A NON-LINEAR, COMBINED FEEDBACK AND FEEDFORWARD, LEARNING CONTROL MODEL FOR MULTIPLE DEGREES OF FREEDOM MUSCULO SKELETAL SYSTEMS, APPLIED TO THE CONTROL OF A HUMAN ARM MO DEL

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ABSTRACT - The focus of this paper is on the development of models of the control of musculoskeletal systems by the central nervous system (CNS). A neuromuscular controller is a non-linear system and combines feedforward and feedback control modes. In this study the controller is represented by a neural network which learns to generate proper neural control signals for all kinds of movements. Results are shown for the control of a human arm model with two degrees of freedom. It is argued that this control methodology may be extended to more complex musculoskeletal systems.

INTRODUCTION

Computer simulation is an indispensable tool to be able to understand the complex interactions between a skeletal system and its muscles, in particular for systems with as many degrees of freedom as the shoulder mechanism. Given an adequate musculoskeletal model typically a forward optimisation procedure is applied to calculate the neural input signals for the multi-muscle, multi-joint co-ordination of a skilled movement. Application of such an optimisation procedure assumes that the optimal neural control signals can in some way be generated by the central nervous system (CNS). In reality, the CNS is of course not a perfect optimal control system which has complete and direct information of the musculoskeletal system and the external forces acting on it, but it is a complex control system with feedback as well as feedforward control modes and with delayed sensoric information. In this paper a general model of a neuromuscular control system is discussed which represents a step which goes beyond forward optimisation only.

What are some of the most important characteristics of a neuromuscular control system?

- It is a non-linear control system, which is necessary to have good control of a musculoskeletal system with prominent non-linear features in the dynamics of the muscles as well as the skeletal system.
- It has a feedforward or open loop control mode. Ideally, the feedforward control represents the inverse dynamics of the musculoskeletal system and its interaction with the environment. It is highly unlikely that the feedforward control can represent these inverse dynamics aspects perfectly, because of the complexity of the inverse dynamics of the musculoskeletal system and the lack of complete a priori knowledge of the external forces.
- It contains feedback or closed loop control to compensate for external disturbances and for errors in the internal model of the inverse dynamics, i.e. the feedforward control.
- It typically has to deal with multiple degrees of freedom.
- It typically has to deal with actuator redundancy, meaning the control system has to make a proper choice which muscles or muscle parts should be actuated for a certain task.
- It is an adaptive control system, since it can learn by experience.

In this paper a model of a neuromuscular control system which shares these characteristics with the CNS is discussed.

NEUROMUSCULAR CONTROL SYSTEM

The scheme of the neuromuscular control system which was employed in this study is shown in Figure 1. It consists of a motor control system which generates the neural control signals u, a muscular system which generates muscle forces F and a skeletal system. The movements of the skeletal system (y) are caused by the muscle forces F and the external forces F_e. The control decisions of the motor control system are based on a desired trajectory y_{ref} and on the feedback signals F, F_e and y. The feedback signals are only available to the motor control system are a delay τ, which was chosen 50 [msec]. The muscle forces F may be provided by Golgi tendon organs, external forces by pressure receptors in the skin, and length and velocity data by muscle spindle organs. It is assumed that both the reference y_{ref} and the achieved trajectory y are specified in joint coordinates. This assumption is in accordance with experimental results of Shadmehr and Mussa-Ivaldi (1994) which suggest that 'planning and control of reaching movements are undertaken by fundamentally different computational elements in the nervous system: while the planning trajectory for the arm is in an extrinsic frame of reference, the model for the dynamics of the task is in an intrinsic frame.'

