NRI: Design and Fabrication of Robot Hands for Dexterous Tasks

1 Summary

Dexterity is a Grand Challenge goal in robotics today, and is on the critical path to capable robots in almost every domain: home, work, space, medicine, disaster scenarios... With advances in rapid prototyping and design optimization, we are well poised for dramatic progress in robot dexterity. Rapid prototyping technologies are becoming available in every lab. New robot hands are being designed at an unprecedented pace.

However, we are missing one crucial ingredient: we do not yet fully understand manipulation. We have no clear guidelines for creating the robot dexterity that would cause a transformative advance. The lack of clear design goals is a great barrier to further progress, and we as a field are struggling greatly to create reliable, apparently effortless dexterous behavior.

Our proposal aims to address this gap. We have observed patterns in human manipulation strategies and actions such that we are able to create Grasp Nets representing families of dexterous behavior. These Grasp Nets provide the design focus that has been lacking. Our expertise in grasp and manipulation analysis (PI Pollard) and optimal design, rapid prototyping, and control (PI Coros) make us the perfect team to convert these observations into robot hands that present previously unseen levels of robust dexterous behavior.

Intellectual Merit: Our working principles and research questions are that: (A) On-task compliance reduces actuator requirements. This is important for dexterous manipulation, because keeping number of actuators low and size of actuators small makes it possible to design lightweight hands with less tendon routing or other actuator complexity. (B) Joint limits improve robustness to error and likely make it easier to learn a task. (C) Working from specific Grasp Nets (such as we observe people to use) focuses design efforts to make possible the next leap in design for dexterous manipulation.

We will advance the state of the art in: (1) Grasp Nets capturing manipulation capability observed in human performance. (2) Novel optimization techniques to design mechanisms tuned for manipulation. (3) Mechanism optimization considering joint limits and compliance. (4) Analysis of manipulation with joint limits. (5) Fast tests for robustness through linear projection of uncertainties into geometric subspaces. Together, these contributions will make possible for the first time reliable and broadly varying dexterous behavior from accessible prototyping technologies.

Broader Impact: Having dexterous robots will affect many areas of our lives. Dexterous robots can render competent assistance in manual tasks to improve our quality of life, our health, and our safety. Educational broader impact includes K-12 outreach efforts. For example, we have recently brought the discussion of robot hands in to the elementary school classroom. Evaluation metrics will be available as grasping and manipulation benchmarks. Grasp Nets and robot hand designs will be made available so that others can access and build upon our results. The PIs have an excellent track record with mentoring underrepresented students and undergraduates and will continue this trend.

2 Introduction

Robot dexterity is critically important for robots working alongside people and for robots working in human spaces. Robots must be able to manipulate human objects and use tools made for people in order to assist people in performing tasks from mission critical to everyday.

Figure 1: We propose to develop the underlying analysis techniques and mechanism optimization approaches to enable us (and others) to design robot hands from the ground up to perform robustly dexterous manipulation tasks such as these.

Unfortunately, despite decades of development, dexterous manipulation has remained elusive. Robot hands cannot lift a wrench in a pinch grasp and slide it into a secure grasp for use with ease. Robot hands cannot handle a pair of pliers with competence. Even the simple task of grasping and turning a lever or knob can be a challenge; compare to the variety of modes of the "twist" action shown in Figure 1. Our view is that robots fail in these tasks in large part because no one has designed a robot hand from the ground up to be robustly competent at exactly these kinds of manipulations.

The 2013 Robotics Roadmap [12] states:

> *Robot arms and hands will eventually out-perform human hands. This is already true in terms of speed and strength. However, human hands still out-perform their robotic counterparts in tasks requiring dexterous manipulation. This is due to gaps in key technology areas, especially perception, robust high fidelity sensing, and planning and control. The roadmap for human-like dexterous manipulation consists of the following milestones:*
>
> - *5 years: Low-complexity hands with small numbers of independent joints will be capable of robust whole-hand grasp acquisition.*
> - *10 years: Medium-complexity hands with ten or more independent joints and novel mechanisms and actuators will be capable of whole-hand grasp acquisition and limited dexterous manipulation.*
> - *15 years: High-complexity hands with tactile array densities, approaching that of humans and with superior dynamic performance, will be capable of robust whole-hand grasp acquisition and dexterous manipulation of objects found in manufacturing environments used by human workers.*

Dexterous manipulation is not mentioned for the 5 year milestone. Dexterity is expected in limited form at 10 years, and approaching human levels in 15 years.

We propose to enable dexterity at the 5 year mark by designing robot hands from the ground up to do the kinds of dexterous manipulation tasks we see in Figure 1.

There are many very excellent research groups working on the critical areas of sensing, planning, and control. Our approach is orthogonal and complementary to these efforts. We aim to reduce the load on sensing, planning and control by designing the mechanism to be as favorable to the intended task set as possible by developing new analysis and design tools for optimizing the robot hand to make dexterous manipulation easier from the start.

