Combining Analytical Modeling and Learning to Simplify Dexterous Manipulation With Adaptive Robot Hands

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***Abstract*— In this paper, we focus on the formulation of a hybrid methodology that combines analytical models, constrained optimization schemes, and machine learning techniques to simplify the execution of dexterous, in-hand manipulation tasks with adaptive robot hands. More precisely, the constrained optimization scheme is used to describe the kinematics of adaptive hands during the grasping and manipulation processes, unsupervised learning (clustering) is used to group together similar manipulation strategies, dimensionality reduction is used to either extract a set of representative motion primitives (for the identified groups of manipulation strategies) or to solve the manipulation problem in a low-d space and finally an automated experimental setup is used for unsupervised, automated collection of large data sets. We also assess the capabilities of the derived manipulation models and primitives for both model and everyday life objects, and we analyze the resulting manipulation ranges of motion (e.g., object perturbations achieved during the dexterous, in-hand manipulation). We show that the proposed methods facilitate the execution of fingertip-based, within-hand manipulation tasks while requiring minimal sensory information and control effort, and we demonstrate this experimentally on a range of adaptive hands. Finally, we introduce DexRep, an online repository for dexterous manipulation models that facilitate the execution of complex tasks with adaptive robot hands.**

***Note to Practitioners*—Robot grasping and dexterous, in-hand manipulations are typically executed with fully actuated robot hands that rely on analytical methods, computation of the hand object system Jacobians, and extensive numerical simulations for deriving optimal strategies. However, these hands require sophisticated sensing elements, complicated control laws, and are not robust to external disturbances or perception uncertainties. Recently, a new class of adaptive hands was proposed which uses structural compliance and underactuation (less motors than the available degrees of freedom) to offer increased robustness and simplicity. In this paper, we propose hybrid methodologies that blend analytical models with constrained optimization schemes and learning techniques to simplify the execution of dexterous, in-hand manipulation tasks with adaptive robot hands.**

***Index Terms*— Adaptive hands, dexterous manipulation, grasping, underactuated mechanisms.**

I. Introduction

TRADITIONALLY, the planning of fingertip/pinch grasps and dexterous, in-hand manipulation tasks relied on fully actuated, multifingered, rigid robot hands that required the use of analytical models, the computation of the hand object system Jacobians, and extensive numerical simulations. However, certain grasping and manipulation tasks involve dynamic phenomena such as uncontrolled slipping and rolling that are impractical, difficult, or even not possible to model. Furthermore, even minor uncertainties in the modeling space (e.g., perception uncertainties like object pose uncertainties that are due to sensor noise or other errors) could easily render the execution of stable grasps or the computation of a set of realizable dexterous manipulation paths infeasible. Thus, 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 terms of practical applications and the execution of dexterous, in-hand manipulation tasks remains difficult to accomplish.

Over the past decade, a new class of adaptive robot hands has been proposed to simplify the grasping and manipulation problems. These hands use structural compliance (e.g., fingertip, finger pad, or joint compliance) and underactuation [fewer actuators than the available degrees of freedom (DoF)] to facilitate by design the extraction of stable grasps and the robust execution of dexterous, in-hand manipulation tasks. Adaptive hands can grasp and hold firmly a wide range of everyday life objects, even under significant object pose uncertainties and they do not rely on accurate, preplanned motions or strategies [1]–[5]. For the aforementioned reasons, most researchers that work with adaptive hands choose to control them in an open-loop, almost "ON–OFF" fashion without requiring any sensor feedback. Regarding manipulation, a few studies have also focused on demonstrating the efficiency of adaptive hands in executing dexterous, within-hand manipulation tasks [6]–[8]. However, adaptive hands also have certain limitations and drawbacks. The use of underactuation complicates the planning problem, introducing certain kinematic

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constraints imposed by the cable-/tendon-based transmission, while the use of compliant elements in the robot hand structure (e.g., flexure joints based on urethane rubber) complicates the kinematics and dynamics analysis. These drawbacks when combined with dynamic phenomena like the uncontrolled slipping and rolling that typically affect the execution of in-hand manipulation tasks, make modeling, planning, and control with adaptive robot hands particularly challenging. Furthermore, upon contact with the object surface, the hand object system tends to reconfigure to an equilibrium configuration that depends on the contact forces exerted at the fingertips and on the hand and object parameters (e.g., finger link lengths, object geometry, joint stiffness etc.), imposing a parasitic object motion that cannot be easily modeled.

