which learning is split into different phases of growing complexity. Unfortunately, the splitting procedure needs to be supervised by an engineer who need to define the different steps or phases of the learning procedure. Taking into account the physical development of the infant can strongly change and simplify this meta learning problem [Pfeifer and Scheier, 1999], [Lungarella and Berthouze, 2002] (how to control and adapt the learning mechanism). The solution consists in finding a minimal architecture and the related adaptive mechanisms that allows such a system to exhibit different phases of development, i.e the building

of a developing system [Metta et al., 2000]. For instance, navigation problems do not need to be addressed before the baby is able to move, while grasping first needs the development of the hand muscles. The progressive physical maturation constrains and simplifies the field of the possible sensory-motor associations to be learned, and the complexity of the related space to explore. Besides, being inspired by human development promotes the idea that the same control architecture should be able of versatility, that is able to adapt itself to a wide variety of tasks and solve many issues often tackled separately in the field of autonomous robotics and artificial intelligence. It also had been emphasized that the developmental process should be tackled from a situated and dynamic point of view, by linking the simultaneous development of sensory, motor, and cognitive abilities [Berthouze et al., 1998], [Thelen et al., 2000], where both noisy (elementary perceptions and motor control) and goal oriented (innate tracking of preferred stimuli) processes play an important role in the acquisition of stable behaviors.

This paper examines the interest of a developmental approach applied to both the design of autonomous robots and the understanding of brain capabilities. We will propose a Neural Network (N.N.) architecture and some guidelines that can be used as a generic way to conceive autonomous control architectures and to understand the brain in its ability to learn the control of highly redundant and complex sensori-motor systems. On the other side, we will show that our robotics experiments advocate the theory of a co-development of the sensori-motor and imitation capabilities and therefore differs from the approaches that suppose a clear difference between human imitation capabilities and animal mimicking capabilities. Indeed, numerous psychologists [Guillaume, 1925], [Wallon, 1942], [Tomasello, 1990], [Heyes, 2001] and roboticist [Kuniyoshi, 1994a], [Schaal et al., 2000], tend to separate "true imitation" [Thorpe, 1963] and its related high-level mechanisms which are considered to be specific to human adults, from low-level imitations or "mimetism" [Wallon, 1934]. In robotics, this approach leads to build a model of the demonstrator's geometry in the robot controller and perception problems are supposed to be independent of higher order cognitive capabilities. Then, a strong simplification

in the imitation architecture consists in using symbolic knowledge to characterize the demonstrator's behavior or his/her movements. The demonstrator/teacher wears for instance an exoskeleton [Ijspeert et al., 2001] which allows the robot to directly "read" the values of the different joints (this procedure is called an imitation). For more realistic interactions, dedicated sensors are tied up to the different parts of the body to imitate [Billard and Mataric, 2000] but then the development of imitation capabilities cannot be explained since the considered imitation and their associated perception capabilities are hardwired in the system and available as symbolic data (no learning to recognize a demonstrator, no explanation of how perception and action evolve together in order to allow more and more complex imitation capabilities). Hence, even if precise reproductions of a motor behavior is already possible, we will argue they do not represent correct solutions for the understanding of the development of imitative capabilities (precision of the reproduction is certainly not the only way to judge the quality of an imitation architecture).

In this paper, We will show that low level imitations can be the result of a side effect of a simple neural architecture devoted to the learning of sensori-motor coordinations. Hence, low level sensori-motor architectures could be the bootstrap of more and more complex imitative capabilities (emergent behaviors). As a consequence imitation must not be studied and modeled separately from the sensori-motor development. We will show how to design an unique generic control architecture relying on simple and minimalistic principles, which can adapt itself to a wide variety of tasks (versatility), inspired by the development of babies. Therefore, our approach is not concerned with the optimal nor accurate solving of a particular and well defined robotic task, but rather with finding minimalistic principles allowing the emergence of many coarse but different sensory-motor behaviors at the same time, such as tracking, visuo-motor coordination, target reaching and low-level imitation. Our approach is characterized by a continuous on-line, epigenetic, and auto-supervised learning process, triggered by a random sensory-motor exploration of the surrounding environment and a coding in a visuo-motor map.

In the following section, we will examine some psychological and developmental data related to our sensori-motor approach of imitation. Next, the problem of the control of a robotic arm with a single pan/tilt CCD camera will be addressed. The architecture allows the learning of a visuo-motor coordination and its use in simple imitation games. Three aspects of this modeling will be emphasized to illustrate the following properties:

First, the use of simple perception-action loops [Gaussier and Zrehen, 1995] based on the principle of an auto-supervised learning that can be used to perform reliable visuo-motor transformations. Such a mechanism will be used to turn around the ill-posed[1] problem of the visuo-

motor coordination between a 3 degrees of freedom (DOF) robotic arm and a simple pan-tilt monocular camera.

Second, the core of what looks like different perception-action loops can be the result of a unique internal dynamic computed using Amari equations of neural fields [Amari, 1977], [Schöner et al., 1995]. The resulting activity can be viewed as an "amodal" coding (not fully visual nor motor coding) that greatly simplifies the problems of motor control and builds the basis of multiple different behaviors such as reaching, tracking, imitation of simple gestures or more complex trajectories. Moreover, we show that a given behavior only depends on the sense of the information carried by the connections between the different perception-action loops. Hence, the choice of a neural network modeling avoids to dissociate the control issue from the more cognitive issues (learning, imitation, recognition, planning...).

Finally, we will show that our developing system does not need to build any internal model of the "other", to perform real-time and low-level imitation of human movements despite the related correspondence problem [Nehaniv and Dautenhahn, 1998] between man and robot.

II. Psychological and developmental motivations

At birth, vision and motor control of the neonate are relatively coarse. The neonates perceive outlines of figures, with a particular sensibility to movements in the peripheral vision [Hainline, 1998], [Slater, 1998]. They are able to follow a moving target with saccadic eyes movements, but the motor control of the neck and the other muscles will come progressively later, along the cephalo-codal [2] and proximo-distal [3] axis [Braun, 2000].
Our embodied robots could be in a way compared to newborns: they have a pan-tilt camera, a mechanical arm and a gripper, they have sensors, a CCD camera, etc. In other words they can move, they can perceive their environment, but they still need to develop the proper control architecture to act in a suitable way. Designing such a control architecture remains complex, due to the amount of possible sensory-motor associations related to the many degrees of freedom. Learning to coordinate the movements of the arm [Marjanović et al., 1996], [Schaal et al., 2000] to reach and grasp a visible object [Niemeyer and Slotine, 1988], being able to imitate very simple gestures or movements [Cheng and Kuniyoshi, 2000], or perform sequence of actions from observation [Kuniyoshi, 1994b], [Kuniyoshi, 1994a] are all complex issues, often referring to separate solutions in the field of robotics. Conversely, the young developing infant is able to solve all these tasks around the age of twelve months [Vinter, 1985], [Nadel and Butterworth, 1999], and quickly uses these skills as a new repertory for more complex tasks. To bootstrap the development process, we based our solution on two important observations

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[1]The problem is "ill-posed" since a single image is not enough to determine the depth of a target in the 3 dimensional space, and at the same time, several arm configurations/solutions are possible to reach a given target location.

[2]the movements of the head will be controlled before the movements of the trunk and feet

[3]the movements of the shoulders will be controlled before the movements of the wrist and fingers

of the newborns behaviors, described in the two following subsection.

