

Dynamical Synergies in Multidigit Hand Prehension

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Abstract— Hand prehension requires a highly coordinated control of contact forces. The high dimensional sensorimotor system of the human hand although operates at ease, poses several challenges when replicated for prosthetic control. This study investigates how the dynamical synergies, coordinated spatial patterns of contact forces, contribute to the contact forces in a grasp, and whether the dynamical synergies could potentially serve as candidates for feedforward and feedback mechanisms. Ten right-handed subjects were recruited to grasp and hold mass-varied objects. The contact forces during this multidigit prehension were recorded using an instrumented grip glove. The dynamical synergies were derived using principal component analysis (PCA). The contact force patterns during the grasps were reconstructed using the first few synergies. The significance of the dynamical synergies and the current challenges and possible applications of the dynamical synergies were discussed along with the integration of the dynamical synergies into prosthetics and exoskeletons that can possibly enable near-natural control.

Clinical Relevance—This research presents dynamical synergies observed in contact forces during hand grasps. These dynamical synergies could help in improving feedforward force control and sensory feedback in hand prosthetics and exoskeletons.

I. INTRODUCTION

The human hand is a dexterous and sophisticated sensorimotor system, capable of performing complex motor functions. Currently, a large population of individuals is suffering from the loss of hand mobility, including amputations, stroke, and spinal cord injury. Loss of dexterity can significantly affect the level of autonomy and the capability of individuals to perform their activities of daily living (ADL), and they need the compensation of assistive devices, prosthetics or exoskeletons. Current prosthetic solutions can substitute the appearance and function of the limb and accomplish motor control by providing basic functions. However, two of the major limitations still constrict the completion and dexterity of the normal hand motor capabilities. One is the high-dimensional control and another is the sensory feedback [1][2].

It has been hypothesized that the central nervous system (CNS) is able to control the complex movements of the human hand by controlling synergies instead of controlling the individual joints or individual degrees of freedom (DoF), thus reducing the computational burden [3]. Mathematically, by using linear and nonlinear dimensionality reduction

methods and matrix factorization methods, the synergies are derived from different measurements of hand movements and from joint angular velocities, such as kinematic synergies [4][5] postural synergies from hand postures [6][7], and dynamical synergies derived from the contact forces during the grip tasks [8]. According to [16], the dimensionality reduction using synergies is not only limited to the motor control, and but also can be used to reduce a large number of sensory inputs to a small set of manageable and controllable representations in the prosthetic design.

During a grasp, the hand formulates the manipulative contact forces based on the task environment, the task constraints and the task requirements while maintaining a stable grasp [9][10]. The optimal contact forces must be not too small to cause slippage or not too large to damage either the hand or the object under grasp. Since such a grasp involves a larger number of DoFs that need to be controlled simultaneously, several studies have hypothesized and observed that this could also happen in a lower-dimensional space [11]. Similar to kinematic synergies, we hypothesize that the dynamical synergies can characterize coordinated contact force patterns in low dimensional space. Since the interaction of the motor and sensory function are important to help restore hand function, whether the integration of these dynamical synergies into prosthetics can improve their performance may provide alternative solutions to simplify the challenge.

In this study, we focused primarily on how the dynamical synergies i.e., the synergies derived from the contact forces in different object grasping tasks contribute to the coordination of contact forces from multiple hand areas, and how these patterns of coordination vary across the different weights of the objects, replicating our tasks in the activities of daily living.

II. METHODS AND ANALYSIS

A. Experiment protocol

A total of ten right-handed, healthy subjects (4 male and 6 female) were included in this experiment under the approved IRB protocol at the Stevens Institute of Technology. They were asked to sit in front of a table to perform four object grasping tasks—ball, door handle, bottle cap and water bottle corresponding to four typical hand postures—whole hand grasp, hook grasp, precision grasp and cylindrical grasp, respectively. To investigate the effect of the weight of the object on the grip force, these objects were prepared with four different weights (170, 320, 470 and 620 grams). The surface of the objects was wrapped by the same kind of material to remove the bias induced by friction forces.