Figure 2: This trivial Grasp Net nonetheless captures two important grasps and a dexterous motion to move between them.

This is a **high risk / high reward proposal**. The risk is that dexterous manipulation is complex. However, we observe commonalities in how people perform manipulation tasks that indicate sufficient structure to make design optimization feasible. For the reward, consider the change that can be effected by a robot hand that can manipulate the same objects and tools as its human counterpart in a cooperative task and carry out dexterous actions easily because it was designed to do just that.

Our approach centers around several elements: **”Grasp Net” benchmarks** to explore manipulation at its full complexity (Section 8), **Mechanism design** focused on manipulation tasks (Section 6), Strategic Placement of **Actuators, Joint Limits, and Compliance** (Section 4), and later in the project Strategic consideration of **Sensing** (Section 7).

Figure 3 shows a very simple robot hand which we developed to illustrate the potential. Through our design optimization process, we went from an initial manually designed version that was fiddly and difficult to coordinate to one where the manipulation almost does itself. A hand designed to do the manipulation tasks in Figure 1 as robustly as possible will change the landscape in terms of potential robot applications, especially in real-world applications such as where humans and robots work together and cooperate to accomplish a goal.

3 A Simple Example

Consider the trivial Grasp Net shown in Figure 2. This figure shows two grasps. Grasp A is a precision pinch grasp, typical for lifting objects from a surface, placing them down, performing certain dexterous actions such as using tweezers, and as a staging point for moving to other grasps. We observe that many objects are initially acquired from a surface in a pinch grasp and then moved to a final grasp that is more useful, comfortable, or powerful. Forces in the pinch grasp oppose one another along the local y-axis.

Grasp B is a lateral grasp, often called the key pinch grasp, useful for comfortably and securely holding objects, for certain assembly operations (e.g., put a key or a card into a slot), and for offering an object to a person (or another robot). Forces for the lateral grasp in this example oppose one another along the x-axis. Greater forces may be desired for this grasp.

Manipulation 1 is used to move between the two grasps. In this case we can imagine the ”thumb” pivoting around the ”index finger,” although in our final design, the motion may be generated by either

Figure 3: (Left) One final solution. (Right) A physical implementation inspired by this design.

or both fingers. The variation in object widths creates a family of curves describing motion of the thumb relative to the finger. The manipulation is specified to utilize sliding contact on the finger and rolling frictional contact with the thumb. There is a collection of benchmark objects of varying width, required grasp force, and other physical properties. The design problem is to choose degrees of freedom, place actuators and joint limits, and select passive compliance for the mechanism. A successful design must be able to accomplish Grasp A, Grasp B, and Manipulation 1 in the presence of uncertainties.

Figure 2 shows one solution that was derived based on the goal of minimizing the total number of actuators and the number of actuators per finger while ensuring that the mechanism could accomplish the task. This design relies on spring forces to close the fingers at both Grasp A and Grasp B, while using actuators to open the fingers. If both actuators are engaged briefly in a coordinated way, the grasp can be shifted from A to B or from B to A, performing Manipulation 1 in both directions. The coordination could be done mechanically for some range of objects, leading to a one actuator system. Such a system would be reminiscent of a body-powered prosthesis with a voluntary-opening end effector [37]. However, instead of a single available grasp, we have been able to accomplish two different grasps and a dexterous manipulation between them. A physical instantiation of this solution is also shown in Figure 3.

4 Dexterous Manipulation with Joint Limits and Compliance

One keystone of our approach is strategic consideration of joint limits and compliance. We illustrate the importance of these elements for the simple example. Specifically, we show that (1) Careful design of compliance can reduce the number of actuators and actuator load, and (2) Joint limits can be important for robust performance. Following this discussion, we present an approach to analyze grasps and manipulations to properly consider joint limits (Section 5) and approaches for design optimization to handle much more complex Grasp Nets to accomplish tasks such as those shown in Figure 1 (Section 6).

(1) Compliance matters. Table 5 shows parameters for four tendon driven designs, which were optimized to perform Grasp A, Grasp B, and Manipulation 1 for objects having widths from 1 to 4 finger radii. Quasistatic analysis was performed for each design, with actuators for the thumb moving in the X direction, and actuators for the finger moving in the Y direction. The quasistatic analysis ensured

Figure 4: Several designs with the goal of robust pushing.

