A biologically inspired robotic model for learning by imitation.

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ABSTRACT

This paper proposes a biologically inspired model for motor skill imitation. The model is composed of modules that are high-level abstractions of the spinal cord, the primary and pre-motor cortex, the cerebellum, and the temporal cortex. Each module is modeled at a connectionist level. Primary motor behaviors, such as rhythmic movements of arm and legs for open-loop walking, are predefined in the spinal cord. Learning of new combination of movements is done by the DRAMA [8] neural architecture, which allows learning of time series and of spatio-temporal invariances in multimodal inputs. The model is implemented in a mechanical simulation of two humanoid avatars, the imitator and the imitatee[1]. We present three types of sequence learning: 1) repetitive patterns of arm and leg movements; 2) oscillatory movements of shoulder and elbows; 3) precise movements of the extremities for grasping and reaching.

1. INTRODUCTION

A better understanding of the neurological substrate of learning by imitation is relevant to both neurobiologists and roboticists. Roboticists would benefit from the possibility of implementing a control mechanism that enables the robot to learn new skills (which would otherwise require complex programming) by the sole ability of observing another agent's performance([4], [12], [21], [22], [26], [32]). Teaching by demonstration and in particular robot learning by imitation has been used in diverse experiments for teaching a robot new motor skills (e.g. [13], [16], [10], [23], [36]); see [2; 36] for reviews. In our previous work, we used imitation as an indirect means to teach the robot new cognitive skills such as learning of a language. There, the robot's ability to imitate the teacher is used to lead the robot to make specific perceptual experiences upon which the robot grounds its understanding of a proto-language [5; 7].

[1] In this paper, we refer to the imitator when speaking of the agent that imitates and of the imitatee when speaking of the agent being imitated.

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Our present work aims at developing a complete architecture for learning by imitation in a humanoid agent. Our architecture is biologically inspired in its function, as its composite modules have functionalities similar to those of specific brain regions, and in its structure, as the modules are composed of artificial neural architectures. The model is loosely based on neurological findings in primates and incorporates an abstract model of the spinal cord, the primary and premotor cortices, the cerebellum, and the temporal cortex.

Most related to our work are studies which develop biologically inspired models of motor control (e.g. [3; 11; 18]) and learning (e.g. [15; 20; 37]), and in particular robotic models with specific application for learning by demonstration. The latter include models of visuo-motor coordination for directing head movements [14], for directing hand movements for object manipulation [23], and for generating trajectories in space [35; 24]. The work reported in this paper brings three new contributions to robotics research on imitation. First, it proposes a complete model of learning by imitation from visual segmentation to motor control. Second, the model allows imitation using all degrees of freedom of a complete humanoid body rather than a restricted set of joints. Finally, the model is biased by biologically motivated constraints. These are the use of a connectionist representation and the building of a hierarchical neural mechanism for motor control, including a set of *evolutionary primitive* skill substrate.

Our model is validated in a mechanical simulation of two humanoid avatars, the *imitator* and the *imitatee*. We present experiments in which the imitator avatar learns different sequences of limb movements, initially demonstrated by the imitatee avatar. We present three types of sequence learning: 1) learning of repetitive patterns of arm and leg movements; 2) learning of oscillatory movements of shoulder and elbows, using video data of a human demonstration; and 3) learning of precise movements of the extremities: grasping and reaching.

Our work in humanoid motor control and imitation is biased by neuroscience literature on motor primitives [9; 30]. These constitute motor programs that generate complete movements (such as reaching), and are sequenced and superimposed to generate a broad repertoire of motor control. Our previous work [27; 29; 28] has experimented with different types of motor primitives applied to humanoid simulations, including Cartesian and joint space force fields and sequenced Cartesian space impedance end-point controllers. In all cases, the primitives coded for relatively high-level behaviors, that is, individual moves of a dance (the Macarena in our case), such as extending the arm out, putting a hand behind the heck, etc.

In this work, we take an evolutionary perspective and define primitives to be innate and evolutionarily old motor control mechanisms: central pattern generators (CPGs) [38]. Compared to our previous work, these are lower level, in terms of the behaviors they individually code for, but also provide a more general parametric substrate for motor control. Furthermore, they are directly rooted in biological motor control.

