Chapter 7

Discussion

This chapter contains a discussion of the results in the general context of human motor control and in view of other research works. Some open problems and suggestions for future research are discussed and a short final remark concludes this thesis.

7.1. Learning Motor Control of Redundant Systems

One of the salient characteristics of the biological motor control system is its apparent redundancy (Bernstein 1967, Latash and Turvey 1996). A writing task, for example, is defined in two dimensions, however, the human arm consists of seven kinematic degrees of freedom, and the fingers add another nineteen degrees of freedom (see Potkonjak et al. 1998). Most of the joints are surrounded by more muscles than needed to produce any desired moment. The muscles themselves are composed of many motor units that enable many possibilities of producing the same force at the tendon. These redundancies lead the controller (i.e., the nervous system) to act on a many-to-one (MTO) system. Only one of the many possible commands is chosen in each execution of a movement.

The problem of redundancy in the biological system has been known for many years and a large volume of literature has been dedicated to the issue of finding the optimization criterion to choose the best single solution (e.g. Flash and Hogan 1985, Jordan 1990). Frequently, the formulation of the question provides half of the answer. We believe that redundancy should be regarded as a *virtue* rather than a *problem* and therefore the biological system has to find an optimal way to *exploit this virtue* rather than to *solve this problem*. Instead of just looking for a single optimization criterion that yields a single solution, we suggest in addition, a multiple-solutions multiple-criteria system that can choose a different solution under different circumstances.

There are two competing views in the literature of motor control: one is the *dynamical* view that asserts that the dynamics of the system "finds" the solution and therefore reduces the redundancy and simplifies the control scheme, see examples in chapter 4. The other view is sometimes called *hierarchical*, which suggests that the CNS is aware of the details of the controlled system and calculates proper control signals, e.g., by means of an inverse model. We think that they both exist at different levels of the control (a similar idea was suggested by Latash and Anson 1996 in their response to a peer commentary). In this view we suggest that the biological system resolve the redundancy by means of two mechanisms: A natural reduction due to the dynamical properties of the system and a selection from many possible solutions in real time at a higher level, see chapter 3. In chapter 4 we illustrated the first mechanism, the DDSS and then in chapters 5 and 6 a new architecture and theoretical framework was developed for the second mechanism the MC.

In the rest of this section, we discuss these ideas and this thesis results in view of some recent research and other contributions from the literature.

7.1.1. Nonlinear time-varying many-to-one system

There is a strong engineering and mathematical foundation for modeling linear, time-invariant (LTI) systems (see for example Kwakernaak and Sivan 1991, Porat 1994, Karniel and Inbar 1999b). Some man-made machines satisfy these conditions, however biological systems do not. The biological system presents enormous plasticity, which means that the system is a time varying one (e.g., in processes like regeneration and fatigue). It also generally demonstrates non-linear behavior, such as logarithmic relations, thresholds, hysteresis, saturation and cut-off (i.e., minimum and maximum bounds). In some cases, a linear time-invariant approximation can be made, but only for a small signal and for a short duration. It is important to remember that the biological system evolved to improve its prospective survival and therefore its properties should not be considered as a problem but rather regarded as means to improve the reliability and flexibility of the system. Exploiting the non-linearity for simplifying the control, exploiting the time varying features by adaptation and learning, and exploiting redundancy by multiple controller as suggested in this thesis are much more appropriate approaches than the classical LTI control design models.

Goodman and Gottlieb (1995) wrote that the fast reaching movement plays a role similar to the impulse response in linear systems studies. We accept their observation regarding the importance of the rapid human movement as a building block of complex movements. However, we wish to stress that the musculoskeletal system is clearly not linear or time invariant. Therefore, the superposition property does not hold and the nonlinear properties of the muscles must be considered. In chapter 4 the nonlinear properties of the muscles were proved to be essential in order to achieve the stereotypical features of reaching movements with simple control signals.

Many papers described the features and invariance of rapid movements (see for example Gottlieb et al. 1989). A recent study by Plamondon (1995) suggests a kinematics theory of rapid human movement, which considers a linear system and describes the movements via seven parameters. This model is called the $\Delta\Lambda$ law. We suggest that a physiological nonlinear model can produce similar results with the same order of the number of parameters and with the great advantage of being closely related to physiological and neurological measurements. The parameters of the $\Delta\Lambda$ law have no physiological meaning while the parameters of the pulses in a proper muscle model can be related to the integrated muscle electrical activity.

