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Analysis of the synergies underlying complex hand manipulation

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Abstract—**Coupling of actuators into motor synergies has been observed repeatedly, and is traditionally interpreted as a strategy for simplifying complex coordination problems. This view implies a small number of task-independent synergies. We have shown that optimal feedback control also gives rise to synergies in the absence of any simplification; the structure and number of such optimal synergies depends on the task. To compare these hypotheses, we recorded hand postures from a range of complex manipulation task. The structure of the synergies we extracted (via PCA) was task-dependent, and their number significantly exceeded previous observations in a simpler grasping task. Our results lend support to an optimal control explanation rather than a "simplicity" explanation.**

Keywords—**Synergy, hand manipulation, PCA**

I. INTRODUCTION

The notion of motor synergies, or high-level "control knobs" that have distributed action over sets of low-level actuators, arose in the context of motor coordination [1] and has remained a central topic in discussions of motor control. While synergies mean different things to different people [2], dimensionality reduction is generally accepted as the signature of synergistic control. Indeed, recent studies [3-5] have demonstrated that the set of experimentally observed postures, or muscle activation patterns, spans only a small subspace of the available multi-dimensional space. But what do such results tell us regarding the control strategies employed by the CNS?

The usual interpretation is in terms of a simplifying strategy: since the control of redundant biomechanical systems is a challenging problem, the CNS might simplify its life by coupling the actuators and effectively reducing the dimensionality. Such a view implies that the number of synergies is small, their structure is fixed in advance of learning a given task, and is therefore task-independent. Note that synergies simplify the solution of a new control problem only if they are fixed in advance; if instead we attempt to adapt them to the new task, we end up solving a synergy learning problem has the same dimensionality as the original control problem. This "simplification" view dominates the synergy literature, and consequently an implicit agenda of researchers has been to demonstrate small numbers of task-independent synergies.

Our optimal feedback control theory of motor coordination [6] offers a very different perspective on the origin of synergies. We have shown that optimal control laws for redundant systems obey a "minimal intervention" principle: they correct deviations from the average behavior only when such deviations interfere with task performance. Task-irrelevant deviations are better left uncorrected, because that reduces control effort and control-dependent noise. This selective control has two consequences: (i) variability in redundant dimensions is allowed to accumulate (as quantified by the Uncontrolled Manifold method); (ii) only a subspace of the available control space is utilized in the context of any given task – i.e. the actuators are synergistically coupled. Such task-optimal synergies of course reflect the biomechanical system, but they also reflect the task. In particular, the number of synergies is expected to increase in more complex tasks.

The goal of the present paper is to contrast these two hypothesis, by analyzing dimensionality reduction in a wide range of complex hand manipulation tasks.

II. EXPERIMENTAL DESIGN

Six right-handed subjects participated in the experiment. Each subject was fitted with a right-handed CyberGlove, which recorded all 20 joint angles of the hand. Each subject participated in 7 experimental conditions (see Fig 1):

0. Subjects were instructed to generate a set of extreme hand postures, designed to reach all joint limits. The data from this condition was only used for calibration.
1. Subjects were asked to turn a pair of Chinese **balls** in their hand, at a comfortable speed. The task was to make several turns in one direction, then reverse the direction.
2. Subjects were asked to flip through the pages of a **book**. The book was placed on a table and held with the left hand for support; the right hand was used to separate and flip the pages.
3. Subjects were asked to turn a credit **card** in their hand. There were two conditions: turning the card in the palm, and also turning it between the fingers.
4. Subjects were asked to **grasp** a credit card presented by the experimenter, with the two fingers nearest to the card. The experimenter positioned the card near the subject's right hand, in a random position and orientation. The subject had to grasp the car lightly, pause, and then return to a relaxed starting posture.
5. The experimenter placed a **key** chain in the subjects palm (which was facing up at the beginning of each trial). Then the experimenter identified a desired key (using a verbal description), and the subject was asked to place that key in their hand in a position suitable for unlocking a door.
6. A square sheet of **paper** was placed in the subjects hand (palm facing up). The task was to crumple the paper and turn it into a paper ball, using only one hand.

7. The final task was a control, designed to measure the maximum number of effective degrees of freedom available. The subject was asked to move one **joint** at a time, while keeping all other joints stationary. Note that if subjects succeeded in doing that, the measured dimensionality of the hand postures will be 20.