A. Bootstrapping the developmental process

The first observation states the relative maturity of the visual system of the newborn in comparison with the motor system [Slater, 1995]. Thus, the visual system appears to be sufficiently developed to induce interest for some preferred stimuli (such as motion detection), and provide some goal-directed behaviors while the non accurate motor control provides random movements. This combination of random motor control and goal oriented behaviors induces an efficient sensory-motor exploratory behavior. Such behaviors are characterized by repeated movements and the matching of the corresponding perceptions. Slowly, a coarse to fine categorization of the sensory-motor space is learned, which can consequently serve as a new building block for a more complex sensory-motor repertory. Moreover, numerous studies highlight the evidence of such a sensory-motor coupling underlying the development of many capabilities at the same time: from birth, visuo-motor exploration induces maturation of tracking, prereaching and reaching [Bower et al., 1970], [VonHoften, 1982], [VanderMeer et al., 1995], and low-level imitation of movements [Nadel and Potier, 2002]. Such processes constitute an interesting *bottom-up* guideline for the design of autonomous robots. It suggests that stable sensory-motor associations can be learned by self-triggered exploration of the environment. The importance of such a developmental course could be useful for complex robots. It would allow to learn and categorize correctly the sensory motor space, according to their own embodiment, dynamics and physics. Thus, the bootstrap of the development process of our architecture is a perception-action architecture that links:

• elementary perceptions such as movement detection, providing selective behaviors (interest in the moving part of the visual field),
• noisy motor control on the robot actuators inducing random movements.

From this simple setup, we will test an on-line learning algorithm that allows the architecture to learn associations about movements of its arm, between the visual and motor spaces.

B. Development and imitation

The second observation that inspired our approach is the important role that imitation plays in human development. Imitation is a mechanism that witnesses emerging representational capabilities [Piaget, 1945], and at the same time it seems to be an important trigger of higher social behaviors [Nadel, 2000]. A striking example is given by the neo-natal imitation [Zazzo, 1957], [Maratos, 1973], as observed on young babies imitating [Meltzoff and Moore, 1977] tongue protrusion or eye blinking, as young as 10 minutes old [Kugiumutzakis, 1999]. Of course, the interpretation of such a puzzling behavior, that links, at birth, "seen-but-not-felt" face movements of others with "felt-but-not-seen" face movements of self, is still a debate in the developmental community. For authors neonatal imitation is produced by the conjunction of rather inate or pre-wired mechanisms such as a "supra-modal module" [Meltzoff and Moore, 1997] linking vision and proprioception (afferent copy of the motor action) and a "social module" leading the neonate to explore and discriminate the social environment [Meltzoff and Moore, 1999]. Conversely, a study from Jacobson [Jacobson, 1979] tends to show that neonatal imitation response could be an elicited low-level response determined by a particular spatio-temporal configuration of a non-human stimuli [4]. Moreover, the observations of more complex imitative capabilities come with the progressive development of the baby (see [Nadel and Potier, 2002] for a review of the role of imitation in human development, from birth on to 22 month old). For example, imitation of arm movements is observed from the age of 2 months, as soon as arm coordination is starting to be acquired by the baby. This example leads us to ask the following questions: at a given level of sensory-motor development, does imitation require much more features than a simple arm coordination? If a simple perception-action coupling between visual and motor information can explain tracking or pointing behaviors, can this coupling also explain imitative behaviors? We will show that a low level imitative behavior can be obtained as a side effect of the perception ambiguity [Gaussier et al., 1998]. "Perception ambiguity" must be understood in this context as a difficulty to discriminate objects (is this my arm or another's one?), or to decide between different interpretations (is this a useful object, or an obstacle?) without any additional information. Perception ambiguity was first introduced by Gestaltists, assuming that local features in a perceived scene were always ambiguous (only the global contextual information and the dynamic of the perception-action loop allow to suppress ambiguity). According to this principle, an imitative behavior of an autonomous robot can be bootstrapped as follows (Fig 1): Let's suppose a simple robot using visual information to control the movements of its arm. Let's now suppose that this robot processes only motion detection to perceive its own arm. Such a system can't differentiate it's extremity from another moving target, such as a moving hand. As a result, moving in front of the robot induces changes in the perceptions that the robot considers as an unforeseen self movement. It will then try to reduce the error by an action in the opposite direction of the perceived motion, inducing the pursue of the demonstrator's gestures (perception of a ego motion in the opposite direction of the real external motion induces a reaction in the good direction).

Whereas this hypothesis can be seen as very speculative, numerous psychological works show comparable human behaviors when visual perception is ambiguous. In 1963, Nielsen proposed an experiment in which subjects are placed in front of a semi-reflecting mirror [Nielsen, 1963]. In a first condition the mirror is transparent, and the sub-
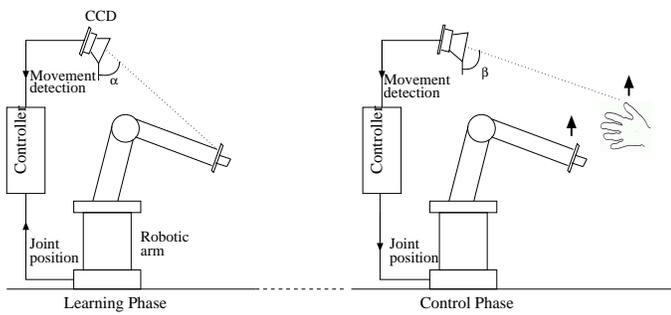
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[4]This study was never reproduced

Fig. 1. Low-level imitation principle applied to a robotic arm. In a learning phase, a controller robot learn the correspondence between its arm proprioception (the joint position) and its position in its visual field. To do this, the controller detects movement. Once the associations are learned, if the robot focuses its attention in a human teacher's moving hand, it will reproduce the teacher's simple movement just because it will perceive a difference between its proprioceptive and visual information. It will try to reduce the proprioceptive error of its arm position according to what it believes to be the visual information linked to its arm (the detection of movement in the visual field)! An external observer will then deduce the learner robot is imitating the teacher.

ject sees his own hand placed on a table under the mirror. In a second condition the mirror reflects, and the subject sees another hand (the demonstrator's hand) that he will mismatch for his own hand. Because a black glove has been put on both hands, the subject has the feeling to see his own hand and does not imagine there is another hand in the experiment. During each trial, the subject has to draw a straight line with a pen in the direction of his own body axis. When the perceived hand is his own hand, the performance is perfect. When the mirror reflects, the subjects "imitate" the other hand movements and do not perceive any difference if both hands are almost synchronous. If the perceived hand moves in a quite different direction, the subjects tend to correct the error by a drawing in the opposite direction but they never suspect the presence of another arm (they believe that the "wrong" trajectory is due to their own mistake!). This experiment was reproduced in a more modern form by [Fourneret and Jeannerod, 1998], [Jeannerod, 1999]. It demonstrates that an automatic visual control of the action can be trapped when the perception is *ambiguous*. Obviously, a robotic transposition of this experiment requires that our robot learns first the visuo motor association allowing arm movements in the visual space. After describing the neural network control architecture, we will show that a developing sensory-motor system is able to acquire a stable visuo-motor coordination that could be used for pointing or reaching behaviors. Moreover we will also show that our robot is able to exhibit low-level imitations without adding any additional features (no prior information about what is a hand, an arm, a human, etc.). Finally, we will stress how the imitative capability also constitutes a new trigger for human robot-interactions, carrying on the development process.
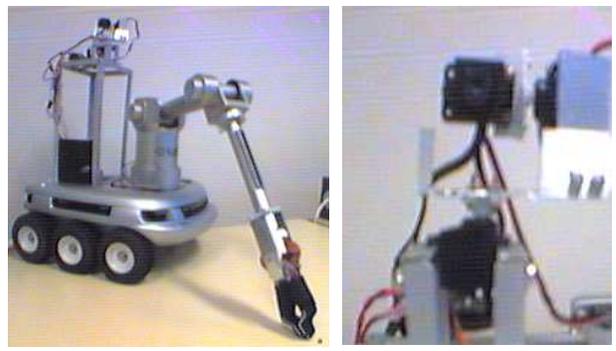

Fig. 2. The robot. A Katana robotic arm and a home-made pan tilt camera (right) are mounted on a mobile Koala robot (left).

III. Material and methods

A. Robotic system

The robot system is a Koala mobile platform (see fig. 2) equipped with one pan-tilt "head" and a 5 degrees of freedom (DOF) Katana arm. The pan-tilt head can rotates 180 degrees horizontally and vertically, and the motors support one single CCD color camera (no stereo vision) which can thus observe the entire work space. In the present experiment, only 3 joints of the arm are concerned: the arm can pivot around its base (θ_1), and the other two joints allow the arm to rotate in a vertical plane (θ_2,θ_3).