The importance of the mechanical part of the motor control system cannot be over stressed. The kangaroo saves energy by exploiting the mechanical properties of his tendons and storing energy in their stiffness. Butterflies can use the mechanical resonance frequency of their wings in order to save energy. This idea is well described in Full (1994). In this thesis, we add new examples for this idea. Many previous studied of reaching movements used linear models and simplified muscle model, and were forced to design complicated computation schemes in order to produce the stereotypical features of rapid movements. We have demonstrated that the stereotypical features of reaching movements are facilitated by the nonlinear properties of the muscles. The role of the nonlinear properties of the muscles is recently also acknowledged in an experimental study of Krylow and Rymer (1997) and in the papers of Barto et al. (1999) and of Gribble et al. (1998).

7.1.2. Feedback and forward control

In this thesis, we used a feed-forward control model. In this model the biological system uses the sensory information for learning rather than for improving the control in real time. This approach is well justified as a model for the biological system for rapid movements, due to the large delays in the system, see chapter 2. Nevertheless, there are other possible ways for the use of sensory information (e.g., see Ghez et al. 1990 for discussion and experimental study of the possible role of proprioceptive information). In this subsection, we discuss the usage of sensory information by the motor control system.

Our general model (see Figure 18) allows real time influence of feedback within the lower level, which is called DDSS. For example, the EPH that is considered part of the lower level in our general model can include feedback as part of the system that regulates the behavior of the muscles. Other examples can be found in some extended muscles' models that incorporate properties of the reflex loop, such as the one-fifth power law that was described in Chapter 4.

When we move to the higher level in our general model, we prefer to view the system as pure feed-forward control, where the feedback is used after the execution of the movement for the purpose of learning. One possible role of the feedback beyond learning is to correct the movement and maintain equilibrium posture after the ballistic part of the movement (see, e.g., Hirayama et al. 1993). Another possible role of the feedback is to enable corrective ballistic movements. Recent experimental and theoretical research supports this idea. Hanneton et al. (1997) found evidence that a tracking movement consists of small rapid movements. They propose a model that suggests that whenever the error between the desired path and the actual path exceeds a certain threshold, a simple feed-forward controlled rapid movement is initiated in order to correct the tracking error. This approach harmonizes with the work of Berthier (1996), which suggests that infant reaches are a series of submovements.

Another result that supports this view is the work of Henis and Flash. They suggest that in case of a change in the target location during the movement, an additional corrected movement command is added to the original motor command, rather than replacing the original command, see Henis and Flash (1995) for human reaching movements, and Gat-Falik and Flash (1999) for application to robotic manipulators.

Other approaches suggest combination of feedback with feedforward control that act together in parallel, see e.g., Bhushan and Shadmehr (1999). In this type of combined control scheme one has to decide how much confidence do we have in the sensory information, that is, what portion of the control should be based on feedback. In this respect a beautiful suggestion was raised by Wolpert et al. (1995), that used the optimal estimation theory of Kalman (see, e.g., chapter 35 in Levine 1996) in order to calculate the gain that determines the amount of "trust" given to the sensory information. This model can explain some general experimentally observed features of motor control, however this model is a simplified linear model which constitute a major drawback in trying to account for the biological motor control system, as discussed in the previous subsection.

The way the biological motor control system uses the feedback sensory information is still an open question. Further modeling and experimental work is needed in order to conclude which one of the suggestions above best fits the biological system.

7.1.3. Multiple controllers

In this thesis a multiple inverse controller is defined as a controller that can issue all the possible control signals that could derive the controlled redundant system to any desired state. A formal definition is given in Chapter 3, and a novel architecture is suggested and analyzed in Chapter 5 and Chapter 6. There are other similar and related architectures in the literature and we discuss some of them in this subsection.

