

Neural mechanisms of synergy formation *

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Abstract

Morasso, P., 1992. Neural mechanisms of synergy formation. *Human Movement Science* 11, 169–180.

The paper discusses a neural modelling approach to synergy formation which is based on the concept that the elastic properties of the human musculature not only represent a significant low-level feature of the motor system, but can also provide an organizing principle for the global computational architecture. The approach is based, on the one hand, on 'equilibrium-point models' and, on the other, on the dynamics of 'relaxation networks'.

Introduction

The generation of synergies of motor commands and of the predicted patterns of their motor consequences are two complementary aspects at the core of motor control. The connectionist framework that is proposed here is based on the concept that the elastic properties of the human musculature not only represent a significant low-level feature of the motor system, but can also provide an organizing principle for the global computational architecture. Muscle elasticity allows one to define a global elastic potential function, tuned by the patterns of neuromuscular activity, whose equilibrium configurations determine postures, i.e. what we may call *postural attractors*. At the same time, muscle elasticity provides a unified treatment of posture and movement because postural attractors can be turned into mecha-

* This work was supported by the Esprit Projects FIRST and ROBIS, by a National Programme on Robotics of the Italian Research Council and by a National Programme on Bioengineering of the Italian Ministry of University & Research.

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nisms of trajectory formation by modifying the shape of the potential field in the direction of the intended movement.

The origin of this concept can be traced back to the pioneering work of Astratyan and Feldman (Astratyan and Feldman 1966; Feldman 1966) and to the subsequent development of so-called *equilibrium-point models* (Bizzi et al. 1976; 1984; Hogan 1984; Mussa Ivaldi et al. 1985; Feldman 1986). However, these studies did not provide a computational model of the neural mechanisms that underlie the selection and the continuous modification of equilibrium points, compatible with task constraints. In order to obtain this goal, a principle was formulated (Mussa Ivaldi et al. 1988), called the *Passive Motion Paradigm* (PMP). According to this principle, the continuous modification of equilibrium points which is instrumental for synergy formation can be produced via a central neural mechanism that simulates *passive movements*, i.e. movements driven by *virtual force impulses* that correspond to the intended movement direction.

The rationale of PMP is based on the following points:

- Passive motion occurs quite naturally in the interaction between the musculo-skeletal system and the environment (during a passive motion the musculo-skeletal system performs a mechanical relaxation).
- Passive motion has the remarkable property of selecting patterns of joint-rotation and muscle lengthening/shortening that solve the inverse kinematic problem, independently of the degree of redundancy and the kinematic degeneracy which occurs at the limits of the workspace.
- A central neural mechanism that is capable of simulating passive motion is the most natural way to incorporate musculo-skeletal competence in the central neural controller. It is essentially a complex pattern generator that incorporates biomechanical constraints.
- The mechanism can be used directly for synergy formation in the sense that the muscular and articular variations that result from the simulation are an effective representation of the pattern of motor commands. Although it operates in a feedforward way, it does not rule out feedback compensatory loops, at different levels down the stream, that fine-tune the spatio-temporal structure.
- On the other hand, PMP does not have perceptual and temporal competence, which must come from other neural mechanisms,

concerned with planning and initiating a movement: PMP is basically a *degree-of-freedom cruncher* that provides a *friendly interface* to higher motor centers.

A parallel and distributed computational architecture has been proposed (Morasso et al. 1989; Morasso and Sanguineti 1990) as an implementation of the mechanism discussed above. It is an analog device in several senses:

- (1) It operates as a dynamic system (an analog computer) and not as a symbolic system.
- (2) It has a structural similarity with the neuromuscular system, i.e. it is somatotopically organized.
- (3) Its dynamics reflects *neural relaxation* that strictly mirrors the corresponding mechanical relaxation of passive movements.

The implementation is called M-net (motor relaxation network). It is constructed as a network of units which correspond to the different constituent parts of the musculo-skeletal system: skeletal segments, muscles, and ligaments. The units exchange force and displacement signals and the dynamics of the network automatically seeks an equilibrium configuration.

