Benchmarking a Robot Hand's Ability to Translate Objects Using Two Fingers

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***Abstract*—This paper presents a novel benchmark called the Asterisk Test that characterizes a hand's ability to translate an object on a table in eight linear directions using only two fingers. The benchmark is agnostic to the controller, object, and robot hand used. The benchmark also enables a measure of the symmetry (about the plane's principal axes) of the hand's ability to maneuver objects. The Asterisk Test's utility is demonstrated on two common robot hand designs: a parallel jaw gripper and a two-linked, two fingered gripper. The method to analyze the performance data in order to evaluate the hand is also provided. We conclude with a comparison of this benchmark to previous dexterity measures, such as manipulability. We also discuss how improved performance in this benchmark is indicative of simpler hand control.**

***Index Terms*—New benchmarks and evaluation methods that focus on robotic grasping and manipulation; New modelling, design, and control methods for robotic grippers and hands; Skill transfer between humans and robots for robust grasping and dexterous, within-hand manipulation**

I. Introduction

QUANTIFYING the ability of finger-based robot hands in grasping and manipulation tasks is complex as they are made of three sub-systems: hardware (physical design and actuation), software (low-level controllers and high-level planners), and sensors (oftentimes omitted). Within these three sub-systems, a robot hand's physical design is perhaps the most difficult to benchmark because the hand design must rely on the other subsystems for movement. This reliance makes it difficult for researchers to normalize and study aspects of robot hands, because even minor differences in hand design require different control strategies. The number of variables to consider, both for the hand and the task, are prohibitively high.

Traditionally, manipulation metrics have focused on the successful completion of end-to-end tasks, providing little insight into *what* worked and why [1], [2], [3],

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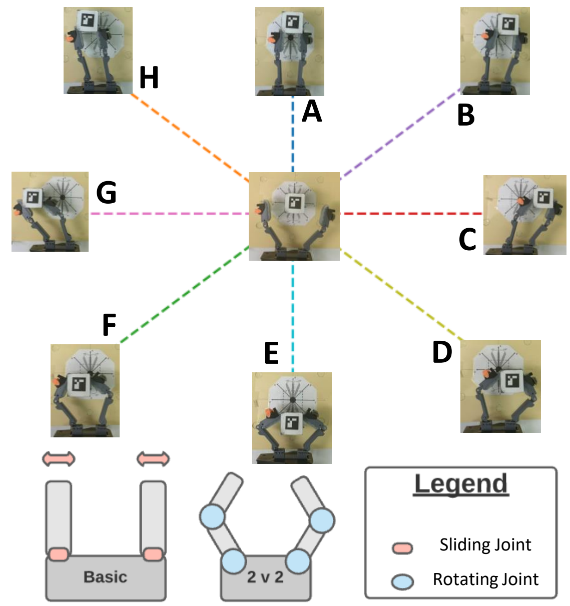


Fig. 1: The Asterisk Test empirically measures, in a systematic way, how well a hand design maneuvers an object through its kinematic workspace. This is measured by how far and how well a hand moves a standardized object along a designated path. This benchmark is controller, object, and hand agnostic.

[4], [5]. For time-sensitive competitions such as the IROS Robotic Grasping and Manipulation Challenge (RGMC) [6], [7], hours may be spent working with a hand design to find that it will not complete the tasks.

So far, there exists no commonly-accepted standards for characterizing a robot hand's performance in complex multi-step tasks or in primitive movements with or without an object of interest. This hampers the robotics community's efforts to develop a scientific understanding of how a robot hand's subsystems influences functionality. The desire in the robotics community for a standard is evidenced by the numerous workshops and special topics journal issues on this and related issues in grasping and manipulation benchmarking [8], [9], [10], [11].

A promising development has been on object-centric methods to characterize a robot hand's task performance [5], [12], [13], [14], [15]. These methods benchmark how the object moves when it interacts with the hand. This approach simplifies the benchmarking process for manipulation, since this sidesteps the many variables in the robot hand (such as degrees of freedom, joint compliance, and actuation). Object-centric methods have also been used specifically for manipulation — Hazard et al. optimized hand designs for specific manipulation trajectories [16].