The issue of kinematics redundancy is well treated in the robotics literature (see Baker and Wampler 1988, Baker 1990). The most common practice is assuming that only one solution of the redundant manipulator is interesting (e.g., Gorinevsky and Connolly 1994). The virtue of redundancy is occasionally acknowledged in this literature, generally for the purpose of avoiding singular points and for improving the manipulability of the robot (see Yoshikawa 1984, Katayama et al. 1996). Almost all the research on this subject actually use pseudo-inverse (e.g., Katayama and Kawato 1991, Lee and Oh 1997, Frolov and Rizek 1995) some also use the pseudo-inverse control as a model for the biological system (e.g., Dean and Porrill 1998). Nevertheless, recently some research studies do consider the exploitation of redundancy by means of a controller that can use different solutions in different circumstances. DeMers (1993) suggests a set of algorithms that are based on clustering and self organizing maps in order to learn a parameterized representation of the possible solutions (see also DeMers and Kreutz-Delgado 1994,1998). His work is well demonstrated for robotic manipulators. However, it is not clear how it extends to general redundant systems. Lu and Ito (1995) suggested solving the inverse kinematics of a redundant arm with a modular neural network, where each network learned part of the configuration space; but as they admit, the regions can overlap. Lee and Lee (1995) suggested a multi-resolution radial basis competitive and cooperative network. Their method is based on separating the data into hyper-ellipsoidal clusters. A different approach was developed by Ghahramani (1994), where he proposes using density estimation of the joint distribution via the expectation maximization (EM) algorithm and then forming the conditional density of the output given the input in order to construct the inverse that can be multiple. There are some other related approaches such as the parameterized self-organizing maps of Walter (1997) that suggest flexible use of redundant degrees of freedom by means of free parameters in the same controller that can determine different solutions in different circumstances. See also Water and Ritter (1996).

All the papers described above are preliminary trials of exploiting the virtue of redundancy. In this thesis, we start building a concrete basis for the future development of multiple controller. Indeed, for a specific robotic configuration, there might be other practical methods for control that do exploit the redundancy and some of them might be better than the MI-PMLE proposed in this thesis. However, the MI-PMLE is applicable for any redundant system whatsoever, and it is proved to be able to represent all the possible solutions of any redundant system. The mathematical restriction of being a piecewise linear approximateable do not exclude any known physical system. Piecewise polynomial approximation could be used (see, e.g., Chaudhuri 1994). However, one should be careful that each polynomial region would be monotonic function in order to have a piecewise invertible approximation. The best basic function depends on the specific problem, and in general, it is preferable to work with the simplest method. Piecewise linear is indeed a simple nonlinear approximation, and it is easier to analyze than other nonlinear approximation, see e.g., Sontag (1981). Therefore piecewise linear approximation was chosen for the PMLE. Another advantage of the MI-PMLE is the straightforward parallel implementation as a mixture of experts, which enables fast real time calculation. The analysis in chapter 6 is a beginning of a theory for learning multiple controller and it will allow future comparison between prospective architectures that will probably be developed.

There are some related concepts that have a tight connotation with the notion of multiple controller, and sometimes even has the same name. However, they are generally not related to the problem of redundancy that was the main issue in this thesis. Let us mention some of them here, in chronological order. Gain scheduling has been used for many special cases, such as autopilots for aircrafts, and today it can be easily implemented in computer-controlled systems. See chapter 9 in Astrom (1995a) for an overview and examples of gain scheduling. The main principle of gain scheduling is to find auxiliary variables that correlate well with the changes in the dynamics of the plant, and then to change the parameters of the controller as a function of these auxiliary variables. For nonlinear systems, a typical gain scheduled design procedure is to select several operating points and to design the gains of a linear controller in each point. Between these points, the gains of the controller can be interpolated or switched, i.e., scheduled, thus resulting in a global controller (see Shamma and Athans 1990). This approach is related to our notion of multiple controller only in the idea that the controller has a set of parameters that can be changed in different circumstances. However, the gain scheduling approach has nothing to do with redundancy. The process of gain scheduling can be analogous with minor changes to our learning part of the model (see Figure 16), but not to the notion of redundancy regulation. Jacobs and Jordan (1993) proposed a modular architecture that is actually an extension of the gain scheduling idea. Instead of designing the controller, as is the case in gain scheduling, they learn it by means of adaptive control with artificial neural networks. See also Jordan and Jacobs 1995 for a short review of their modular networks. Recently there is an increasing use of the terms multiple models and multiple controllers, see Murray-Smith and Johansen

(1997), and Narendra and Balakrishnan (1997). These terms are also used in order to describe biologically plausible modular control architecture in Wolpert and Kawato (1998), Ghahramani and Wolpert (1997), Wolpert et al (1995) and in a review paper of Wolpert (1997). These models are generally not related to the issue of redundancy. Nevertheless, they are based on adaptation and on modular structure which both appear in the biological system. These architectures could be modified and extended in order to serve as a multiple inverse controllers and exploit the redundancy. We believe that there is a promising potential in developing these architectures as models of the biological system and use the biological system in order to extract new ideas and insights for better adaptive and modular artificial architectures.