Primitives are important tools for motor control and learning in primates. Motor control is hierarchical [34; 40] and learning of new skills is the result of a mechanism which builds on top of primitive motor patterns. The understanding of these mechanisms is interesting to robotics for designing controllers showing similar efficiency, robustness and adaptability as that of animals. Moreover, it would enable modularity and reuse of controllers for different robotic platforms. The experiments reported in this paper are a first step towards the design of such a controller. We present a hierarchical neural mechanism for visuo-motor control in robots, which includes predefined neural pattern generators coding for primitive motor skills upon which new skills are built.

The rest of the paper is organized as follows. In Section 2, we briefly describe the architecture (a complete description is given in [6]). Section 3 describes the mechanical simulation of two humanoid avatars and reports on the results of the experiments. We conclude this paper in Section 4 with a short summary of the work presented followed by a brief outlook on our continuing work.

2. THE ARCHITECTURE

Our architecture is inspired by neurological models of visuo-motor processing. Figure 1 shows a schematic of the modules in the architecture. The architecture is divided into three parts, visual recognition, motor control and learning and is composed of seven modules. Visual recognition is performed by the visual and attentional modules. The temporal cortex module (TC) performs recognition of the direction of movement of each imitatee's limbs relative to an intrinsic frame of reference. It takes as input the Cartesian coordinates of each joint of the imitatee's limbs in an extrinsic frame of reference. Its output activates a series of cells coding for the six possible join angle distributions[2]. The larger the angle, the greater the output excitation of the cell. The attentional mechanism generates inhibition, preventing information to flow from the primary motor cortex to the premotor cortex and further to the cerebellum. The inhibition stops, thus allowing learning of new movements, whenever a significant change of position (relative to the position at the previous time step) in one of the limbs is observed.

[2]Note that if there are fewer than three degrees of freedom in a joint, then fewer than six nodes will be activated for representing the possible orientations of that joint, as shown for the elbow in Figure2.

Motor control is directed by the spinal cord module and the primary motor cortex (M1) module, both of which have direct connections to motor neurons. Motor neurons activate the avatars' muscles (see Section 3.1). M1 can also activate spinal cord neurons. Learning of new motor sequences is done in the premotor cortex (PM) and the cerebellum module. The neural connectivity inside the visual cortex, spinal cord, and M1 is predefined, while that inside the PM, and the cerebellum builds up during learning. Learning builds the connectivity between M1, PM and the cerebellum and within PM and the cerebellum. The drive module controls the passage between observing and reproducing the motor sequences. It is implemented as a set of if-then rules and has no direct biological inspiration.

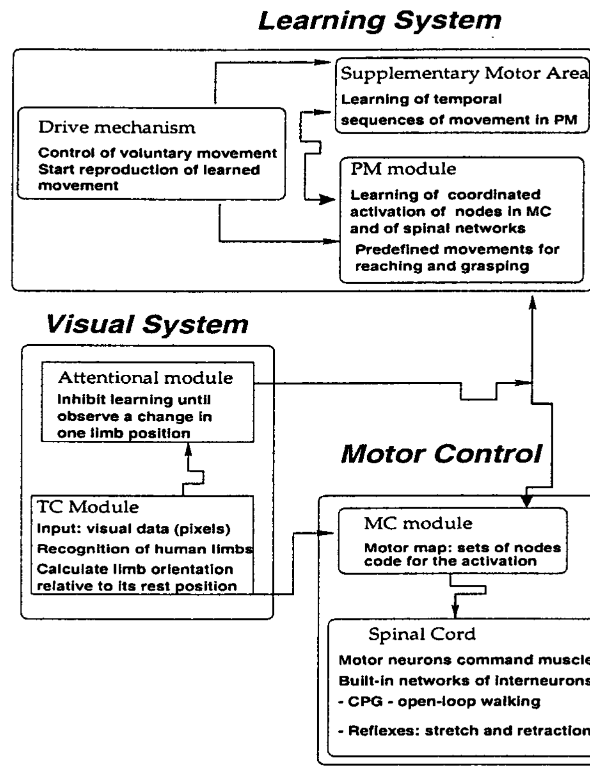

Figure 1: **The architecture is divided into three parts, visual recognition, motor control, and learning, and is composed of seven modules.**