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During each trial of the experiment, the subjects first placed their hands around the object as if they were grasping it without contact. The minimal forces at this point that could be due to the device noise were used as a baseline. After two seconds, the subjects were cued by an auditory beep to grasp, lift and steadily hold the object for four seconds. After hearing the stop cue, the subjects put the object to the original place and withdrew their hands back to the initial position. The objects were grasped in random order, and 20 repetitions were conducted for each weight. The contact force during the whole period was recorded by a GripGlove (Tekscan, Boston, MA), an instrumented glove embedded with sensors to measure contact forces.

B. Processing

Data was recorded by Research Foot software (Tekscan, Boston, MA) from GripGlove. As shown in Fig.1, the force sensors were divided into 12 areas including upper palm (UP), lower palm (LP), five distal phalanges (T1, In1, M1, R1 and P1 represent thumb to pinky respectively), thumb proximal phalanx (T2) and four middle-proximal phalanges (In2, M2, R2 and P2 represent index to pinky respectively, as shown in Fig.1B). Two types of data were saved from the steady-hold period in this study. One was the average force within each of the above 12 areas (Fig.1C), and the other was a spatial matrix of raw forces of the hand selected from the fourth second represented as a pixelated spatial force map (Fig.1D).

C. Reconstruction of Natural grasps and ASL postures

The contact force dynamics considered in this study, were represented by the averaged force from the steady-hold

period and the spatial force maps. The effects of the weight of the object were analyzed individually to investigate how it influences the movement dynamics and reconstruction of the force patterns.

We hypothesized that the force patterns can be modeled as a weighted linear combination of a few dynamical synergies, and the first few synergies represent the most variance among diverse grasp force patterns. Here, principal component analysis (PCA) was performed using singular value decomposition (SVD) to extract the dynamical synergies as shown below:

$$V = U\Sigma S \quad (1)$$

where V is the force matrix with dimensions $m \times n$, where m is the number of hand grasps and n is the number of forces recorded from the hand areas. For the averaged force data, the force matrix contains 12 forces, calculated from 12 hand areas; for the spatial force maps, the forces are represented as concatenated pixels, where a total of 361 pixels were included. S contains the principal components (PCs), which are considered as the dynamical synergies. Σ is a diagonal matrix (with eigen values of $\lambda_1, \lambda_2, \lambda_3, \dots, \lambda_n$) and the magnitude of the PCs were determined as $W = U\Sigma$.

Three-fourths of the grasping tasks were used to extract the dynamical synergies and the remaining one-fourth were used for testing the synergies in reconstruction of force patterns, and it was evaluated with a four-fold cross-validation. After the dynamical synergies were derived, the magnitude of the dynamical synergies for the testing data were calculated by least squares approximation. The force patterns were reconstructed by recruiting a few top order dynamical synergies. The reconstruction error between the recorded force pattern (F) and reconstructed force pattern (F') was determined as follows:

$$err = \frac{\sum_i (F_i - F'_i)^2}{\sum_i F_i} \quad (2)$$

III. RESULTS

The dynamical synergies were extracted from two types of force patterns—the averaged force from the steady hold period and spatial force maps. Since the top-ranked PCs or the top order dynamical synergies, represent the most significant variance directions among all the forces involved in the hand grasps, the fraction of variance would help to determine the number of dynamical synergies that could be used for optimal force pattern reconstruction. The reconstruction error of testing data across ten subjects and the variance accounted are illustrated in Fig. 2.