7.1.4. Learning schemes

In Chapter 5 the first stage of finding a piecewise linear estimation is performed by the hinging hyperplanes algorithms of Breiman (1993). This algorithm was chosen due to its elegance and simplicity. There are many alternative approaches to construct a piecewise linear approximation (e.g., Friedman 1979, Kavli 1990, Hush and Horne 1998, and Pucar and Sjoberg 1998). The last two methods might be better than the HH of Breiman, however, there is no one uniformly best method, and the performance of each method depends on the underlying function that is being approximated. These methods can easily replace the HH algorithm with minor changes to the transformation algorithm of section 5.2 (or no change at all for the algorithms in Pucar and Sjoberg 1998, since it is another algorithm that produces the same HH representation). The final result of a multiple inverse controller will be exactly the same, and whatever the learning algorithm is, the multiple controller can be straightforward implemented in a parallel architecture. A parallel implementation of the PMLE would allow real time calculation of the control signal, and even a real time switching between criteria for choosing the preferred solution.

In Chapter 6 we present some issues from learning theory and suggested some criteria for learning inverse control of redundant systems. This issue of learning many to one mapping was not treated in the literature, however there is a related path of research that deals with multi-class, multi-label classification problems. Schapire and Singer (In press) discuss these issues. They do consider many-to-one mapping however their framework is restricted to a finite class of output labels, while our problem is of function approximation, which is an uncountable class of output possible values. This approach is not suitable even for finite redundancy with finite control signals, since they require that the examples will contain all the possible labels. This is translated to the requirement that each example would include an output and all the possible inputs, while in our problem we have only one input and one output each time. Nevertheless, it might be worthwhile to follow this path of research since it seems to be developing faster than the research in the field of learning motor control.

Another issue that was analyzed in chapter 6 is the difference between two methods of learning an inverse model, the BEI and the IBE. The essence of this issue is a linear regression problem of the difference between inverse and direct regression. This issue appears in some advanced textbooks, see, e.g., Draper and Smith (1998), and Ryan (1997). However, this problem, even in its simplest formulation as linear regression problem seems to be a source of everlasting confusion. We traced this debate between methods of learning inverse regression back to December 29, 1938 when Dr. C. Eisenhart presented it before the American Statistical Association in Detroit (see Eisenhart 1939). He says there, "*It does not seem to be generally realized that the fitting should be done in term of the deviations which actually represent 'error.'*", and then he presents some problems in linear regression, and in particular the difference between direct and inverse fitting. However, Krutchkoff (1967) presented some numerical examples for the opposite case, see also Krutchkoff (1969). This debate continues with the work of Halperin (1970). We do not wish to go into the details of these papers, however it is clear that the proper method depends on the exact definition of the aim of the fitting. Another related discussion recently appears in Chow and Shao (1990) with an example from the US pharmaceutical industry that used the improper method of estimation. We learned from these previous studies that this issue is definitely not trivial as we considered it the first time we noticed this problem. For control problem, one has to remember that regression for control is not similar to regression for prediction (see, Hahn 1974). For control purpose, one has to notice that the aim of the fitting is to reduce the error in the output of the system and not in the control command signal. The analysis in section 6.2 clearly shows that for control purposes the IBE method is superior. The field of neural computation introduces many new possible methods for learning control with ANN. Many researchers are not aware of this difference and they use the wrong method. We hope that this result would clear this issue, at least in the area of learning inverse controllers.

Since we discuss different learning methods, both biological and artificial, we wish to stress that the learning algorithms discussed in chapters 5 and 6 and the PMLE architecture are not claimed to be biologically plausible. The only biologically inspired part in this architecture is the modular parallel structure and the notion of exploiting the redundancy and the ability to use different solutions at changing circumstances and even in the same circumstances. The specific details, such as the hinging hyperplanes algorithm and the transformation to mixture of expert are just used as engineering tools in order to enable further analysis and discussion of this proposed structure. A biologically plausible architecture would have to relate to specific neural structures, such as the spinal cord, the cerebral cortex, the cerebellum and the basal ganglia. We expect the new developing imaging tools to boost this type of physiological motor control modeling.