Figure 2 shows a schematic of the neural structure of each module and their interconnections. Similarly to human motor control [19; 40], our model of motor control is hierarchical. On the lowest level is the *spinal cord*, composed of primary neural circuits made of *motor neurons* (afferent to the muscles spindles and responsible for the muscle activation or inhibition) and *interneurons*[3]. The spinal circuits are

[3]Inter- and motor- neurons are common terminology for describing the spinal cord neurons with no direct and direct input to the muscles, respectively.

built-in and encode extending and retracting arm primitives, as well as rhythmic movements of legs and arms involved in locomotion, i.e., *central pattern generators* [38]. The primary motor cortex (M1) contains a *motor map* of the body [31]. It is divided into two layers of three-neuron networks, each activating distinct (extensor-flexor) muscle pairs. The first layer of neurons gets excited by the output of the visual system (TC module) for the recognition of specific limb movements in the imitatee's behaviors. The second layer of nodes gets activated by the outputs of the premotor area – for activating a motor command ordered by the drive module through the cerebellum and the premotor cortex. The premotor cortex in humans plays an important role in coordinating and planning complex sequences of movements [34]. In our model, the PM module is the location of the first stage of the learning of movement sequences. It learns combinations of excitation of the neurons in the first layer of the M1, which encode the recognition of limb movements in the imitatee.

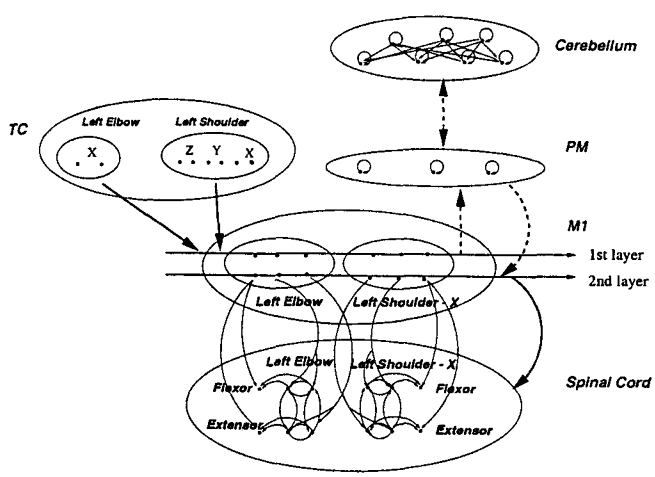

Figure 2: The neural structure and connectivity of each module.

In addition to the spinal and motor cortex areas, another level of motor control is provided by the cerebellum. In primates, the cerebellum has been shown to participate in motor learning [17] and in particular in learning the timing of motor sequences [39]. The cerebellum module in our model is used to learn temporal combinations of movements encoded in PM. Learning of the connectivity between cerebellum, PM, and M1 modules follow the rules of the DRAMA architecture. DRAMA (Dynamical Recurrent Associative Memory Architecture) is a fully-recurrent neural network architecture which allows learning of time series and of spatio-temporal invariances in multi-modal inputs. A complete description of the network can be found in [8]. In DRAMA, learning is bidirectional. Thus, activation of nodes in the cerebellum after learning reactivates the learned sequences of node activation in the PM, which further activates nodes in the M1 and finally the motor neurons. Below are the DRAMA equations for the unit activation function and the training rules:

Unit activation function

$$y_i(t) = F(x_i(t) + \tau_{ii} \cdot y_i(t-1) + \sum_{j \neq i} G(\tau_{ji}, w_{ji}, y_j(t-1))) \tag{1}$$

F is the identity function for input values less than 1 and saturates to 1 for input values greater than 1 ($F(x) = x$ if $x \leq 1$ and $F(x) = 1$ otherwise) and G is the retrieving function whose equation is given in 2. w_{ji} is the weight of the connection leading from unit j to unit i.

