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# Deriving Dexterous, In-Hand Manipulation Primitives for Adaptive Robot Hands

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***Abstract*— Adaptive robot hands have changed the way we approach and think of robot grasping and manipulation. Traditionally, pinch, fingertip grasping and dexterous, in-hand manipulation tasks were executed with fully actuated, rigid robot hands and relied on analytic methods, computation of the hand object Jacobians and extensive numerical simulations for deriving optimal and minimal effort grasps. However, even insignificant uncertainties in the modeling space could render the extraction of candidate grasps or manipulation paths infeasible. Adaptive hands use underactuated mechanisms and structural compliance, facilitating by design the successful extraction of stable grasps and the robust execution of manipulation tasks, even under significant object pose or other environmental uncertainties. In this paper, we propose a methodology for the automated extraction of dexterous, in-hand manipulation strategies / primitives for adaptive hands. To do so, we use a constrained optimization scheme that describes the kinematics of adaptive hands during the grasping and manipulation processes, an automated experimental setup for data collection, a clustering technique that groups together similar manipulation strategies, and a dimensionality reduction technique that projects the robot kinematics to lower dimensional manifolds. In these manifolds, control is simplified and hand operation becomes more intuitive. In this work, we also assess the effect of the extracted manipulation primitives on the object pose perturbations. The efficiency of the proposed methods is experimentally verified for various adaptive robot hands. The extracted primitives can simplify the operation and control of the open-source robot hand designs of the Yale Open Hand project in dexterous manipulation tasks.**

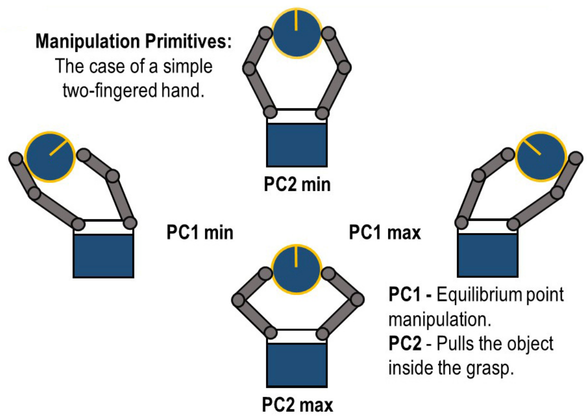


Fig. 1. Example of manipulation primitives derived for the simulated version of the Yale Open Hand model T42. The first Principal Component (PC) is responsible for performing equilibrium point manipulation tasks, while the second PC pulls the object inside the grasp. The yellow line is used to depict the object orientation.

## I. Introduction

The state-of-the-art of robot hand designs is still dominated by fully actuated, multi-fingered, rigid and expensive robot hands that require advanced sensing elements and complicated control laws in order to grasp and manipulate objects or to interact with an unstructured or dynamic environment. As a result, despite the sophisticated designs and the numerous studies that have focused on dexterous manipulation over the last 50 years, there has not been much progress in the field in terms of practical applications and robust within-hand manipulation still remains difficult to accomplish.

Adaptive, underactuated robot hands have gained popularity in robot manipulation over the past decade, largely due to their ability to grasp objects even under significant object pose uncertainties and often in an open-loop manner [1]–[5]. The particular hands use underactuated mechanisms and elastic joints in order to facilitate the extraction of stable grasps, even in the presence of large uncertainties about the object. More recently, they have been used to demonstrate the potential for robust, dexterous, within-hand manipulation [6]–[8]. However, the use of compliant elements in the robot structure and the kinematic constraints imposed by the under-actuation, combined with many of the typical uncertainties in unstructured manipulation tasks, make modelling, planning, and control with these hands, particularly challenging.

In this paper, we propose a methodology for the automated extraction of dexterous, in-hand manipulation strategies / primitives for adaptive robot hands that simplify the planning and control process (see Fig. 1). To do so, we use a constrained optimization scheme that describes the behavior of these hands during the grasping and manipulation processes, providing intuition about the mechanics of the problem. Then we synthesize an automated data collection procedure and a learning scheme that uses: a) a clustering technique to group together similar manipulation strategies and b) a dimensionality reduction technique to project the robot kinematics to a lower dimensional manifold. In the low-d manifold, the control problem is simplified and the hands' operation becomes more intuitive. The proposed methodology also assesses the effect of the extracted manipulation primitives on the object pose perturbations and the effect of the object size on the extraction of representative and generalizable manipulation primitives.