The learning in our general model occurs in the higher levels. Changes in the lower level are mainly the result of feedback and adaptation. The lower level determines the general characteristics of the movements by the system dynamics and the higher level sends general commands such as the parameters of pulse excitation. An example of this concept is the model of reaching movements control that was mentioned in Chapter 4 and described in details in Karniel and Inbar (1997). In this model the higher level controller has to learn the parameters of pulses and the lower level uses these pulses in order to execute a smooth bell shaped speed profile. Another work with a similar approach is the work of Barto et al. (1999) where in addition to the physiologically plausible model of the lower level they present a physiologically plausible model of the cerebellum that learns the control parameters. However, for two degrees of freedom, they seem to need a much more complex scheme in order to produce the desired movements, see Fagg et al. (1998). In that study they used reinforcement learning (Sutton and Barto 1998) in order to learn a straight-line path. Here again, as in Karniel and Inbar (1997), when we try to model the higher levels of motor control we are frequently still unable to restrict ourselves to the anatomy and physiology of the system and we use different kinds of artificial learning schemes in order to describe the behavior of the system.

Another promising approach to the study of learning motor control is by means of psychophysical experiments with infants; see Bertenthal and von Hofsten (1998), Berthier (1996) and Berthier et al. (1999). The research of Berthier et al. suggest that infants learn to reach by performing small movements first, and then learning to combine them into large reaching movements. Another aspect of their findings is relevant to the issue of redundancy. They found that infants tend to use their shoulder and torso and only later use their elbow, in a proximodistal structure of learning, see also McDonald et al. (1989) for a similar result in an experiment of dart throwing. These results suggest that at the beginning of learning we tend to use a limited number of degrees of freedom, and only after a long period of learning we are able to master the control of all the degrees of freedom of our redundant motor control system. The same phenomenon was also pointed by Bernstein (see Latash and Turvey 1996) in one of his nice examples about how children learn to ride bicycle by means of training wheels that reduce the redundancy. Once you learn how to ride a bicycle without training wheels, you don't want to put them back again and this is one of the most convincing popular examples for the virtue of redundancy and for the potential in introducing redundancy to artificial systems. However, this procedure of learning was not included in the model presented in this dissertation and it is suggested to be the subject for future research.

7.2. Open Problems and Future Work

In this section we extend our discussion to describing and to conceiving prospective future research both in regard to the specific models and tools that were developed in this thesis and in the general field of human motor control.

7.2.1. Reaching movements and the system dynamics

We mentioned the minimum Jerk hypothesis of Flash and Hogan in Chapter 4. Recently, Harris and Wolpert (1998) suggested that the observed speed profiles of human movements are the result of a minimum-variance theory that they have developed, rather than of minimum Jerk. In this thesis, we suggest that the property of the muscle dynamics simplifies the control that is needed in order to achieve the observed movement. It would be interesting to compare the predictions of minimum Jerk, minimum variance, and these of a physiologically plausible mechanical model with a simple control strategy, and see whether the mechanical model can produce the physiological trajectories. This simulation experiment should focus on movement where the prediction of these models deviates. If our conjecture, i.e., the idea of DDSS, is correct then such simulation experiment could reveal the target function that is optimized by the biological system. A crucial part of this research is the structure of the dynamical model. This brings us to the following suggestion.

The simulation studies in chapter 5 demonstrate the stereotypical features of reaching movements for a single joint. In Karniel and Inbar (1997), there are also similar results for two joints reaching movements. It would be interesting to continue this study for multiple joints systems and check whether the same simple nonlinear models are sufficient in order to produce the stereotypical features in a multi degrees of freedom system, such as the human arm in a three dimensional space. It would be very appealing if the results will be the same for the multi-joint system. However, another possibility is the participation of spinal cord mechanisms that produce synergies in order to facilitate the stereotypical features in the multiple-joint case. This last possibility is still within our DDSS block that includes some spinal cord mechanisms.

It would be worthwhile to build a general computational model that will include the major nonlinear properties of the muscle and to try and combine it with a model of the spinal cord. Numerous muscle models were developed, however the advance in computers and robotics technology may allow us to simulate complex computational models and even build advanced physical models. Hannaford et al. (1995) built an anthropomorphic arm with pneumatic artificial muscles and ther are trying to use it in order to improve our understanding of reflexive control of movements and posture. There is a related research in the University of Massachusetts that pays attention to the nonlinear properties of the muscles (see Barto et al. 1999). They also plan to build an anthropomorphic robot with nonlinear dynamic properties that are similar to those of human arms. It would be most interesting to follow these projects.