Consequently, the perceptive space of the robot is two-dimensional (2D) while the working space of the arm is three dimensional (3D) space. The motor space of the arm is also 3D because of the number of joint available on the robot arm. With such a dispositive, the control of the arm from the sole visual information is an ill posed problem, since the position of a target cannot be completely defined from the sole 2D visual information. Moreover, the robot arm has 2 degrees of freedom in the vertical space, so even in a 2D space they are several way to reach a target in the visual space. Thus, our architecture will have to solve the core issue of being able to position its end effector in the work space according to its 2D vision and 3D joint information, during its developmental course.

B. Elementary perceptions

Motion detection is first processed by a 2D *camera-centered* referential. The motion detection algorithm is a real time computation of the intensity difference in each pixel between summed image packets (more details on the algorithm can be found in [Gaussier et al., 1998]). The result of this computation is projected on a 2D *body-centered* map of neurons representing the whole visual working space (Fig 6). The body centered map is a reconstruction of all the possible views that the pan tilt mechanism offers. Therefore, our robot has a 2D flat visual perception of its environment, without assumption or reconstruction of the 3D real environment. Indeed, an elementary process such as motion detection is sufficient to extract the position of the extremity of the arm for most human and robot gestures. The end point of a moving arm is generally the area

with the highest motion intensity, due to the summation of the angular speed of each joint. Thus, even if the motion
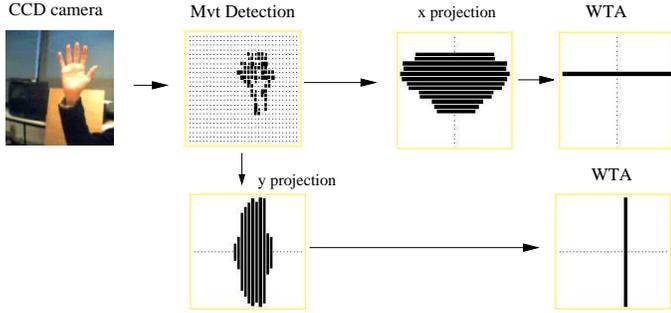

Fig. 3. Example of end point tracking (here a hand) using movement detection. The movement detection (on the center) is computed from the image flow (here, the experimenter was waving its forearm). The activity of the 2D map is projected on two 1D maps of neurons. Then, each projection map is connected to a WTA computing the position of the maximum of movement in the scene (Computation performed at 20 images /s).

is perceived on the whole arm, the maximum of the intensity will be located almost always on the hand. Thanks to this property, our robot will track its end effector when performing random arm movements. A *Winner Take All* (WTA) mechanism operating on two 1D projections of the movement detection map will allow the detection of the vertical and horizontal position of the moving end point(fig 3). We assume that this simple process is sufficient for a first approach (bootstrap situation) since it can be performed in real time and it preserves the dynamic of the perceived stimuli [5].

C. Introduction to neural fields and dynamical systems

If the computation of the maximal intensity of a movement usually provides the position of the end point of a given gesture, it is nevertheless still an unstable information. Even if we consider the simple case of a single arm moving in the visual scene (we do not want to limitate our system to such situations) the detection of the maximal motion values can be very noisy. The detected extremity can switch from the hand to the elbow for a short time (especially if the arm movement of the demonstrator is a circle or a height), or simply disappear for a short time if the movement is occulted. Therefore, the output of the motion detection and intensity competition can not be used as a valid information for a direct motor command. Instead, such perceptions must be filtered by an internal dynamic to allow a stable decision taking. The internal dynamic will constitute the core of the perception-action link of our architecture and the kernel of our robot's behaviors. Dynamical equations take advantage of motion perception to produce a robust information for the motor control (temporal coherence of the motor commands). This information is processed by a "motor" group of neurons simulating a

continuous field of neurons, called Neural Field [Schöner and Dose, 1992]. In this model, we suppose that each motor or proprioceptive group of neuron uses a population vector coding expressed on a topological map. For sake of simplicity, the topological organization of these input and output maps is directly given (but the learning with a Kohonen map should be possible). This simplifies the problem of the association between the activity of a motor neuron and the order that must be transmitted to the robot. In our model, neurons of a primary motor group controlling a single joint are ordered according to the angle they represent (from a minimal angular position ϕ_{min} to a maximal angular position ϕ_{max}). The neuronal activity of this motor group is controlled using neural field equations (eq 1, [Amari, 1977]):

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

Without input, the homogeneous pattern of the neural field, $f(\theta,t) = h$, is stable. The inputs of the system, $I(\theta,t)$, represent the stimuli 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 Difference of Gaussian (DOG) function. V_θ is the lateral interaction interval. $g(f(\theta,t))$ is the activity of the neuron coding for angle θ according to its potential $f(\theta,t)$. The activity of the neural field can be used either for position or speed control. Position control could be simply achieved by checking the maximal activity on the map but in case of several possible motions with almost the same activity the action choice can be very unstable (from one iteration to the next the winner can switch between very different angular positions, due to noisy input data). The advantage of the speed control relies in its intrinsic stability. A spatial derivative of the NF is performed ($\frac{df}{d\theta}$). 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. If each local maximum is associated to a particular target or goal then the behavior will be correct and much more stable than a position control (this is the case in all our applications). Lateral interaction will allow the most active goals to override/inhibit the smaller activity bubble and will induce smooth joint movements from one goal to the next one. This robust and dynamical representation allows to get the following properties[6] for free:
- The bifurcation properties of the equations allow a reliable decision making if multiple stimuli are presented.
- The time constant induces a remanent activity of the neural field, proportional to the intensity and to the exposure time to the stimulus. This memory property is a robust filter of non stable or noisy perceptive stimuli.

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[5]We have developed more complex and robust networks learning the shape of an object [Moga and Gaussier, 1999], [Lepretre et al., 2000], [Moga et al., 2001], [Baccon et al., 2002], but their computation time is not yet fast enough to be merged in our real time architecture.

[6]See [Moga and Gaussier, 1999] for experimental results on the use of NF as control architecture for autonomous robot.
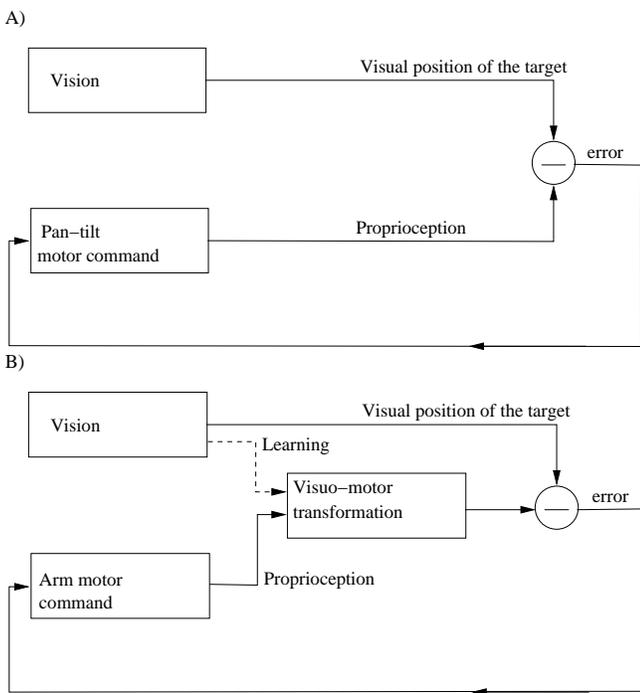
A)

B)

Fig. 4. Elements of the basic control system. A) A tracking behavior for our robot's head can easily be obtained by a simple homeostat. In this case visual and motor informations are at the same format (vision is in 2D pixel space, and motor commands of the head are in a 2D pan/tilt space), and can easily be matched. B) The application of the homeostatic principle for the control of the robot arm requires a complex transformation of 3D motor informations in 2D visual information. This transformation will be progressively performed during a learning sequence. Our final architecture is built on both homeostats: the head is able to track visual targets, while the arm is able to reach the target, using visual feedback.