We define a benchmarking method that quantitatively assesses a robot hand's ability to perform simple in-hand translations. Our choice of manipulation benchmarking tasks were directly inspired by the object-based tasks in Bullock and Dollar's manipulation taxonomy [17], but generalized away from a specific hand design (in their case, the human hand). Our focus on fundamental manipulation tasks in addition to our benchmark enables a quantitative study of the performance of a full robot hand system. The characterization method's object-centric nature makes the test controller, object, and hand design agnostic. We call this set of manipulation tasks and measures the *Asterisk Test*.

The Asterisk Test samples the in-hand manipulation space using a set of simple in-hand manipulations as seen in Figure 1. Due to its three agnostic natures (object, controller, hand) this test can be used to study the effect that a robot hand subsystem has on manipulation ability while keeping the other variables constant.

In the Asterisk Test demonstration in this paper, we vary the hand design because it is an aspect that has received the least focus in robot manipulation. In our work, we accomplish this using Physical Human Interactive Guidance (PHIG) [1] to normalize the controller (a human subject) across hand designs.

We can also generalize the Asterisk Test results to the rest of the kinematic space by analyzing the symmetries across the asterisk paths. Specifically, we assess how symmetric a hand's asterisk test performance is and make generalizations as to how uniformly a hand behaves across its object-centric, kinematic workspace. We define symmetries by computing nine metrics on each path and explore for statistical similarity.

Contribution: We propose an object-centric manipulation benchmark which characterizes a robot hand's ability to translate an object using two fingers. We demonstrate this benchmark to quantitatively assess the performance of two common robot hands and also quantify the symmetries in the robot hands's performance.

II. Related Works

To date, researchers have most commonly used a combination of time-based, task-specific, and binary measures for quantifying robot hand capability. These types of metrics have been used to study manipulations to characterize a wide range of hands and controllers [1], [2], [3], [4], [5], [18]. Other metrics have been used to characterize elements of the robot hand subsystem; for example characterizing a hand's strength and speed [19], characterizing a finger's kinematic workspace and how they overlap on a hand design [20], characterizing how well a hand rotates an object in hand [15], and optimizing finger placement and link length on a hand design for both grasping and manipulation [16], [21].

Our approach is inspired by the grasping vector fields introduced by Aukes et al. [13], [22], and Manipulability [23]. Both works not only consider the kinematic workspace of the hand, but also how an object (or manipulator) moves through that space.

Our work considers how the hand's kinematics affect its ability to move an object in eight cardinal directions on a flat surface.We judge the *quality* of a hand's ability to manipulate by comparing the object's path to the ideal path using nine metrics. We extended this characterization to also quantitatively assess how symmetrical the robot's performance is across the x and y axes.

The proposed benchmark is also relevant to public competitions such as the IROS Grasping and Manipulation challenge [6], [7]. Specifically, this method can be used to predict an existing robot hand design's ability to perform the challenge tasks. This method removes the need to test a hand *directly* on the challenge tasks, which can be difficult due to the task's complexity.

III. The Characterization Method

The Asterisk Test measures how a hand maneuvers an object through its workspace. The Asterisk Test utilizes ARuCo tags placed on the test objects to track the object's position and orientation using an overhead camera [24]. During the Asterisk Test, the hand will maneuver the test object through each of the asterisk directions (see Figure 1). We provide a custom python library to run the Asterisk Test and to analyze data at the following URL: https://github.com/OSUrobotics/asterisk_test

Due to the extrinsic (object-centric) nature of this test, the Asterisk Test can be easily adapted for most objects, hands, and controllers. For the purposes of introducing this benchmark, we use the Asterisk Test to study cube manipulation with two generic robot hand designs, a parallel jaw gripper with independent finger movement and a two-linked, two-fingered gripper, controlled by PHIG [1]. We included these hands because they represent the most common robot hands used today.

We focus on in-hand translation in this work. Further, we limit translations to occur in the 2D plane of the table that the hand manipulates on. Any directions with no movement were not analyzed. Consequently, only directions "*C*" and "*G*" were counted for the basic hand. All directions were counted for the 2v2 hand. See Figure 3 for each asterisk.

