A MODEL FOR LEARNING COORDINATED FAST MOVEMENTS

Markus Gruber, Arndt Kraft, and Albert Gollhofer
University of Stuttgart, Germany

Coordinated fast movements are characterised by an effective intermuscular interaction. The result of this intermuscular coordination is a straight path towards a given target. The speed profile of the movement is "bell-shaped", so that a movement with a smooth stop results (an overshoot is not observed). In this work an artificial neural network acts as a controller of an idealised human arm during a catching movement. The model arm is taken from the literature with minor changes. The nervous system is modelled by an artificial neural network (ANN). It consists of a sensory map that is connected to a motor map by an intermediate associative layer. The results demonstrate that simple neural networks in interaction with musculoskeletal dynamics are able to model the ability of the central nervous system to coordinate fast movements.

KEY WORDS: neural network, motor control, coordination, feed forward controller

INTRODUCTION: Coordinated fast movements are basic motor actions. They can be easily described by measuring speed, force and electromyographic data. This class of movements involve nearly all aspects of motor control - from vision and proprioception (sensor input), to associative memories and motor output, to the muscles and joint kinematics. In the literature there is no accepted comprehensive model to describe these processes.
In this work the control of a fast movement is modelled. It is a voluntary movement of the arm to catch an object (a thrown ball). Fast movements imply a duration of a few hundred milliseconds. Considering such time intervals, visual feedback can be neglected during the movement, since visual interpretation takes at least a hundred milliseconds. Even proprioceptive feedback is not considered to play a role in fast ballistic movements (Hollerbach, 1982). Hence, we use a feed forward model to control the movement.
Reaching movements towards a given target are well studied (Abend et al. 1982; Gottlieb et al. 1989; Jordan et al. 1994; and others). Two observed facts are important. First the hand path is nearly straight and second the speed profile is "bell-shaped". These features seem to be a result of the muscular and neuro-muscular dynamics and not of neural optimisation (Karniel et al., 1997). In accordance with these results we use a Hill-type non-linear muscle model. For fast movements non-linearity due to muscle fatigue is ignored. There are many complicated schemes of motor control discussed in the literature . It will be shown that with a biological orientated model of the muscular system, a typical movement can be learned and controlled by a very simple feed forward control exciting the muscles with rectangular pulses to the agonist and antagonist (Gottlieb et al., 1989; Riener et al., 1996). In the model presented here, an algorithm to learn the parameters of coordinating and activating the involved muscles is proposed. A simple model consisting of a feed forward control artificial neural network, a Hill-type non-linear muscle model and learning from knowledge of results are described.

METHOD: The model consists of an artificial neural network, which gets data from the outside and calculates muscle excitation. A musculoseletal model transforms these data by a Hill-type non-linear muscle model into forces that act on joints, producing the actual movement. The result (ball caught / not caught) of this movement is fed back to the ANN and processed by an associative inner layer. To keep the sensory analyser simple, we use the parameters speed of ball, size and throwing angle directly after applying minor filters to simulate sensory fuzziness. The model is shown schematically in Figure 1.