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In order to validate the efficiency of the proposed framework, we present extensive experimental work that focuses on controlling various adaptive robot hands using the identified primitives to manipulate a range of sensorized, 3D printed objects. The extracted manipulation primitives can simplify dexterous, in-hand manipulation with adaptive hands and allow an intuitive operation of the Yale Open Hand devices [9] or other similar devices.

The rest of the paper, is organized as follows. Section II, presents the related work on robot grasping, dexterous, in-hand manipulation and manipulation primitives extraction. Section III presents the techniques and methods used in order to formulate the proposed methodology, Section IV presents the experimental setup used and the robot hands examined, Section V presents the extracted manipulation primitives for each robot hand, the object ranges of motion for a set of exemplary primitives and the relationship between the object size and the coefficients of the identified primitives. Finally, Section VI discusses the main challenges and the best practices for extracting a set of representative manipulation primitives in an automated fashion, while Section VII concludes the paper and discusses future research directions.

## II. Related Work

Over the last decades, dexterous manipulation has become increasingly important for robots to interact with their environment, as it facilitates the execution of dexterous / meaningful everyday life tasks. The term dexterity originates at the Latin word *dexteritas* that means skillfulness. Dexterity is highly correlated with the functionality of human hand and vice versa. Bicchi et al [10] [11] defined dexterity as "*the capability of a robot hand to change the position and orientation of the manipulated object, from a reference configuration to a different arbitrary chosen configuration within the hand workspace*" and as "*the ability of a hand to relocate and reorient an object being manipulated among its fingers, without losing the grasp*". Li et al [12] describe dexterity as the process of manipulating an object from one grasp configuration to another, while Okamura et al [13] define it as the cooperation between multiple manipulators or fingers, to grasp and manipulate objects.

Thus, dexterity is highly associated with the grasping and manipulation processes and people tend to characterize as dexterous, robot hands that have multiple fingers, multiple actuators and many degrees of freedom. These hands are typically rigid, heavy, expensive, complex, they require sophisticated sensing elements and complicated control laws and although they are indeed dexterous their dexterity requires increased computational effort. On the other hand, the new class of adaptive robot hands offers a simplified and affordable ``dexterity" and robustness in the execution of dexterous manipulation tasks. In their case, dexterity is directly evaluated (in a qualitative manner) in the object space (how efficiently and delicately the objects are manipulated) and not by hand design specifications and attributes.

Regarding applications, the classic approach for modeling the robot grasping and dexterous, in-hand manipulation problems, involves analytical and constrained optimization methods for computing the hand and hand-object Jacobians, extracting stable grasps, maintaining the force closure properties of the grasp and respecting task constraints. Such an approach can be found in [14], where the authors proposed a methodology for planning in-hand manipulation tasks with multi-fingered hands that takes into account all possible task constraints and derives stable grasp configurations that guarantee the successful execution of the desired tasks. Similar methods have been proposed also in the grasping literature for synergistic, cable-drive, underactuated hands [15].

Recently, there has been also a significant research effort in the development of simple, minimalistic solutions for both robot grasping and dexterous manipulation. In [7], the authors provided evidence that a reduction in the number of hand actuators and constraints, simplifies the manipulation problem and relaxes the required control effort. In [16], a human inspired, open-loop manipulation methodology was proposed that facilitated the execution of flip and pinch tasks by adaptive hands and allowed them to pick objects from a table surface. In [17], Mason et al proposed a learning scheme that employs sensor data to perform object recognition and in-hand object localization or to reject the grasp, using a minimalistic approach that the authors call "grasp first – ask questions later". In [18], the concept of extrinsic dexterity was introduced and the ability of simple hands to perform manipulation tasks using extrinsic to the hand resources (e.g., gravity, external contacts, dynamic arm motions, parts of the environment etc.) and a set of re-grasping actions, was demonstrated. Although all re-grasping actions were open-loop and hand scripted they were also surprisingly robust.