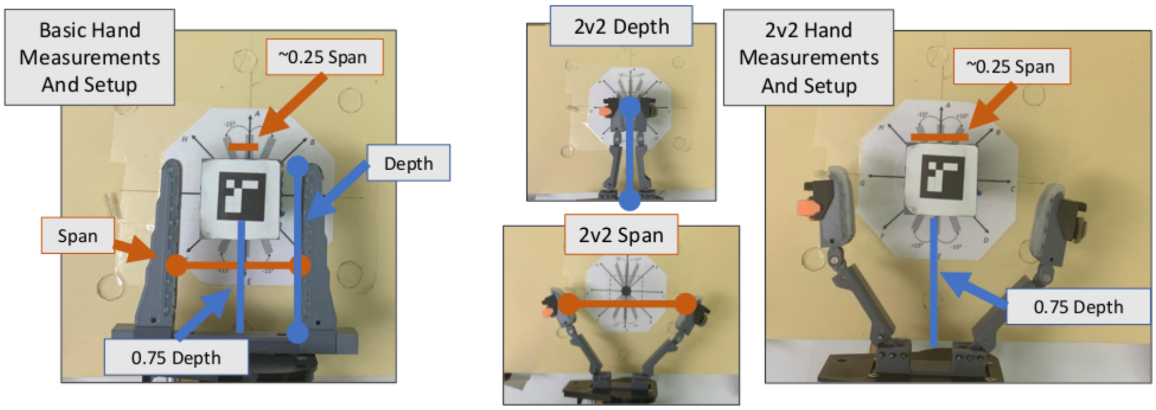


Fig. 2: Hand Span and Depth measurements and asterisk test setup for both the basic (left) and 2v2 hand (middle, right). Relevant dimensions and setup images were taken from top-down camera. Each object is sized smaller than the ARuCo code.

A. Setup

The Asterisk Test requires a testing object tracked by an overhead camera. The Asterisk Test supports any object that can have an ARuCo tag attached to it. In this paper, we demonstrate the Asterisk Test using a 3D-printed cube that has an ARuCo tag placed on top of the object [24]. We track this ARuCo tag using an overhead camera (Intel Realsense D415), however any RGB camera can work for this purpose.

The Asterisk Test can be performed on many object sizes and at different initial distances. In this demonstration, we sized the object to be between 20-25% of each robot hand's span (the maximum distance between distal links which still performs a valid precision grasp). We placed the object 75% of the hand's depth from the palm (with fingers closed as close together, the distance from the tip of the distal link to the hand's palm) [25]. See Figure 2 for hand span and depth measurements on both hands. Both of these attributes were chosen empirically to maximize the symmetric performance of the hands.

B. Protocol

The Asterisk Test focuses on how a hand maneuvers an object in each of the asterisk directions and does not qualify how the hand accomplishes the object's movement as long as the hand-object interaction meets some basic conditions. This is how the Asterisk Test can support many different controllers and hand designs.

When performing the asterisk test, subjects were tasked with moving the object as far as possible in a specified direction and with as direct of a movement as possible. Subjects were also instructed to minimize object rotation as much as possible. During each translation, the subjects had to maintain contact on the object at all times — however the *location* of the contact (on both the object and distal links) was up to the subject. Sliding and rolling contacts were permitted — rotation of the test object was tracked throughout a trial. If contact on the object was lost, the trial was discarded and repeated.

We demonstrated the Asterisk Test using hands which were human operated (using PHIG [1]). Three subjects were recruited to operate two robot hand designs in the PHIG study. Each subject used either hand to manipulate the object in the eight directions of the asterisk (see Figure 1), repeating each direction five times.

Both hands shown in this work were generic 3D-printed designs: one a parallel jaw gripper with single-link fingers (basic hand) and a two-fingered gripper with two links on each finger (2v2 hand), see Figures 1 and 2. Both designs had fingers which could move freely and independently of each other.

When reporting Asterisk Test data we strongly recommend reporting *all* testing variables (the hand design, controller, object size and shape, and initial object positioning) used in testing, as well as any other changes to the standard protocol, to enable comparison with other Asterisk Test studies.