Figure 1. Illustration of the seven experimental conditions. See text for details

III. DATA ANALYSIS AND RESULTS

Data was collected at 100Hz. For each subject and each condition, our dataset contained on average 9000 hand postures (corresponding to 1.5 min of continuous recording). Rest periods were excluded by pausing the recording. The CyberGlove measures the integrated curvature over the span of each of its bend sensors, and encodes that measurement using 8 bit resolution. The measurements are known to be a linear function of integrated curvature, however the gain and offset of that function are subject-specific. The calibration problem is rather complex, and does not appear to have a reliable solution at present. For our purposes, however, having absolute joint angles was not critical. Instead, we normalized each joint angle for each subject to a 0-1 range, using the minimum and maximum sensor reading obtained in the calibration condition. This representation was the basis of most analyses. When absolute joint angles were needed, we scaled the normalized 0-1 range of each joint to the corresponding joint angle range of a commercial hand model (Poser 5). A third form of scaling used in the analyses was the following: for each subject, condition, and joint angle, the data was scaled to have unit variance.

A. Dimensionality Reduction

The dimensionality of the hand postures was analyzed using Principal Components Analysis (PCA). The eigenspectrum of the covariance matrix in each condition is shown in Fig 2:

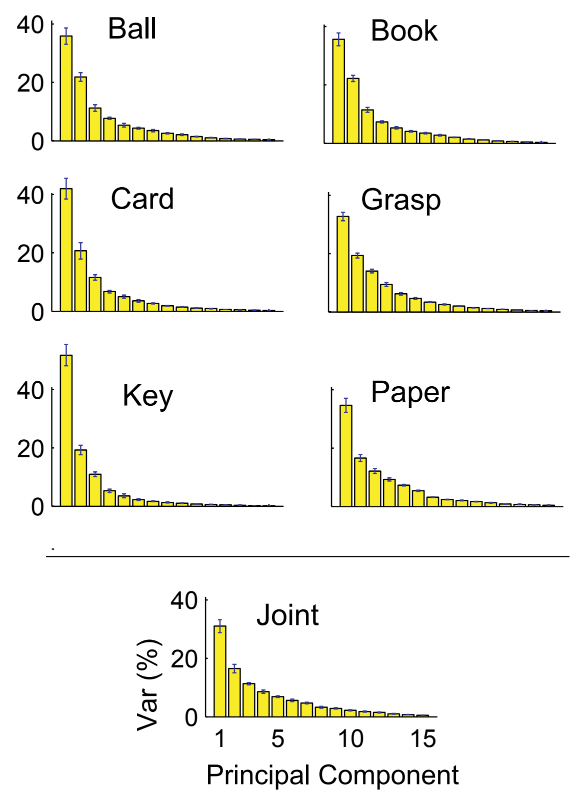

Figure 2. Variance accounted for by the first 15 principal components in each task. Results are averaged over subjects.

The fall-off in the bar graphs corresponds to dimensionality reduction, i.e. if the entire posture space was being used uniformly the plots in Fig 2 would be flat. If hand shapes were controlled by recombining N postural primitives, we should observe a relatively flat profile up to PC number N, and then a sharp fall-off. In reality the fall-off in PC plots is never sharp, which makes counting synergies complicated. To facilitate comparisons with previous results [3], we count the number of principal components needed to account for 95% and 85% of the variance respectively. In the grasping task studied in [3], these numbers were 4 and 2.

Detailed synergy counts are shown in Tables 1 and 2, and the results summarized in Table 3. We present results in posture space (Table 1), and velocity space (Table 2). Instantaneous joint velocity was obtained by numerically differentiating position, and smoothing (mildly). Note that it may be possible to interpret postures as states, and velocities as controls that change states, although we will not pursue that interpretation here. In each table, we counted synergies from the absolute angle data, the 0-1 range data, and the unit variance data. This allowed us to assess the effects of data scaling. In general, absolute angle data [3] has a tendency to underestimate dimensionality: if two joints with very different ranges are controlled independently, the two principal components will account for different amounts of variance simply due to the different scale. The 0-1 range data and the unit variance data avoid this problem. Note that the covariance matrix for unit variance data is equal to the correlation matrix by definition. For each type of data scaling, we obtained synergy counts using all 20 joint angles, as well as a reduced set of 15 angles recorded previously [3]. Eliminating joint angles also has the effect of reducing dimensionality. As expected, the different ways of counting yield somewhat different results (Table 1, 2), but overall, the dimensionality we observed is much higher than previously found [3].