Design	x0	y0	kx	ky	cost	actuated x range	actuated y range
(A) 4 tendons, no compliance	-	-	-	-	1600	(-4, 0)	(-4, 0)
(B) 4 tendons, compliance	-1.887	-2.58	0.54	0.43	**107.65**	(-1.36, 1.02)	(-1.61, 1.11)
(C) 2 tendons, spring open	7	7	min	min	1600	(-4, 0)	(-4, 0)
(D) 2 tendons, spring closed	-5.883	-4.998	0.45	0.5	**445.3**	(0, 2.65)	(0, 2.49)

Figure 5: Optimal parameters, cost, and actuator range for several mechanism designs to perform Grasp A, Grasp B, and Manipulation 1.

that forces required for Grasp A, Grasp B, and Manipulation 1 could be generated by the mechanism. Each design was optimized using CMA [18] to require the minimum total actuation force, expressed as squared actuated forces summed over actuators, objects, and time samples. Where compliance was considered, linear springs were assumed, with zero point and stiffness given as parameters to the optimizer. Optimal parameters, cost, and range of actuated forces are shown in the Figure.

Design (A) contains 4 tendons, which give active control in the negative and positive X directions for the thumb and the negative and positive Y directions for the finger. This design considers no passive compliance. Design (B) contains the same 4 tendons, but it also includes linear springs. Note that the cost of forces provided by the actuators is less than 7 percent that of Design (A). Design (C) has two tendons which act to close the hand, with elastic return springs to open the hand. The presence of the spring elements reduces the total number of actuators, but does not reduce the cost of the design. Design (D) also has two tendons, which act to open the fingers. In Design (D), the spring elements close the hand and provide grip force. The cost of Design (D) is 28 percent of that of Design (A), and the design achieves this result with half the number of actuators. Clearly, compliance matters. If we are able to maintain 4 actuators, compliance allows us to reduce forces to a small fraction of their magnitude without compliance, even while handling a variety of object sizes. Adding compliant elements makes it possible to reduce the number of actuators to two and *also* reduce forces to a fraction of their original value. Fortunately, it has become increasingly easy to incorporate compliant elements into a design using 3D printing and other technologies, such that we can consider this just one more design element available to optimize.

(2) Joint Limits matter. We observe that joint limits are not avoided in human motion. In contrast,

Test Case	Errors at Gaussian perturbation (radians)				
	None	0.1	0.2	0.3	0.4
(A) Joint limits, learn with perfect mechanism	**0.01**	0.90	1.63	2.32	3.61
(B) Joint limits, learn with perturbation	**0.04**	**0.05**	**0.08**	**0.21**	1.42
(C) No joint limits, learn with perfect mechanism	**0.01**	1.05	2.13	2.84	4.06
(D) No joint limits, learn with perturbation	**0.03**	**0.06**	1.43	4.38	5.75

Figure 6: This exploration shows the value of joint limits. Mean error of an optimized manipulation is shown as perturbations to the perfect mechanism grow in magnitude. Standard deviation is in parentheses. The test having both joint limits and optimized while seeing small perturbations is able to handle perturbations three time the size of any other situation tested.

in the human system, joint limits and singularities are exploited. The limit at our knee that facilitates straight leg walking is a well known example, but there are many examples in grasping and manipulation as well. In a lateral grasp (which motivated Grasp B), the moderately flexed fingers can passively support large forces, even though the force that can be actively generated by the fingers in that grasp is small, coming from small intrinsic muscles in the hand, such as the interossei [1]. The large grasp forces are available because the fingers are operating near their joint limits in this direction. As another example, large forces can be transmitted through our palm all the way up to our strong shoulder muscles, or even through to the ground in some cases. Pressing hard with a fingertip also exploits joint limits.

Here, we show one simple example that joint limits can make a practical difference. In this set of tests, we explored the ability to learn robust open loop control for Manipulation 1. Motor velocities for the thumb and finger were represented as linear functions of time, with three velocity control points per finger, resulting in a search space of six parameters. CMA was used to optimize these parameters. Box2D [2] was used to simulate the manipulation for any given parameter set. The cost at the end of each simulation was the difference between the final object configuration and that desired for Grasp B. Once an optimal open loop motion had been identified by the optimizer, it was evaluated on a series of 5 test sets, each involving 100 simulations having perturbations in the direction of motion of the finger. Finger motion direction was perturbed about its intended direction using a normal distribution with standard deviation of 0, 0.1, 0.2, 0.3, and 0.4 radians. The motivation for this choice is that in a more complex hand, it is often difficult to know exactly where the fingers are relative to one another, and this variation can affect ability to manipulate robustly. When a test used joint limits, the limits for the thumb were placed in the X direction, both at the thumb's origin in Grasp A and at a wide open position that gave clearance twice the width of the largest object. Joint limits for the finger, when used, were placed in the Y direction, both at its destination in Grasp B and in a wide open position that gave clearance twice the width of the largest object.