C. Performance Metrics

Our data gathering step generates an object path for each trial. Each path was normalized by the hand's dimensions. Specifically, the x translations were normalized with a hand's maximum span; the y translations were normalized with a hand's maximum depth [25]. Figure 2 shows the maximum span and maximum depth measurements for the basic hand and the 2v2 hands.

We compare each object path to the desired straight-line path and to the limit of the hand's dimensions. We call this path the *target line*. In general, the magnitude of the target line is based on the distance between the object's initial position and the hand's span and depth. Each target line has a magnitude of half the normalized

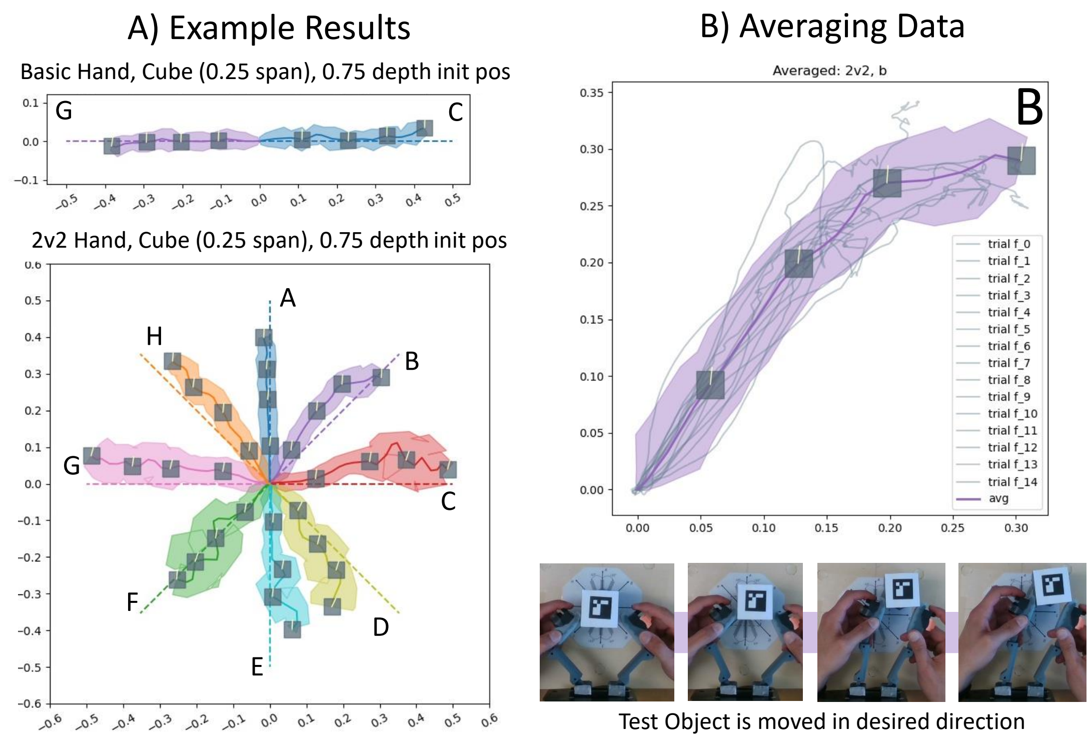


Fig. 3: *A)* Averaged results for the basic and 2v2 hands using PHIG, a cube test object (0.25 span), and a 0.75 depth initial position (in the "*E*" direction). To illustrate the test object's rotation through the object path, we have added dials along the path with a white line that indicates the object's orientation, with up indicating zero degrees rotation. Overall, rotation was small. *B)* Complete data for direction "*B*", 2v2 hand. Images of a typical trial are shown below the averages to illustrate what the overhead camera would see.

distance (normalized by either hand span and/or depth, depending on the direction) because the object was placed centered to the hand's palm (see Figure 3).

We use the following nine metrics for evaluating the difference between the target line and the object path (using the "similaritymeasures" python library [26]):

Trial Distance: The distance that a trial went in the target line direction. We calculate this as the magnitude of the object path projected onto the target line.

Arc Length: The length traveled on the object path.

Movement Efficiency: The total distance divided by arc length.

