A Neural Network Generating Force Command for Motor Control of a Robotic Arm

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1 Introduction

Brain can be considered as a system that generates motor commands for a given perception. Understanding how movement is generated and controlled still represents unanswered questions [7]. In [3], an arm controller that learns visuo-motor associations can let emerge immediate and deferred imitation. Visual input activates some attractors in the motor space that are used to generate a speed command to control the arm. In this architecture, visual information gives the motor position to be reached. In [2], a Gaussian Mixture based arm controller can enable a robot to reproduce a sequence of gestures that was demonstrated during a first phase. In [4], a similar Gaussian Mixture model is compared with a neural network based sequence learner that uses fast learned state/action couples [5]. The comparison is done on a simple navigation task for which the neural network is designed. The Gaussian Mixture model was adapted for navigation. A left over issue is whether and how such a neural network architecture could be adapted for arm control in the motor space. These considerations about arm controlling lead to looking for a model that could work with both visuo-motor associations and motor state/action paradigms. Several issues are raised as how the attractors can be encoded, what the parameters of the motor controller are and how they should be controlled by the system. Some tests on how the attractors can be constructed have led to a model that defines independent attractors for each articulation of the robot. Biological data give us hints about answers to some of the raised questions. The basic biological motor action is to contract muscles and thus to perform force control of the position of the limbs. As we aim at studying how high level and low level aspects of motor control can be interconnected, we developed a neural network architecture that generates force commands. In this architecture, the higher level structures converge on an internal representation of the motor position that is provided to a homeostatic low level force controller. Some part of the architecture is tested on a real robot in a simple experiment as the reproduction of a temporal sequence of gestures demonstrated during passive manipulation. The influence of some of the parameters that determines the robot behavior reinforces the idea that higher level structures should have specific accesses to the low level control.

2 A neural network architecture generating force signals for motor control

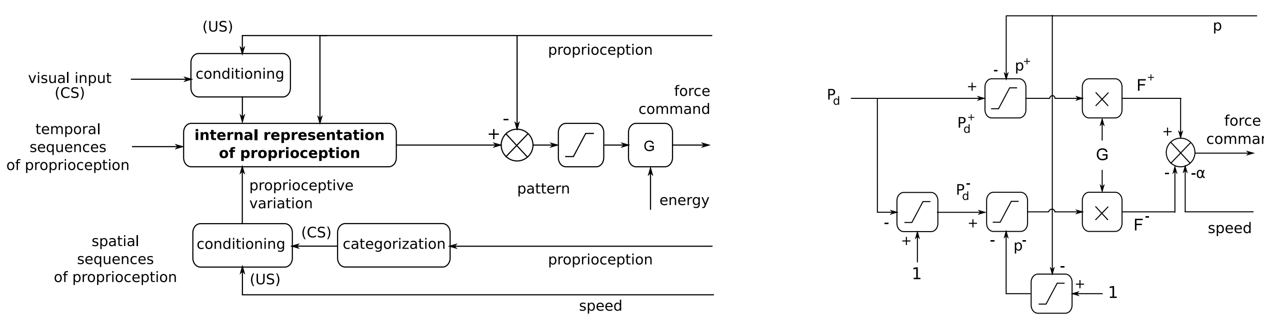


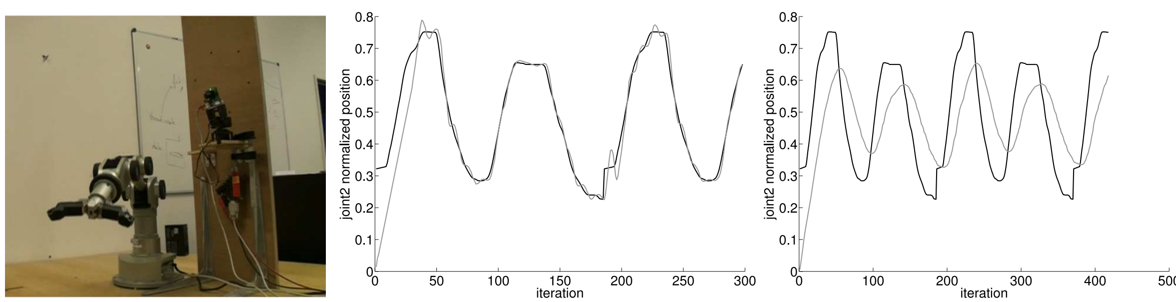
Figure 1: *Left:* Global architecture. The internal representation of proprioception can be built from various structures: visuo-motor conditioning, temporal sequences, spatial sequences etc. *Right:* Force control part of the architecture.