The inputs to an M-net are virtual force impulses which express the intended direction of motion. These forces displace the equilibrium state of the network and the ensuing dynamics provides two streams of output data at the same time: a stream of *muscle activations* and a stream of *kinematic expectations*.

The synergy formation architecture that we propose comprises a programming network (the M-net) and a planning network. In comparison with other neural models of motor control (Bullock and Grossberg 1989; Eckmiller 1990; Jordan 1989; Kawato et al. 1990; Massone and Bizzi 1989, among others), the proposed model is characterized by the exploitation of the mechanical properties of muscles, i.e. the explicit incorporation of biomechanical constraints.

The organisation of M-nets

As previously outlined, there are three types of units in an M-net:

- S-units, that model skeletal segments;
- M-units, that model mono- and poly-articular muscles;
- L-units, that model mono- and poly-articular ligaments;

These units are defined by the local computations they perform: M-units and S-units behave as impedances, i.e. they receive positional information and react feeding back force information; S-units, on the contrary, behave as admittances, i.e. they receive force information and react, modifying positional parameters. With these devices it is possible to build networks that can relax in a similar way to the underlying musculo-skeletal system. In this sense, an M-net may be viewed as a computational *musculo-skeletal body schema* that implements the pattern generator required by the equilibrium-point hypothesis.

S-units

S-units model the different skeletal body segments, considered as rigid bodies to which complex sets of forces are applied. The input variables are the various types of force vectors that can be grouped into two classes: *internal forces* (applied by M-units, L-units, and gravity) and *external forces* (used to express intended directions of movement). The latter, in particular, are the global inputs to the network and are applied as sequences of impulses. (These impulses are generated outside the network by a *motor planner* which is described later on.) The output variables are the current position vectors of the insertion points of all the forces impinging on the unit; their local coordinates are the parameters of the unit. The activation function computes the output variables simulating a viscous motion of the body: the *twist* of the unit (the combination of angular and translational velocity) is chosen proportionally to the resultant *wrench* (the resultant force and torque vectors). At equilibrium, the resultant vectors are null.

M-units

M-units model single and multi-joint muscles as elastic cables passing through pulleys and fixed at their extremities onto two different bones. The cables are divided into a number of tracts and, if we ignore friction, we can assume that tension is constant in all the tracts of the same muscle. Only some tracts change their length during movement (they are dubbed *active* because only their tension influences the equilibrium of S-units) but also the other tracts are relevant because the muscle force is a function of the total length of the muscle. The input variables are the insertion points of the muscle and

the output variables are the pairs of force vectors in each active tract. Mono-articular muscles only have one pair of force vectors, whereas poly-articular muscles have multiple pairs. The two vectors of each pair add up to zero and are applied to the two S-units that are connected by that muscle tract. The characteristic function of M-units is represented by a family of length-tension curves, which are indexed by the muscle control variable. These variables are adaptable, i.e. their values are changed during the simulation process, as is explained in the following.

L-units

L-units are used primarily to model joints. Joints are kinematic constraints among adjacent linkages that allow restricted motions within joint limits. L-units model both types of constraints in a soft way, as appropriate ensembles of (high stiffness) springs. For example, in the case of ball-and-socket joints, the kinematic constraint can be represented by a single spring with zero rest-length; in the case of hinge joints we need a pair of springs whose terminals approximately identify the rotation axis; in the case of a saddle joint we need two pairs of springs. Joint limits can be represented by means of additional springs. For example, two more springs are sufficient for the hinge-type joint in order to constrain the rotations within a specified angular range.

M-nets as generalised Hopfield networks

The purpose of an M-net is not to build an exact model of the human skeleton but to rather provide a computational schema that represents the biomechanical constraints of the synergy formation system. From the network modelling point of view, M-nets are dynamic systems with a well defined Liapunov function and therefore are similar to the content addressable memories (CAM) initially investigated by Hopfield (Hopfield 1982, 1984) and by Cohen and Grossberg (1983). Fig. 1 shows the schematisation of an M-net interpreted as a special kind of Hopfield net, in the following sense:

- The role of neurons in Hopfield nets is played by S-units (big circles in the figure); the difference is that inputs and outputs in M-nets are vectors, not scalars, and the activation function is more complex.