Max Error: The distance of the furthest point on the object path to the target line. This metric is normalized by the trial's arc length.

Frechet Distance: The minimum of the maximum pairwise point distances between two discrete curves without respect to time. This metric enables comparison of the entire object path to the target line. A lower value indicates lines are more similar to each other. See [27] for a description using the analogy of a dog on a leash.

Total Area Between Curves: The area between the object path and the target line.

Region of Max Error: The largest area between the two curves within a sliding window of width 20% of the total distance. We also record the window's center location at the point of max area, called the **Location of Max Error**, represented as a percentage along the full target line.

Max Rotation Error: The largest object rotational deviation from the starting orientation along the object path. In this work, the benchmark prefers no rotation.

When analyzing the data, these metric values were aggregated by direction and compared to other directions as a set. When comparing each object path to its target line, we scale the target line to the *Trial Distance* for a fair comparison.

D. Combining Trial Data

On the asterisk plot we represented the average path of each direction, shown in Figure 3. We averaged each trial by sampling 20 points along the target line and averaging all points on all valid object paths within a certain bound around each sample point. We also calculated the error of each point in the average from the average point.

We represent the magnitude of the average error at each averaged point and represented this on the asterisk plot as a shaded region.

We eliminated anomalous trials which either a) had a deviation $> \pm 40$ degrees from the correct direction at any point on its path (a deviation $> \pm 40$ degrees on the asterisk), b) had significant backtracking, or c) have noticeably poor performance relative to other trials. On average about 1.25 trials were removed from each direction.

E. Calculating Symmetries

We define a symmetry as a direction pair that is similar to another. We determine symmetries by calculating the p-value between each direction's set of metric values for each metric separately using the Welch (Unequal Variance) T test. If less than 1/3 of the metrics indicated a statistical significance, we considered the direction pair symmetrical.

For the 2D asterisk test there are 28 (8*7/2) possible direction pairs. We focused on assessing symmetries across the *x* ($\overline{CG}$) and *y* ($\overline{AE}$) axes of the asterisk. We used these two groups of symmetries (six direction pairs total) to represent the symmetry of the entire hand.

IV. Example Results

In the Asterisk Test, we first averaged the trials in each direction and plotted them with their respective target lines (see Figure 3). Then we assessed the symmetries present in the basic and 2v2 hand data. See Table I for symmetry results.

The basic hand had only one direction pair to assess for symmetry: "*C*" & "*G*". Only one metric out of the nine indicated a statistical significance: Trial Distance. We believe this metric indicated statistical significance due to an observed right handedness in our subjects. However, it should also be noted that the average and standard deviation values for both directions are close.

For the 2v2 hand, we assessed the full set of symmetries across the *x* ($\overline{CG}$) and *y* ($\overline{AE}$) axes of the asterisk. Of these 6 direction pairs, only four were calculated to be symmetrical: *A*-*E*, *B*-*H*, *C*-*G*, *D*-*F*. These direction pairs show a hand symmetry around the *y* axis.

For direction "*A*" on the 2v2 hand, the hand was able to reach 0.4 normalized distance, despite the object being placed at 0.75 depth. In this direction, our subjects grasped the object near the corners closest to the palm in order to maximize translation. Subjects similarly grasped the corners opposite the palm to maximize translation in the"*E*" direction.

Overall, rotation error was small. See Table I for specific rotation error values.

V. Discussion

A. The Asterisk Test as a Benchmark

Quantifying the manipulation capabilities of a robot hand is challenging due to the inherent complexity and variety of manipulation tasks [28]. The Asterisk Test benchmark focuses on primitive in-hand object translation (see [17]) and will ultimately pave the way for characterizing more complex manipulations across different robot hands and controllers.

While we have demonstrated the Asterisk Test using a human controller in this paper, the Asterisk Test itself does not rely on human operators — it is *controller agnostic*. This test can be conducted for hands driven by actuators and various controllers. Researchers can also compare an automated controller's performance against the hand design's maximized performance. This makes the Asterisk Test generalize well to study all aspects of the robot hand system.

