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A Two-Way Model for Motor Control of Redundant Systems

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Abstract - The biological motor control system is an adaptive system exhibiting vast redundancy at all its hierarchical levels. Redundancy improves reliability and flexibility and might be the salient reason for the superb dexterity of human motor control. However, introducing redundancy in an inversely controlled object results in an ill-posed problem.

We describe a general two-way model for redundancy control. This model includes the selection of a single solution by the dynamics of the system at the lower level, and a multiple controller that can use different solutions under different circumstances at the higher level. We demonstrate the role of the system dynamics in facilitating the stereotypical features of rapid movements, and suggest an architecture as well as a theoretical framework for many-to-one function approximation and inversion.

***Key words* – Inverse problem, Redundancy, Multiple controller, Rapid movements, Motor control**

I. Introduction

The Russian physiologist Bernstein considered redundancy as the most remarkable feature of the biological system (see Bernstein 1967, and Latash and Turvey 1996). The quality of redundancy improves both flexibility and reliability. We have excess resources in many parts of our body, and this property allows us to perform the same task in many different possible ways. The question is how the biological motor control system learns to master many possible solutions and how it chooses a single solution for the specific execution of a given motor task.

We concentrate on open loop feed-forward control. This view is justified for rapid movements where there is no time for effective use of the sensory information due to the large delays in the biological system. In this control method, the best controller is an inverse of the controlled system (see Inbar and Yafe 1976). The control of redundant systems involves an ill-posed problem of inverting a many-to-one mapping.

Most of the previous work addressed this issue using a pseudo-inverse or other criteria to find a single solution, see, e.g., Jordan (1990). The recent progress in computer technology and in the field of neurocomputation enables us to consider an architecture that finds and retains all the solutions, and chooses one of them in real time according to a criterion that might be altered under different circumstances. This framework involves many new problems in control and learning theory, see, e.g., Demers (1993) for a model to control redundant robot.

In addition to these high level computational issues, one cannot ignore the important role of the system dynamics. For example, there are many motor units that could be activated in many different ways; however, the size principle (see Hanneman et al. 1965) dictates a single recruitment order; Mussa-Ivaldi et al. (1994) found that muscle synergies produce force fields that can be combined linearly. These and many other finding suggests that the system dynamics can simplify the computational task of the higher level.

We suggest a general two-way model for learning motor control of redundant systems (Figure 1).

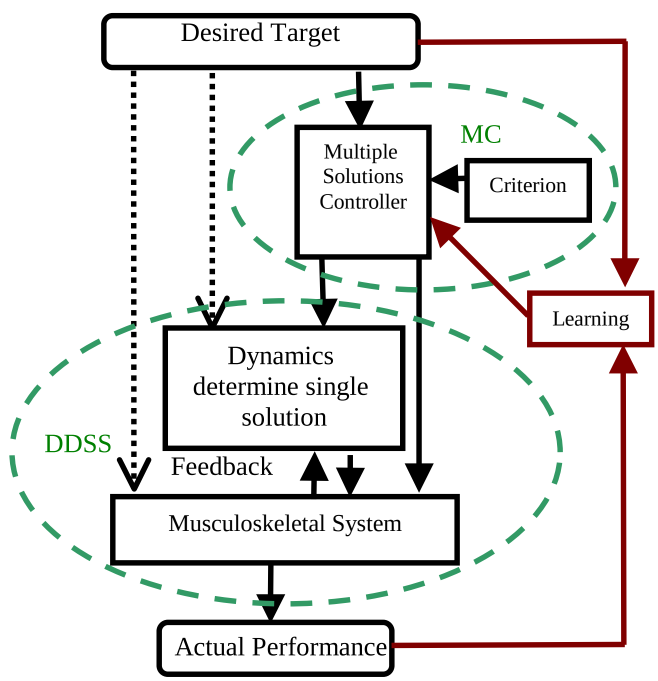

Figure 1: An illustration of a biologically plausible general two-way model for learning redundant system control. In the lower level, the dynamic of the system determines the solution, and in the higher level, a multiple controller can choose different solutions in different circumstances.