The force command generator model follows some of the hypothesis developed in the VITE-FLETE model [1] as they are biologically relevant and enables to realize a minimal motor controller. However, the current model is biologically less accurate as it does not focus exclusively on the modelization of the biological data but it also aims at being easily adaptable for motor control in real robots. The gobal architecture of the system (Figure 1) has been designed as a primary loop that provides an homeostatic control of an internal representation of the proprioception. Perturbation on the internal representation can generate the movements of the arm. As shown in Figure 1, the different channels $^+$ and $^-$ correspond to the channels of agonist and antagonist muscle proprioception. The force activation signal that is generated for each channel depends on the desired internal proprioception $P_d^{+/-}$, the current proprioception $p^{+/-}$ and a non-specific energy gain G. This energy gain is part of the Pattern-Energy Factorization used in VITE model [1]. It relies on biological data that displays the non-specific influence of the Globus Pallidus from the Basal Ganglia on the strength of the movements. We introduce a fluid friction force as a mechanical constraint from the muscle. The forces are thus the voluntary agonist/antagonist forces $F^+ = G \cdot [P_d^+ - p^+]^+$ and $F^- = -G \cdot [P_d^- - p^-]^+$ and the friction force $f_v = -\alpha \cdot v$ with $[x]^+ = 0$ when $x < 0$, x when $0 \leq x \leq 1$ and 1 when $x > 1$. The relation $p = p^+ = 1 - p^-$ links p^+ and p^-. According to the equation of classical dynamic $m \cdot \dot{p} = F$, the continuous dynamical equation of the system can be simplified in (2). This neural network force generator is equivalent to a second order "mass damping" dynamical system for the control of one articulation. This kind of dynamic motor control has been used with success in robotics in the reproduction of demonstrated tasks [6],[2].

$$F = G \cdot [P_d - p]^+ - G \cdot [p - P_d]^+ - \alpha \cdot \dot{p} \tag{1}$$

$$\ddot{p} = \frac{G}{m} \cdot (P_d - p) - \frac{\alpha}{m} \cdot \dot{p} \tag{2}$$

3 Implementation on a robot and reproduction of a demonstrated gesture



(a) (b) (c)

Figure 2: *a:* The robot is composed of a Katana electrical arm from Neuronics AG and a monocular camera mounted on a pan-tilt servo motor setup. In this experiment, only the arm was used. *b:* The value of the desired position from the recorded trajectory (black) and the position in reproduction (grey) are compared for one joint of the arm. With a high energy gain, there are overshoots and oscillation. Here, $G = 20$ and $\alpha = 1$. *c:* A smaller gain enables to have a smoother trajectory. It also induces a phase shifting and a decrease of amplitude in the variation of position. Here, $G = 3$ and $\alpha = 10$.

This architecture has been implemented in a robotic setup (Figure 2(a)) that is made of a Katana robotic arm from Neuronics AG with 6 degrees of freedom and a monocular camera mounted on a pan-tilt servo motor setup. The industrial Katana arm is designed for position control possibly using spline trajectories. An acceleration control is not possible on this arm. A speed control can be realized by modulating the maximum speed of variation of the joint angle while moving to extremum positions. There is no direct access to the real joint speed of the arm. The neural network architecture has been modified to provide speed commands that are generated from the integration of the force signal and an estimation of the speed. The estimation is based on the time derivative of the position of the joints. In the framework of the french project INTERACT, a hydraulic robot is going to be built so that the models can be tested without these limitations.

The capabilities of the motor controller of the robot were tested in the reproduction of a passive demonstration. In a first phase, the robot is set in passive mode ie. a human can manipulate the arm. The movement of two loops is shown to the robot. The recorded data are then provided to the motor control as the desired position P_d. Figure 3 plots together the demonstrated trajectory and the reproducted trajectory in the 3D Cartesian space. According to the parameters of the system, the reproduction can be close to the original trajectory. If the energy gain G increases, the arm tries to follows each variation of the demonstrated trajectory. The joint position makes some overshoots and oscillates around the desired position. If the gain decreases, the trajectory becomes smoother, the system does not try to follow each variation of the demonstrated trajectory (Figure 2). The trajectory is also smaller than the demonstrated trajectory even if it respects the topology of the demonstration: two slightly shifted loops. There is no perfect value for the gain G as having a small and smooth trajectory can be as interesting as having an accurate reproduction of the demonstration. The evaluation of the movements can only depend on other factors like a reinforcement signal.