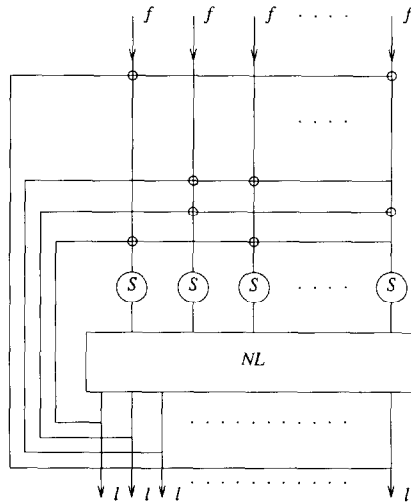


Fig. 1. Motor relaxation network: a generalised Hopfield network.

- The role of connections (which are linear functions in Hopfield nets) is played by M-units and L-units (small circles in the figure), which are non-linear functions; an additional non-linearity in the feedback path is due to the connectivity of the musculature on the skeletal system, which maps the set of insertion points into the corresponding set of muscle lengths.

- The role of input signals is played by the external force vectors.

In spite of significant differences, in both cases we have a similar relaxation behaviour which is driven by a potential energy function. In the Hopfield continuous model, this function is the total electrostatic energy stored in the membrane capacitances. In the M-net model it is the total mechanical elastic energy, stored in M-units and L-units.

However, the purpose of the relaxation is quite different:

- A CAM can store multiple patterns as equilibrium configurations (points of minimum in the energy landscape) and the purpose of the relaxation is to recover a pattern from an initial representation which may be partial and/or corrupted.
- In an M-net, there is only one significant equilibrium configuration but this is changed during the simulation process because the purpose of the M-net is to implement the passive motion principle.

Therefore, the pseudo connection-weights represented by M-units must be adaptively changed during relaxation and this can be obtained by interleaving, during the simulation, a *passive phase* and an *active phase*. In the passive phase, an M-net reacts to the application of input force impulses by relaxing to a new equilibrium state in an iso-electric way, i.e. without changing the control variables of M-units. At equilibrium, these control variables are changed in order to shift the point of minimum of the energy landscape to the current configuration; this is the active phase.

In other words, the neural relaxation process operates in such a way that the point of minimum in the potential field *tracks* the sequence of equilibrium configurations determined by the sequence of virtual force impulses. Symmetrically, the mechanical relaxation induced by the neural relaxation evolves the other way around: the potential field leads the current posture and attracts it.

Is this a plausible biological mechanism? First of all, the units in an M-net must be conceived as cell assemblies, such as cortical columns, not as single neurons. Such assemblies can be treated as small neural networks replicated in a great number of exemplars. Their function is to compute the linear and non linear vector operations that we described above and this could be accomplished with standard multi-layer networks, appropriately trained. Therefore, an M-net can be considered as a network of networks, implying a two-level architecture:

- On a microscopic level, a number of small neural networks reproduce the geometric/mechanical behaviour of the components of the musculo-skeletal system.
- On a macroscopic level, the pattern of connectivity among the local neural networks replicates the topology of the musculo-skeletal system and is characterized by a neural relaxation dynamics which is analogous to the mechanical relaxation.

In my opinion, the current knowledge of the functions of the pre-motor and motor cortices does not rule out this kind of architecture.

In the network modelling field, the idea of a network of networks is beginning to attract the attention of researchers. For example, Kawato, et al. (1990) have studied an architecture where the inner layer contains replicas of a multi-layer network that solves direct-dynamics/direct-kinematics and the outer layer is a Hopfield network that

minimizes a torque-change criterion over a whole movement. This requires 'unfolding' the network in time, which amounts to replication of the network modules for each time step. Our approach, on the contrary, is incremental. However, the two models cover different classes of motor behaviour: optimization of specific skills in the former case, and general purpose synergy formation in the latter.