• The same NF can be used efficiently to control several joints if they turn in the same plane (several different apparent dynamics control by a single internal NF).

IV. A NEURAL NETWORK ARCHITECTURE FOR VISUO-MOTOR DEVELOPMENT

Our first N.N. architecture is designed as a simple perception-action control loop. The loop itself is designed to respect the *homeostatic* principle [Ashby, 1960] (Fig. 4.A). In other words, the system tends 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. Obviously, if the visual and motor space are the same, the implementation of the control loop (see fig. 4A) allowing a tracking behavior is direct. The 2-D visual perception matches directly the 2-D pan-tilt motor commands. In our experiments, the tracking behavior is directly obtained with such a neural network loop. The "error" value is processed by two 1-D neural field and readout mechanisms computing the head horizontal and vertical speed vectors (the solving of more complex oculo-motor tasks with developmental and learning considerations can be found in [Berthouze et al., 1996], [G.Metta et al., 1999]).

Intuitively, an efficient visuo-motor coordination of a complex device, for example a mechanical arm, could be achieved by a similar NN architecture (Fig. 4.B) implemented as a *feedback loop*. The loop processes visual information to correct the movements of the arm, but in such a case, visual and motor spaces are often different and the architecture requires the learning of associations between both spaces.
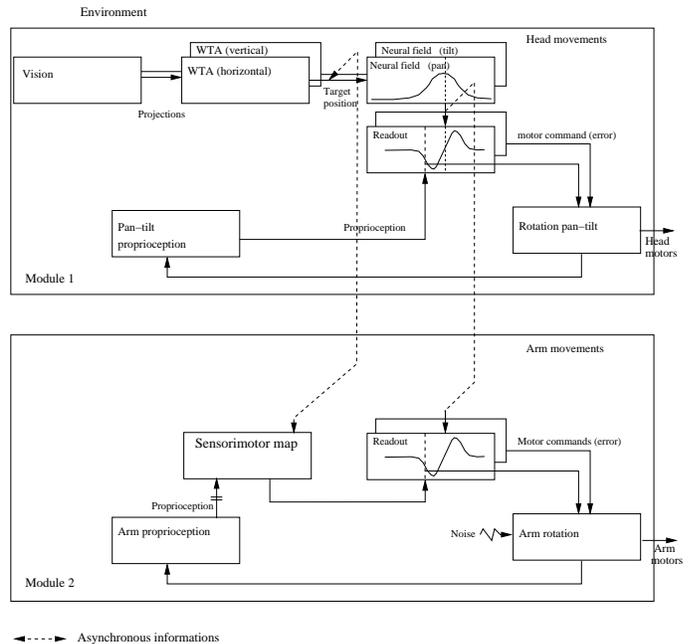

Fig. 5. The architecture is build from 2 modules in parallel. Each module is an independent neural network exchanging asynchronous informations with the other module. The figure shows the 2 main networks: The first module computes the 2D visual perceptions and 2D internal dynamic (NF). The second module merges and learns the proprioception of the arm and visual information in a *sensory-motor* map composed of clusters of neurons (this module is also responsible for the motor command of the arm). After learning, the arm proprioception triggers the correct activity of the sensory-motor map and can be used to compute the right movement to reach a possible target. Each module is executed concurrently, exchanging asynchronous informations (see bidirectional dashed arrows). This setup also allows the experimenter to reverse any information flows to obtain different behaviors without altering the modules of the architecture.

Thus, the control architecture is based on the multiplication of such neural network loops. Each loop is an homeostat controlling a different device. In the present architecture, we use two loops, one for the head motor command and the second for the arm motor command (Fig. 5). Both loops are executed concurrently on separate computers. They process separate proprioception (from the head or the arm) but share the same visual perceptions, and, more importantly, the same neural field outputs. 3 computers and the PVM library (Parallel Virtual Machine) are used to simulate the complete neural network. The use of the dynamical neural field allows to deal with the asynchronous exchanges of information (and the difference of sampling rate or speed) between the 2 parallel sub-networks.

A. Learning the motor control in the visual space

Self-Organized Maps (SOM) such as Kohonen [Kohonen, 1982] networks are often mentioned as an interesting solution for the learning of end effector positioning of robotic (or simulated) arms using vision. Intuitively, the self-organizing and topology features of the network should allow a reliable learning with a reduced amount of movements during training. A given neuron activated by one visual input can code for a given vector position of the different joints of the arm. The neighboring neurons will learn neighbor vector position due to the topology of the network. Rojas [Rojas, 1996] proposed, for instance, a didactic solution to the problem of learning to position the end effector of a simulated 2 DOF robotic arm on a sensitive flat area. Closer to our problem, [Ritter et al., 1989], [Martinetz et al., 1990] propose the use of a 3D Kohonen net (also called a Kohonen lattice) to allow a simulated robotic arm equipped with two external cameras to position its end effector in a 3D environment. The first drawback of this solution is the necessity of using stereo vision to detect the position of the end-point in the 3-D environment. Moreover, a 3D Kohonen net will work under the assumption that there is a bijection between the angle of the joints and the position of the end effector (i.e: only if a one-to-one mapping is possible). But with more complex arms (such as the one we use), the same position of the extremity corresponds to multiple vector positions of the joints. From this situation arises the problem of a many-to-one mapping, as well as the related problem of selecting one of the possible configurations to exhibit smooth movements. If a many-to-one learning is possible (by using, for example many kohonen nets at the same time), then a simple minimization criteria on the joint's position will allow smooth movements [Ritter et al., 1992]. In this case, the neural network algorithm is functioning in the manner of a look-up table. The Kohonen lattice delivers the joint's angle positions needed to reach the visual target. The movement is then a step by step approximation of the final position.

Also inspired from the self-organizing properties of the Kohonen net, our neural network algorithm is nevertheless quite different from the Kohonen Latices. The reasons are the following:

First, since the perception of our robot is flat (only one camera), a 3D kohonen lattice is no more suitable. And a 2D kohonen map cannot encode the many-to-one associations. Our solution is inspired by the micro-columns of the brain [Kandel et al., 1996] which consists of a 2D arrangement of neural functional units, each units learning the many-to-one associations (see fig. 6).

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. The main advantage of this choice is to limit the complexity of the computation needed for positioning (or processing further more complex tasks) to the 2-D visual space (even if the

arm is 15 DOF). Consequently, we propose a 2-D map of micro-columns, also called *clusters* that learns associations between vision and proprioception (Fig. 6). The topology of the map is the same as the visual map, and each cluster associates a single connection from one neuron of the visual map with multiple connections from the arm's proprioception. Thus, this coding allows a joint configuration of the arm to be represented in the visual space. The main advantage of this approach is that movements can be computed in the visual space and benefit from the intrinsic properties of the neural field used for motor control (eq. 1). The instantaneous speed of the different joints is easily obtained as well as smooth arm trajectories (without a complex speed control that usually involves an a priori cinematic model of the arm). More precisely, a cluster of neurons i, j (see the small drawing in Fig. 6) is composed of :

• One input neuron $X_{i,j}$ is linked to the visual map. This neuron responds to the V information and triggers learning.

• One *submap* of neurons, a small population of $Y_{i,j}^k$ neurons ($k \in [1, n]$) which learn the associations between 3-D proprioceptive vectors and one 2-D visual position (this population is a small topological map with the same self-organizing properties as the SOM maps).

• One output $Z_{i,j}$ neuron, merging the activities from the neuron $X_{i,j}$ and the maximum of the $submap_{i,j}$ activity.