Four cases were considered (Figure 6). In Case (A), joint limits were included, and the manipulation action was optimized assuming a perfect mechanism. Case (B) is similar to Case (A), but included random perturbations during the learning phase, having a standard deviation of 0.2 radians. In cases (C) and (D), joint limits are not included. Figure 6 shows the results. Empirically, results with error less than 0.5 in our scale produced consistently good manipulations. These results show that when a task is optimized assuming a perfect mechanism, the effect of joint limits is not clear. However, when the optimization process has the opportunity to see perturbations, the optimizer learns to use the joint limits to create robust strategies. Case (B), including both joint limits and learning with perturbations, is able to handle three times the amount of disturbance of any other case. Here, clearly joint limits matter. Intuitively, this is because driving a joint to its limit reduces uncertainty and reduces the need for control to be exact (i.e., many controls can drive the joint to its limit). Whenever such limits can be used, they offer great advantage. Fortunately, it is easy to build in joint limits as well, as part of shape optimization. For our instantiation of the Simple Example, we used geometric features to limit range of motion of the fingers.

In addition to joint limits and compliance, there are of course other things that matter. One design element is shape. Consider, for example, how we can make good use of our palm and its ability to conform. Another is surface properties. It may be beneficial to have some parts of the hand be slippery and others have high friction. For example, in the Simple Example we had the object slide on the finger and roll on the thumb. Another aspect is ability to sense unexpected slip, force, or motion. We propose to investigate these options in the context of the larger goal of dexterous manipulation.

5 Grasp and Manipulation Analysis with Joint Limits

One research challenge addressed in this proposal is to expand our analysis tools to deal well with joint limits. We illustrate the problem and sketch a solution through the simple example in Figure 4. Consider first Figure 4 A. The goal is to push into a surface, holding the object in the given grasp. There will be variation in the task, as the object may contact the surface at different points and with different surface contact normals, resulting in varying force directions and moment about the object center of mass. Each finger has one tendon to actuate it, with directions of actuation shown. We assume the two fingers on the sides have considerable compliance in the horizontal direction. Actuating these fingers does not help, as this will only cause the fingers to slide along the object surface. With the design as shown in Figure 4 A, the grasp will only be able to apply a very small range of task related forces to the object.

We can examine the force balance equations. Because the fingers are very compliant, forces on the fingers must be balanced to prevent them from moving:

$$f_{s,i} + f_{a,i} + f_{JL,i} + f_{c,i} = 0 \tag{1}$$

Parameter $f_{s,i}$ is the spring force, with a component due to deviation of the initial contact location c_i from rest position $c_{i,0}$ and a second component due to object motion that results from unequalized forces ΔX_o, which is intended to be small for a good grasp. Matrix K_i encodes stiffness as seen at the fingertip and G_i is the grasp matrix for finger i.

$$f_{s,i} = -K_i(c_i - c_{i,0}) - K_i G_i^T \Delta X_o \tag{2}$$

Parameter $f_{a,i} = D_i P_i A_i$ is force generated by the actuators as in [27], and is expressed using activation levels A_i, $0 \leq a_i \leq 1$, diagonal matrix P_i of maximum actuator forces, and matrix D_i of actuator directions.

Parameter $f_{JL,i}$ is the novel component compared to other treatments that consider grasp quality for compliant systems (e.g., [28]), and can be expressed for a frictionless joint limit surface as:

$$f_{JL,i} = -k_{JL} N_i S_i N_i^T G_i^T \Delta X_o \tag{3}$$

with joint limit normal matrix N_i and (large) stiffness experienced at the limit of k_{JL}. Note the selector matrix S_i which indicates which joint limits relevant to finger i are currently engaged by some external or active force.

Parameter $f_{c,i}$ is the contact force, which must be within the friction cone at the contact and contributes to balancing a desired external wrench W_{ext} due to the pushing contact with the ground in this case:

$$-\sum_i G_i f_{c,i} = W_{ext} \tag{4}$$

For a given value of selector matrices S_i, we can solve the resulting linear system for actuator forces A and object motion ΔX_o. In a valid solution, ΔX_o must be consistent with selection matrix S_i such that the object motion pushes the object into the limit to engage it. The system as a whole can be resolved through pivoting or other discrete search techniques.

A similar analysis gives guidance for design of joint limits. Following [27] we can identify the worst case task wrench. Knowing this wrench, we can attempt to place a joint limit to oppose it. To visualize this process, note that in two dimensions a task wrench is a line with direction and moment about the origin. We wish to identify the joint limit to supply the opposing wrench nearest to this line, with the added consideration that task wrenches or other actuators must engage this limit.

In the case shown in Figure 4, a search for optimal joint limits may result in Figure 4 B, which is similar to using two fingers laterally as guides while pushing with a middle finger. Here, the range of task forces that can be applied is considerably greater. Torques due to ground contact forces at the object base engage one of the joint limits, allowing a force balance to be created.

A third option, shown in Figure 4 C, is to add an additional actuator that can actively engage the joint limit opposite to it. The result is a very strong grasp, reminiscent of human power lateral grasps, which can easily provide the task forces and many more. As a side benefit, the two previously useless actuators can now contribute to the task, sharing the load with the actuator of the top finger.