The non-linear, adaptive motor control system with interconnected feedback and feedforward control modes is represented by a neural network. The neural network is specified by:

$$u(t) = \Gamma_2\left(W_2\Gamma_1\left(W_1 s(t) + b_1\right) + b_2\right) \qquad \text{(Eq.1)}$$

with s(t) the network input vector, u(t) the network output vector, W_1 and W_2 weight matrices, b_1 and b_2 bias vectors, and Γ_1 and Γ_2 arrays of sigmoidal functions γ:

$$\gamma = 1/(\exp(-x)+1) \qquad \text{(Eq. 2)}$$

The input vector s(t) consists of the reference and feedback signals. The output vector u(t) represents the neural input signals of the muscles. Appropriate input-output behaviour of the neural network can be attained by choosing suitable weight matrices and bias vectors. This neural network structure is a useful tool for modeling a motor control system, because it can represent a wide range of non-linear functions and does not require any prior specification except for the size of the network. There exist numerous articles on neural networks, a good introduction to this subject may be found in the book of Haykin (1994).

The capabilities of the discussed neuromuscular control scheme will be illustrated for a model of the human arm for movements in the horizontal plane. Figure 2 shows a schematic drawing of the musculoskeletal system. The skeletal system consists of two links and two revolute joints which represent the upper arm and the forearm, respectively. The skeletal system is moved by four (lumped) monoarticular muscles and two biarticular muscles. An external force may act on the end of the forearm, i.e. on the hand assuming a locked wrist. The applied muscle model is a simplified version of the model proposed by Winters and Stark (1985). It represents excitation-(de)activation dynamics and length and velocity dependent contractile forces. A more extensive description of the applied musculoskeletal system as well as of the motor control system may be found in Stroeve (1996).

How can the parameters of the motor control system be tuned so that desired movements of the arm are achieved? Tuning of the motor control system is performed in a way which is similar to the way humans learn to move: just try to move and learn from your mistakes. The motor control