A submap of neurons is computed exactly as a simple Kohonen map except that its learning is only possible when its associated visual input $X_{i,j}$ is activated (self organization of all the proprioception associated to a given visual position). $Y_{i,j}^k$ is the kth neuron of the submap associated to the i, jth cluster. The activity of $Y_{i,j}^k$ neurons is proportional to the distance between the input proprioception $P = (\theta_1, \theta_2, \theta_3)$ and the weights of the neurons on the map. (eq 2).

$$Y_{i,j}^k = \frac{1}{1 + \sum_{l=1}^{3} |\theta_l - W_{i,j,l}^k|} \qquad (2)$$

On each submap, a winner is computed according to eq. 3:

$$winner_{i,j} = max_{k \in n}(Y_{i,j}^k) \qquad (3)$$

The learning of a submap is dependent of the activation of the corresponding $X_{i,j}$ neuron, triggered by a visual input (eq 4). Thus, each submap learns the different proprioceptive configurations independently.

$$X_{i,j} = \begin{cases} 1 & if\ V_{i,j} \cdot U_{ij} > \theta \\ 0 & otherwise \end{cases} \qquad (4)$$

If no visual information V is present, the proprioception P triggers the response of the associated cluster in the map. On the sensori-motor map the global potential $Z_{i,j}$ of the neuron coding for the position (i, j) is computed as follows (eq 5) :

$$Z_{i,j}' = max(X_{i,j}, winner_{i,j}) \qquad (5)$$

A simple competition process is then performed on the output Z neurons of the map (eq 6).

$$Z_{i,j} = \begin{cases} 1 & if\ Z_{i,j}' = max_{u,v \in n}(Z_{u,v}') \\ 0 & otherwise \end{cases} \qquad (6)$$
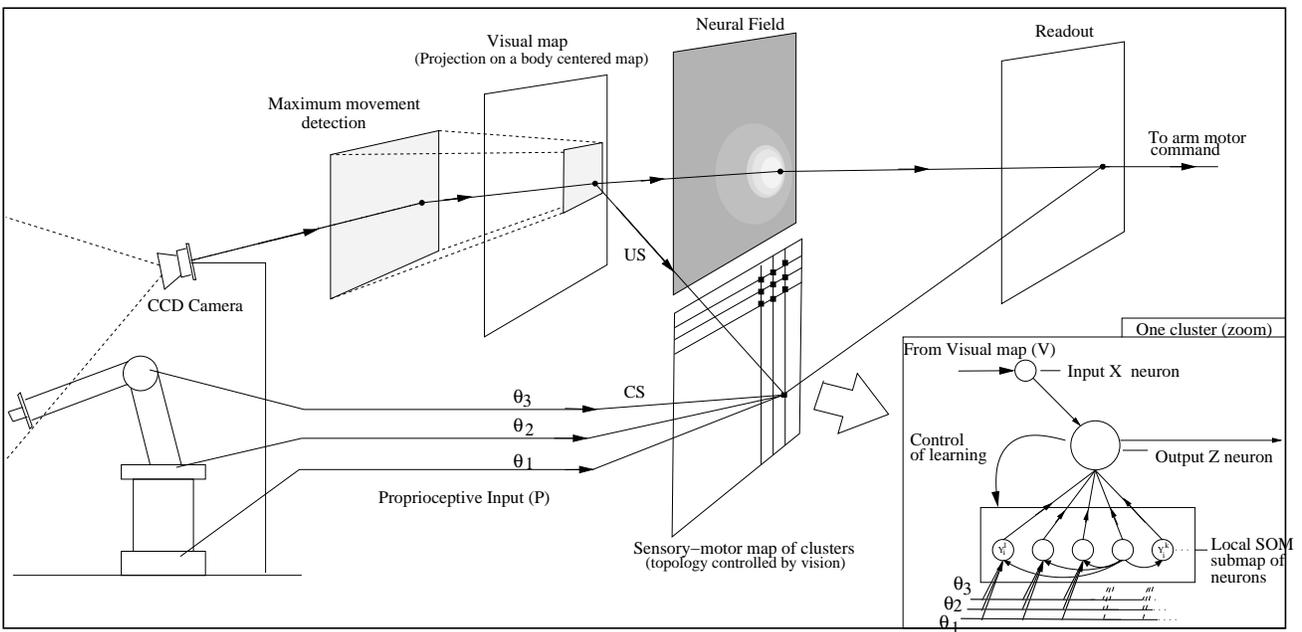
Fig. 6. The neural network controller for arm movements (simplified architecture). This controller learns visuo-motor association about the end point position of the arm. Learning is made by the sensory-motor map of clusters. The map has the same dimensions (2-D) as the visual map. Thus the activity of one neuron of the visual map will trigger (in the manner of an Unconditional Stimulus, US) the learning of the corresponding cluster of the sensory-motor map (one-to-one links,). The right picture details one cluster of neurons of the sensori-motor map. Each cluster has one link with one neuron of the visual map. This link carries out visual inputs detected by the X neuron. Activation of X triggers Z and the learning of its associated *submap*. The learning consists in a self-organization of the Y_{ij}^k neurons associating proprioceptive signals(θ_1, θ_2, θ_3 of the arm, Conditional Stimuli) to one visual unconditional information.

The winner neuron $Z_{i,j}$ 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 proprioception (thanks to the independence between each cluster).

B. On-line learning on the VM map

During the learning phase, the robot is put in a static environment, (learning with moving distractors would require much more presentations to detect the stable part of the sensory-motor associations). A crucial part of the learning process is linked to the choice of the learning parameters. Like in SOM algorithm, learning is uniquely controlled by the "shape" of the lateral inhibition between Y neurons of a submap (ϵ, Nn, Pn, involved in eq 7). The learning of the synaptic weights of a neuron k in the cluster i,j is computed as follow:

$$W_{i,j}^k = W_{ij}^k + \epsilon \cdot Y_{i,j}^k \cdot \delta(d(winner_{i,j}, k), Pn, Nn) \cdot Z_{i,j} \quad (7)$$

where ϵ is the learning rate. The d function computes a simple distance between the kth neuron and the winner neuron of the submap. The δ function computes the values of the lateral excitatory/inhibitory connections modulating the learning of the winner neuron's neighborhood. δ is a DOG function whose shape is defined according to the size of the positive and negative neighborhood (respectively defined by Pn and Nn).

The modification of the lateral inhibition influences the coarse to fine process which is mainly represented by two
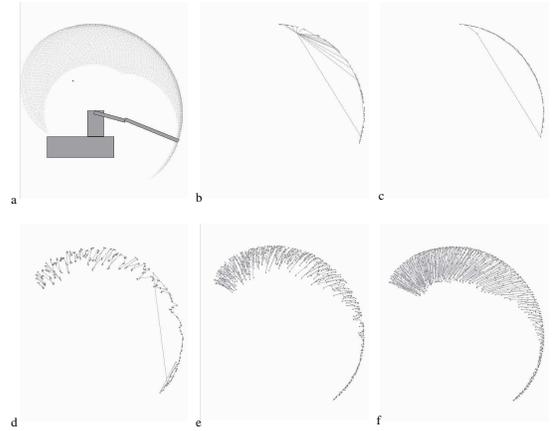

Fig. 7. A sensory-motor vector of 146 clusters learning vertical movements (only the θ_2 and θ_3 joints of the arm where freed). Each cluster is composed of a self-organizing submap of 6 Y neurons. a): Representation of the arm, and the theoretical working space. Each point is an accessible positions of the extremity of the arm, to be learned. On b)c)d)e)f) examples, each point represents a position learned by an Y neuron. These points are plotted according to the values of the Y neuron's weights learning the θ_2 and θ_3 values, using a simulation of the robotic arm. b) and c): the coarse stage. d), e), f): Progressive dissociation of Y neurons during the tuning stage.

different stages:

a coarse stage: at the beginning of the learning process, each cluster learns one visuo-motor association, self-supervised by vision (fig 7.b, 7.c). ϵ is maximal, Pn is high and there is no lateral inhibition (the shape of the lateral interaction is a positive Gaussian). At this stage,

the system does not cope with multiple arm positions for one visual position. The robot can perform either random or continuous arm movements, since the topology is forced by the presence of a visual signal $V_{i,j}$. The learning parameters are: $\epsilon = 0.9$, $Pn = 7$, $Nn = 7$. Figure 7.c required 300 learning iterations.

a tuning stage: The system learns the equivalences between the multiple proprioceptive information of the arm and a single visual position of its extremity (fig 7.d, 7.e, 7.f). This phase consists of the specialization of the neurons on each submap. The shape of the lateral inhibition and its amplitude are decreasing with the time in order to allow a more precise learning of the multiple arm positions (progressive stabilization). The robot has to perform numerous random arm movements to provide a sufficient amount of different arm positions for the learning of each cluster.