There are some recent findings that suggest a small set of force fields that are the basis of motor control (see, e.g., Bizzi et al 1991, Mussa-Ivaldi and Bizzi 1995, Tresch et al. 1999). These force fields are generated by muscle synergies that are organized in the spinal cord, and therefore this approach perfectly fits the DDSS level in our general model. This prospective promising research could be developed in two main directions. One is in understanding the higher levels and how they use these force fields. The other direction is in understanding how these force fields are generated, and for this purpose, a good model of the dynamics of the muscles and spinal cord is essential as suggested above.

7.2.2. A comment on models and experimental results

Latash and Zatsiorsky (1993) wrote about the extensive abuse of the term stiffness and suggested new terms such as apparent stiffness and quasi stiffness. These new terms are tailored to experimental setups. However, it is not clear how they could be incorporated in future modeling. Zatsiorsky (1997) wrote a similar paper on viscosity. Their observation is justified and it is definitely important to be precise about the measured quantity. However, instead of introducing new terms, we prefer using the notion of impedance where possible, and physiological nonlinear models in order to describe the system's behavior. This kind of discussion brings us to the following comment.

Since we do not have the correct model of the system, the process of calculating means and variances of the measured data always reduces significantly the information that remains about the system. In our opinion, it would be worthwhile to publish the complete raw data of an experimental work, along with the usual precise description of the methods and measured quantities. This practice will allow the modeler to estimate the parameters of his model by means of a large bulk of data from many experiments, of course with the appropriate acknowledgment and citation. It is a pity that the results of many brilliant experimental studies are reported in view of a single model. Even the best model can frequently occlude interesting aspects of the data. Indeed, it is much easier to read means and variances and to conclude the experimental results with respect to a specific model, e.g., by accepting or rejecting a specific hypothesis. Indeed, it is unacceptable to fill a journal paper with tables of numerical results. However, today with the broad accessibility of the World Wide Web we can enjoy both methods for reporting experimental results, and allow the reuse of experimental results in order to compare prospective models.

7.2.3. Multiple controllers

In this thesis a general framework and a specific architecture for multiple inverse controllers was suggested. There are many options to extend this research and to explore versions of the proposed architecture.

The proposed method suggests building a multiple controller that is able to produce all the possible solutions by choosing a value for the parameter p. Further investigation is needed in order to describe the values of the parameter p and in choosing the appropriate solution. This stage depends highly on the specific control problem, its constraints and goals. For example, in the case of many motor units around a single joint and in a single muscle, the solution can be chosen as a function of time, e.g., cyclic switching between solutions in order to minimize the fatigue. Another example can be the inverse kinematics of a robotic manipulator, where the solution can be chosen as a function of obstacles in the environment of the manipulator.

The extension to MIMO systems described in section 5.2.3 is the simplest possible. It demonstrates that this extension is possible and that the general theoretical results about the capabilities of the PMLE and the MI-PMLE are still valid for the case of multiple outputs system. However, this method is very expensive: It produces many experts, and it does not exploit the spatial structure of the multidimensional data and the possible correlation between the outputs. An improved method could be developed in order to learn the minimal number of experts that is needed for a given approximation. One direction could be to extend the HH algorithm for multi-dimensional output and the other direction could be to use other methods of learning piecewise linear approximation in order to construct the PMLE directly. The prediction of multivariate responses could be improved by considering all the outputs and inputs together (see Breiman and Friedman 1997).

In Chapter 6 some basic preliminary tools for learning multiple inverse were introduced for the first time. Since this field is new, there is a lot of potential for future research concerning proper definitions, tighter bounds, and criteria for learning and generalization. Many results from the field of function approximation should be imported and extended to the case of a one-to-many relation approximation.

For artificial systems, the price of a complex controller is very low, since modern computers are quite cheap and powerful. Therefore, the concept of multiple controller can be useful in control of redundant systems (see the example in section 5.8). We even suggest that it might be worthwhile to introduce redundancy into the system in order to reduce it later. This practice will increase the reliability and flexibility of the system, and allow rapid adjustment to changes in the required performance. For example, a plant with structural redundancy could learn to exploit each part in its own optimal working point, and then switch in real time between criteria, such as maximum accuracy, minimum energy consumption, minimum acoustic noise, and so on and so forth.