In [19], a reinforcement learning methodology was proposed for acquiring in-hand manipulation skills for adaptive robot hands equipped with tactile sensors. The methodology does not rely on dynamic or kinematic models and it generalizes to new objects without a significant loss in performance. In [20] the authors proposed a machine learning scheme that can accurately predict whether a grasp is stable or not, facilitating dexterous manipulation with a multi-finger hand equipped with tactile sensors [21]. Finally, in [8] we proposed a hybrid methodology based on a combination of analytical models, constrained optimization methods and machine learning techniques for performing dexterous, in-hand manipulation with simple, adaptive robot hands, by employing task-specific manipulation models that account also for dynamic phenomena (e.g., uncontrolled slipping and rolling).

Regarding primitives or synergies, many studies have focused on the projection of human and robot kinematics in lower dimensional manifolds where the motion analysis and control are simplified. Santello et al [22], [23], first demonstrated that the control of hand posture involves only a few postural synergies (the first two principal components describe more that 80% of the variance). In the robotics literature, synergies and motion primitives have been used not only for grasping [24]–[27] and dexterous manipulation [28], [29], but also for deriving new bioinspired robot hand designs [30] or design specifications for the development of new robotic devices.

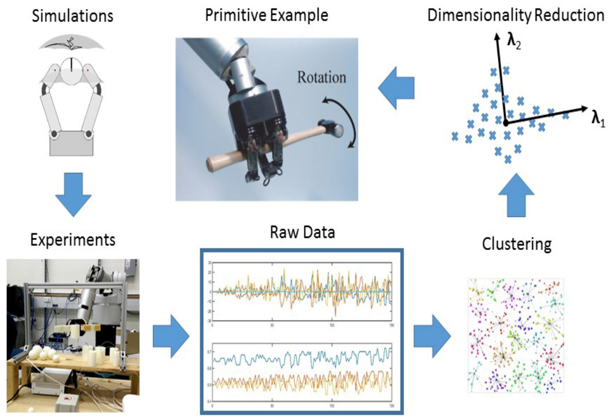


Fig. 2. A visualization of the structure of the proposed manipulation primitives extraction methodology. The simulations module explores the feasible manipulation tasks using analytical models and constrained optimization schemes that describe the behavior of adaptive hands. The automated experimental setup gathers real raw data of the identified feasible manipulation tasks. The raw data are clustered using the k-means algorithm into groups of similar manipulation strategies (groups of similar manipulation paths). A standard dimensionality reduction technique (Principal Components Analysis – PCA) is used to represent the problem in low-d manifolds where control is simplified and intuitiveness of operation is maximized.

## III. Methods

### A. Methodology Overview

In order to automate the extraction of dexterous, in-hand manipulation primitives we used a combination of constrained optimization methods, analytical models and machine learning techniques, as well as an automated experimental setup that is able to collect "big data" of manipulation actions.

More precisely, the constrained optimization scheme and the analytical models (that describe the behavior of adaptive hands) are employed by a simulation module that explores feasible manipulation paths for each hand design and provides some good initial estimates to the automated data collection procedure. The automated experimental setup gathers data of numerous manipulation trials without supervision, detecting unstable grasps or the loss of a particular grasp. The raw manipulation data are stored into a database and a clustering method (k-means algorithm) is used to group together similar manipulation strategies. The feature variables used for clustering, are: a) the final object pose (3 variables for 2D tasks and 6 variables for 3D tasks) and b) the equivalent motor positions at the beginning and the end of the manipulation task. The extracted groups of manipulation strategies are projected to a lower dimensional manifold using a dimensionality reduction technique (Principal Components Analysis – PCA). Appropriate primitive / synergy matrices are extracted that facilitate an intuitive and simplified control of the examined devices in dexterous, in-hand manipulation tasks (see Fig. 2).

### B. A Simulation Module

In order to model the behavior of adaptive hands and precompute a range of feasible manipulation paths without conducting time consuming experiments, we created a simulation module based on the analytical models and the constrained optimization methods that we introduced in [8] and [31].

Given the potential energy of the hand $V(\mathbf{q})$ (e.g., $V(\mathbf{q}) = \frac{1}{2}\mathbf{q}^{\mathrm{T}}\mathbf{K}\mathbf{q}$ for the simple case of spring loaded pin joints, where $\mathbf{q}$ is the vector of the joint angles and $\mathbf{K}$ is the stiffness matrix that represents the pin joint compliances), the problem is formulated as a constrained minimization of the function $E(\boldsymbol{\tau}) = -\nabla_q V(\mathbf{q}) + \mathbf{J}_p^T\mathbf{f}$ ($\mathbf{f}$ are the imposed forces, e.g., contact forces) subject to a set of robot hand and task constraints as described in [32]. The particular scheme predicts the hand configurations, the fingertips velocities and the object pose and velocity using the grasp matrix and the hand object Jacobian.