In each case, the force balance equation as shown here, along with a straightforward linear optimization, have made it possible to evaluate the effect of any new design element on the ability of the push grasp to achieve task forces.

Extension to complex and redundant mechanisms is more complex but can follow the same line of reasoning. Developing and evaluating these analysis tools is one task of the proposed research.

6 Dexterous Hand Design / Optimization

We will develop mathematical models and algorithmic approaches to co-design the mechanical structure of a robot's hand and the control policies needed for specific dexterous manipulation tasks. Our hypothesis is that by complementing each other and working in unison, control policies can be significantly simpler and mechanical structures – joint stops, compliance, etc. – can passively improve the robustness of the task while reducing sensing and actuation requirements.

The design process will begin with a specific family of tasks (i.e., a Grasp Net). In particular, we assume as input the set of time-varying contacts and contact forces between the hand and the object being manipulated. We further assume that a fully actuated robot hand controlled with perfect state knowledge would be able to generate these contacts and contact force trajectories. Through an iterative process, our mathematical models will be used to replace active degrees of freedom with appropriate passive mechanical structures such that a balance between adaptability and simplicity is achieved. We illustrate the proposed iterative design process with several use cases.

6.1 Designing Linkage Structures

In prior work, CO-PI Coros developed a computational system for design complex linkage structures that generate a desired motion []. This work, which we briefly summarize here, constitutes the starting point for our investigations.

The input to the design system consists of set of rigid links connected to each other through virtual actuators. The angle trajectories executed by the actuators define the target motion. As an example, such a structure could represent one finger of a hand performing a manipulation task (Fig **??**). In principle, if space allows, physical actuators could be directly used to replace their virtual counterparts when fabricating the robot hand. However, this would come at an increased cost, a more complicated mechanical design, a heavier setup, and it would require a sophisticated control policy that coordinates all the actuators. As an alternative, the computational design system proposed by CO-PI Coros iteratively replaces virtual actuators with new rigid links that couple the motion of different parts of the mechanism. The new attachment locations and length of the new rigid links are automatically optimized such that changes to the original motion of the kinematic chain are minimal.

More details will follow, as well as brief descriptions for extensions to include compliance and stop limits and reasoning about forces too, and not just kinematics.

6.2 Cable-driven, continuously deforming structures

Talk about the option of starting with an elastically-deforming structure for each finger of the hand. We can either start with a large number of actuated virtual tendons, and figure out which to remove, or add them one by one, optimizing routing points.

7 Research Tasks and Questions

Primary tasks and research questions for this project follow.

(1) Extend Quasistatic Grasp and Manipulation Analysis approaches to consider Compliance and Joint Limits. Extend the simple example of Section 5 to more complex scenarios, including multiple degree of freedom fingers, redundant mechanisms, actuators and links of various types, different varieties of joint limit surfaces. Our goal is to quickly evaluate the effect of any design change so that alternative designs can be explored and the hand can be optimized in a very fast search loop.

(2) Fast techniques for Evaluating Robustness. Quasistatic Grasp and Manipulation Analysis as discussed in (1) considers a specific scenario. However, we care very much about robustness to uncertainty, even (especially!) in the mechanism design stage. In Section 4, we showed how robustness could be evaluated through rollouts of the manipulation under samples of a distribution of likely scenarios. Using rollouts to evaluate success is functional, but slow. Using simulation rollouts may not scale well to the breadth of situations we plan to address.

Previous research by PI Pollard has resulted in techniques that can use a simple and fast linear projection to analyze robustness to errors in placing the fingers on an object [34]. We have extended the process to evaluate robustness for manipulation tasks [32] (Figure 7) and shown that the same approach can be used to express ability to grasp objects of different geometries [35] and to work with tendon driven systems [27].

Briefly, the idea we have exploited in this previous research is to portion variations out to different parts of the mechanism (e.g., to each contact). As long as each contact is confronted with a situation within its portioned space of variations, we can guarantee that overall, the task can be completed at

Figure 7: [ADD ALON PIC AND ROBOT EXAMPLES. (Left) Our manipulation task can succeed for any of these (and more) geometries. Inclusion in this set can be determined by linear projection. (Right) Two examples of performance of the same manipulation on different geometries. We propose to develop similar fast methods to test robustness of a mechanism to perform a manipulation in the inner loop of a design process.

least X percent as efficiently as an example. Decreasing X gives more freedom, but less efficient results (e.g., for lower X we may need to reduce weight limits on manipulated objects). Unlike many other approaches, which scale exponentially with number of contacts, this approach scales only linearly with number of contacts and works better and better as number of contacts increases; with large numbers of contacts comes great ability to adapt to uncertainties and variations. Many human manipulation tasks benefit from large numbers of contacts and we expect to exploit this property.