We chose the nine metrics in the Asterisk Test because they provide detailed information about the path the object is moved along by the robot hand along principal directions. Furthermore, these metrics are useful to generalizing the hand's performance in *regions* of the hand's kinematic workspace in-between the principal direction. Finally, the metrics also enable an analysis of the symmetry in the hand's capability. We assess these symmetries using a super majority statistical significance approach.

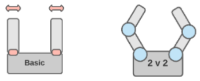
Another useful feature of the Asterisk Test is the normalization of the object paths with respect to a hand's dimensions (span and depth, see Figure 2 and [25]). This enables us to directly and quantitatively compare robot hand designs to *each other* for in-hand translation.

We used human operators in the PHIG study [1] to demonstrate a useful feature of the Asterisk Test. Our human operators enabled us to test a robot hand design at an earlier state of development than is possible with typical methods — in our case, on hands without actuators or any sort of automatic controller, which would enable study of a hand design's contribution to manipulation performance alone.

Our human subjects transferred their own 'controller' onto the robot hand. This human controller, as is universally understood, can adapt well to many end effectors (for example: prostheses, holding tools, etc) with an appropriate amount of training. This means the human controller can be an effective tool to approximate the maximized performance potential of a hand design or to normalize a controller across different hand designs.

B. Assessing Symmetries

We use symmetries in the nine metrics for directional pairs to generalize the in-hand translation of a hand to



Assessing Symmetries by Direction Pair*

*Dir pairs must have < 1/3 of metrics indicate a sig. diff.

	Trial Dist	Arc Len	Mvt Eff	Max Error	Frechet D	Tot Area	Area Reg	Area Loc	Rot Err (°)	*
C	0.37 ± 0.03	0.74 ± 0.33	0.59 ± 0.24	0.02 ± 0.01	0.04 ± 0.01	0.01 ± 0.0	0.0 ± 0.0	0.49 ± 0.19	1.42 ± 0.65	y
G	0.33 ± 0.04	0.54 ± 0.11	0.64 ± 0.19	0.03 ± 0.01	0.03 ± 0.01	0.0 ± 0.0	0.0 ± 0.0	0.43 ± 0.19	1.84 ± 1.56	
A	0.35 ± 0.05	0.94 ± 0.29	0.4 ± 0.12	0.03 ± 0.01	0.05 ± 0.03	0.02 ± 0.01	0.0 ± 0.0	0.63 ± 0.09	5.86 ± 1.22	y
E	0.25 ± 0.1	0.85 ± 0.43	0.34 ± 0.14	0.04 ± 0.02	0.05 ± 0.03	0.02 ± 0.01	0.0 ± 0.01	0.32 ± 0.17	7.48 ± 4.1	
B	0.35 ± 0.05	0.79 ± 0.27	0.49 ± 0.17	0.11 ± 0.05	0.07 ± 0.02	0.03 ± 0.02	0.01 ± 0.0	0.61 ± 0.09	6.61 ± 1.85	n
D	0.23 ± 0.06	1.76 ± 1.41	0.21 ± 0.14	0.07 ± 0.03	0.09 ± 0.04	0.05 ± 0.04	0.01 ± 0.01	0.37 ± 0.09	18.8 ± 9.65	
B	0.35 ± 0.05	0.79 ± 0.27	0.49 ± 0.17	0.11 ± 0.05	0.07 ± 0.02	0.03 ± 0.02	0.01 ± 0.0	0.61 ± 0.09	6.61 ± 1.85	y
H	0.36 ± 0.06	0.76 ± 0.23	0.51 ± 0.13	0.12 ± 0.05	0.08 ± 0.02	0.03 ± 0.01	0.01 ± 0.0	0.62 ± 0.14	7.43 ± 2.59	
C	0.37 ± 0.1	0.82 ± 0.45	0.52 ± 0.14	0.13 ± 0.05	0.09 ± 0.03	0.03 ± 0.03	0.01 ± 0.01	0.55 ± 0.15	8.9 ± 2.51	y
G	0.35 ± 0.1	1.23 ± 0.73	0.34 ± 0.12	0.09 ± 0.04	0.09 ± 0.04	0.05 ± 0.04	0.01 ± 0.01	0.54 ± 0.22	9.82 ± 0.22	
D	0.23 ± 0.06	1.76 ± 1.41	0.21 ± 0.14	0.07 ± 0.03	0.09 ± 0.04	0.05 ± 0.04	0.01 ± 0.01	0.37 ± 0.09	18.8 ± 9.65	y
F	0.29 ± 0.07	1.08 ± 0.36	0.3 ± 0.12	0.09 ± 0.04	0.1 ± 0.04	0.04 ± 0.03	0.01 ± 0.01	0.49 ± 0.14	13.2 ± 9.63	
F	0.29 ± 0.07	1.08 ± 0.36	0.3 ± 0.12	0.09 ± 0.04	0.1 ± 0.04	0.04 ± 0.03	0.01 ± 0.01	0.49 ± 0.14	13.2 ± 9.63	n
H	0.36 ± 0.06	0.76 ± 0.23	0.51 ± 0.13	0.12 ± 0.05	0.08 ± 0.02	0.03 ± 0.01	0.01 ± 0.0	0.62 ± 0.14	7.43 ± 2.59	