### C. Clustering Similar Manipulation Strategies

In order to group together similar manipulation trajectories from those identified by the simulation module, we perform a clustering of the collected manipulation data using as feature variables the final object pose of the object (3 variables for 2D tasks and 6 variables for 3D tasks) and the equivalent motor positions, at the beginning and the end of the manipulation task. The clustering technique that we employ is the k-means algorithm [33]. K-means is a vector quantization method that partitions n observations into k clusters. Upon clustering each observation belongs to the cluster with the nearest mean. In this work, different values of k have been considered for the different hand designs and the results of the clustering algorithm were always evaluated by an expert. The role of the expert was twofold: a) to evaluate the quality of the data that the clustering algorithm uses (e.g., to reject noisy data) and b) to evaluate the structure of the extracted clusters. The extracted clusters are used by a dimensionality reduction technique in order to project the robot kinematics to a lower dimensional manifold where control is simplified and the hands operation becomes more intuitive.

### D. Dimensionality Reduction

In order to project the collected manipulation data to a lower dimensional manifold, we use the Principal Components Analysis (PCA). PCA is a dimensionality reduction technique that employs orthogonal transformations in order to convert the provided and possibly correlated variables into a set of linearly uncorrelated variables called the principal components (PC). For an initial *n*-dimensional space the numbers of PCs available are always equal to *n* and they can be used to project the initial data to a manifold of fewer dimensions. The 1st PC accumulates always most of the variance and is derived so as to account for as much of the data variability as possible. Each subsequent PC is orthogonal to all previous PCs and has as much of the remaining variance as possible. More details on PCA can be found in [34].


Fig. 3. The examined robot hands are depicted. All hands have been developed by the GRAB Lab at Yale University. Models T42 and O are freely distributed through the Yale Open Hand project website [9].

## IV. Experimental Setup

### *A. Robots Used*

#### *1) A Robot Arm for Prepositioning the Hands*

The robot arm used is the Barrett WAM [35]. The WAM has 7 degrees of freedom arranged in anthropomorphic fashion and is a research oriented, cable-driven, compliant robotic manipulator that can support a payload of 3 kg. An appropriate, 3D printed wrist coupling of the Yale Open Hand project [9] was used for mounting the examined hands at the end-effector of the robot arm.

#### *2) Robot Hands Examined*

Different hands are used and their most representative dexterous, in-hand manipulation primitives are extracted. Namely, the examined hands are the Yale Open Hand models T42 and O, the GR2 gripper, the P3 gripper, the AS gripper and the FG gripper.

Model T42, is a compliant, underactuated, two-fingered, robot gripper that has two phalanges and a dedicated actuator for each finger. The T42 can be developed with either spring loaded pin joints (denoted with the letter P) or flexure joints (denoted with the letter F) implemented with elastomer materials (Smooth-On, PMC 780 urethane rubber). So a T42FF refers to a version with two flexure joints per finger, while the T42PF refers to a version with one spring loaded pin (proximal) and one flexure joint (distal) per finger. The Spherical hand is a variation of model O and has three fingers (with two phalanges and a dedicated motor each), as well as a motor responsible for a coupled abduction adduction of two of the three fingers.

The GR2 gripper is based on linkages and works similarly to the T42 robot hand [36]. The P3 gripper is actually a T42 that has a finger with only one phalange instead of two. Such a choice makes the design non-symmetric and changes the feasible manipulation workspace.

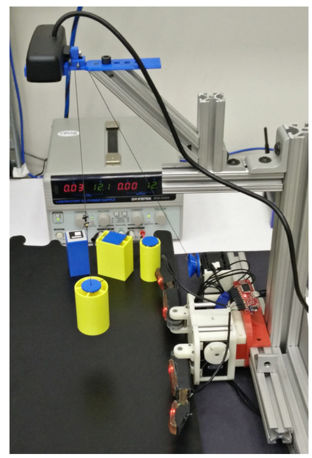

Fig. 4. The setup used for data collection. The frame is created with a set of T-slotted profiles of the Industrial Erector Set (80/20). The blue 3D printed camera holder has a pulley attached for repositioning the object (using the dedicated motor in the middle of the image). The red base of the hand is a 3D printed wrist coupling of the Yale Open Hand project [9].