$$G(\tau_{ji}, w_{ji}, y_j(t-1)) = A(\tau_{ji}) \cdot B(w_{ji}) \tag{2}$$

$$A(\tau_{ji}) = 1 - \Theta(|y_j(t-1) - \tau_{ji}|, \epsilon(\tau_{ij}))$$

$$B(w_{ji}) = \theta(w_{ji}, \delta(w_{ij}))$$

$\Theta(x, H)$ is a threshold function that outputs 1 when $x >= H$ and 0 otherwise. ϵ is an error margin on the time parameter. It is equal to $0.1 \cdot \tau_{ij}$ in the simulations, allowing a 10% imprecision in the record of the time delay of units coactivation. The term $\delta(w_{ij})$ is a threshold on the weight. It is $\frac{\max_{y_j>0}(w_{ji})}{\theta(w_{ij})}$. $\theta(w_{ij}) = 2$ in the experiments of Section 2. $\max_{y_j>0}(w_{ji})$ is the maximal value of confidence factor of all the connections between activated units j and unit i, which satisfy the temporal condition encoded in $A(\tau_{ji})$.

Training rules

$$w_{ji}(t) = w_{ji}(t-1) + a \tag{3}$$

$$\tau_{ji}(t) = \frac{\tau_{ji}(t-1) \cdot \frac{w_{ji}}{a} + \frac{y_j(t)}{y_i(t)}}{\frac{w_{ji}}{a} + 1} \tag{4}$$

3. EXPERIMENTS

3.1 The avatar environment

We use Cosimir[33], a three dimensional simulation of two humanoid avatars (see Figure 3). One avatar is the teacher (imitatee), the other is the imitator. Both avatars have the same dynamics. Each has 65 degrees of freedom (DOF): hip-, shoulder-, head-, wrist-, and ankle joints have 3 DOF; elbow-, finger- and knee joints have 1 DOF. Fingers have three joints, except the thumbs which have only two.

We developed a basic dynamic simulation for the avatar, implementing two muscles (flexor and extensor) for each DOF of the joints. Each muscle is represented as a spring and a damper[25]. The external force applied to each joint is gravitation. Balance is handled by supporting the hips; ground contact is not modeled. There is no collision avoidance module. Finally, the internal torques which keep the limbs connected are not explicitly calculated.

The equation of the forces acting on a joint with angle θ is given by:

$$m \cdot \frac{d\dot{\theta}}{dt} = (k_e \cdot E - k_f \cdot F) \cdot \theta + (kp_f - kp_e) \cdot \dot{\theta} - m \cdot g \cdot sin(\theta)$$

where m is the mass of the limb, $g = 9.81[m/s]$ is the gravitation constant, E, F are the amplitudes of the motor neuron signals for the extensor and flexor muscles, $\alpha = 5$ is a factor of conversion of muscles strength resulting from the motor neuron excitation. $k_e = 0.3$, $k_f = 0.3$ are the spring constants of the muscles. $kp_f = 30$ and $kp_e = 30$ are the damping constants of the muscles.

The video data used in the second sequence example in Section 3 were captured using a real time tracking system [41]. The system is limited at the moment to tracking movements of the upper body in the plane only. For this reason, movements of Sequence 1 and Sequence 3 in Section 3 could not be recorded from a human demonstration and were generated in simulation using the imitatee's avatar.

3.2 Results

We present three examples of sequence learning implemented with the two avatars. Sequence 1 is a series of movements involving the shoulders, elbows, hips and knees. Sequence 2 consists of oscillatory movements of the two arms. For this sequence, we used video data of a human demonstration as input. Sequence 3 is a series of movements of the right arm, hand and fingers: reaching, followed by grasping (contraction of all fingers), a wrist rotation and arm retraction with bending of the elbow. Our choice of these sequences was motivated by our wish to demonstrate different aspects of the work, namely 1) that learning of repetitive patterns of movements is possible (Sequence 1); 2) that the algorithm can use real data as visual input (Sequence 2); and 3) that the algorithm allows learning of all limb movements, including precision movements of the extremities (Sequence 3).

Figures 3, 4, and 5 show the intermediate positions of three sequences of movements. Animations of each of the three simulations and the video of the human motion recording can be seen at the following Web site:
http://www-robotics.usc.edu/~billard/imitation.html. Figure 7 shows superimposed activity of the motor neurons of the imitatee (dashed line) and the imitator (plain line) during the imitatee's demonstration and the imitator's reproduction of the movements in Sequences 1 and 3. Fig. 6 shows (top) superimposed plots of the hand and elbow positions during the human demonstration of arm movements and (bottom) the oscillatory activity of the avatar's motor neurons during the replication.