As a model for the biological motor control system, this line of research calls for challenging experimental procedures. In order to reveal the internal structure of the controller that is implemented by the CNS, one has to carefully design an experiment that will show the ability to learn and to use different solutions for the same task, and then the ability to use different solutions in different circumstances. This is not an easy task. There is a recent experiment that validates the ability to learn two different control strategies for the same task by means of changing the force field of the environment (see Shadmehr et al. 1995 and Brashers-Krug et al. 1995). However, even for the same task and the same environment, one can occasionally find evidence for different solutions for the same task. Unfortunately, most of the reports in the literature ignore this phenomenon and look just at the solution that is chosen most frequently. This brings us back to our previous comments on the advantage of publishing the raw data of experimental studies.

7.2.4. Degeneracy redundancy and parallelism

Recently, Tononi et al. (1999) suggested mathematical definitions of degeneracy and redundancy by means of the notion of mutual information that is extensively used in information theory. They distinguish between two types of systems according to the origin of the functional redundancy. If the functional redundancy is caused by different subsystems that perform the same function, they call this system degenerate rather than redundant. It is most interesting to consider this structural approach and to further explore the consequences of their definitions and of using the notion of mutual information in order to construct a unified theory that will address both functional and structural redundancy.

There are other aspects of redundancy exploitation that were not specifically analyzed in this thesis and still wait for being modeled. The structural redundancy in the sensory system and in the motor system has a role in reducing the noise and improving the accuracy of the transferred information. This redundancy could explain our high fidelity sensory and motor performance in the face of low fidelity sensors and actuators. Another utilization of the redundancy is in using a different solution in each movement for the sake of distributing the load and stress evenly between the muscles, the bones, and the joints, or for flexible response to unpredictable events (see Robertson and Miall 1997). A qualitatively semi-popular description of the exploitation of redundancy by jugglers is given in chapter 5 of Wilson (1998), and a description of some interesting aspects of redundancy with neural networks modeling is given in Guenther and Barreca (1997). We expect that the main results and proposals of this thesis will facilitate the building of future models for the exploitation of redundancy by the biological motor control system.

7.2.5. BEI Vs IBE in the biological motor control.

In section 6.2, we showed that the difference between the BEI and the IBE is significant. It might be possible to determine experimentally, which one is more biologically plausible. Following is a tentative idea for such an experiment:

A simple experiment should measure one input variable and one output variable, (e.g., EMG amplitude and one-joint movement distance), introduce noise to the system, e.g., by visual illusion, and instruct the subject to try and learn to bring the output variable to a set of desired points. After these points were learned efficaciously, we can assume that the CNS has these points as a set of examples for the underlying input/output relation.

In the second phase of the experiment, another larger set of desired-inputs should be introduced and the performance should be measured. Then one can ask which performance measure was minimized, and whether the CNS learns the BEI or the IBE.

This type of experiment could prove (or maybe disprove) the common belief that the direct inverse learning method (i.e. the BEI) is not biologically plausible.

7.2.6. The general model

In Chapter 3 a general model was introduced. In this model, we focus on two mechanisms the DDSS and the MC. Many existing theories and open questions can be analyzed in order to be fitted into this general model, any exploitation of redundancy could be considered as a result of the MC and any observed invariance could be considered as a result of the DDSS. We have demonstrated in Chapter 4 some stereotypical features of reaching movements as a result of the system dynamics. There are many other such features that could be examined in a similar method. For example, in eye movements there are simple rules (Donder's and Listing's Laws) that determine the eye path and orientation for each target gaze direction and a similar rules for 3-D arm movements are the subject of recent studies (see Hore et al. 1992, Soechting et al. 1995, and Gielen et al. 1997). The origin of these constraints is probably not mechanical, however our DDSS does include low-level neuronal structures. As a continuation of this thesis approach about the DDSS, It would be interesting to find a biologically plausible neuro-mechanical model that would produce the observed movement with simple control signals and in this way will reduce the redundancy and the control complexity of the higher CNS levels. As a continuation of this thesis approach about the MC, it would be very interesting to observe the exceptions to these rules and how a MC might learn to activate different mode of operation in different circumstances.

One of the interesting questions in the general respect is in what level of abstraction the motor programs are planned, i.e., what are the coordinates of Y_d? For example in the task of reaching to a visual target, the target obviously appears on the retina, and at the end of the process, the hand reaches the target. The first question is, in what level the CNS represents the task, is it just the target position, a path for the hand, a path for each joint in the body, or a specific trajectory of the position, velocity, and force at each moment during the movement. The second question is in what coordinates this task is represented, e.g., the world or body coordinates. This problem is known as the question of the frame of reference and it was extensively discussed in many papers (see Soechting and Flanders 1995 for a review with many references on eye and limb movements). However, these are still key questions in the ongoing strive for understanding the biological motor control system.