The AS gripper uses a steady thumb with an active surface (a moving belt) and a finger with two phalanges. The moving finger has a set of freely rotating compliant rollers that constrain the object in caging grasps, allowing it also to be manipulated within the hand (by the belt). Finally, the FG gripper is a minimalistic, four-fingered robot hand that has two pairs of tendon-driven, underactuated fingers that are kept decoupled by an independent, central, rotating axis. The hand was developed for finger gaiting tasks, but it can also perform equilibrium manipulation tasks, using only the two opposing fingers.

All hands were created by the GRAB Lab at Yale University and are depicted in Fig. 3. The designs of models T42 and O are distributed in an open-source fashion, through the Yale Open Hand Project website [9].

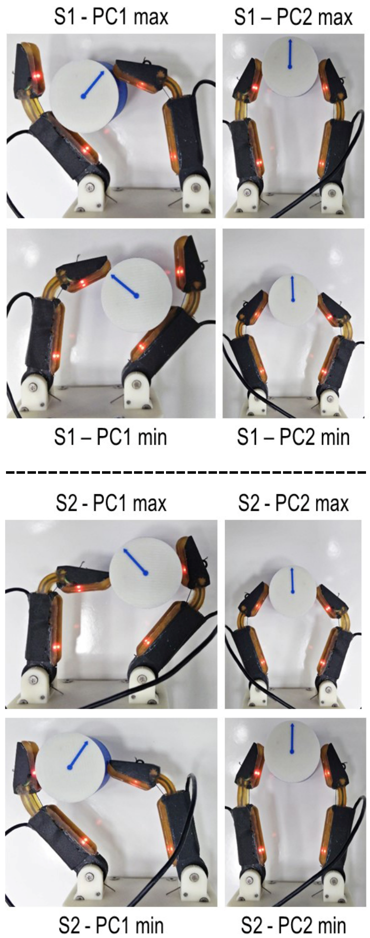


Fig. 5. The extracted manipulation synergy sets for the case of T42PF Takktile. The first primitives concern the execution of equilibrium point manipulation tasks (broad & coupled object rotation and translation for S1, stronger rotation for S2), while the second primitives are pulling the object inside the grasp.

### B. Automated Data Collection Procedure

For the 2D tasks we created a vision based experimental setup that uses a frame based on T-slotted profiles of the industrial erector set and a dedicated actuator for repositioning the object to its initial configuration. The frame supports the wrist coupling mechanism of the Yale Open Hand project [9] and the 3D printed base of the camera. The camera base, has a pulley incorporated that facilitates the repositioning of the objects at the center of the field of view of the camera (initial pose). The setup is depicted in Fig. 4.

For the execution of 3D, in-hand manipulation tasks we attach the examined hand at the end-effector of the Barrett WAM robot arm (see Fig. 6) and it reaches a precomputed grasp configuration (with a certain wrist offset from the object). The developed frame is once again used for repositioning the objects. Each experiment starts with the hand grasping the object at specific contact points. Upon contact that hand starts exploring the identified by the simulation module, feasible manipulation tasks. For each task, after the execution is completed, the hand releases the

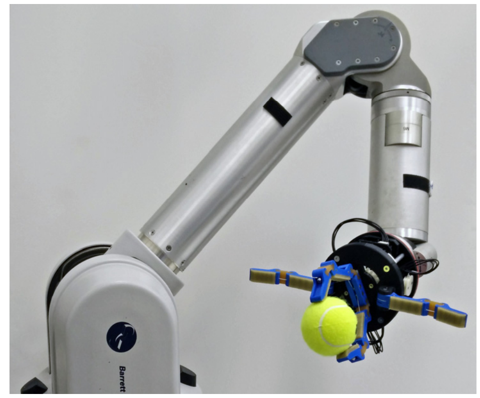

Fig. 6. The Barrett WAM - Yale model FG arm hand system, while grasping a tennis ball with a precision grasp.

object and the repositioning mechanism drives the object back to its initial configuration. All steps described are repeated until all feasible manipulation tasks have been explored.

