NRI: Design and Fabrication of Robot Hands for Dexterous Tasks

1 Summary

Introduction:

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 to get them off board of the hand). (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 and will make possible the next quantum leap in design for dexterous manipulation.

We will advance the state of the art in: (1) Creation of Grasp Nets capturing broadening collections of grasping and manipulation capability as observed in human performance. (2) Design, modeling, and optimization of compliant elements to simplify manipulation task performance. (3) Analysis of manipulation with joint limits. (4) Design and optimization of joint limit surfaces to improve robustness of grasping and manipulation actions. (5) Development of models of error and variation in state of the art manufacturing technologies as they relate to dexterous manipulation. Together, these contributions will make possible for the first time reliable and broadly varying dexterous behavior from accessible designed prototyping technologies.

Broader Impact:

Having truly dexterous robots will affect many areas of our lives. If robots can suddenly use their hands in a dexterous manner, they will be able to create nontrivial effects on the world and be capable of rendering competent assistance in manual tasks and applications can 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 to be part of the continuing efforts to develop grasping and manipulation benchmarks. Grasp Nets and robot hand designs will be made available so that others can easily 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.

Unfortunately, despite decades of development of high degree-of-freedom dexterous robot hands since the 80's, dexterous manipulation has remained elusive. Dexterity is a Grand Challenge goal. In fact, the 2013 Robotics Roadmap [2] 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.*

In this set of milestones, dexterous manipulation is not mentioned for the 5 year mark. 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 through task directed design with emphasis on the role of joint limits and compliance.

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 crafting the robot hand to make dexterous manipulation easier from the start.

Our approach centers around several elements: (1) "Grasp Net" benchmarks to explore manipulation at its full complexity, (2) Mechanism design focused on specific tasks that are well known (i.e., the Grasp Nets), (3) Strategic Placement of Actuators, Joint Limits, and Compliance, and (4) Strategic consideration of Sensing.

(1) "Grasp Net" benchmarks to explore manipulation at its full complexity. 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 [3] where evaluation metrics for dexterous manipulation are needed.

(2) Mechanism design focused on specific tasks that are well known (i.e., the Grasp Nets). Mechanisms will be designed specifically to accomplish grasps and manipulations within the Grasp Nets, manufactured, and evaluated on the Grasp Net benchmarks in an iterative process. Even the initial Grasp Nets will include families of objects for generality. They will reflect real-world manipulations and assume considerable uncertainties and variation. But they will be concrete lists of benchmarks that the hand must accomplish, facilitating rapid evaluation and design exploration. Our goal is to pursue generality while rooting our evaluation of possible hand designs solidly in useful tasks in the real world.

(3) Strategic Placement of Actuators, Joint Limits, and Compliance. We believe that the keys to robustness of hand designs will be selection and placement of a small number of actuators, generous use of joint limits, and strategic use of built-in compliance. We will explore a variety of actuator designs and mechanisms. We will develop new tools to analyze manipulation capabilities in the presence of are scale compliance and joint limit surfaces. Theoretical developments and models will be validated and improved with experimental data collected from many design iterations, component testing, and system testing.

(4) Strategic consideration of Sensing. 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). Primarily reflex and error correcting behaviors will be considered, e.g., response to slipping of the grip, total loss of contact, or stopping of expected motion. 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 with characteristic corrections. Our first line of attack will be to enable similar behavior.

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.

3 A Simple Example

Consider the trivial Grasp Net shown in Figure 1. This figure shows two grasps. Grasp A is a 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 1: This trivial Grasp Net nonetheless captures two important grasps and a dexterous motion to move between them.

Figure 2: (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 pen 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 [7]. However, instead of a single available grasp, we have been able to accomplish two different grasps and a dexterous manipulation between them. Figure 2 also shows a physical device created to test this solution.

Figure 3: 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 4: Optimal parameters, cost, and actuator range for several mechanism designs to perform Grasp A, Grasp B, and Manipulation 1.

4 Dexterous Manipulation Analysis with Joint Limits and Compliance

From the simple example of Figures 1 and 2, we can show two things: (1) Careful design of compliance can reduce the number of actuators and actuator load, and (2) Joint limits can be important for robust performance of a manipulation and perhaps also contribute to making the manipulation easy to learn. Furthermore, using a different example shown in Figure 3, we show a little of how (3) we can expand our analysis tools to consider design with joint limits. Finally, in the next section, we discuss optimization of complex mechanisms to accomplish Grasp Net tasks.

(1) Compliance matters. Table 4 shows results for four tendon driven designs, which were optimized to perform Grasp A, Grasp B, and Manipulation 1 for 4 objects of varying widths. 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 quasi static analysis ensured that forces required for Grasp A, Grasp B, and Manipulation 1 could be generated by the mechanism. Each design was optimized using CMA [4] to require the minimum total actuation force, expressed as squared actuated forces summed over objects, actuators, and time samples. Where compliance was considered, linear springs were assumed, and the algorithm optimized for spring zero point and stiffness. Optimal parameters, cost, and range of actuated forces are shown in the Figure.

Design (A) contains 4 tendons, which give active control in both 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

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 5: 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.

only two tendons, which are used as elastic return springs, opening 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 are employed to open the fingers. Here, the total cost is 28 percent of that of Design (A), and has been achieved with half the number of actuators. Clearly, compliance matters to reduce the total number of actuators and to reduced actively applied forces for actions in the Grasp Net.