7.2.7. Human motor control - The next challenge

Fifty years ago, the computer could outdo almost any intelligent human being in numerical calculations. Five years ago, the computer defeated the world champion in the game of chess. These are popular milestones that marks the achievements in the ongoing strive for artificial intelligence. We suggest that the next challenge of the engineering society should be in building a robot that will beat a human being in a complex motor control task. Let us conclude this section of prospective research with some general quite speculative ideas that might be developed in future research: conscious, analogue and quantum computation, and a test for motor intelligence.

The concept of consciousness is gradually entering the scope of scientific research (see Searle 1998, Grossberg 1999, and Taylor 1999). We follow the definition of Taylor (1999) that suggests that consciousness is a dynamic process of a race to achieve the attention of the brain. An interesting research in the field of motor control could be in exploring the relationship between consciousness and the process of learning new tasks. We speculate that learning motor control require this kind of attention. We suggest two parallel different mechanisms of motor control. The first mechanism is conscious where attention is required. Its characteristics are (i) slow movements, (ii) closed loop, i.e., the sensory information is used during the movement, (iii) rapid adaptation and learning. The second mechanism is unconscious. Its characteristics are: (i) rapid movements, (ii) open loop, i.e., the sensory information is used only after the movement in order to initiate a corrective movement if needed, (iii) there is no learning, only a very slow adaptation. The main hypothesis is that learning requires attention. We introduce here a delicate distinction between unconscious automatic adaptation and conscious learning. This distinction might further clarify our hierarchy of learning and adaptation, which was introduced in subsection 3.2.1. This model should be rigorously defined and then checked against the anatomy and physiology of the brain, with psychophysics experiments, and computational models. This model could be also considered as a method for robot control.

How the brain performs its' computational task is an open question. We are familiar with the Turing machine, which is probably not a good model for the brain. Artificial neural network models have many advantages as models for the biological systems, however, all the results in this field have been demonstrated by simulation on a Turing machine. Nevertheless, ANNs are suggested to have super-Turing capabilities (see Siegelmann 1999). This result emphasizes the superiority of analogue computation, however it is not clear yet whether this difference reflects some major qualitative difference or just an abstract mathematical distinction. There is another, more controversial idea, that the brain uses quantum mechanics principles as the basis for its computations (see Penrose 1994). This idea fits our suggestion of stochastic selection that was described in section 3.5. This idea can be further discussed and lead us to some quite interesting speculations, such as quantum parallel computation. We suggest that a multiple controller could be represented by a wave function and then the selection of a single solution can be the process of measuring, i.e. collapsing. A possible location for such quantum calculation can be in the microtubules as suggested by Penrose (1994). This possible mechanism is indeed far too speculative, however, it is much more economic than many large ANN models especially in the case of uncountable redundancy representation and reduction. The stochastic selection of a solution can also be helpful for exploration and for learning all possible solutions in order to use them in a deterministic method when needed.

In the Turing test (Turing 1950), a computer and a human being are asked questions by a human interrogator and reply by printed answers. When the interrogator cannot distinguish between the human and the computer then the computer is said to be intelligent. The Turing test checks the *linguistic* intelligence of the computer. Recent studies suggest abandoning the notion of one measure of intelligence and preferring multiple intelligences (Gardner 1993). We suggest the following test of *motor* intelligence: A robot and a human being should wear a costume that does not reveal their nature, and a human interrogator should ask them to perform a motor task and observe their behavior. A simplified motor intelligent test can be based on a puppet, which could be activated by a robot, or by a human hand. This test is suggested as a measure of our improvement (as engineers) in imitating the biological motor control. Imitating does not guarantee understanding, however we believe that it is a major milestone in the way to understanding.

Robots are superior to humans in performing monotonic and repetitive tasks, and in extreme environments. However, in dexterous motor control humans are still much better. There is an extensive research in both directions, in the design of robots that are inspired by the biological system, and in the development of biological models for motor control that are inspired by artificial architectures. See, e.g., Hollerbach (1982), McFarland and Bosser (1993), Flash (1995), Bekey (1996), Miyamoto et al. (1996), Beer et al. (1998), Schaal (1999). This gap between human beings and robots is constantly being reduced. Will this gap be closed and what the consequences would be are the great open questions of this fascinating field of research.

7.3. 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. In this thesis, 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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