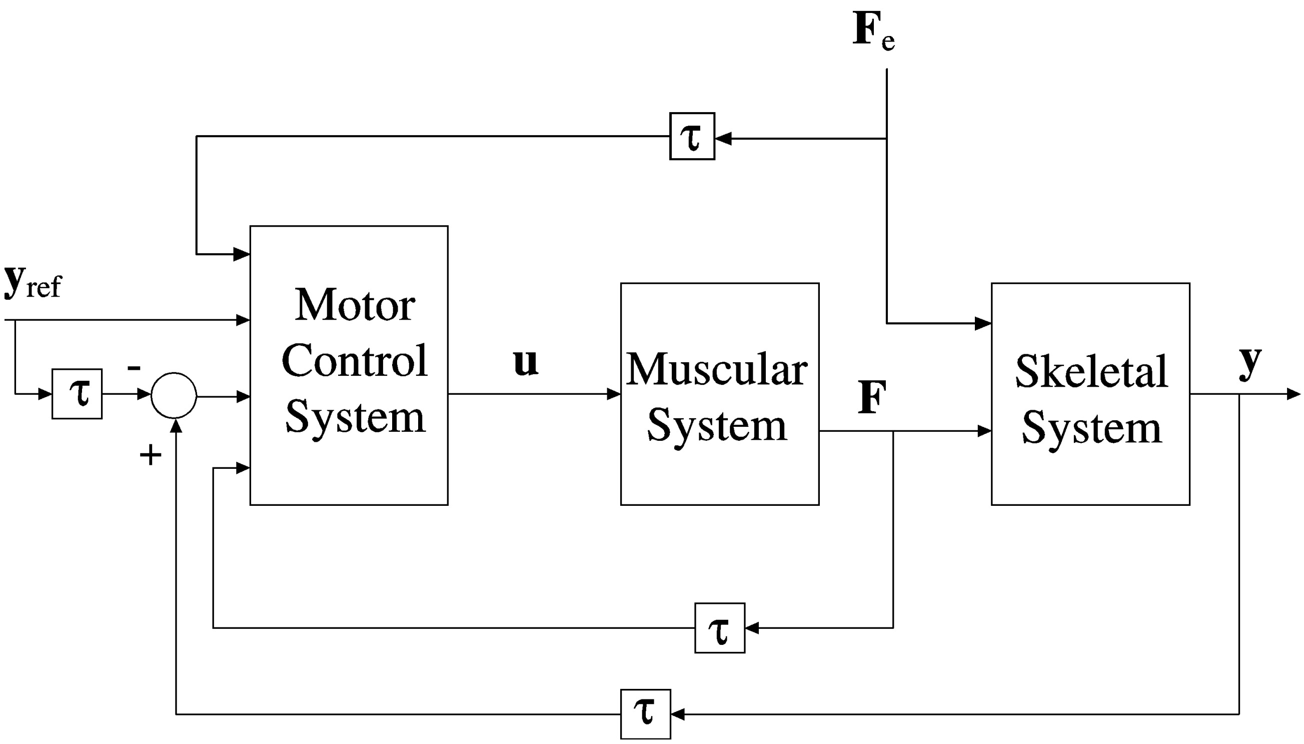

Figure 1- *Structure of neuromuscular control system (explained in text).*

system is trained by trying to perform all kinds of movements (fast and slow, short and long) through the workspace of the arm. After a movement has been completed, it is evaluated and the motor control system is adapted such that its performance increases. In particular the weights of the network are adapted such that a cost function J is minimised:

$$J = \frac{1}{T}\int_0^T \sum_{i=1}^{n} \left(\theta_i(t) - \phi_i(t)\right)^2 + \alpha \sum_{j=1}^{m} V_j a_j^2 \Big\} dt \quad \text{(Eq. 3)}$$

with T an evaluation time, θ_i a joint angle, ϕ_i a reference angle, n (=2) the number of joints, α a weighing parameter, a_j the activation and V_j the muscle volume of muscle j and m (=6) the number of muscles. Minimisation of J thus achieves low errors between the reference and achieved joint angles as well as low muscular activation. It was shown by Happee (1992) that realistic predictions of muscle forces can be attained by applying a load sharing criterion which weighs the quadratic active state with the muscle volume. In Stroeve (1996) the learning procedure is discussed more extensively.

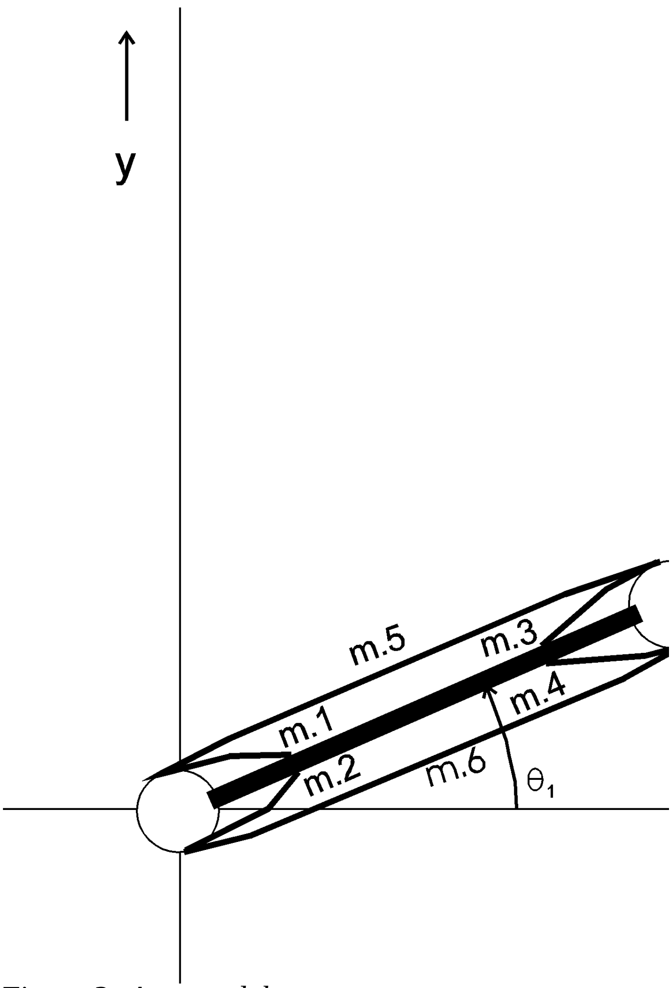

Figure 2- *Arm model*.