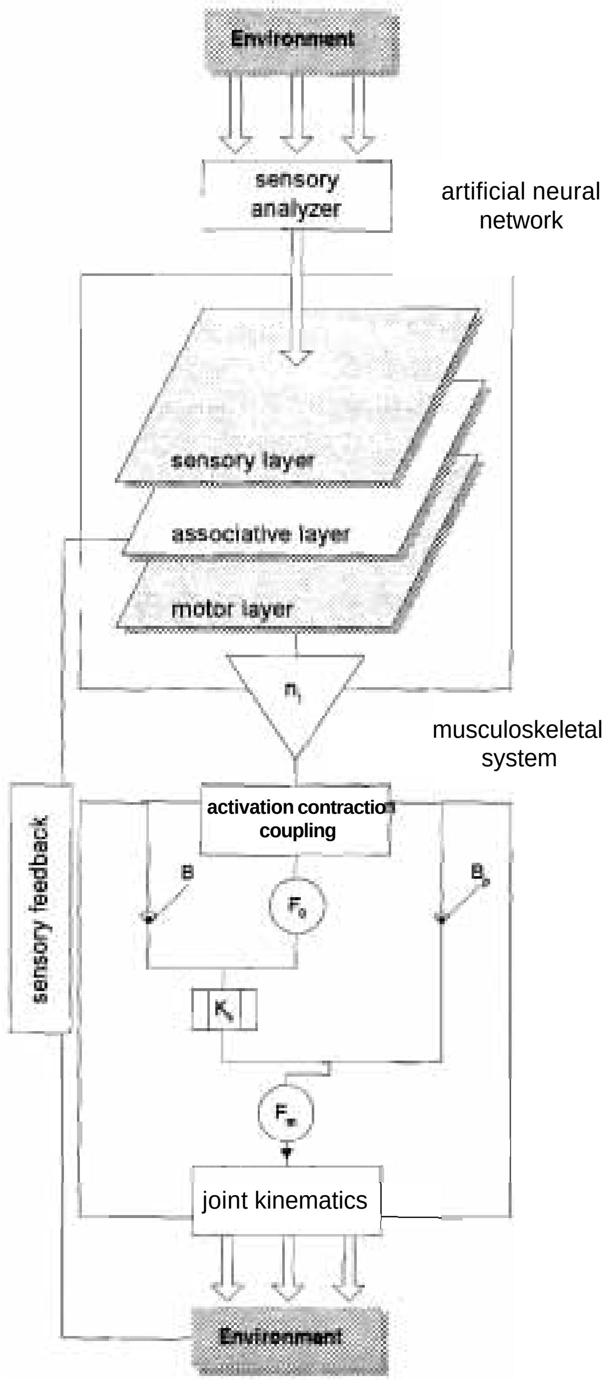

Figure 1 - Schematic diagram of the ANN and the musculoskeletal system (n_i: neural input, B: relation between force and velocity from Hill's model, B_p: parallel elastic properties, K_s: contractile properties, F_0: normalised hypothetical force, F: force acting on the joint).

The artificial neural network: The input is mapped on the sensory layer, which is a Kohonen map (Kohonen, 1987; Obermayer, 1992; Gruber et al., 1997). The input is transformed by a feed forward net to the motor layer, which is responsible for the excitation of the muscles (Lemon, 1988; Ritter et al., 1990). Based on the short duration of the movement the information about the performance is presented only after the execution of the movement (Hollerbach, 1982; Keifer et al., 1994). The sensory information is analysed and the weights of the associative neural net which connects the sensory layer and the motor layer are changed according to the error. The shape of the control pulse is not changed during the simulation. The timing and the amplitude of the two pulses controlling the agonist and antagonist are changed in accordance to the error and learning parameters of the ANN.

The musculoskeletal system: The musculoskeletal system acts as a translator of the pulses given by the artificial neural network. The human arm has many muscles that act on a single joint. To simplify the model we use a reduced number of muscles and calculate the torque at each joint by the sum of the forces of the muscles that act on this joint. For each muscle a Hill-type non-linear model is used (Winters, 1990). For the simulation the parallel elastic components were not taken into consideration, because they have no effect on fast movements. The simulation stops at the end of the catching movement. The steady state, where the parallel elastic elements cause a drift towards the resting point of the muscle is not important for this work and therefore not modelled.

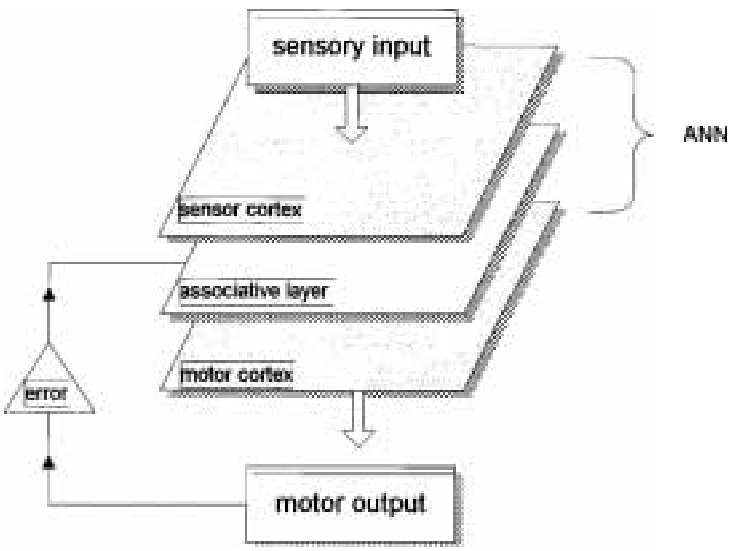

Figure 2 - Schematic diagram of the ANN and the learning algorithm.