To get a summary statistic, we simply averaged over all different ways of counting – Table 3. In the manipulation tasks, the effective dimensionality of hand postures was 6.5 on average. Remarkably, the dimensionality in the individuated joint task was 8.7, or only 2 higher. The latter task is designed to reveal the maximal number of degrees of freedom humans have access to. Why this number is not 20 is unclear; the most likely reason is biomechanical coupling, although limitations in neural control may also play a role. Furthermore, the number 8.7 intuitively seems too low – suggesting that such counting methods may underestimate the true dimensionality. Whatever the reason for this surprisingly low number, the fact remains that we counted synergies in the same way for the manipulation and individuation tasks, and found a difference of only 2. In other words, the neural controller is actively eliminating only 2 of the synergies it potentially has access to. The number of utilized synergies – 6.5 – was much greater than the 3 synergies found previously using similar counting [3]. Velocity DOFs were on average one more than position.

POS	Angle		0-1 range		Unit var	
	20 j	15 j	20 j	15 j	20 j	15 j
Paper	8 4	7 4	10 6	8 5	11 6	9 6
Book	6 3	6 3	8 5	7 4	9 6	9 6
Key	8 5	7 4	10 6	8 5	10 6	9 6
Card	8 4	7 4	9 6	8 5	10 7	8 6
Grasp	9 5	7 4	9 6	8 5	11 7	9 6
Ball	7 3	6 3	7 3	6 3	9 5	7 4
Joint	10 7	9 6	11 7	10 7	12 8	10 7

Table 1. Synergy counts in position space. See text.

VEL	Angle		0-1 range		Unit var	
	20 j	15 j	20 j	15 j	20 j	15 j
Paper	9 5	8 5	11 7	9 6	12 8	9 6
Book	8 4	7 4	10 6	8 5	11 7	9 6
Key	10 6	8 5	11 7	9 6	12 8	10 7
Card	9 5	8 5	11 7	9 6	12 8	9 7
Grasp	10 5	8 4	11 7	9 6	13 8	10 7
Ball	8 4	7 3	9 5	7 4	11 6	8 5
Joint	12 8	10 7	12 8	10 7	14 10	11 8

Table 2. Synergy counts in velocity space. See text.

SUMMARY	Pos DOFs	Vel DOFs
Manipulation	6.5	7.6
Individuated	8.7	9.8

Table 3. Summary of synergy counts.

B. Differences between tasks and subjects

We defined two measures of the difference between sets of synergies extracted from different datasets. Given two D-dimensional datasets, we perform PCA in each, and keep the first N principal components. This gives us two N-dimensional subspaces. How different are those subspaces? One measure is the average principal angle (a generalization of the notion of angle between two lines). The other measure is something we developed. Project one dataset in its N-dim subspace, and denote the trace of the projected covariance by T1. Then project again in the other N-dim subspace, and similarly define T2. When the two subspaces are identical T1=T2, otherwise T1>T2 (because projection reduces variance). Thus, 1-T2/T1 is a sensible difference index.

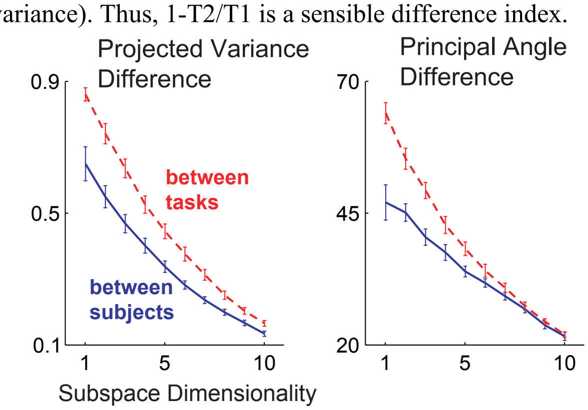

Figure 3. Average difference between tasks (same subject), and between subjects (same task), for different N.