In all three examples, the imitator's reproduction of the sequence is complete (the reader can refer to the video and animations on the above mentioned web site for observing the complete reproduction of the sequence 2). The sequential order of muscle excitation is respected and all steps in the sequences are reproduced. However, the exact timing (the duration of excitation of each muscle) and the amplitude of the excitation is not perfectly reproduced. This is due in our model to the error margin ϵ in Equation 1 which permits up to 10% (in these simulations) imprecision on the measured time delay of units' coactivation. In order for a motor neuron to reach the maximum of its amplitude and hence to activate the muscle, it must receive an external excitation during a sufficiently long time delay. When the duration of activation is too short (due to an imprecise reproduction of the timing of excitation/inhibition of the excitatory M1 neurons), the motor neuron excitation is very weak (as in sequence 1). This problem can easily be overcome by reducing the error margin. However, this decreases

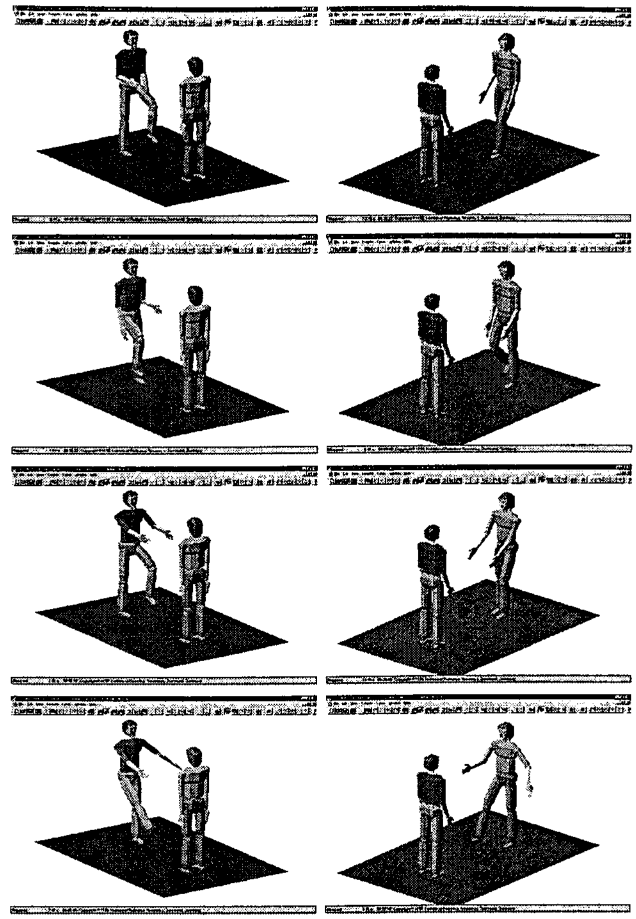

Figure 3: **Snapshots of intermediate positions in the taught sequence 1: The figures show, on the left, the imitatee's demonstration and, on the right, the imitator's reproduction.**

the robustness of the learning in the presence of noisy input and this presents a tradeoff between the two issues. In our previous work on learning of time series with an autonomous robot[8], we proposed an algorithm to adapt the parameters ϵ and θ in equation 1 during the learning. This algorithm will be implemented in our future experiments with noisy data.

Figure 8 shows the building of the connectivity between the PM and M1 during learning of the three sequences (starting with sequence 1 followed by sequences 2 and 3). Initially, some nodes in M1 and PM are already connected. These connections encode the the activation of the spinal oscillatory movements for open-loop walking, the reaching movements (in the two frontal directions) and grasping using each hand. During learning, new connections are created between the PM and M1 to represent new coordinated activation of muscles, resulting from excitation of specific M1 neurons. E.g., Sequence 1 creates connections between the PM and M1 to represent the coactivation of muscles of shoulders, elbows, legs and knees in each of the five steps of the sequence (see Figure 3). Similarly (not shown here), connections within the cerebellum and with the PM are cre-

