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A Model of Acquisition of Discrete Bimanual Coordination Skill for a Humanoid Robot *

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1. Introduction

The development of coordination between limbs is one of the principal factors of skills acquisition in humans. This process starts from early stages of child's development and continues during the whole life. Particularly bimanual coordination plays a crucial role in routine life, making possible wide range of manipulation activities.

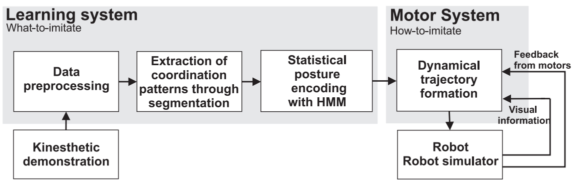

Figure 1: The model overview.

There are several motivations for adapting the concepts of bimanual coordination originating in human motor control to humanoid robotics. Amongst the most important reasons we can highlight are the following: 1) guarantee adequate performance of humanoids in dual-arm tasks; 2) make their movements more effective and natural-looking for humans; and 3) provide the basis for more complex forms of inter-limb coordination, e.g., quadro-manual coordination between robotic/human collaborators in the case of joint task execution.

Robot Programming by Imitation proved to be a useful methodology for transferring various skills from a human to a robot through direct interaction. Although learning of manipulation tasks has received a lot of attention in this framework, none of the works address the problem of inter-limb coordination explicitly by extracting high-level features of coordination.

This work attempts to shed some light on what are the main aspects of bimanual coordination to guarantee satisfactory robot's performance in simple manipulation tasks and how these aspects can be learnt. We investigated two types of coordination constraints: spatial constraints (e.g. two arms must adopt a specific spatial relation to one another) and temporal constraints (two arms must synchronize and should reach a target position at the same time). Satisfactory performance was deemed achieved when the robot managed to go through the set of required postures, adhering to a proper timing. The robot was, however, free to depart significantly from the arm trajectories shown during the demonstration in between each of these postures.

Our model is inspired by the research in bimanual coordination in human movement science. We hypothesize, analogously to the rhythmic case [2], that for discrete goal-directed movements the relative position between two arms is an appropriate candidate for the collective variable. The collective variable contains information about coordination patterns – spatio-temporal constraints typical for a certain movement and thus governs cooperative behavior of two arms. Stable positions (attractors) in this variable's state space represent stable coordinated postures (coordination patterns) that must be reached in sequence to perform a task.

2. Model Overview

The proposed model is composed of two principal systems (see fig. 1): a *learning* and a *motor system*. A *learning system* accounts for building a model of a observable skill. The model of a skill consists of a set of spatial constraints – stable relative postures between the two end-effectors and temporal constraints - a mean postures' duration and a time of their emergence.

The model is built automatically from trajectories recorded during kinesthetic demonstrations of a task (a human operator moves the robot's arms). First, the data is processed by resampling and aligning. Then the relative position between the two end-effectors is segmented to extract the stable postures and associated with them temporal constraints. In general, the set of postures after segmentation contains spurious postures, thus we encode the sets obtained after several demonstration with Hidden Markov Models to get the relevant set of the postures. Each single hidden state represents a stable posture with its time properties.

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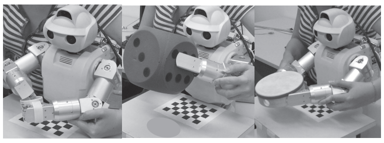

Figure 2: Set-ups of 3 experiments. *Tea task*: put the piece of sugar into the cup. *Cube task*: grasp the cube, lift it, and put it on top of the pedestal. *Tray task*: grasp the tray with two arms, lift it, and move it forward.

Once built the model of a skill is fed into a *motor system*. The *motor system* generates movements' trajectories with respect to the coordination constraints and ensures synchronization between the two arms. In previous works of ours [3] a dynamical hybrid controller that generates uni-manual reaching movements in robots was proposed. It is based on Grossberg's computational model of human reaching movement [1]. Here we extend this controller for both arms and add constraints that guarantee reproduction of a learnt task.

The hybrid controller is described by the following set of differential equations (here we present only the equations for the right arm, as the equations for the left arm are identical):

$$\ddot{\theta}_t^{R,d} = \alpha_\theta^R(-\dot{\theta}_t^R + \beta_\theta^R(\tilde{\theta}_i^R - \theta_t^R)); \quad (1)$$

$$\ddot{x}_t^{R,d} = \alpha_x^R(-\dot{x}_t^R + \beta_x^R(\tilde{x}_i^R - x_t^R)); \quad (2)$$

where θ_t^R is a posture of the right arm in the joint space; x_t^R is a end-effector position in the Cartesian space, upper index "^{d}" refer to "a desired position" that is corrected each time step to satisfy constraints, $\tilde{\theta}_i^R, \tilde{x}_i^R$ are current target positions (mapping of spatial constraints into the attractors of the dynamical systems (1)-(2)); $\alpha_x^R, \alpha_\theta^R$, $\beta_x^R, \beta_\theta^R$ are empirically derived constants.

To endow the *motor system* with the desired behavior (spatio-temporal coordination) and guarantee the consistency between robot's end-effectors position and arms' postures, we apply the following constraints on the system (1)-(2):

1) The robot's body constraints ensure consistency between generated postures and end-effector positions:

$$x_t^R = K(\theta_t^R);$$
$$x_t^L = K(\theta_t^L); \quad (3)$$

where $K(.)$ is the forward kinematic function of an arm.

2) Spatial constraints preserve coordination patterns learnt from the demonstrations at given stages of a movement:

$$\dot{x}_t^R - \dot{x}_t^L = 0 \quad (4)$$

We then solve the constraint optimization problem to find the values $\{\theta_t^R, x_t^R, \theta_t^L, x_t^L\}$ in the neighborhood of the desired values $\{\theta_t^{R,d}, x_t^{R,d}, \theta_t^{L,d}, x_t^{L,d}\}$ that satisfy the above mentioned constraints.

3) Time constraints guarantee the synchronization of the arms (adaptation of one arm's velocity to another one) and the timing of the whole movement. These constraints are expressed in the form of a specific procedure for computing the parameters α, β of the controller:

$$\alpha_x^R = 2\frac{log(\frac{A_x^R}{\Delta_x^R})}{\Delta t}; \beta_x^R = \frac{4\frac{\pi^2}{\Delta t^2} + \alpha^2}{4\alpha}; \quad (5)$$

where A_x^R, Δ_x^R are respectively the amplitude and the precision of a movement, Δt is its mean duration.

3. Experiments

We conducted three experiments to illustrate our approach and test it (see fig.2). We were interested in testing both abilities of the system to learn manipulation tasks as well as abilities of the motor system to reproduce tasks and adapts to external perturbations. Fig.3 shows the result of reproduction of the *Cube task* (grasp the cube and lift it up, and put it on top of the marked pedestal. The robot had to adapt to both changed position of the cube (synchronization) and changed position of pedestal (spatial coordination)), the trajectories of the two arms are projected into an axial plane.

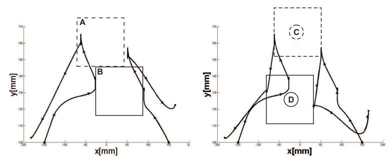

Figure 3: Reproduction of the *Cube task*. Left: the robot tries to grasp the cube while its position is changed from A to B and it simultaneously adapts both arms to grasp the cube at position B. Right: while the robot is carrying the cube, the position of the pedestal is changed from C to D, the robot puts the cube on the new location preserving the relative position between its arms.

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