The learning parameters are: $\epsilon = 0.4$ down to 0.05, $Pn = 7$ down to 1, $Nn = 7$ down to 3. The results presented figures 7.g were obtained after 8000 learning iterations of random movements.

Theoretically, the fine learning phase can work on its own, but it requires a very long convergence time. "Fine" also refers to the learning constants which in this case are small, to allow a slow, progressive but accurate modification of the weights. Starting with the fine stage would only takes a long time before all the clusters would be separated.

Practically, and especially in the case of learning robots, a coarse stage induces a quick and large categorization of the space: each cluster is easily separated from others, and the robot is already able to perform coarse but consistent movements. Consequently, the coarse to fine learning is not a necessary condition for the learning algorithm even if it greatly simplifies the learning problem (reducing the learning period). This coarse to fine procedure could be considered similar to the maturation of the baby sensori-motor system (even if we do not simulate the details of the different loops involved in human motor control).

C. Invariant coding of motor behaviors

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. This error has to be then converted in an appropriate movement vector to move each joint toward the target. The problem is to decide in which coordinates the minimization has to be performed. The originality of our solution is to compute a dynamical attractor (see materials and methods section) expressed in the "visual" space. The attractor can then be simply centered on the target stimulus. If the minimization was performed in the motor space, it should be necessary to propose a final proprioceptive configuration in order to compute each Neural Field (each dynamics) associated to to each degree of freedom. The problem is that the desired configuration of some degrees of freedom might depend of some other degrees of freedom (i.e. the link between the shoulder and the trunk...). Hence, if a motor behavior such as doing a circle is learned form a particular

proprioceptive configuration, it will be difficult to compute it from another body configuration (a complex coordinate transformation should be learned and applied to solve the correspondence problems). For instance, learning a movement with one arm and reproducing it with the other arm should be possible (the reproduction with another type of device like a leg should also be possible...). To solve this apparently difficult problem, we have decided to learn the motor trajectories in a space invariant from the joints positions. One evident solution is the body peripheral space that can be seen as an extended visual space such as a 2D cylindrical map (for more complex tasks, a 2.5 dimensional space where depth would be added should be sufficient to deal with complex trajectory and 3D grasping problems).

Hence, the two spatial derivates of the two NF activities are interpreted as the horizontal and vertical speed commands for every joints in order to reach the target (*read-out* mechanism [Schöner et al., 1995]). According to its proprioceptive position, each joint will move at a speed corresponding to the spatial derivates of the NF activity measured on the neuron corresponding to its current proprioception value (we suppose first that each neuron on a 1D neural field codes for a particular proprioceptive value and next that neighbor neurons code for neighbor proprioception - 1D topological map). Each joint will then contribute to the global movement of the arm toward the visual target. This coding of movements induces the following properties:

• The simultaneous activation of different joints creates new globally coherent dynamics. These dynamics are an emergent property of the two 1D neural fields used to decide the joint's speed.

• The speed profile is smooth with acceleration and deceleration phases of the joints at the beginning and end of the movement (important for a stable control of the arm).

• The desired arm configuration (reaching a particular position) is a stable position (the stabilization of the motors on the target - $df = 0$).

V. EXPERIMENTAL RESULTS

After the learning phase, the architecture was tested for pointing and low-level imitation tasks. The pointing task aims at testing the internal dynamic (the *read-out* mechanism), and how the coherency of the learned associations successfully drive the extremity of the arm to a desired visual area in the working space. The imitative task aims at testing the robustness of the dynamical equations and the real time capabilities of the overall architecture. The imitative experiment also validates theoretical work assuming that a generic controller is able to perform the imitation of human gestures [Gaussier et al., 1998], [Andry et al., 2001].

A. Pointing

Figures 8 and 9 show the results of one pointing test experiment. To simplify the plotting of the results, the pointing was made using only two DOF of the arm (θ_2, and θ_3 in the vertical plane). Nevertheless, the pointing test preserves the complexity of the issue since these two

DOF are redundant in their contribution to the vertical movements of the end of the arm.
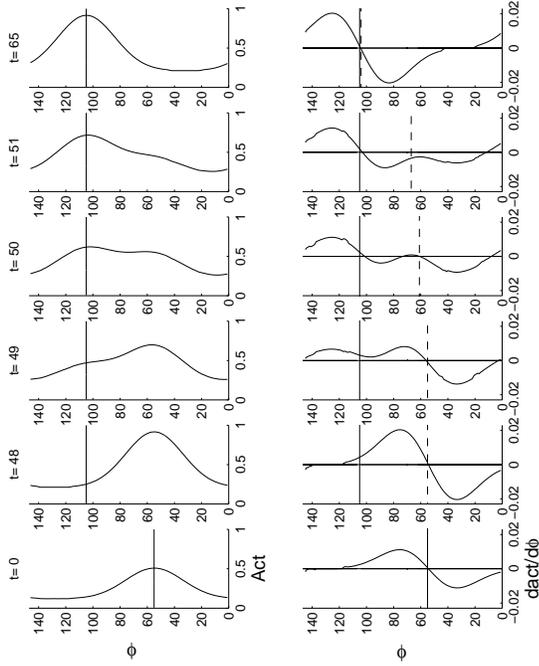

Fig. 8. Internal activities of the neural field and read-out mechanism during a pointing task. From $t = 0$ to $t = 47$ the neuron 55 is stimulated. From $t = 48$ to $t = 65$, the neuron 105 is stimulated. Up: snapshots of the neural field's activity. A single stable attractor can be seen at $t = 47$ and $t = 65$. Between $t = 47$ and $t = 65$ the attractor travels from the first stimulated point (neuron 55) to the second one (neuron 105). Bottom: corresponding activity of the NF spatial derivative. From $t = 47$ to $t = 65$, the resulting read-out mechanism moves the arm toward the new attractor (dashed lines represent the visual position of the extremity of arm, and $dact/d\phi = 0$ represents a null speed of the associated joint).

The pointing test was performed as follow: Vision from the CCD camera is disabled (no visual information), and the activity of the neural field is directly controlled by the experimenter, simulating a perfect perception. At the beginning of the experiment (from $t = 0$ to $t = 47$), there is no error between the activated area (centered on neuron 55) of the neural field and the position of the arm, inducing no movements. At $t = 48$, the experimenter stops the activation of the neuron 55, and starts to stimulate the neuron 105. The resulting traveling wave (from $t = 48$) on the NF's activity (fig 8,up) induces modifications of the shape of the associated spatial derivative (fig 8, bottom), and starts to move (from $t = 49$) the arm's joints toward the new equilibrium, progressively centered on the neuron 105. Figure 9 shows a plot of the recorded positions of the arm corresponding to the modifications of the NF's activity between $t = 48$ and $t = 65$ according to both modalities. In the first experiment, the θ_2 joint was blocked, and only the θ_3 joint was able to point to the direction of the target (figure 9.1). In the second experiment, both joints θ_2 and θ_3 where freed and able to reach the target (figure 9.2). These records show that with both modalities, successful pointing is achieved by the system. We can notice that the

pointing is achieved with an error inferior to 3 degrees (with a resolution of 1.5 degrees of the neural network coding). Second, the sensory-motor map has learned a reliable visuo-motor space (no incoherent or discontinuous movements), and third different apparent dynamics can be achieved and controlled by the same internal dynamics when some DOF are frozen or freed. Hence, this system adaptation does not need any internal re-mapping nor weight adaptation between the different situations (see Fig 9 1 and 2).
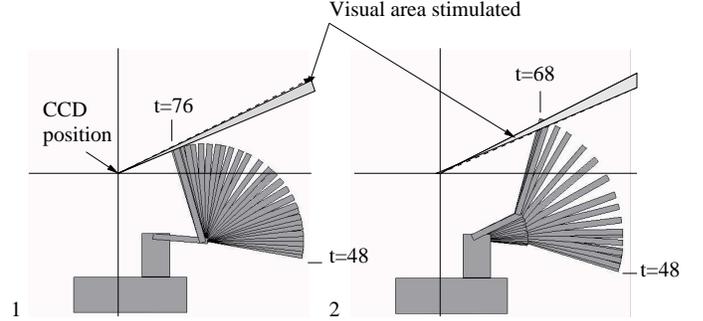

Fig. 9. Pointing results, resulting of the NF activity plotted in figure 8. Left: one DOF modality. Right two DOF modality. In both examples, the same internal dynamic succeeds to drive the arm to the area of the visual space stimulated.