Use of this idea in a design process is as follows. Suppose a mechanism design for which we wish to test robustness. Given a solution to manipulate one object, we develop a test that utilizes a small number of linear projections to evaluate the expected success of any combination of uncertainties in mechanism and variations in object geometry, following the approach of apportioning out variation spaces to different parts of the mechanism as outlined above. These projections will be trivially fast and will not require analyzing details of each object or computing a mechanism trajectory.

Funding for this proposal will give us the opportunity to investigate this idea properly. The potential impact is large, both for manipulation planning and mechanism design, as having linear projections in the inner loop of a planning or optimization process as opposed to simulation rollouts to evaluate the same thing can speed these operations by orders of magnitude, allowing real-time planning and user-in-the-loop interactive design optimization.

(3) Design Optimization Tools that Scale to Large Grasp Nets and manipulator complexity. [STELIAN FLESH THIS OUT A BIT]

(4) Understanding the Delta Provided by different Sensing Approaches. Sensor design will be considered in later stages of the project with the point of view of what type of sensor could most improve performance of the mechanism on its intended tasks (e.g., increase generality or robustness and/or eliminate catastrophic failure). We hypothesize that the best role for sensing in many manipulation actions is to identify when things are going very wrong and to make a straightforward adjustment to compensate. Reflexes are a good example, response to slipping of the grip, total loss of contact, or stopping of expected motion. One type of response may be to lift the object and move it aside to clear

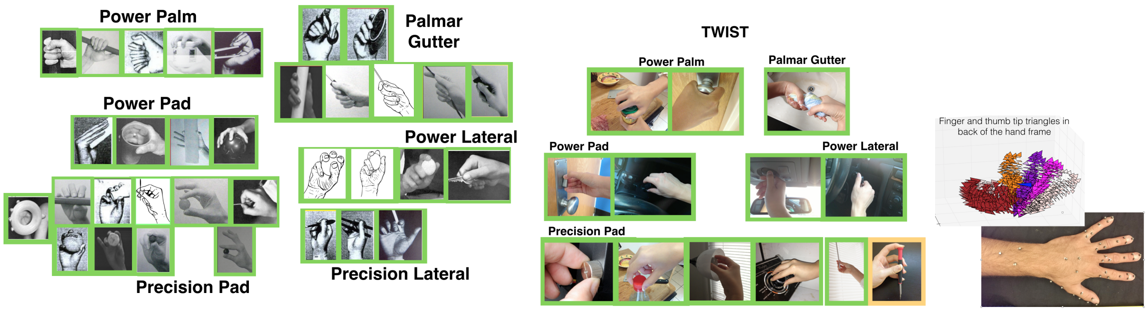

Figure 8: (Left) The 33 grasps of the Feix et al. taxonomy [15] can be grouped into six classes. (Middle) Examples of 5 of these classes in use for the ”twist” action. (Right) Marker set and sample data from capture of a preliminary Grasp Net.

an obstacle. It is encouraging that in our human subjects studies we observe frequent failures such as collisions prior to reaching the intended destination, which are resolved (after a delay of approximately 100ms) with characteristic corrections. Our first line of attack will be to enable similar behavior. The proposed research will assess sensors as any other design element in terms of their expected value in completing the intended manipulation tasks.

8 Grasp Net Benchmarks

To tackle dexterous manipulation head-on, we must consider grasping and manipulation in its full complexity. We take inspiration from human dexterity. Full scale humanlike dexterous manipulation may appear enormously complex. However, we have observed a relatively small number of grasping tasks and manipulations that are used over and over, with common actions linked to one another, forming what we call Grasp Nets. These Grasp Nets give us a way to proceed without oversimplifying. We propose to create Grasp Net benchmarks to cover expanding portions of the dexterous manipulation space. In tandem, we will develop evaluation procedures that test ability of a mechanism to accomplish Grasp Net tasks in the presence of uncertainty. One project goal is to create and debug these tests to contribute them to the Roadmap to Progress Measurement Science in Robot Dexterity and Manipulation [14] where evaluation metrics for dexterous manipulation are needed.

In this section, we provide some examples to illustrate the idea of a Grasp Net and some of the organizing principles we have observed through various human subject studies [29, 30, 7, 8, 31]. These observations are as yet unpublished.

Consider first the grasp taxonomy recently developed by Feix and colleagues [15], which pulls together the wealth of research on grasp classification over the last century. There are 33 grasps in this taxonomy. However, we find that they can be placed into six groups (Figure 8, Left),. Variations within a group depend mostly on object geometry, and occasionally (scissors, knife, chopsticks,...) on function. Figure 8, Middle shows examples of the ”Twist” action, uncovered in one of our studies [31]. Twist actions are found for five of the six categories. Only the last, Precision Pad, requires intrinsic motions of the fingertips to achieve the twisting action. In the remaining cases, most of the motion is performed by the wrist and/or arm.

