LOW DIMENSIONAL MOTOR CONTROL AND MUSCLE SYNERGIES

Max Berniker [1] Emilio Bizzi [2], and Matthew Tresch [1]

[1] Northwestern University, Chcicago, IL, USA
[2] M.I.T., Cambridge, MA, USA
E-mail: mbernike@csail.mit.edu

INTRODUCTION

A number of recent studies have suggested that the central nervous system reduces the complexity of motor control by using a low dimensional control strategy. In this hypothesis, complex behavior results from the combination of a small number of 'muscle synergies'. Each muscle synergy specifies a particular balance of activation across a set of muscles, such that within a given synergy, the activation of muscles will covary. To produce movements, the CNS can simply specify the scaling and timing of these synergies, thereby greatly simplifying motor control.

Several questions regarding this hypothesis remain unclear. For example, why are particular muscles within a given synergy? More basically, can muscle synergies actually produce effective control of complex behaviors? The present study evaluates one principle for the specification of muscle synergies: that they are chosen to allow for the most effective control of the limb.

METHODS

All analyses are based on a physiologically realistic model of the frog hindlimb (Kargo et al. 2002). Our goal was to create a low dimensional representation of this high dimensional, non-linear dynamic system. This representation should capture the significant input-output dynamics of the system, i.e. it should succinctly summarize how control inputs are transformed into motor outputs. To find this representation we used a recently developed technique for empirical balancing for non-linear systems (Lall et al. 2002). This technique attempts to find a transformation from the original state, *x* (here a 17 dimensional vector consisting of hip and knee joint angles, joint velocities and 13 muscle activation states) to a reduced order state, *z*. With this transformation we can then find a reduced order model of the original system,

$$\begin{Bmatrix} \dot{x} = f(x,u) \\ y = g(x) \end{Bmatrix} \Rightarrow \begin{Bmatrix} \dot{z} = A_k z + B_k u \\ \hat{y} = C_k z \end{Bmatrix}$$

The equations to the left define the original high dimensional system, with state *x*, control input *u*, and output *y*. The equations to the right define the reduced order model with state *z* and estimated output, $\hat{y}$. The subscript *k* denotes the dimension of the reduced order system; here we consider *k*=6. Since the dimension of *u* (here 13, one motor command for each muscle) is greater than k, B_k has a null space. We can therefore define a set of low dimensional motor commands, analogous to muscle synergies. Further, since empirical balancing captures the significant dynamics of the original system, these synergies will be those that are most effective for controlling the frog hindlimb. To evaluate the performance of these synergies defined using empirical balancing (referred to BAL synergies), we compared them to a set of synergies defined according to a different principle. These synergies simply spanned the space of end point forces (referred to as FS synergies).

RESULTS AND DISCUSSION

We first found that the reduced order model of the frog hindlimb was able to capture the input-output dynamics very well, explaining more than 94.5% of the variance in limb trajectories. We then compared the MOR and FS synergies to those found experimentally a range of frog behaviors (Cheung et al. 2005). We found that each of the 6 MOR synergies was significantly correlated with at least one experimental synergy ($p < .05$). In contrast, only 3 of the 6 FS synergies were significantly correlated to an experimental synergy. The synergies used during natural behaviors are therefore similar to the synergies which are most effective for control.

We then evaluated whether these synergies could in fact be used to produce a range of behaviors. We considered 3 cases of control: using the MOR synergies, using the FS synergies, and using commands without restriction. This last case represents the best possible solution for the frog hindlimb. Commands for each case were found using optimal control techniques. An example movement for each case is shown in Figure 1. Although there were qualitative differences between some trajectories (see Fig. 1A), on average, both the MOR and FS synergies produced output trajectories close to the best possible (correlations of 0.99 ± 0.02 and $0.96 \pm .03$, $p > .05$). However, the commands used to produce these trajectories were very different ($p < .01$; Fig. 1B). The commands found using the MOR synergies were very similar to the best case without restriction on commands (correlation of $0.89 \pm .10$), whereas the commands using the FS synergies were quite different (correlation of 0.51 ± 0.15). As a consequence, the total control cost (a combination of trajectory error and control effort) was substantially higher when using the FS synergies ($p < .01$). On average, the ratio of MOR cost to optimal cost was 2.06 ± 1.01, whereas for the FS synergies this ratio was 16.69 ± 8.53. These results show that movements using MOR synergies allow for near optimal control. Further, this near optimal performance is not a feature of any set of synergies, but is a special aspect of the synergies identified according to the principle outlined here.

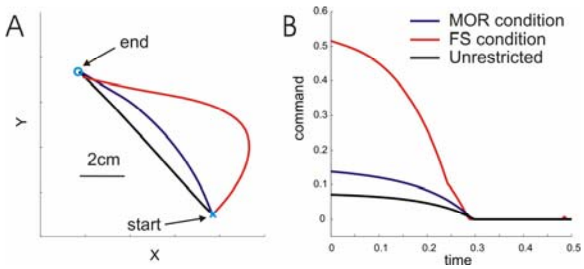

Figure 1. A. Example endpoint trajectories, starting at the x and ending on the circle. The three conditions are MOR (blue), FS (red) and unrestricted (black). B. Three muscle commands from the same movement.

CONCLUSIONS

These results suggest that the nervous system uses muscle synergies that allow for the most effective control of the limb. Such a strategy might allow for simplification of control while still allowing for a range of behaviors.

REFERENCES

Kargo et al. (2002) *J. of Exp. Biology*, 205, 1683-1702.
Lall et al. (2002) *Int. J. Robust and Nonlinear Control*, 12, 519-535.
Cheung et al. (2005) *J. Neuroscience*, 25, 6419-6434.