These examples of pointing show that our architecture exploits efficiently the 2D visual information for positioning the robotic arm in the 3-D surrounding space. The 2-D to 3-D position equivalence of the extremity of the arm is performed due to the previous learning of the sensory-motor map, which topology favors minimal cost movements by minimizing the distance of each joint between the current proprioceptive configuration and the desired visual target position of the extremity. The visually forced topology of the sensory-motor map ensures that the arm extremity follows the shortest path to reach the target, while the dynamical neural fields ensure the proper speed profile of the arm extremity whatever the number of joints involved is (all the available joints contribute to the whole movement). Finally, to test the correct learning of the interactions between different modules of the architecture, the motor control of the arm and the CCD camera have been inhibited. In these conditions, the experimenter takes the robot's extremity and moves it (passive movement of the robot arm). We observe that even without visual perception, the robot head follows the movements of the robot hand. This experiment shows that the proprioceptive information from the different joints of the robot arm is sufficient to correctly activate the sensory-motor map and the pan-tilt camera (reciprocal connections between the active vision system and the control of the arm defining the homeostatic control).

B. Gesture Imitation

The previous learning process allows the constitution of a primary behavioral repertory. Thus, an elementary imitative behavior can now be triggered by exploiting the ambiguity of the perception. By shifting manually the

head horizontally (without modification of the proprioceptive signal), we ensure that a perceived moving object will be associated to the robot own arm. The generated error will induce movements of the robotic arm reproducing the moving path of the human hand: an imitative behavior emerges. Using this setup, we show that our robot can imitate several different movements (Fig. 10). During the experiment, the experimenter was naturally moving his arm in front of the robot's camera making simple vertical or horizontal movements, squares, or circles. 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. Hence, it is no more necessary to perform a brutal shift of the camera in order to avoid the robot to perceive its arm. If the teacher arm moves first, he generates a first stable attractor that the robot will consider as the position to reach even if the robot perceives next its own arm (building of a second attractor that will not be chosen if the robot arm falls in the attraction basin generated by the movement of the teacher arm).
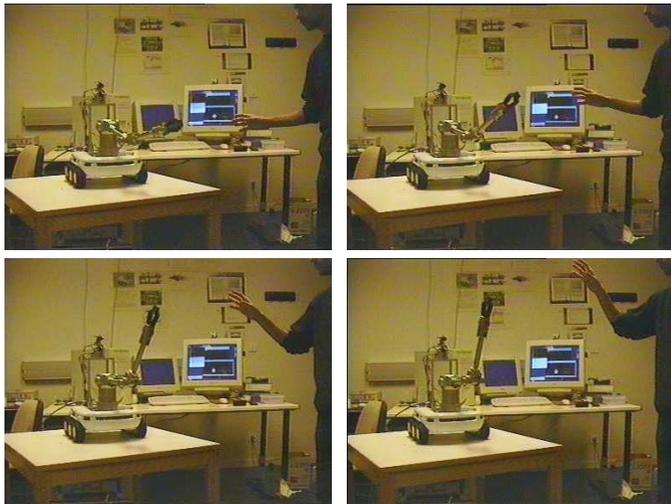

Fig. 10. Real time imitation of a simple vertical gesture. To obtain a low-level imitative behavior, we simply shift the head's orientation according to the body and the arm orientation (shift = 90 degrees). Thus, a perceived movement is interpreted as an error, inducing corrective movements of the arm: an imitating behavior emerges

C. Learning complex trajectories via imitation

Once our robot is able to perform an imitative behavior, it can reproduce a wide variety of movements demonstrated by a human. These movements can be combined in a more complex trajectory. For example, a succession of simple movements can be involved in a complex action, as shown in figure 11. Such an action involves movements, objects, and maybe goals or intentions. As a first step toward the learning of complex actions, our goal is to show here that the complete trajectories of the demonstrator arm can be learned in a simple way due to the N.N. architecture pre-

sented in the previous section.

Fig. 11. Exemple of an action. The demonstrator grasps a cube on the table, then moves his arm up, left, and he releases the cube down. The succession of simple gestures plays an important role in this action

To learn sequences of gestures, two main problems must be solved:
• recognition and extraction of the shape of the demonstrator arm trajectory (the path followed by his arm),
• extraction and learning of the appropriate information for a correct motor reproduction.
Our solution to these problems is directly related to the importance of the perception-action coupling in our architecture. In previous works, we have already shown that the immediate imitation of a moving human by a mobile robot allows the robot to learn its own sequence of movements [Gaussier et al., 1998]. The immediate imitation mechanism allowed the robot to convert and filter the perceptions by its own internal dynamic, and the related wheels movements were learned as a temporal succession of orientations. Intuitively, the learning of sequences of gestures with a more complex robotic arm can be realized in the same way: the immediate imitative behavior allows our robot to learn about its own motor dynamics, about the movements it is performing. In this case, the motor activity of our robot is a filtered response of its perceptions, and the related signal is therefore more continuous and less noisy than the visual information.

But the present robot is much more complex. Multiple joints act at the same time and can have redundant effects on the movement of the end effector. Moreover, we would like our model to be the same, independent of the complexity of the device, and we would like it to reproduce a trajectory even in case of errors on a set of articulations. Once again, we assume that only the position of the extremity matters.

We propose that the learning of significant changes in the movement directions should be performed at the level of the sensory-motor map (see Fig. 12). This solution presents the following advantages. First, the output of the sensory motor map is expressed in the 2D visual space, and the related informations are independent of the dimension of the proprioceptive signal, i.e of the number of joints. Hence, the complexity of the "sequence learning" network is directly fixed by the number of dimensions in the visual space (2D or 3D for instance) instead of being dependent on the complexity of the motor space. Second,
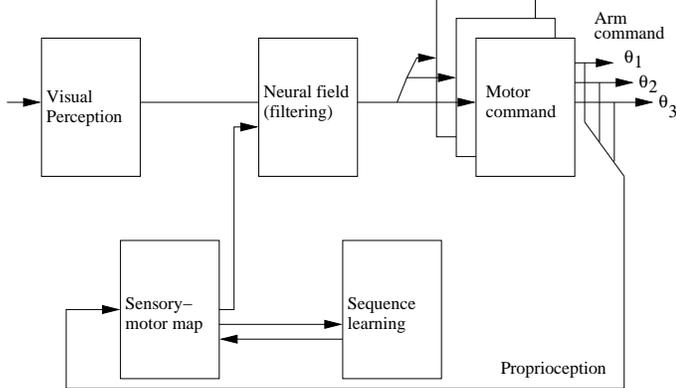
Fig. 12. In our current system, we must take into account the multiplication of the joints contributing to the final move of the arm. Instead of learning the variations of each joint (non robust solution), we propose to learn the variation of the attractors produced by the sensory-motor map. The dimensions of this signal remain independent (expressed in the 2-D visual space) to the number of joints and ensure robust reproductions (fault tolerant solution).
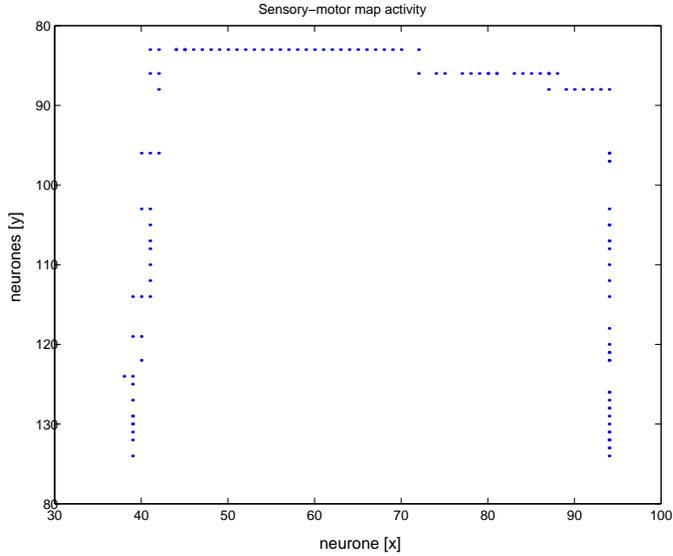