We examine two different approaches to the problem. The first puts the emphasis on the dynamic properties of the muscles and the spinal cord, and the second approach emphasizes the higher nervous system and computational methods to learn the control commands. We suggest that there is no contradiction between these approaches since we locate them in different places in the motor control hierarchy (see also Latash and Anson 1996, in response to a commentary).

This paper summarizes a longer study that is fully described in Karniel (1999). Parts of this study have already been presented in Karniel and Inbar (1997), Karniel et al. (1998), Karniel and Inbar (1999), and Karniel et al. (1999).

In the Models and Methods section, the general model is presented and the two parts of this model are described. The results section lists the main contribution of this study; and the discussion section concludes this paper.

II. MODELS AND METHODS

The General Model

A comprehensive model should permit the following methods to exploit redundancy. (i) A simple fixed optimization that is dictated by the dynamics of the mechanical and neural systems, for example the size principle of motor unit recruitment and the smooth speed profile of reaching movements. (ii) A systematic registration of all the solutions and a mechanism to choose the optimal one in real time.

Figure 1 is an illustration of our general model that includes these methods and their speculated place in the biological system. The first method, i.e., fixed optimization, can be the result of the muscles' dynamics and of the spinal cord (SC) dynamics. We relate to the mechanism by which the dynamics of the system determine the single solution by the acronym DDSS. The second method can be implemented by a multiple controller (MC).

To be more concrete, let us think about the control of rapid movements and see how it fits into our general model. Rapid movements have been intensively studies and were found to be generally performed according to a set of stereotyped features. See for examples, Robinson (1964) for invariant features of saccadic eye movements, and Flash and Hogan (1985) for the speed profile of reaching movements. Invariant features of the speed profile were also found in the octopus arm movements, see Gutfreund et al. (1996). We suggest that these stereotyped features are the result of the dynamics of the lower level, i.e., the result of the DDSS part of our general model. We suggest that the CNS has to determine just a simple set of parameters and the trajectory of the movement is determined by the dynamics of the lower level. We will supply evidence for this view in the next subsection. However, the redundancy is still there even after this stage and one can choose many possible ways to perform the same task by means of these stereotyped rapid movements. For examples, one can look at the a desired target by mean of eye saccade, head movement or body movement; complex movements can be a combination of many possible sets of stereotyped arm reaching movements; and the octopus can reach for his target by means of many possible arms. We suggest that the motor control system can learn to use many possible methods to perform the same task, and to use different solutions under different circumstances. This is the idea of the MC in the higher level of our general model. After the next subsection, we describe a new theoretical framework for the purpose of analyzing the performance of MC.

Muscles model:

As a demonstration of the DDSS block in our general model, we present here two simulation studies of two different nonlinear models of the system dynamics. Both studies suggests that the dynamics of the system have a significant role in simplifying the control strategy and producing the stereotypical features of rapid movement, i.e., determining the single solution out of many possible solutions.

The first model is the Hill-Type model (see Zangemeister et al. 1981). We have previously demonstrated that the bell shaped speed profile that was observed in rapid movements could be achieved with simple control signals, see the right plate in Figure 2. This result was achieved without any complex computational method as needed for the linear muscle model. For further details, see Karniel and Inbar (1997).

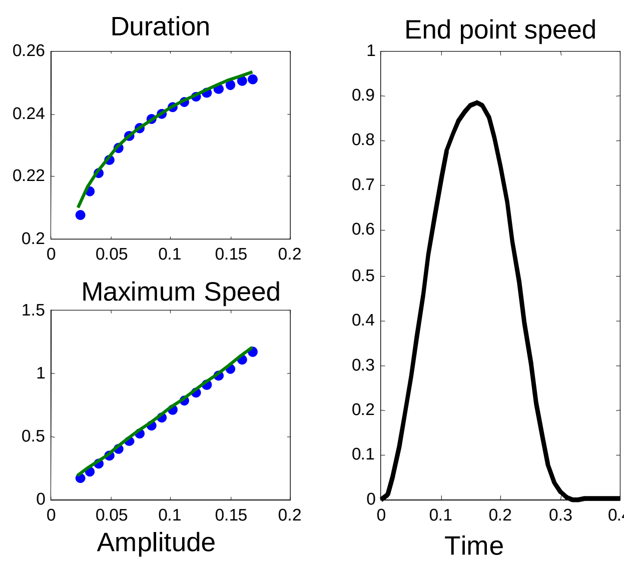

Figure 2: Two simulation studies that demonstrates the DDSS concept and the role of the nonlinear muscles properties in producing the stereotypical features of rapid movements with a simple rectangular control signals. On the right, the bell shaped speed profile that is a result of a Hill-type mechanical model. On the left, the log-like relationship between amplitude and duration and the quasi-linear relationship between amplitude and maximum velocity as a result of a fractional power dumping model. For further details, see Karniel and Inbar (1997) and Karniel and Inbar (1999).