The learning algorithm: The sensory data is mapped to the sensory layer in a self-organized process, using Kohonen´s algorithm. The output of the sensory layer is projected to a feed forward net, which acts as an associative layer. In this step only the rule of Hebb plays an important role (Hebb 1949). The information is then mapped on the motor map, which is another self organizing map (SOM). The output of the motor map are excitation pulses defining the physical movement. The output error is then fed back to the associative layer and the affected weights are updated (Figure 2).

The environment: The relevant parameters for the simulation are defined by speed and angle of the ball, the distance between thrower and catcher and the abstracted model of the human arm. OpenInventor™, a three-dimensional graphical library, is used for the visualisation. The simulation area, consisting of a thrower, ball, catcher and the movement of ball and catcher, is rendered. The joints of the arm are drawn using spheres (Figure 3).

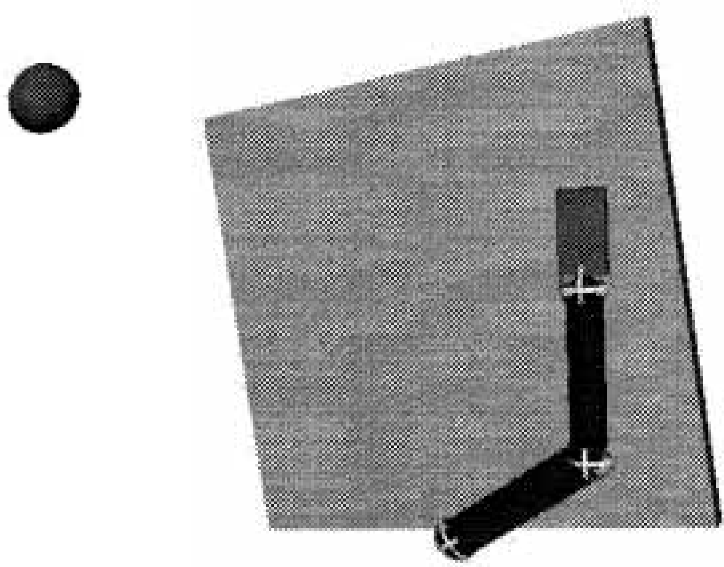

Figure 3 - Sample screenshot of the simulation area. A human arm with three joints and a set of muscles is modelled. The movement of the ball and the arm is rendered.

RESULTS AND DISCUSSION: The model discussed above is able to abstract adequately complicated natural processes needed to generate a controlled fast movement with a "bell-shaped" speed profile. Only rectangular excitation pulses are needed to control the non-linear musculoskeletal system. It is not necessary for the nervous system to calculate the trajectory of the ball or the trajectory of the hand catching the ball. A typical catching movement is achieved by a few simple parameters that are learned by a self-organizing leaming algorithm. This simplifies the controller and is physiologically supported through the hierarchic control of pattern generators (PG´s). The rectangular pulses are an adequate simplification of the large set of control shapes that can be observed in biological systems. The proposed control scheme works well with proper pre-processed parameters. With a Hill-type nonlinear muscle model the desired direct movement to the target without mechanical overshoot and a smooth stop at the end can be achieved.

CONCLUSION:
Movement analysis yields information on the kinematics, kinetics and neuromuscular aspects of human motion. With our technical instrumentation we describe and analyse the output of a highly complex system without a thorough consideration of the neural control mechanisms. A comprehensive physiologically based model capable of representing the complex motor control mechanisms in the human nervous system that explains adaptive leaming is needed.
The motor learning process depends on many parameters. Each step from sensor input to motor output plays an important role in learning a target-oriented movement. The presented model solves the problem of redundant information and appears to be an adequate model to describe the control of coordinated fast movements. The computational capabilities of the used mapping algorithm are demonstrated in sensory mapping and motor control. The model has a hierarchical structure. The relevant parts are separated and can be easily adapted and gradually improved to suit other purposes. The model can be improved to describe slow movements by adding sensory feed back mechanisms during the movement phase. The model constitutes a valuable step towards understanding of how the organisation of higher levels of synaptic modification rules can occur without the need for extensive instruction beyond exploratory sensory and motor experience.

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