Synergy formation architecture

In the synergy formation system I propose, an M-net is the task-independent part that incorporates the basic biomechanical constraints. It is activated by virtual force impulses and it reacts by relaxing to a new posture and shifting there the point of minimum of the potential field. Therefore, while the M-net has a comprehensive biomechanical competence, it has no competence as regards goal selection and timing. This requires another neural mechanism which is the second half of the synergy formation system and logically operates at a more abstract level: a planning network (P-net).

In fact, the factorization of trajectory and timing is an important functional feature for the acquisition of motor skills, as has been remarked by Bullock and Grossberg (1989). In that paper, in particular, the authors propose the VITE model that operates directly on patterns of muscle lengths and achieves speed control by means of a single gating signal (named GO). Although this kind of mechanism is reasonable and well motivated, it is questionable that the representation level of muscles is the right place to apply it. At that level, i.e. when arrays of muscle lengths are considered, it is difficult to discriminate different task components that frequently occur concurrently and require separate planning actions.

The M-net structure, on the contrary, allows the planning network to operate on representations that are directly linked to the task and there is reason to think that this kind of representation is actually present in the pre-motor and motor cortices, as the experiments on reaching by Georgopoulos suggest (Georgopoulos 1988). The inputs to an M-net are indeed sequences of virtual force impulses that express intended directions of movement of a selected 'end-effector', according to the specific nature of the task. The generation of such sequences can be performed with different types of neural mechanisms,

for example a version of the VITE circuit applicable to task-level representations or a simplified M-net (Morasso and Sanguinetti 1990).

Summing up, the synergy formation architecture is composed as follows:

- A planning system that has an analogic and a symbolic component. The former component consists of a set of neural networks that can generate sequences of virtual force impulses and the latter is a set of rules for setting up these sequence generators and for connecting them with the underlying M-net. The symbolic component has the semantic competence, whereas the analogic components has the timing and targeting competence.
- A motor programming system, an M-net, which is a somatotopically organized relaxation network of local networks. It has the biome-

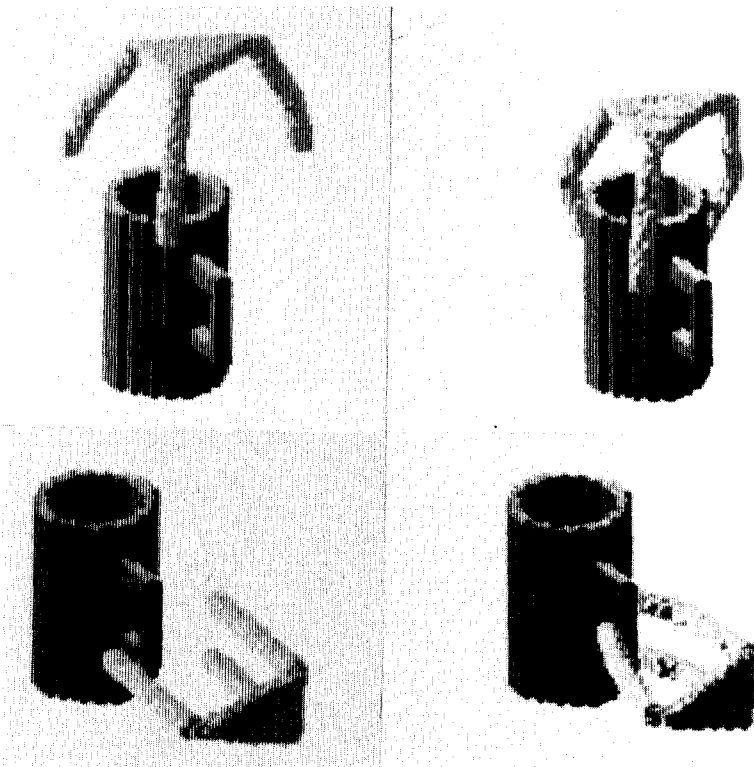


Fig. 2. Coordination of finger movements during grasping.