The second model is a fractional power dumping model, that is also known as the one-fifth power law (see Wu et al. 1990). This is a simple nonlinear model that successfully modeled human wrist movements. Following Barto et al. 1999, we used this model with a simple step and hold control signals. We generated simulated movements with various pulse amplitudes, and fixed all the other parameters to typical values. We found that the simulated reaching movements obey the well-observed stereotypical relationships between duration, peak velocity and amplitude of rapid movements. See the two plates on the left of Figure 2.

These two recent results along with many previous ones reinforce the notion of the DDSS that is suggested in our general model at the lower level.

The definitions of redundancy and of a multiple controller

We define a redundant system as being many-to-one function and suggest a set of definitions for different types of redundancy. These definitions provide a solid ground for discussing learning issues and for suggesting and analyzing new architectures for the control of redundant systems.

Definition-1: A <u>system</u> is defined by a function $f : X \to Y$.

Remember that a definition of a function includes a definition of a mapping and definitions of input and output domains. In this definition, we do not restrict the input and output domains; they can be scalars, vectors, continuous or discrete functions, or Laplace or Z transform domain functions.

Definition-2: A system $f : X \to Y$ is <u>*redundant*</u> if there exist $y \in Y,\ x_1 \in X,\ x_2 \in X,$ such that $x_1 \neq x_2$ and $f(x_1) = f(x_2) = y$.

Thus, a system is redundant if and only if it is not injective (injective being a one-to-one mathematical function). We further differentiate between three types of redundancy, *finite, countable* and *uncountable* according to the maximal size of the set of solutions that is available for any given output element.

The main idea behind the concept of a multiple controller is to learn all the possible control signals and choose one of them in real time according to a modifiable criterion.

When the system is redundant, finding an inverse is an ill-posed problem. We suggest to regulate the redundant system by expanding the output space Y to $Y \oplus P$, where $\oplus$ stands for a direct sum (i.e., each element in the expended space consist of one element from *Y* and one element from *P*). Then we suggest constructing a multiple inverse function $f_P^{MI}(y_d)$, where *MI* stands for Multiple Inverse and the parameter p determine which of the many possible solutions is chosen.

Definition-3: Let $f : X \to Y$ be a redundant system. The system $f_p^{MI}(y) : Y \oplus P \to X$ is called the <u>multiple inverse system</u> (or function or controller) if for every input value $x \in X$, there is a parameter $p \in P$, such that $f_p^{MI}(f(x)) = x$.

In practice, the system $f(x)$ is frequently unknown, and we are given a series of input and output vectors $\{x^l, y^l\}$, representing the unknown system. In this case the formal requirement is that for any given accuracy value ε, one can construct $\hat{f}_P^{MI}$, such that for any value of y_d, and for any value of the parameter p, the following inequality will hold.

$$\left| f\left(\hat{f}_P^{MI}(y_d)\right) - y_d \right| < \varepsilon$$

In order to construct a good approximation for a multiple inverse controller, this requirement should be coupled with a requirement for completeness, i.e., that all the solutions are achievable.

Polyhedral Mixture of Linear Experts (PMLE)

The PMLE architecture is suggested to serve as a multiple inverse controller. The PMLE learns a piecewise linear approximation of the system. Each area is governed by a linear function, which is called an expert, and one can invert each expert and get the multiple inverse. In the general case where the dimension might be greater than one, each expert governs a polyhedral region in the input space and hence the name polyhedral mixture of linear experts. The advantage of the PMLE over other forward models is in the simplicity of the construction of the multiple inverse PMLE (MI-PMLE). This architecture was first presented in Karniel et al. (1998) and it was shown to be capable of approximating inverse functions. For further details about this architecture, see Karniel (1999).