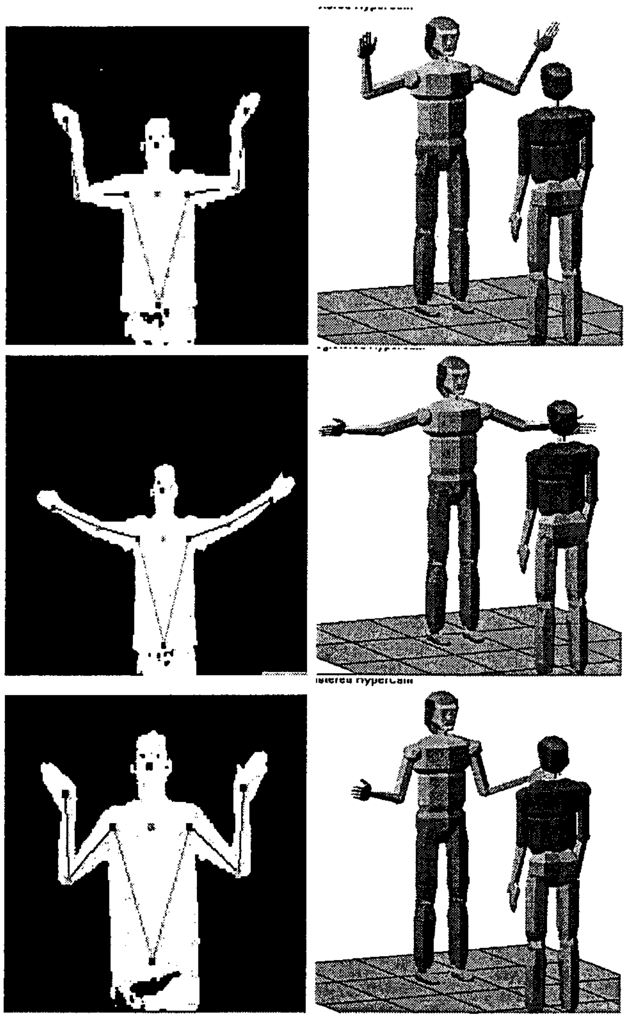

Figure 4: **Snapshots of intermediate positions in the taught sequence 2 (Osculations of shoulder and elbow) of the human demonstration (top) and of the avatar replication (bottom).**

ated to represent the sequential activation of coordinated muscle activation, learned in the PM, that is the time delay between the steps in the sequence.

3.3 Limitations

The architecture we propose gives a very high-level and abstract representation of the functionality and not the detailed structure of the modeled brain areas. An important number of biological features are not represented in our model. Motor control is done without sensory feedback. The mechanical simulation of the avatar is only a first approximation of the human biomechanics and is incomplete. Our model did not address a number of problems in relation to visuo-motor control: 1) the neural processes involved in visual recognition of human shapes, decomposition of limb movements and frame of reference transformation; and 2) learning of fine motor tuning in the presence of noise and in coordination with sensory feedback. Our current and continuing work will address some of these issues, taking inspiration in other models of motor learning, e.g. [1; 20; 37].