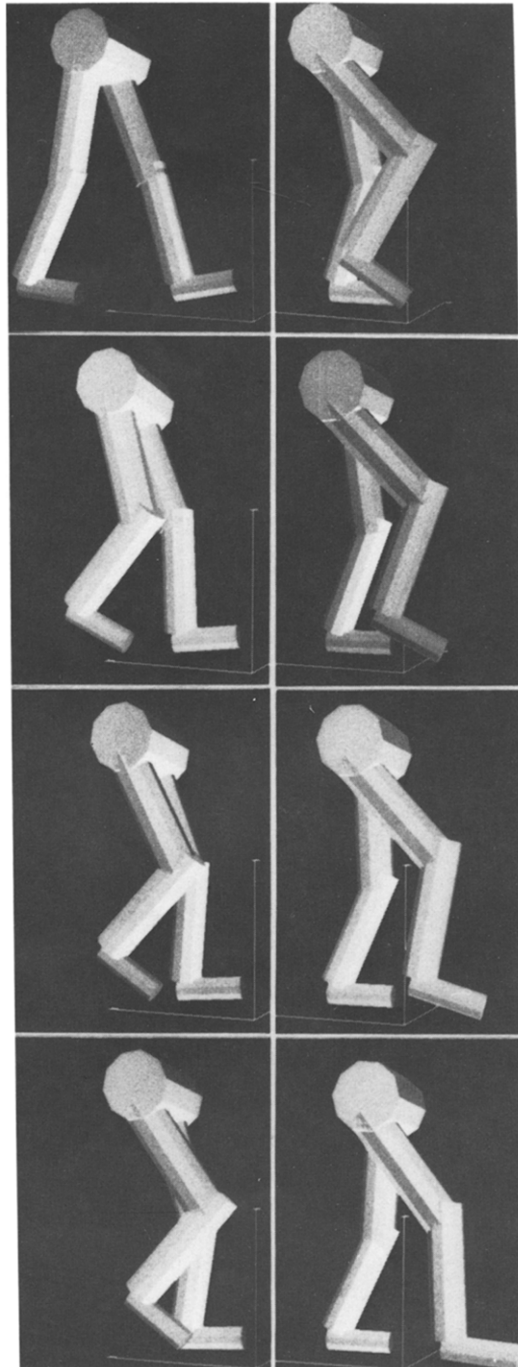


Fig. 3. Simulation of a walking synergy.

chanical competence: it is able to absorb the different sequences of virtual force impulses produced by the planning system and to integrate them in the overall motor pattern.

Examples

Let us consider two examples to get the flavour of the fundamental simplicity of the proposed architecture. The first example is a simulation study of grasping movements. Consider the final closure phase, in which the movements of the fingers must be co-ordinated and targeted to the object. In our simulation environment, the M-net contained the kinematic chains of the three fingers and the planner generated one target for each finger (fig. 2 shows the pre-shaped robotic hand in front of an object and the final configuration after grasping.) The symbolic part of the planner selected the pre-shape of the hand and a triplet of targets for the three fingers, while the analogic part generated a sequence of moving targets from which a sequence of virtual force impulses was derived and then relayed to the fingertip-units of the M-net. These force impulses were integrated by the M-net, producing a co-ordinated motion pattern of the three fingers.

The second example concerns a walking synergy (fig. 3). The planning network, in this case, generates two attractors and one repulsor. The two attractors are linked to the trunk and the swinging foot, respectively, and point in the direction of the next 'footprint'. The repulsor connects the ground and the swinging foot. At each heel-strike event a new triplet is computed and this replaces the old triplet when the swinging foot is placed on the ground. The finite state automaton that performs the simple network set-up operations is a part of the symbolic component of the P-net. We wish to stress that there is no clock to synchronise all the joint rotations or muscle contractions: the synchronisation is a side-effect of network dynamics. The model does not produce a completely faithful copy of actual walking patterns because details and adjustments come from the interaction of the synergy with passive phenomena and segmental active mechanisms. Nevertheless, the resemblance of the simulated walking pattern to those that are observed is encouraging.

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