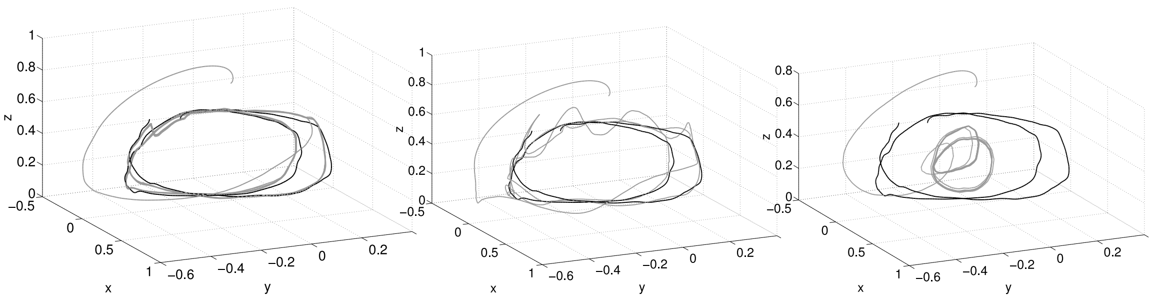


Figure 3: Trajectory of the end effector of the arm in the 3D Cartesian space. The black line is the demonstrated trajectory that corresponds to two successive loops. The grey trajectory is the reproduction done by the robot. The reproduction has been done with different values for the energy gain G and the fluid friction coefficient α. *Left:* $G = 20$,$\alpha = 10$. *Center:* $G = 20$, $\alpha = 1$. *Right:* $G = 3$, $\alpha = 10$.

4 Perspectives

This work raises the question of the control of the parameters of the low level controller. Self-evaluation of the action or social interaction may provide a feedback to determine the adequate values of the parameters, but it is also possible that they should be learned as well with the movement trajectory.

In the presented experiment, the robot is reproducing a trajectory that was entirely recorded. This is one possible way of using this architecture. This system will also be tested with the visuo-motor associative architecture to check the property of emergence of imitation is still present. The state/action paradigm will also be implemented with this system to study the analogy between arm movement planning and navigation planning. Future work will continue to take inspiration from biological data to study the structures that can be used and also how they can be merged all together to increase the ability of real robots.

Acknowledgement

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References

[1] Daniel Bullock and Stephen Grossberg. *Vite and Flete: Neural Modules for Trajectory Formation and Postural Control*, volume 62 of *Advances in Psychology*, book chapter/section 11, pages 253–297. Elsevier, 1989.

[2] Sylvain Calinon, Florent D'halluin, Darwin G Caldwell, and Aude Billard. Handling of multiple constraints and motion alternatives in a robot programming by demonstration framework. In *Proceedings of 2009 IEEE International Conference on Humanoid Robots*, pages 582–588, 2009.

[3] Antoine de Rengervé, Sofiane Boucenna, Pierre Andry, and Philippe Gaussier. Emergent Imitative Behavior on a Robotic Arm Based on Visuo-Motor Associative Memories. In *IEEE/RSJ International Conference on Intelligent Robots and systems (IROS'10)*, pages 1754–1759, 2010.

[4] Antoine de Rengervé, Florent Dhalluin, Pierre Andry, Philippe Gaussier, and Aude Billard. A study of two complementary encoding strategies based on learning by demonstration for autonomous navigation task. In *Proceedings of the tenth international conference on Epigenetic Robotics*, pages 105–112, 2010.

[5] Christophe Giovannangeli, Philippe Gaussier, and G Désilles. Robust Mapless Outdoor Vision-based Navigation. In *IEEE/RSJ International Conference on Intelligent Robots and systems*, Beijing, China, 2006. IEEE.

[6] Auke Jan Ijspeert, Jun Nakanishi, and Stefan Schaal. Learning attractor landscapes for learning motor primitives. In *advances in neural information processing systems 15*, pages 1547–1554. cambridge, ma: mit press, 2003.

[7] Daniel M. M Wolpert, Zoubin Ghahramani, and Randall R Flanagan. Perspectives and problems in motor learning. *Trends in cognitive sciences*, 5(11):487–494, November 2001.