### C. Object Motion Tracking

In order to capture the motion of the objects in planar manipulation tasks we used a simple web camera (Creative Senz3D) that shoots RGB video with an HD 720p resolution (1280x720). The object motion tracking was implemented using the fiducial markers based methodology of the Aruco library [37]. The developed module provides the complete pose of the object for 2D tasks (x, y, theta). All the scripts required for object detection were developed in Python and were incorporated in our grasp planning framework.

In order to capture the motion of the objects during 3D, dexterous, in-hand manipulation tasks, we used the trakSTAR (Ascension Technologies) magnetic motion capture system. The trakSTAR system is equipped with a medium range transmitter (MRT) and eight model-180 2mm diameter magnetic sensors, it is characterized by high accuracy in both position and orientation, it provides a sampling rate of 80 Hz and it derives the poses of the sensors in the format of homogeneous transformation matrices with respect to the global reference frame.

## V. Dexterous Manipulation Primitives

### A. Manipulation Primitives & Synergy Sets

Having identified a set of representative clusters in the manipulation data we use the Principal Components Analysis (PCA) method to project each group to a lower dimensional manifold where control is simplified. The dimensionality of the original space is equal to the number of actuators per hand and is 2D for T42PF, T42PP, P3, GR2 and AS and 4D for model O / Spherical hand and FG.

The extracted manipulation synergy sets for T42PF Takktile are depicted in Fig. 5. The first primitives execute equilibrium point manipulation tasks. Hands that have similar structure and kinematics have also similar manipulation primitives (as seen also in Table I) and some small differences are due to differences in the stiffness of the joints and differences in the link length ratios.

Table I. The most representative manipulation primitives extracted for each hand. Only 2 PCs per Synergy set are depicted.

| Hands | Primitives | | | |
|---|---|---|---|---|
| | S1 - PC1 | S1 - PC2 | S2 - PC1 | S2 - PC2 |
| T42 PF Takktile | [0.7072 -0.7070] | [0.7070 0.7072] | [-0.4756 0.8797] | [-0.8797 -0.4756] |
| T42 PP Takktile | [0.7319 -0.6813] | [0.6813 0.7319] | [-0.5889 0.8081] | [-0.8081 -0.5889] |
| T42 PP | [0.7085 -0.7056] | [0.7056 0.7085] | [-0.4694 0.8829] | [-0.8829 -0.4694] |
| P3 Gripper | [0.6842 -0.7292] | [0.7292 0.6842] | **X** | **X** |
| AS Gripper | [-0.9837 0.1794] | [-0.1794 -0.9837] | **X** | **X** |
| GR2 Gripper | [0.6092 -0.7930] | [0.7930 0.6092] | **X** | **X** |
| FG Gripper | [0.6488 0.1892<br>0.6951 0.2452] | [-0.1526 -0.0925<br>-0.1741 0.9684] | [0.6888 0.7248] | [-0.7248 0.6888] |
| Spherical / O | [0.2708 0.4282<br>0.8370 0.2067] | [0.4799 -0.7118<br>0.0839 0.5059] | [0.7024 0.7089] | [-0.7089 0.7024] |

Table II. The ranges of object motion for each object size per identified primitive of the T42 PP Takktile. The translations are reported in mm and the rotations in degrees. A graphical representation of the ranges of motion is provided in Fig. 7.

| **Object Size** (diameter) | Primitives | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | S1 - PC1 | | | S1 - PC2 | | | S2 - PC1 | | | S2 - PC2 | | |
| | x | y | theta | x | y | theta | x | y | theta | x | y | theta |
| 30 mm | -64,64 | 0,-36 | -46,46 | 0,0 | 0,-34 | 0,0 | -30,30 | 0,-17 | -50,50 | 0,0 | 0,-34 | 0,0 |
| 50 mm | -62,62 | 0,-22 | -40,40 | 0,0 | 0,-33 | 0,0 | -27,27 | 0,-16 | -20,20 | 0,0 | 0,-33 | 0,0 |
| 70 mm | -67,67 | 0,-29 | -6,6 | 0,0 | 0,-22 | 0,0 | -27,27 | 0,-16 | -13,13 | 0,0 | 0,-22 | 0,0 |
| 90 mm | -69,69 | 0,-30 | 0,0 | 0,0 | 0,-14 | 0,0 | -26,26 | 0,-11 | -8,8 | 0,0 | 0,-14 | 0,0 |

