A MODEL FOR LEARNING HUMAN REACHING-MOVEMENTS

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Abstract - Reaching-movement is a fast ballistic voluntary movement towards a given target. The main characteristics of such a movement are straight line and a bell shape speed profile. In this work a mathematical model for the control of the human arm during reaching-movement is presented. In analyzing the model performance in mimicking a Two Degrees Of Freedom (2DOF) human movements, the following results were observed: (I) A nonlinear muscle model yields smooth movements with zero terminal velocity in response to simple control signals. This conclusion agrees with the general idea that the motor control is a combination of muscle dynamics with nervous control. (II) A typical reaching-movement can be performed with a typical rectangular excitation to the muscles, and in this way the dimension of the control problem is reduced.

I. INTRODUCTION

We define a reaching movement as a fast voluntary movement of the arm from a starting point to a given target. In fast movement feedback control cannot be effective. The proper control scheme for such a movement is a forward control and that is the reason such a movement is called a ballistic movement. The salient characteristics of such a movement are a straight line path and a bell shaped speed profile. Flash & Hogan proposed the minimum jerk model that explains these features as a result of optimization criteria to minimize acceleration change [1]. The present work support the suggestion that these features are the result of the arm dynamics, and not of neural optimization. Many control schemes involve a model of the arm. Jordan, for instance, suggested a controller and a forward model to propagate the error through it in order to train the controller [2]. These works shows a typical movement, but the control schemes are complicated since it needs to generate a complete model of the plant and to propagate the error for each movement through movement time. We would show here that for a more biologically non-linear muscle model, the same typical movement can be learned by a much simple controller, without the need to propagate the error through time and to train a net to produce the whole trajectory.

II. THE MODEL

A six muscle model was used recently to create a model of the 2DOF arm [2,3]. This model Includes the kinematics and dynamics of a 2DOF manipulator. The muscle model is a mechanical model that is a simplification of the model in [4]. where a viscosity element B represent the relation between force and velocity from Hill's model. This relationship was assumed, for simplicity, to be a constant in several models [2,3] in order to get a linear muscle model. In the present work the full, non-linear model is used, and this property has turned out to provide the desired performance with a simple control signal. For detailed description of the arm model see [5]. The neuronal excitation to the muscle can be described as rectangular pulses to the agonist and antagonist [6]. We adapt this simplification and use rectangular pulses as excitations to the muscles. Each couple of muscles (flexor and extensor) receive two pulses that come one after the other. A vector of five parameters define these two pulses. The parameters are [Amp, RA, Tall, Tcoact, RT]. see Fig .1.

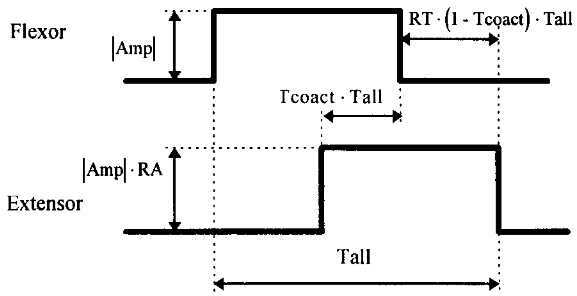

Fig .1. The pulses shape and the parameters that define it. When Amp<0 the flexor proceed the extensor.

Since the reaching movement is a ballistic movement, only the final state of the arm is used for training and adaptation. This idea, to mask the sensory information during the movement and use it only at the end of the movement has a physiological base in the cerebellorubrospinal system [7]. A schematic description of the CNS control model for reaching movement is given in Fig. 2. The target is chosen in the cortex and is the input. According to the target, a set of parameters which define the excitation to the muscles is chosen by the Artificial Neural Network (ANN). The Pattern Generator (PG) generates the appropriate pulses to each muscle and these commands go through the spinal cord to the muscles and generate the movement. At the end of the movement, and only then, the sensory information is analyzed and the error is used to change the weights in the ANN that generate the parameters. These changes would effect the next neural control pulses and though the following movements. The detailed learning algorithm is described and analyzed in [5].