For the averaged force (Fig. 2(A)), 12 PCs were extracted. The first two synergies accounted for over 90% of the variance, and the average reconstruction error reduced to 0.2. With the first four synergies the error further reduced below 0.1. For the spatial force maps, 361 synergies were extracted, and only the first 50 synergies are plotted in Fig. 2(B). The first synergy only accounted for 50% of the total variance and the first five synergies accounted for 80% of the variance approximately. The differences between the synergies obtained from averaged forces and spatial

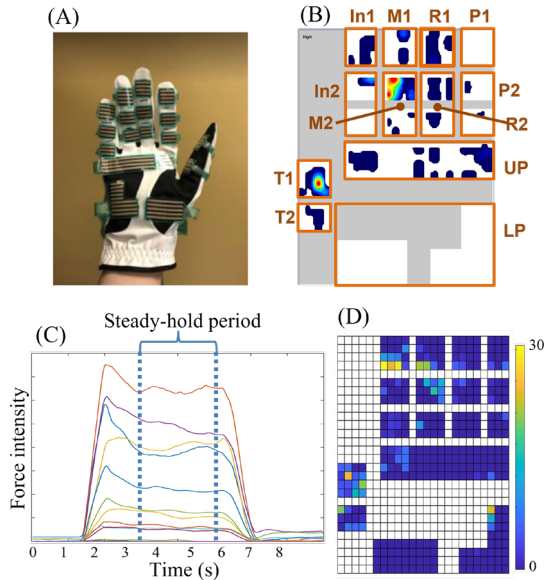


Figure 1. (A) GripGlove (Tekscan, Boston, MA) with 12 sensors to capture the contact forces in the 12 hand areas explained as follows. (B) 12 areas from where hand forces were recorded, including upper palm (UP), lower palm (LP), distal and proximal phalanx of thumb (T1 and T2), distal phalanges of index, middle, ring and pinky fingers (In1, M1, R1, P1) and middle-proximal phalanges of four fingers (In2, M2, R2, P2). (C) Recorded average forces during the steady hold period. Colors indicate the 12 areas. (D) Recorded spatial force maps pixelated corresponding to the 12 hand areas.

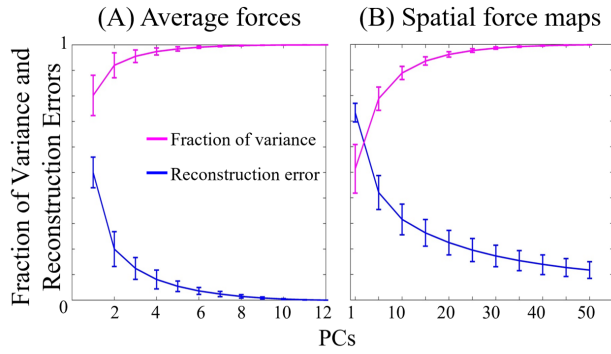


Figure 2. The fraction of the variance accounted for, and the reconstruction errors calculated using the top order synergies. The mean and standard deviation was calculated across ten subjects. (A) 12 synergies were extracted from the averaged force vectors and (B) 361 synergies extracted from spatial force maps (only the first 50 synergies) are shown here.

force maps are intuitive due to the larger dimensional space of the data in spatial force maps.

As for the spatial force maps, each spatial force map consists of 361 pixels and 361 synergies were calculated by SVD. As it was previously shown in Fig. 2(B), the first few synergies accounted for almost 90% of the variance but the reconstruction errors were higher in the range of 0.31 ± 0.06 . However, using the first 50 synergies, the reconstruction error further reduced to 0.12 ± 0.03 . Thus, it can be noted that reconstruction accuracy increases by recruiting more synergies. However, with the use of fewer synergies (as shown in Fig.3), it was possible to summarize the dominant characteristics of the force patterns, such as the thumb, index and middle fingertips which are the dominant force zones in our activities of daily living. Fig.3 indicates that, by recruiting only two dynamical synergies, the reconstructed patterns could successfully capture the dominant grip areas. Additionally, within the same type of grasp, incrementing the weight of the object contributed not only to the increased