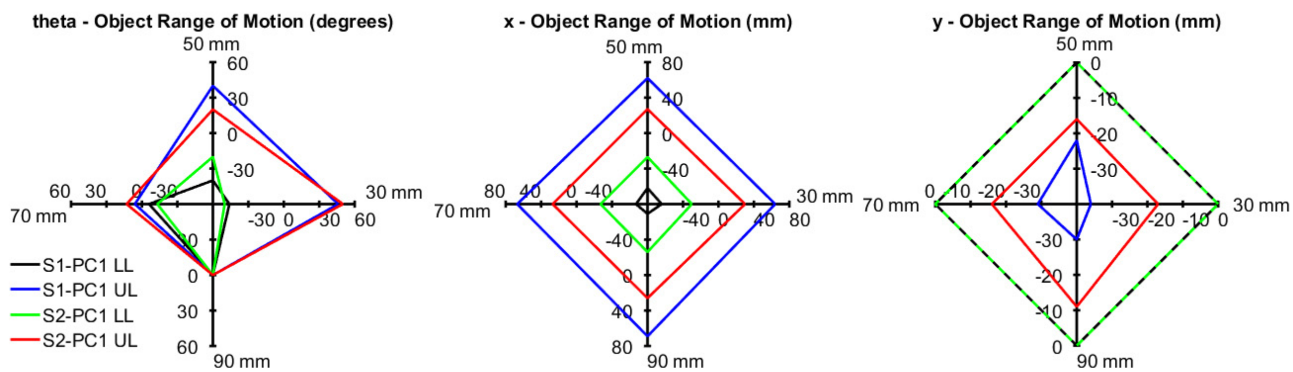


Figure 7. Graphical representation of the ranges of object motions during manipulation with the T42 PP Takktile robot hand and cylinders of various diameters (30 - 90 mm). Each axis corresponds to a cylinder of different size. Only the first PC of each Synergy set is depicted. LL stands for lower limit and UL stands for upper limit.

Table III. Variations of the primitive coefficients for different object sizes (diameters) for T42 PF Takktile.

| Object Size | Primitives | |
|---|---|---|
| | S1 - PC1 | S2 - PC1 |
| 30 mm | [0.7072 -0.7070] | [-0.4756 0.8797] |
| 50 mm | [0.7119 -0.7015] | [-0.4639 0.8859] |
| 70 mm | [0.7060 -0.7082] | [-0.5244 0.8515] |
| 90 mm | [0.6975 -0.7165] | [-0.4512 0.8924] |

It should be noted that if we don't split the manipulation data with the clustering technique (grouping the similar strategies together) and we choose instead to project all the data to a common low-d space, then the strategies of the second synergy sets for T42 disappear and the PCs extracted are similar to the PCs of the first synergy set. Thus, by splitting the datasets we allow a mechanism with only two actuators to have several manipulation primitives instead of two that would be typically derived. Regarding the robot hands examined, the P3 gripper behaves similarly to the T42 class of hands. The only difference is that the second PC of the extracted synergy set for P3 accounts for only 12% of the variance since the one-link finger cannot reconfigure and it has only one remaining finger capable of pulling the objects towards the wrist. The synergy set of the AS is responsible for trapping the object in a caging grasp where the actuator of the belt can operate in continuous mode, statically rotating the object. The aforementioned pinch and caging grasps of the AS gripper are depicted in Fig. 8. The identified representative manipulation strategy for the GR2 gripper is once again an equilibrium point manipulation of the object that involves a lot of rolling at the contacts. It is not surprising that GR2 has quite different primitive coefficients since the design is based on linkages and has a

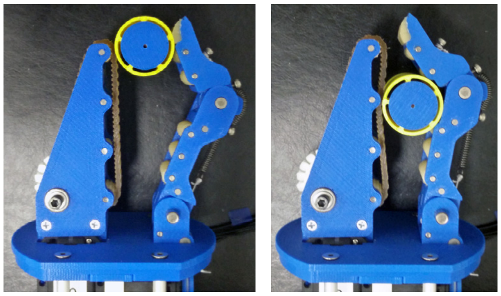

Fig. 8. The transition from pinch grasp to a caging grasp for the AS gripper. In the caging grasp the primitives are no longer required since the belt actuator can rotate the object with continuous rotations.

distinct geometry. The model O / Spherical hand and the FG gripper have more primitives per synergy set, as they have three and four fingers respectively. The first synergy set implements finger-gaiting for FG gripper and equilibrium point manipulation for model O. The second synergy sets use only two of the opposing fingers for both model O and the FG gripper, executing once again equilibrium point manipulation tasks.