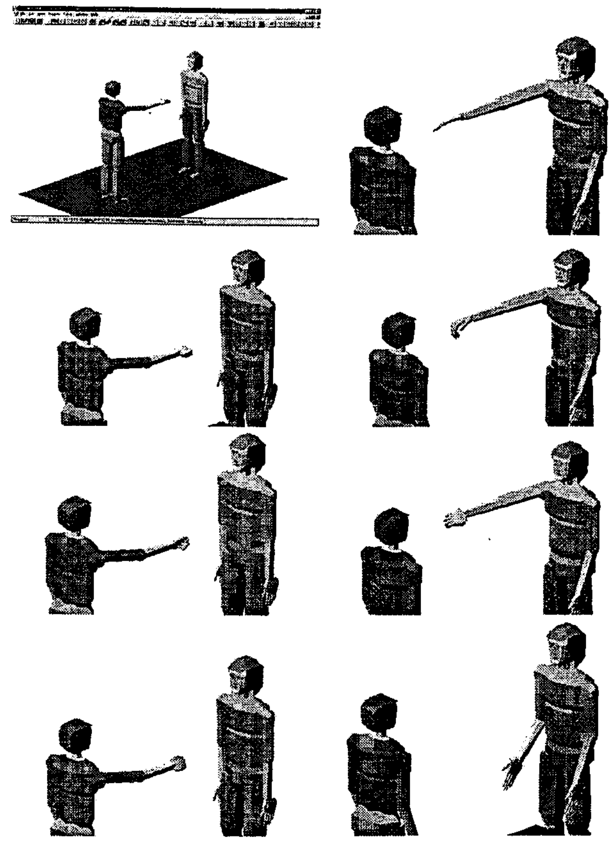

Figure 5: **Snapshots of intermediate positions in the taught sequence 3 (1: reaching a position at about 30 degrees on the right, 2: closing the fingers for grasp, 3: wrist rotation, 4: opening of grasp, retracting of the arm and flexion of the elbow).**

While our modeling of a humanoid avatar's imitation abilities is far from approaching the immense complexity of similar processes in primates, this work might bring some insight to research on imitation: it is the first neural architecture that accounts for the imitation of grasping and reaching movements and which shows that the same architecture could be used for producing imitation of movements of all other joints. As such, it represents a first step towards the development of a complete connectionist model of learning by imitation and towards its implementation on robots.

4. CONCLUSION

This paper presented a biologically inspired connectionist architecture for learning motor skills by imitation. The architecture is composed of modules that are high-level representations of some cortical areas, namely the visual cortex, the premotor and primary motor cortexes, and the cerebellum. It also models the spinal cord as a collection of *evolutionary primitives*, predefined networks of motor- and inter-neurons, i.e., central pattern generators. Learning in the motor cortex and cerebellum results from spatio-temporal associations of multi-modal inputs and is provided by DRAMA, a connectionist architecture for learning time series.

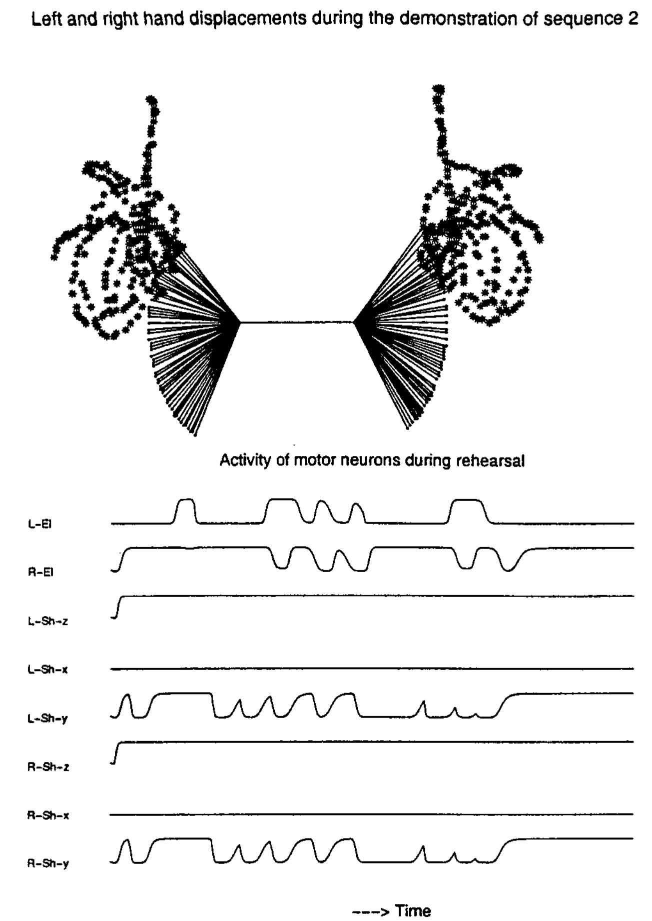

Figure 6: **Top: Superpositions of the hand (star points) and elbow (dots) and shoulder positions during the demonstration. The middle line links the two shoulders together. Bottom: Activity of motor neurons of imitator during repetition of sequence 2. L-Sh-x/y/z is the motor neuron for left shoulder extensor for direction x, y and z respectively.**