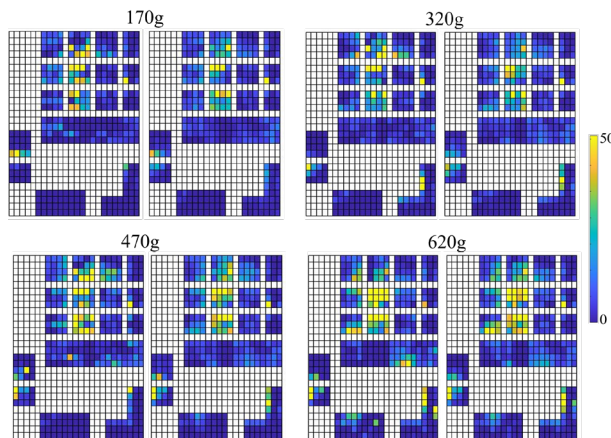


Figure 3. Reconstructed spatial force maps for whole hand grasp for four different weights using the first two synergies for subject 6. Most of the force intensity is concentrated at thumb and middle fingertips when holding the object at 170g. The reconstructed maps using only two synergies could successfully capture the dominant force zones. When extra weights are added to the objects, the force zone enlarges, and fingers involved in grasp increase. Color bar indicates the scale of the contact forces. Increase in the color bar scale indicates increase in the forces due to increase in the weights.

contact area and more fingers recruited in grasping but also an increase in the force intensities. The grip zones enlarged from fingertips to whole fingers even to some parts of the palm with the addition of weights.

The dynamical synergies across four different weights were observed. Fig. 4 illustrates the contribution of each hand area or finger in the first four synergies. The first two synergies shared common load force zones and the dominant areas are located at the thumb and middle finger. High correlations across four weights were found for the first two synergies. This may suggest that the first two dynamical synergies contain the functional basis for the majority of hand dynamics across different weights. The dynamical synergies derived from spatial force maps are shown in Fig.5. Similar to Fig.4, the first two synergies shared similar force distribution among object weights, and the most common

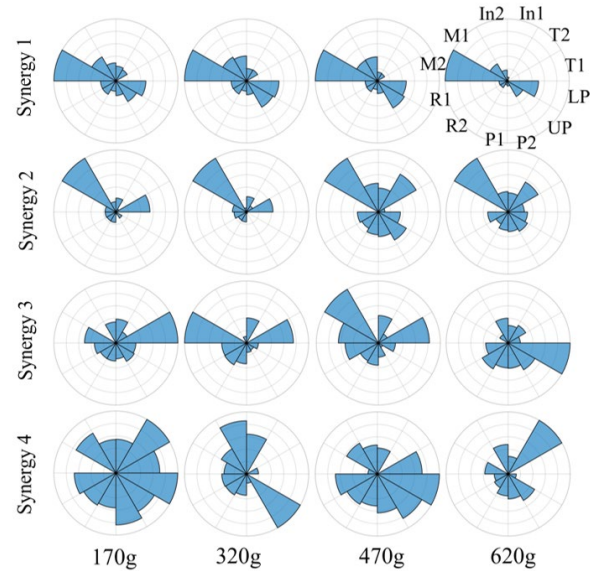


Figure 4. Dynamical synergies extracted from averaged force vectors of subject 8. The first and second synergies share the common load force zones regardless of the object weight. The middle digits (M1 and M2) and thumb (T1 and T2) carried the most dominant force characteristics. High correlations were observed among four weights.

characteristics across varied weights are represented on the thumb and middle finger. For higher-order synergies (third and above), the dominant load force zones differ for different weights.