Fig. 13. Output of the sensory-motor map, corresponding to the reproduction of an inverted 'U' trajectory learned from the visual perception of the experimenter hand motion.
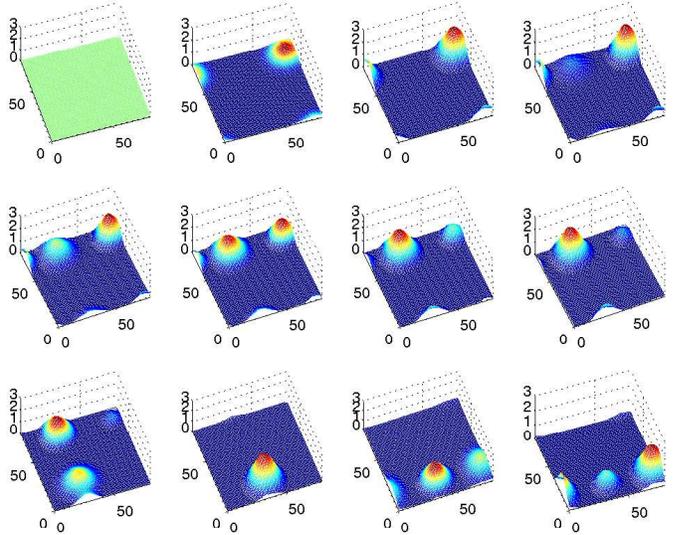

Fig. 14. Representation of the neural field activities associated to the reproduction in the visual space of learned sequence of hand movements. The "sequence learning" system triggers a succession of dynamical attractors. Here the attractors correspond to the trajectory demonstrated in figure 13. They show the trajectory has been correctly learned

the computation is always performed from the proprioceptive information but it benefits from the decision making stability of the NF. Another interest of this approach, is a very efficient and fault tolerant learning mechanism. A trajectory learned with a set of joints, can then be reproduced by a different set (even a different device), because our system only learns the dynamics of the end point (with the assumption that our system has learned a coherent visuo-motor transformation on the sensory-motor map). But the main advantage is that there is no need to introduce an abstract representation of the action to explain the capability to use a skill learned with a particular device on another one (no need to transfer knowledge - the direct coding in our sensori-motor map allows an invariant representation of the action according to the motor device). This strategy could be generalized to other perceptive information if we suppose learning is always performed in a kind of visual space (even for tactile information or spatial aspects of sounds).

Practically, to learn the trajectory efficiently, our system tries to detect the significant variations in the trajectory of the end point of its arm (major changes in the trajectory (pertinent points). The 2D information obtained from the sensory-motor map is simply integrated and then derived $\frac{dinput}{dt} = 0$ to obtain a single information allowing to trigger the learning of a particular via point. The trajectory is then represented by a succession of activities on the sensory-motor map as shown figure 13.

A group of neurons is used to predict when which neuron on the visuo-motor map will be activated according to the previous activations on the map (see [Gaussier et al., 1997], [Gaussier et al., 1998] for a complete description of the network). Because of the feedback connexion to the visuo-motor map, the sole prediction is sufficient to trigger a sequence of activations on the 2D neural field. Fig. 14 shows some snapshots of the temporal activity on this map during a sequence reproduction). The activity bubbles represent the attractors (via-points) of the trajectory expressed in the visual space. Hence, those activations can be used to control any device. The specificities of the trajectory reproduction according to the morphological and dynamical properties of the used device will only depend of the read-out mechanism performed on the result of the visuo-motor transformation (readout previously learned or hardwired and independent of the trajectory/behavior to be learned).

VI. DISCUSSION AND CONCLUSION

In 1990, Edelman et al [Reeke et al., 1990] proposed DarwinIII, a simulated robot with a mobile eye and a 4 DOF

arm able to reinforce the reaching of particular targets. A sensor placed on the extremity of the simulated arm helped the computing of the reinforcement of the movements. Bullock et al [Bullock et al., 1993] presented the DIRECT model, a self-organizing network for eye-hand coordination learning correlations between visual, spatial and motor information. This robust solution allows the successful reaching of spatial targets by a simulated multi-joints arm. Our neural control architecture is inspired from these works, and tries to apply them in the context of a real robot in interactions with humans and other robots. Nevertheless, the main difference is the introduction of a representation of the motor behaviors that is independent of the motor device. The sequence of events is encoded as a sequence of attractors in a kind of "visual" space, wich coherency results of the learning of the sensorimotor map. This encoding greatly simplifies the control problem since the attractor can be defined in a 1D space or at least in a 2D space instead of a nD space (of a n DOF arm).

The computation of the NF equations on the perceptive activity allows a generic encoding of the internal dynamics, independent of the motor devices, and without taking into account the number of DOF of the device, the possible redundancies (this part being managed by the visuo-motor learning), and therefore the possible mechanical changes that can be made during a robot's "life". Hence, the association of an adaptive sensory-motor map with two 1-D neural fields can be seen as a simple global dynamical representation of the working space controlling efficiently an arbitrary number of degrees of freedom according to the 2D information coming from the visual system.

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 robot arm movements, independent of the morphology of the arm. We are close to an *effect level imitation* [Nehaniv and Dautenhahn, 1998], where real-time executions, and dynamics of the movement are enough to provide low-level but efficient imitation. Our imitation mechanism is efficient for interaction, because imitation of movements can be recognized, and it is efficient for learning, because information about the most useful and informative part of the movement, the end point, is used.

These interactions will constitute, in future works, a new way for the system to learn more complex sensory-motor associations, about the physical, dynamical and social properties of the environment. But, if our architecture is already able to exhibit imitative behaviors of different levels of complexity, we believe that it can also be 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, that allows the independence of the device executing an action, can also represent the core principle of a perception-action model unifying immediate and deferred imitation. Indeed, 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[7]. In this paper, we showed that our architecture is able to learn a succession of movements whatever the robotic device is. Because the internal representation of the trajectory is not anchored in the visual environment, and because our control architecture does not need any information about the demonstrator, our robot is almost independent of the motor modalities used by the demonstration. If we now suppose that our system possesses an inhibition mechanism allowing to freeze/free the movements of its arm, our robot will 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. We believe that the issue of the control of inhibitions is crucial in the actual debate about the so-called mirror neurons. According to [Rizzolatti, 2002], mirror neurons are neurons whose activity respond when observing or reproducing hand, arm, or mouth actions. According to the authors, mirror neurons can be explained by two resonance mechanisms. The high level resonance mechanism could explain the firing of the same neurons during the observation or the reproduction of the same specialized action performed on particular graspable objects. The low level mechanism could be responsible of the firing of neurons during the observation or production of meaningless arm movements. If the high level resonance mechanism is out of the scope of our experiments (the recognition/manipulation of objects must be addressed first), the activity of the NF map of our system could be close to a low level mechanism. Neurons of the NF map are active when the robot observe an arm movement or when it reproduces it. If it is obvious that our architecture (and, in fact any control architecture linking visual and motor informations [Schaal, 1999], [Billard, 2001], [Marom et al., 2002]) can contain neurons/variable firing in both condition, it arises the more important question of the underlying mechanism inhibiting the trigger of actions, differentiating the observation situation from the reproduction situation, and the imitator from the imitated.

In conclusion, our architecture could represent the first step of a single sensori-motor model unifying immediate and deferred imitative behaviors often viewed as separated and as constituted of mechanisms of different levels of complexity.

VII. ACKNOWLEDGMENTS

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[7]Deferred imitation consists in the reproduction of a previously observed action in different spatio-temporal modalities from the observation

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