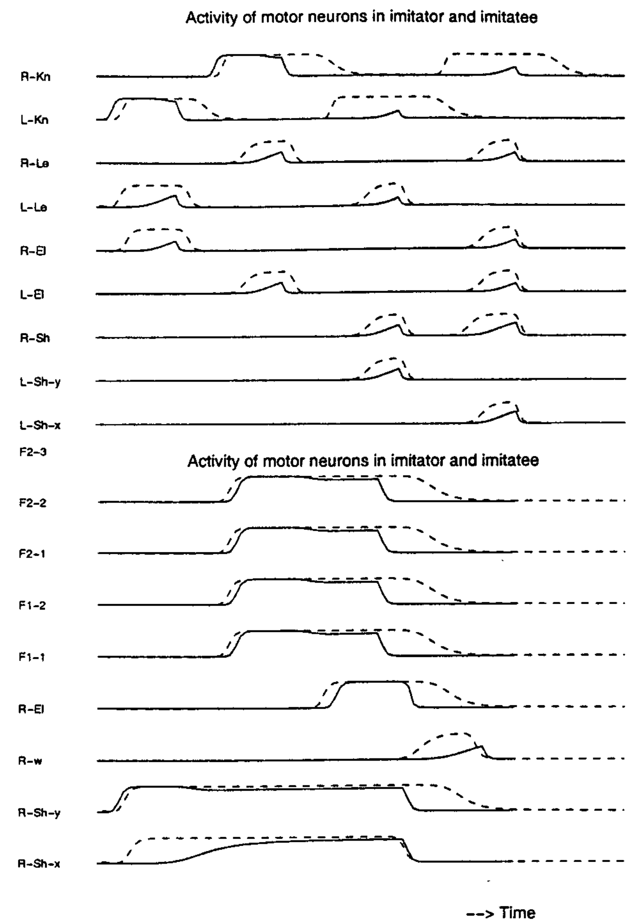

Figure 7: **Activity of the motor neurons in imitator (plain lines) and imitatee (dashed lines) in sequences 1 and 3. R-kn is the motor neuron of the flexor of the right knee. L-Sh-x is the motor neuron of the extensor of the left shoulder in the direction x. F1/2-1/3 correspond to the flexors of the two first fingers and their corresponding joints. The thumb, finger 1, has only two joints.**

The architecture was validated in a mechanical simulation of a pair of high DOF imitator-imitatee humanoid avatars for learning three types of movement sequences. These experiments showed that the architecture can learn 1) combinations of movement involving all joints, including the finger joints, 2) complex oscillatory patterns, and 3) sequences with variable timing, as is the case with the human demonstration.

Our further work will gradually improve the biological plausibility of each of the architecture's modules. We are currently improving the mechanical simulation of the avatars in view of its upcoming implementation in a humanoid robot.

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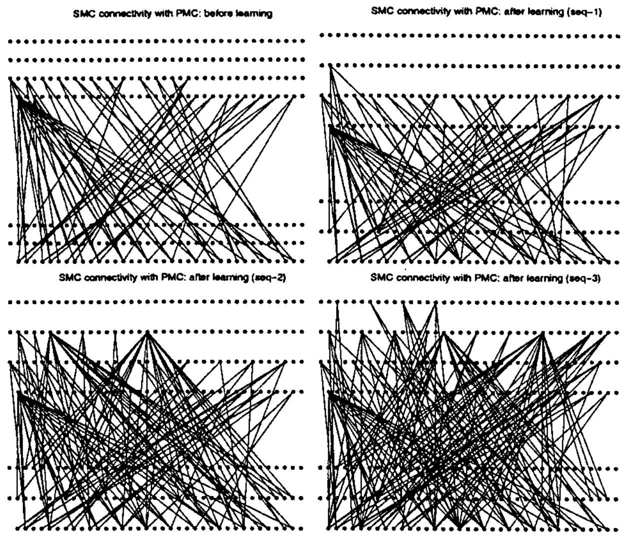

Figure 8: Development of the M1-PM interconnectivity during learning of the three sequences. The set of nodes on bottom of each figure correspond to that of the M1 and those on top of each figure correspond to the PM.

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