(2) Joint Limits matter. We observe that joint limits are not avoided in human motion. In contrast, in the human system, joint limits and singularities are often 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 lateral forces, even though the force that cana be actively generated by forces in that grasp is small, coming from small intrinsic muscles in the hand, such as the interossei [1]. These large 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 will also exploit 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 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 tests, 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. 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. Cases (C) and (D) are variations where joint limits are not included. Table 5 shows the results. Empirically, results with error less than 0.5 in our scale produced consistently good results. These results show that when a task is learned assuming a perfect mechanism, the effect of joint limits is not clear. However, when the learning process has the opportunity to see the perturbations, the optimizer learns to use the joint limits to create compensating 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. Based on qualitative observation only, the cases having joint limits also appeared to present easier learning problems.

(3) We must expand our analysis tools to consider design with joint limits. Consider now the example in Figure 3 A. The goal here is to push into a surface, holding the object in more or less 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, and the directions of actuation are shown. We assume the two fingers on the sides have considerable compliance in the horizontal direction. Actuating these fingers does not help either, as this will only cause the fingers to slide along the object surface. With the design as shown in Figure 3 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 for this situation. 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 stiffnesses 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 [5], and is expressed using activation levels A_i, such that $0 \leq a_i \leq 1$, 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 measures for compliant systems (e.g., [6]), 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 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.

This setup can also be used for design. As mentioned above, the side fingers in Figure 3 A are not at all helpful for accomplishing the task. A search for optimal joint limits may result in Figure 3 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 3 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 to compute the set of task forces that can be equalized (following our own work [5]), have made it possible to evaluate the effect of any new design element on the push grasp.

Extension to complex and redundant mechanisms is more complex, and is the subject of future research.

5 Dexterous Hand Design / Optimization

How we will create the form to follow the function!

Some random thoughts

- Good simulations of the mechanisms that are being proposed are key and are very hard. Can we get good material models? Can we construct good models of uncertainties so that our simulation rollouts match our experiments?
- Can we create a setup that allows lots of randomized tests for this purpose? Making simulations match reality appears to be hot right now.

6 Research Tasks and Questions

(1) Quasistatic Grasp and Manipulation Analysis that considers both Compliance and Joint Limits. Extend the simple example 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. In the Simple Example, we evaluated robustness to variation through different rollouts of the manipulation under samples of a distribution of possible mechanisms and scenarios. Using rollouts to evaluate success in a variety of possible situations (or over a belief state) is functional, but very slow. In other research (e.g., [**?**]) we find the time required to perform rollouts to be a constant bottleneck to allowing complexity of scenarios to increase. Using simulation rollouts will not scale well to the breadth of situations we would like to address in this proposal.

Previous research (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 [**?**]. We have extended the process to evaluate robustness for manipulation tasks [**?**], shown that the point of view can be reversed to express ability to grasp objects of different geometries [**?**]. Following our research in [5], the approach can be extended to work with tendon driven systems and other interesting mechanisms.

There has not been space to discuss it in detail here, but we have a sketch of a solution to extend this approach as follows. Suppose a mechanism design for which we wish to test robustness. Given a quasistatic solution to manipulate one object, 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 geometrically representing solutions that are ”good enough”, e.g. 90 percent as good as the example along some criterion. 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 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 ever Larger Grasp Nets and manipulator complexity. [STELIAN FLESH THIS OUT A BIT]

(4) Making Predictions match Reality. Our various tests and analysis make many predictions, e.g., that one mechanism will result in more robust manipulation actions than another. Do these predictions match reality? We will test this question and investigate how best to use data from real robot and component trials to improve the accuracy of these predictions by improving our models.

(5) Understanding the Delta Provided by different Sensing Approaches. 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, but lifting the object or moving it aside to clear an obstacle.

7 The Grasp Net Benchmark

At least motivate how this might be possible. Show preliminary capture data.

8 Evaluations

- Generality. If we design for a specific task list, who is to say it is broad enough to do everything we would like to do? We can test generality with leave one out tests. That would be an interesting result to have no matter which way it comes out.

- 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 and Barrett 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 fewer actuated degrees of freedom and lower cost. We anticipate that the result may look quite different from the typical dexterous hand existing today.

9 Comparison to Related Work

Researchers have thought a lot about how to evaluate grasps, plan grasps but design of a mechanism for a specific suite of grasp and manipulation actions that is meant to be general is less well considered.

Ciocarlie Frank Hammond III

Trinkle lever-up long train of Bicchi analysis papers

Many dexterous robot hand designs attempt to be as capable as possible – e.g., max manipulability.

In a way, we take the opposite approach – as capable as it needs to be and no more. Because limits help us.

Traditional grasp and manipulation analysis assumes we operate the hand far from singularities and joint limits. In such a case, the dynamics of the system may be linearized and used to estimate our ability to control an object and apply and resist forces within a local configuration space [refs]. Such estimates may be used as a basis for hand design [ref].

However, such analyses are limited when it comes to understanding the broad spectrum of capabilities of a proposed robot hand, and designers have formed other tests, such as workspace analyses [Feix comparing to human hand] and heuristics such as ability to oppose the thumb to each of the fingers.

Abeel results suggest that learning the manipulations on the real robot is possible with small numbers of iterations. We expect even faster learning and more generality because the mechanism is designed exactly to do this.

10 Broader Impact

11 Results from Prior NSF Support

12 Timeline

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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