III. RESULTS

1. We suggest a general model for learning motor control of redundant systems where the dynamics determines the single solution (DDSS) at the lower level; and a multiple controller (MC) can learn and use all the possible solutions at the higher level.
2. We present two simulation studies that suggest that the properties of the system dynamics have a role in simplifying the control strategy and producing the stereotypical features of movements. These examples demonstrate the role of the DDSS block in the general model.
3. We suggest a general framework and algorithms for learning multiple controllers of redundant systems. We present a new architecture named the PMLE.
4. The main properties of the PMLE are encapsulated in the following theorem.

Theorem: a) The PMLE can approximate the inverse of any continuous function. b) The MI-PMLE architecture is able to represent the multiple inverse function of any piecewise linear system with polyhedral decision regions.

Comment: The MI-PMLE is able to *approximate* the multiple inverse of a broad class of function, since a broad class of functions can be approximated by the PMLE.

Proof: The proof of part a' is based on the work of Sontag (1992) where he shows that a two-hidden layer network can approximate inverse functions. The proof of part b' is by construction, where the details of the MI-PMLE construction are described in Karniel (1999).

IV. DISCUSSION

The general model

In our general model, we added direct arrows (dotted arrows in Figure 1) from the desired target block to the DDSS block and to the musculoskeletal block. These arrows represent the direct pathways from the motor cortex to specific muscles and to specific neural pools in the spinal cord. They can be used in order to bypass the MC for rapid execution of stereotyped simple movements by means of the DDSS or for conscious activation of specific group of muscles. The other path is through the MC, which can choose out of the many possible solutions to achieve the task. The MC can send a general command to the DDSS, e.g., parameters of excitation or of stereotypical movement, or alternatively a specific command to the musculoskeletal system. The distinctions made in this model are not strict, we are not positive as to location of each mechanism. It is possible that the spinal cord contains multiple controllers and alternatively that part of the CNS operates according with the DDSS notion. Nevertheless we believe that the proposed general model and the introduction of this twofold mechanism of DDSS and MC will prove to be useful in future development of the human motor control modeling research.

Redundancy

In the literature, the finite and countable redundancies are not always considered as redundant systems (e.g., a manipulator without excess degrees of freedom can posses countable redundancy according to the definitions above, however it may not be considered as a *redundant manipulator*, see for example, DeMers 1993). For linear redundant systems, only uncountable redundancy is possible, and a redundant system is sometimes defined as a system with fewer outputs than inputs (see, e.g., Neilson 1993).

One should notice the difference between structural and functional redundancy. Tononi et al (1999) described the difference between redundancy and degeneracy: redundancy being the result of identical elements in the system and degeneracy of different elements that perform the same function. These definitions are in the structural sense. The definitions in this study are in the functional sense and in this sense both redundancy and degeneracy are functionally redundant.

The issue of redundancy in the biological motor control system is sometimes being referred to as the Bernstein problem (Bernstrin 1967), and in other context even as the curse of dimensionality. We prefer to relate to it as a virtue rather than a problem. Redundancy with a good controller can improve the reliability and flexibility of the system and is probably one of the main reasons for the superb dexterity of human motor control (see Bernstein 1967, and Latash and Turvey 1996).

Final Remark

The main outputs of the brain are motor commands to the muscles. The human brain is first of all a motor controller. Biological motor control is a great challenge for scientists, engineers and physicians. The classical engineering and mathematical modeling tools are appropriate for linear time-invariant injective systems. The biological system does not comply with these qualifiers and therefore there is a place and a need for new modeling tools in order to describe and analyze the biological system, see Karniel and Inbar (2000). In this study, some basic problems of motor control were illustrated. The possible role of the mechanical nonlinear properties of the muscles in simplifying the control strategy was demonstrated. A new architecture, learning algorithms and mathematical tools were suggested in order to exploit the virtue of redundancy. These results constitute another step in the ongoing strive for a better understanding of the biological motor control. An understanding of the biological motor control system will undoubtedly contribute significantly to the welfare of paralyzed and crippled patients, to a new generation of dexterous robots, and to a better understanding of the mysteries of the human mind and how it operates.

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