CONTROL PATTERNS DURING GOAL DIRECTED MOVEMENTS

After the motor control system has been trained it can instantaneously generate proper neural input signals for all kinds of movements. In order to move the system through the whole workspace at a variety of speeds a long training period was applied. Learning is fastest during the first few minutes, but the average costs typically keep decaying slowly for prolonged learning times. The results shown here were obtained after six hours computation on an Indigo II Silicon Graphics Workstation.
As an illustration of the achieved control behaviour Figure 3 shows the control of fast movements for eight movement directions: the task is to move the hand over a distance of 15 [cm] in 250 [msec]. Notice that apart from some overshoot the desired trajectories are followed fairly well. For such fast movements overshoot is also typically found for real human movements (see e.g. the experimental results of Happee (1992)). The neural input signals and the resulting joint trajectories for one movement direction are shown in Figure 4. As previously noticed there is some overshoot of the joint angles, but the reference angles are almost reached after 0.5 [s]. Figure 4 further shows that there is a triphasic activation pattern for all muscle pairs, similar to typical EMG-patterns for the control of fast movements. These triphasic neural input patterns induce acceleration and deceleration of the joints. A more extended analysis of the control of fast as well as slow movements is given in Stroeve (1996).
One of the key characteristics of a neuromuscular control system is its adaptability to new environmental conditions. Shadmehr and Mussa-Ivaldi (1994) studied the learning behaviour of humans who moved there hand in an unexpected, ‘strange’ force-field. Movement in such a force-field requires the formation of a representation of the dynamics of such a task. The learning process described in this paper is well able to control the arm model in force fields as described by Shadmehr and Mussa-Ivaldi (1994). This learning procedure can therefore be employed to analyse the adaptation of the control behaviour during learning, which is impossible with a conventional optimisation procedure.

DISCUSSION

In the Introduction requirements for a valid model of a neuromuscular control system were formulated: (1) nonlinearity, (2) feedback & feedforward control, (3) learning control. The proposed control structure fulfils those requirements. It has been shown that neural input signals similar to EMG patterns are attained during fast arm movements. It follows from a further analysis in (Stroeve, 1996b) that muscular activations as a function of movement direction and neural input signals during slow movements are similar to experimental results reported in the literature. Realistic results can thus be obtained with the proposed neuromuscular control model.
The simulation results with the two degrees of freedom arm model shows that the control system can handle actuator redundancy, actuators acting on several degrees of freedom, interaction torques between the degrees of freedom and non-linear dynamics in general. Since the main phenomena which complicate the control of large musculoskeletal systems with multiple degrees of freedom are (thus) already present in the discussed arm model, there are no principal objections which hinder application of the control structure to large musculoskeletal systems.

A practical problem which may hinder the control of large musculoskeletal systems are the computation times which may become excessive for such a system. Another problem which will be encountered when dealing with the control of systems with multiple degrees of freedom is kinematic redundancy. In accordance with the work of Shadmehr and Mussa-Ivaldi (1994) it was as-