** Grey squares indicate $p < 0.05$ *** The first eight metrics use normalized values

TABLE I: Metric results for the salient direction pairs for basic (red) and 2v2 (blue) hands. The first eight metrics use normalized values. Colored boxes indicate where p-values found a significant difference ($p < 0.05$). We determine a symmetry if less than 1/3 of the metrics indicate a statistical significance between the values (far right column). A "Y" (green color) indicates a symmetry.

the rest of the kinematic space. We do this by assessing the relative symmetries in the hand's performance — using the x and y axis symmetry pairs.

For the basic hand, the symmetry at C-G probably comes from the mechanical constraints of the hand. Coupled with the low error in these directions, we can assume that the hand's performance in this region is fairly consistent. This information is useful when designing controllers for the "*C*" and "*G*" directions.

This is also evident when assessing the symmetries of the 2v2 hand. This hand was generally symmetrical about the y axis. From the symmetries present, we can observe that the upper portion of the asterisk is symmetrical. When considering direction "*A*"'s metric values, we can conclude that the entire upper portion of the asterisk ("*A*", "*B*", "*C*", "*G*", "*H*") is of similar performance. Likewise, the symmetries in the bottom portion of the asterisk ("*D*", "*E*", "*F*") indicate a region of lower consistency — and therefore a region more difficult for hand control. These findings are also supported by a qualitative analysis of the asterisk plot.

Using the knowledge of symmetries gathered from an Asterisk Test would be beneficial to those designing automated controllers. Specifically, a roboticist would know what to expect in each region of the hand — this makes robot hand control more simple.

C. Maneuverability

Previous work has considered manipulability as a metric for manipulator dexterity [23]. This metric only focuses on the manipulator's free-space kinematics, and not on the ability of the robot hand to maneuver an *object*. Maneuverability indeed could be a new metric, that focuses on the manipulator's capability to move an object. Furthermore, the maneuverability discussed in the Asterisk Test in this paper is agnostic to the contact between the object and the hand. Specifically, in the Asterisk Test, the fingers are allowed to slide or roll on the object's surface. Other maneuverability metrics could explore limiting the types of contact between the object and the finger. For example, the fingers could be limited to rolling on the object, rather than sliding, or vice versa.

VI. Conclusion

In this paper we presented a novel benchmark called the Asterisk Test, which characterizes a hand's ability to maneuver an object through its workspace. This benchmark is controller, object, and hand design agnostic, which makes this benchmark adaptable to study many aspects between object size and shape, controllers, and hand designs and how they affect manipulation ability.

We demonstrated the Asterisk Test using two generic hands (the basic and 2v2 hands) and a cube as a test object, controlled by humans using PHIG.

Regarding future possible directions, we plan to use the Asterisk Test to study robot hand designs and how they impact manipulation ability. Due to the high number of variables in the manipulation domain and the Asterisk Test in particular (for example: objects, sizes, initial distances, and metrics to include) , the Asterisk Test provides a strong opportunity for the robotics manipulation community to benchmark robot hands. We also plan to expand the Asterisk Test to three dimensions.

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