We observe common transitions between the six grasping categories shown in Figure 8, such that a brief motion causes a robust transition from one grasp to another. Figure 1, Right shows several examples, with the different colored arrows indicating some of the transition paths from one grasp to another. As preliminary work, we have collected detailed human motion data of a grasp net containing 21 grasps and more than 25 manipulations and have plans for several more such capture sessions. Figure 8, Right shows our marker set and a sampling of fingertip positions in the hand coordinate frame for this dataset.

Beyond the transitions between the six grasp types, a portion of which are shown in Figure 1, a Grasp Net must contain task related manipulations, such as the twist manipulations shown in Figure 8 and manipulations to acquire and release an object. One research challenge will be to map out benchmarks of GraspNet metrics of gradually increasing complexity, but such that each one provides full functionality for a set of tasks (e.g., the robot can get some family of objects into the hand, use them for their intended purpose, and put them back where it found them).

9 Evaluations

Each unit of research will of course be evaluated as we go, but we pose two interesting overall evaluations here.

- Generality. If we design for specific task families, will the resulting robot hand be robust and capable enough to generalize beyond the specific given examples? Because we place such importance on robustness in the design process, we believe the answer will be yes. We will test generality with leave one out tests and by extent of ability to extrapolate beyond the bounds of the object set given in the Grasp Net.

- Comparison to existing robot hands. Is it possible for existing robot hands to accomplish all grasps and manipulations within the grasp net? If not, what fraction can they achieve, based on kinematic structure and load capabilities alone? We can obtain experimental comparisons of our new hands vs. the Shadow, Barrett, Robotiq, Kinova, and other Hands available to us at CMU. Our hypothesis is that we will be able to exceed capability and robustness of existing hands in traversing the Grasp Net Benchmark with relatively few actuated degrees of freedom and low cost. We anticipate that the result may look quite different from the typical dexterous hand existing today.

10 Comparison to Related Work

Design optimization for robot hands has been considered by a number of research groups. Salisbury [REF] designed the Stanford/JPL hand to optimize ability to manipulate a small object held in the fingertips. Dollar and his colleagues optimize hands to improve ability to capture the object in a grasp and considers the manipulation task of lifting an object from a table with a two actuator hand [REFS]. Ciocarlie and colleagues optimize a hand to enclose objects as well as possible, whether they be small and flat or larger and round [REF]. Hammond III and colleagues consider which joint ranges of motion can be reduced (or even eliminated) while maintaining ability to achieve a fixed set of grasps [REF]. [WHO EXACTLY] have designed hands that make use of one or more layers of synergies motivated in part by the major directions of motion of the human hand [REFS]. We are inspired by these and other efforts in robot hand design optimization and wish to take the next leap to optimize for complex manipulation tasks observed to be critical for dexterity in human environments.

There have been many exciting highly dexterous hands designed, some with the explicit goal of duplicating or exceeding the capabilities of the human hand. Just a few examples are found in these references [UTAH/MIT, ACT, SHADOW, GIFU, ITALIAN, JUSTIN, TODOROV]. Perhaps in contrast with some of these works, we begin with the goal to achieve a given network of grasps and manipulation actions, with the approach to make the hand exactly as capable as it needs to be – not less and perhaps not more – because adding limits can help. Our hand may or may not look much like the human hand. How it comes out will depend on the design elements we provide and what is needed for it to do the required manipulations in a robust manner.

There has been a virtual explosion of ideas on how to use rapid prototyping techniques in robot design [DOLLAR], in soft robot design [BROCK, HARVARD, MIT], and design of compliant elements such as joints [DESHPANDE], making this a great time to be exploring the research problems of this proposal.

There has been much work on grasp and manipulation analysis that is also very inspiring [TRINKLE, BICCHI AND PRATTICHIZZO, BURDICK]. We especially appreciate the point of view that we can use ”defective” mechanisms to our advantage and that we wish to configure the mechanism so that abstractly ”if we just squeeze,” good things will happen. We expect to build on and extend this research, which will become more and more valuable as we build robots which exploit limits, singularities, asymmetries, and highly coupled action as a matter of course.

The research of Abeel and colleagues [REFS] suggest that learning manipulations on real robots is possible with small numbers of iterations. We expect even faster learning and more generality and robustness because the mechanism is designed exactly to do the manipulations is is performing.

11 Broader Impact

Having dexterous robots will affect many areas of our lives. Dexterous robots can render competent assistance in manual tasks to improve our quality of life, our health, and our safety. Educational broader impact includes K-12 outreach efforts. For example, we have recently brought the discussion of robot hands in to the elementary school classroom. Evaluation metrics will be available as grasping and manipulation benchmarks. Grasp Nets and robot hand designs will be made available so that others can access and build upon our results. The PIs have an excellent track record with mentoring underrepresented students and undergraduates and will continue this trend.