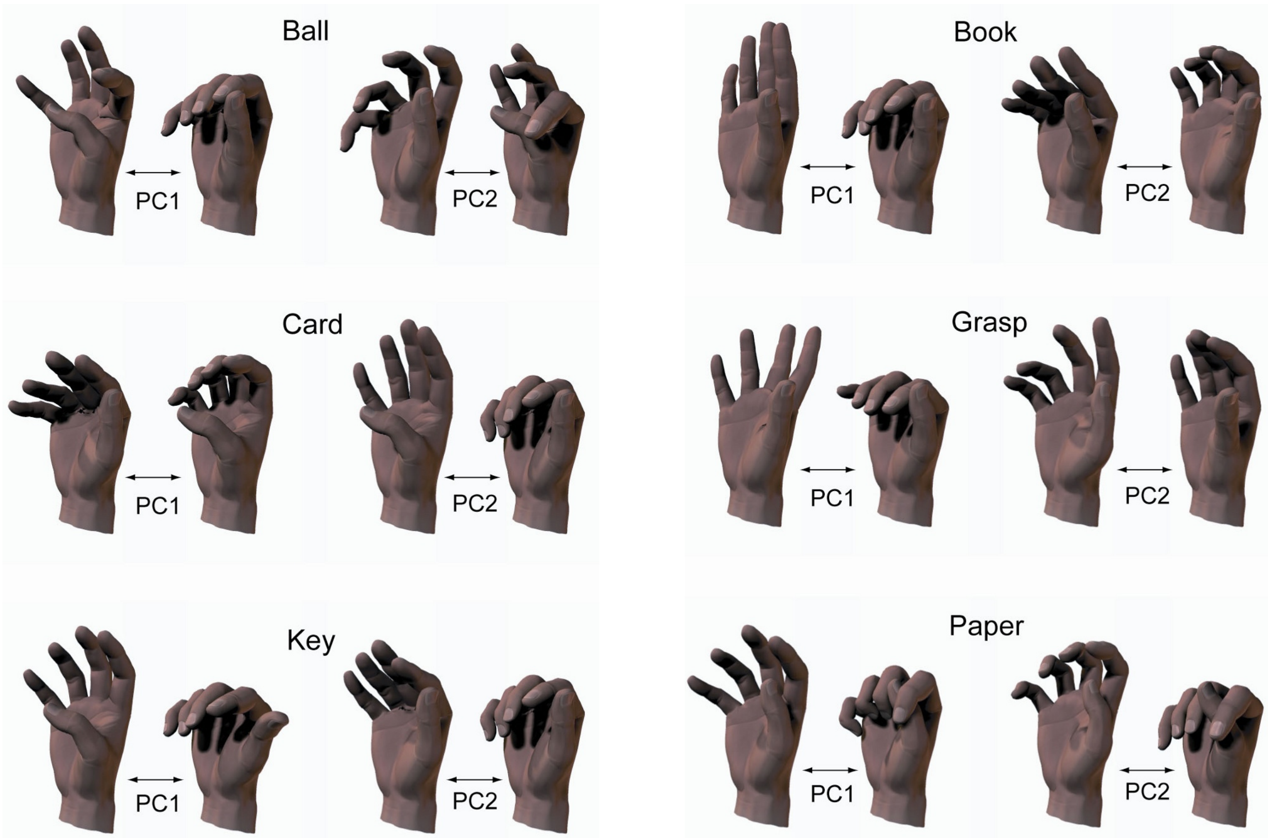

Figure 4. Illustration of first 2 PCs in each task. Each plot is generated by taking the (task-specific) average posture, and adding and subtracting the unit vector describing each PC. Synergies can be thought of as shape deformations.

In Fig 3, all differences decrease as N increases. This is not surprising: in the limit N=D both subspace become equal to the entire space, and there is no difference. The results show that the synergies differ substantially both between subjects and between tasks. However, the task dependence is significantly greater than the subject dependence. Fig 4 illustrates that the first two synergies in each task.

IV. CONCLUSION

Here we studied the hand synergies underlying complex manipulation tasks. The number of such synergies was more than two times higher than the number observed in a simpler grasping task [3] (note that our "grasp" task was more complex, requiring more individuated movements). Further, the structure of the synergies depended substantially on the task – more than it depended on the subject. Overall, our results are more compatible with a task-optimal control origin of dimensionality reduction than a "simplification" origin.

To end on a reconciliatory note, we point out that these explanations may be compatible. Indeed, the best strategy in terms of development and learning may be to start with a large number of synergies adapted to the biomechanics, and gradually select/tune them in the context of each new task.

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