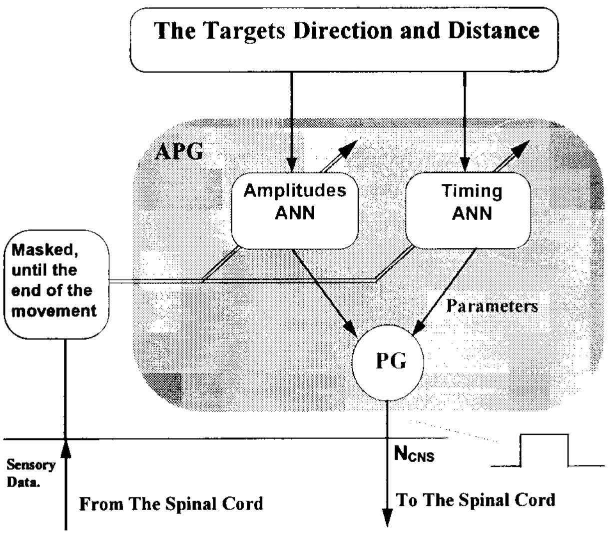

Fig. 2. The CNS model: Ncns is the activation command to the muscles. There is a PG for each muscle, that creates a rectangular excitation according with the timing and amplitudes parameters which are the output of the ANN. The input to the ANN is the desired target. The sensory information is available only at the end of the movement and only then the ANN is updated.

III. RESULTS

The performance of a linear model and a nonlinear model in response to the rectangular control pulses is seen in Fig. 3. The arm with the linear muscle model, in response to pulses, doesn't stop and have an overshoot and an oscillatory behavior at the end of the movement, while the nonlinear muscle can evoke a fast movement with a smooth stop. This example is a representative one of the improved arm performance with nonlinear muscle model under the assumed conditions.

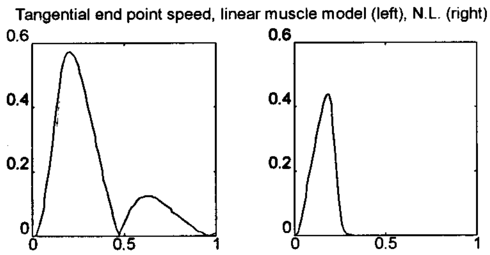

Fig. 3. A comparison between the speed profile of the end point of an arm with a linear muscle model (left) and a nonlinear muscle model (right) as a result to the typical rectangular activation of the muscles. One can see that only for the non-linear muscle model there is a bell shaped speed profile with smooth stop.

In the present work the nonlinear property was necessary in order to create a fast movement with a smooth stop using the simple rectangular excitation. The control of rectangular pulses is much simpler than the creation of a complex profile of excitation during the movement. That is the reason why it is suggested that the nonlinearity in the muscle may play a functional role to allow the use of such simple control signals. The algorithm of learning and performing a reaching-movement was simulated for one and for two joints, for detailed description see [5]. The results of such a simulation are given in Fig. 4. where one can see that the arm reaches the target (in the circle), and the speed profile is a smooth bell shaped profile.

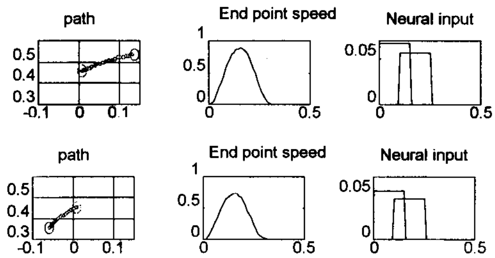

Fig. 4. One joint learning. Two examples from the learning set. The path of the end-point and the initial and final position are at the left. The speed profile is in the middle. The muscles' excitation signals are at the right.

IV. DISCUSSION

The main suggestion of this work is that a typical reaching movement of an anthropomorphic arm can be achieved with simple rectangular activation pulses to the muscles, without the need for a detailed inverse model and without the need for trajectory formation. The nonlinear properties of the muscles are essential to achieve this simple control.

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