12 Results from Prior NSF Support

PI Pollard brings decades of experience in grasping and manipulation analysis and experience working with various robotic hands and systems. PI Coros brings experience in optimal design of creative, complex mechanisms to accomplish user specified tasks, as well as 10 years of experience in control algorithms for complex tasks. This combination of skills is critical for designing and creating robot hands with the capability and skills to grasp and manipulate robustly in complex, real-world scenarios where humans and robots live and work together.

Pollard's prior work on physics-based grasping and manipulation. PI Pollard has extensive experience in grasp and manipulation planning, transfer, and optimization. She has developed algorithms for grasping and manipulation that allow fast transfer of examples from human to robot and generalization to varying object geometries in a manner that is both fast and provides bounds on performance

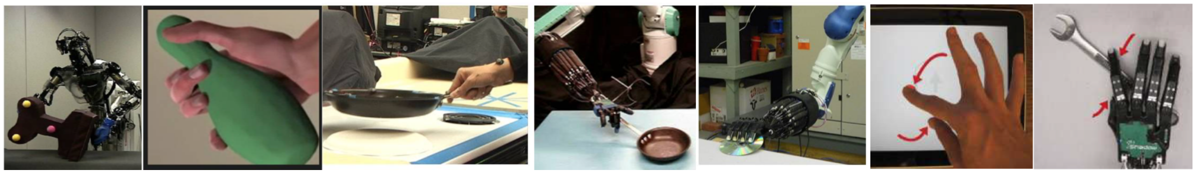

Figure 9: Examples show prior research of PI Pollard in transfer of grasp and manipulation tasks, grasp planning with preparatory manipulation, and teleManipulation.

[34, 32, 36, 27]. She and her students have performed numerous human subjects studies to better understand the complex process of grasping in real-world situations [11, 3, 19, 31] and followed up with more highly capable robot planning algorithms and quality metrics that function well for robot grasping in the presence of uncertainties [9, 21, 24]. She has studied human-in-the-loop manipulation (teleManipulation) [38, 13, 22] and examined anatomical considerations of the hand that may lead to better robot hand designs [33, 16, 6, 4, 5].

Results from Prior NSF Support. Pollard's NSF award most relevant to this proposal is *CCF: Capturing and Animating the Human Hand: Robust Recovery of Hand-Object Interactions* NSF CCF0702443 (PI: Pollard 6/07 - 5/11, $325,000). **Intellectual Merit:** Results include a taxonomy of manipulation actions prior to grasping, findings on rotation prior to grasping, a novel algorithm for planning robotic tasks with preparatory manipulation, robust algorithms for capturing human hand skeletal structure, fast algorithms for simulation of deformable systems, a novel interactive system for guiding simulations, a system for robot teleManipulation using multitouch, and an investigation of new representations for motion that are meaningful across individuals and species (including robots). This award resulted in the following publications [38, 8, 17, 21, 23, 22, 25, 3, 9, 20, 11, 6, 10]. **Broader Impact:** In addition to top venues in Robotics and Computer Graphics, results have been published in the Journal of Motor Behavior, the Journal of Biomechanics, the Journal of Theoretical Biology, and in the book "The Human Hand: A Source of Inspiration for Robotic Hands." This grant supported one female PhD student, Lillian Chang, whose recent dissertation contained many of the core research findings supported by this award. It also provided partial support for two masters students, three undergraduates, and one postdoc.

Coros's prior work on [LOTS OF AWESOME AND RELEVANT THINGS]. [STELIAN, CAN YOU DO SOMETHING LIKE MY PRIOR WORK PARAGRAPH ABOVE FOR STUFF RELEVANT TO THIS PROPOSAL]

Results from Prior NSF Support. PI Coros is an NSF beginning investigator.

13 Punch List

- letter of collaboration Paul Kry (do we want any others?)
- biosketches
- summary

- human subjects protection document
- data management plan
- facilities and equipment
- budget (DDH)
- current and pending (DDH)

Proposals involving human subjects should include a supplementary document of no more than two pages in length summarizing potential risks to human subjects; plans for recruitment and informed consent; inclusion of women, minorities, and children; and planned procedures to protect against or minimize potential risks.

Data Management Plan. All proposals must include a supplementary document no more than two pages in length describing plans for data management and sharing of the products of research, which may include (see sections II.D and VI.A):

The types of data, samples, physical collections, software, curriculum materials, and other materials to be produced in the course of the project;

The standards to be used for data and metadata format and content (where existing standards are absent or deemed inadequate, this should be documented along with any proposed solutions or remedies);

Policies for access and sharing including provisions for appropriate protection of privacy, confidentiality, security, intellectual property, or other rights or requirements;

A dissemination plan for using and sharing software and the robotics operating system, with appropriate timelines, must be included; and

Sustainability plan beyond the term of the award.

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