IV. DISCUSSION

During the steady hand prehension period, a large number of contact areas, considered as DoFs, are involved in a certain grasp. There are redundant DoFs participating in a grasping task that increase the computational load of control by the CNS [3]. The results in this paper suggest that the prehension forces could be characterized by coordination patterns (addressed as dynamical synergies in this paper) and thus reduce the DoFs involved in cortical control to achieve the grasp forces. We hypothesize that the dynamical synergies could represent the primitives of hand prehension dynamics. In other words, the distribution of prehension forces can be considered as a linear superposition of synchronized dynamical synergies. Furthermore, by increasing the

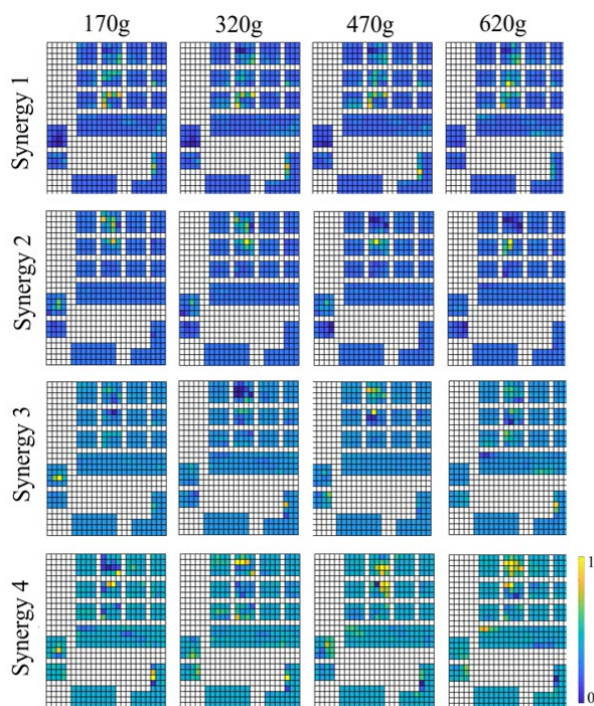


Figure 5. First four dynamical synergies extracted from spatial force maps of subject 8. Similar to Fig. 4, the first two synergies share the common load force zones and there is variability across synergies. Color bar indicates the normalized scale of forces obtained from principal components.

resolution of the pixels in the spatial force maps we can understand precise contact areas and force points that can be of significant benefit to understanding human movement control as well as augmenting or assisting human movement.

Results showed that the top-ranked synergies shared similar force distribution among object weights, and for higher-order synergies, the dominant load force zones differ for different weights. These could be subtle force adjustments that cannot be necessarily attributed to dominant force patterns observed across varied object configurations or different individuals. Nevertheless, the shared patterns of the first synergy suggest that the finger digits that contributed the most to the prehension forces are consistent across various weights and various prehension tasks, providing the probability of diverse types of grip force production using the same set of dynamical synergies. This may suggest that the most significant synergies accounted for variability across various prehensions; the higher-order synergies contain subtle information attributed to specific prehension tasks and are helpful in fine control of hand prehensions [12].

Dynamical synergies intuitively represent the dominant contact areas and force vectors (as shown in Fig.4 and Fig. 5), revealing the common or shared representations across various hand prehensions. According to the similarity of the synergy patterns across different object weights, the dynamical synergies can be used for feedforward force control for precise grip and to provide sensory adjustment in the feedback for precise prehension. Using these dynamical synergies in the context of prosthetics can functionally improve the feedforward control of prosthetics and the sensory feedback from prosthetics to the user. Additionally,

the higher-order synergies can assist to accomplish subtleties in precise force control. These higher-order synergies that seem to differ across subjects and weights can preserve anatomical and physiological differences in grasps across individuals.

V. CONCLUSION

This study provided critical insights and information about the dynamical synergies in hand prehension that can help reduce the grip force variables in biomimetic robotics, prosthetics and exoskeletons. Using these dynamical synergies (force vectors and spatial force maps) in the context of prosthetics can functionally improve the feedforward control of prosthetics and the sensory feedback from prosthetics back to the user. While the consistency of lower-order synergies provides functionality, the specificity of higher-order synergies could provide the user with an increased sense of ownership of the prosthetic and realize finer control. Overall, these dynamical synergies would enhance our understanding on how the CNS might implement a synergistic control of hand prehension. Questions remain unanswered as to how the biomechanical constraints and the neural control contribute to the development of synergies and can integrating kinematic and dynamic synergies improve the performance of prosthetics and exoskeletons.

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