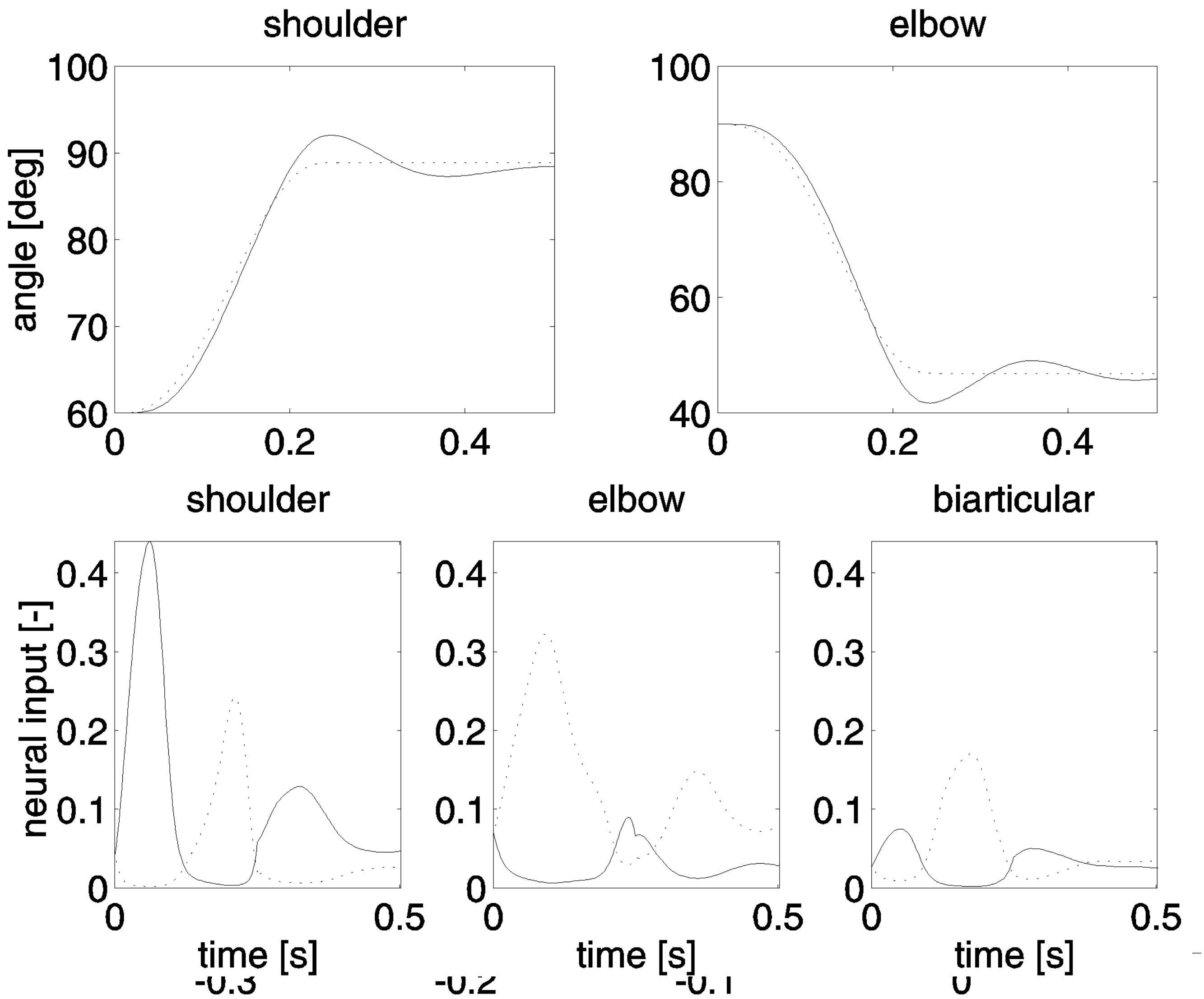

Figure 4 - *The control of a movement in the direction of 135 deg. In the upper figures the dotted lines represent the reference angles and the solid lines the achieved joint angles. In the lower figures the solid lines represent the neural input signals of m1, m3 and m5, while the dotted lines are the neural input signals of m2, m4 and m6.*

Figure 3 - *The control of fast movements in eight directions. The dots represent the desired hand position with intervals of 10 [msec], the crosses represent the achieved position.*

sumed that planning and control of movements are separate actions of the CNS: a reference trajectory is planned in a extrinsic frame and the movement is controlled in an intrinsic frame (e.g. joint angles). Between planning and control an inverse kinematics transformation is thus necessary. If the kinematics are redundant a proper choice for the joint co-ordinates has to be made. In a model of a neuromuscular control system which involves redundant kinematics the inverse kinematics may be represented by a second neural network which is trained by experimentally obtained kinematic data or by employing a criterion which is based on such data. If it is assumed that the kinematics depend on the dynamic task, the inverse kinematics and the motor control system may be represented by one large neural network. The criterion now should contain errors in end-point instead of joint co-ordinates as well as muscular activations.

One of the key characteristics of the model of the motor control system is its non-linearity. It must be non-linear, because the control of a realistic musculoskeletal model is non-linear and its characteristics vary with its working point. Only a model for the control in a small region may be linear. Furthermore, the control system for realistic musculoskeletal model must be an adaptive, learning system; not only because the real system is adaptive, but in particular since a learning methodology is necessary to tune the parameters of a large non-linear motor control system.

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