### B. Generalization Across Object Sizes

Table II presents the relationship between the object sizes and the ranges of motion of the object and it appears that a hand may have completely different manipulation capabilities for different objects. For example, for the S1-PC1 the theta value for a cylinder with a diameter of 30mm has a range from -46 to 46 degrees, while for a cylinder with a diameter of 90 mm the rotation component of the equilibrium point manipulation process is not available and the aforementioned range is eliminated. A graphical representation of the ranges of motion is presented in Fig. 7. In Table III, we present results on the effect of the object size on the values of the primitive coefficients. The particular results demonstrate that primitives do not change significantly for different object sizes.

It should also be noted, that it is safe to use primitives extracted for smaller objects to grasp larger objects as the motion that they will generate will squeeze the objects harder without crushing them, due to the structural compliance of adaptive hands. Primitives extracted for large objects cannot be used for smaller objects since the resulting aperture of the hand could easily be bigger than the object dimensions. In Fig. 9, we present the model T42PP performing an equilibrium point manipulation with a cylinder that has a diameter of 50 mm using a primitive extracted for a smaller cylinder (d = 30 mm).

## VI. Discussion

The proposed methodology takes advantage of the passive compliance of adaptive hands that simplifies the automated extraction of manipulation primitives. In order for a similar methodology to be used with rigid robot hands, appropriate planning and control schemes should be developed. These schemes should guarantee the extraction of stable initial grasps, the avoidance of intra-finger, object or environmental

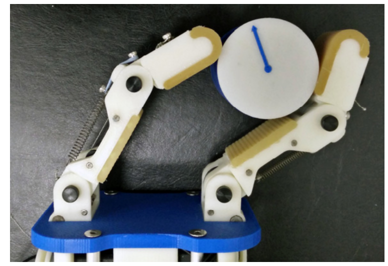

Fig. 9. The T42PP performing an equilibrium point manipulation task with a cylinder that has a diameter of 50 mm using a primitive derived for a smaller cylinder (d = 30 mm).

collisions, the computation of an appropriate set of contact forces (to avoid crushing the object) and the stability of the hand object system during the manipulation process. All these prerequisites are taken care by design in the case of adaptive hands. Moreover, it should also be noted that the control space of fully actuated, multi-fingered hands is highly multidimensional and the partitioning, clustering and identification of a representative set of synergies is much more challenging.

## VII. Conclusions and Future Directions

In this paper, we proposed a methodology for the automated extraction of dexterous, in-hand manipulation primitives for adaptive, underactuated and/or compliant robot hands. To do so, we used a combination of analytic, constrained optimization and machine learning methods and we created a new setup for automated data collection and experimentation. More specifically, the constrained optimization scheme takes advantage of analytic models that describe the bending of spring loaded pin and flexure joints and predicts the behavior of adaptive hands during grasping and manipulation, providing intuition about the problem mechanics. The machine learning scheme uses: a) a clustering technique to group together similar manipulation strategies and b) a dimensionality reduction technique to project the robot kinematics to a lower dimensional manifold. In such a manifold, the control problem is simplified and the hands' operation becomes more intuitive for the user. During the analysis and the extraction of the various manipulation primitives we assessed also the feasible ranges of object motion. The efficiency of the proposed methods and the applicability of the extracted primitives were validated using extensive experimental paradigms that involved various adaptive hands grasping a series of sensorized objects. A derivative of this work is the Yale Manipulation Primitives Database [38], a repository that provides a set of representative primitives that simplify dexterous manipulation with adaptive hands. Regarding future directions, we plan to consider, compare and evaluate different types of clustering and dimensionality reduction techniques for the extraction of manipulation primitives.

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