In this paper, we focus on the formulation of a hybrid methodology that simplifies the execution of dexterous, in-hand manipulation tasks with adaptive robot hands (see Fig. 1). The proposed methodology is considered hybrid as it combines in a synergistic fashion, analytical methods, constrained optimization schemes, and machine learning techniques to extract task-specific manipulation models and primitives that simplify the execution of dexterous, in-hand manipulation tasks. More precisely, a constrained optimization scheme uses analytical models that describe the kinematics of adaptive hands and classic conventions for modeling quasi-statically the grasping and manipulation problems (providing insight regarding the problem mechanics). The constrained optimization scheme is used as a basis for the development of a "simulation module" that analyzes the behavior of adaptive hands and gives a good initial estimate of their grasping and dexterous manipulation capabilities. The learning module consists of a clustering module that groups together similar manipulation motions/paths, a dimensionality reduction technique that projects the robot kinematics to a lower dimensional manifold when the control problem needs to be simplified and finally a supervised learning module that combines classification and regression techniques to map in a task-specific manner, the desired object trajectories to the required robot hand actuator trajectories (acting as an analogous of the inverse of the hand object system Jacobian). Finally, we propose an autonomous experimental setup that consists of a 7-DoF robot manipulator, the examined adaptive robot hands, and object retracting mechanisms that return the manipulated objects passively to the initial pose. The particular setup facilitates an autonomous collection of big data sets over long periods of time.

In this paper, we also focus on accessing the efficiency and the generalization capabilities of the derived manipulation models for different objects (e.g., both model objects and everyday life objects), as well as for different task specifications. To validate the efficiency of the proposed methods, we conduct extensive experiments involving various adaptive robot hands and manipulating a plethora of instrumented, 3-D printed objects and everyday objects. Finally, we introduce DexRep (www.newdexterity.org/dexrep), an online repository that hosts easy to use, intuitive manipulation models that facilitate the execution of dexterous, in-hand manipulation tasks with adaptive robot hands.

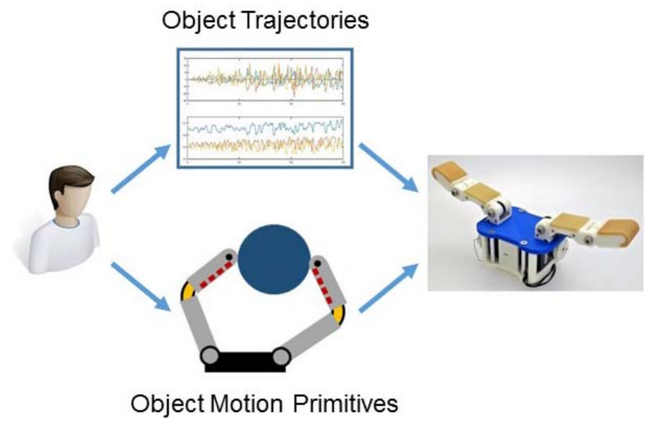

Fig. 1. Different types of user-provided inputs for the proposed methodology. The user may specify the way that the object will be manipulated either by providing the desired object trajectory (in 2-D or 3-D space depending on the hand structure) or by selecting an appropriate object motion primitive (e.g., rotation of the object around a desired axis). The presented hand is the T42PP and is a derivative design of the Yale Open Hand project.

The rest of this paper is organized as follows. Section II presents the related work, Section III presents the methods used to formulate the proposed methodologies and discusses the role of the different modules, while Section IV presents the experimental setup as well as the robot arm and the adaptive robot hands used. Section V focuses on the efficiency and the generalization capabilities of the derived dexterous, in-hand manipulation models and primitives and discusses the limitations of the proposed methodology, while Section VI concludes this paper.

II. Related Work

Dexterous, in-hand manipulation has become increasingly important as it allows robots to interact with their surroundings and execute meaningful tasks (e.g., grasping a handle, opening a door, turning a knob etc.). In [9], dexterity has been described as the process of manipulating an object from one grasp configuration to another, while in [10], as the cooperation between multiple manipulators or fingers, to grasp and manipulate objects. Thus, dexterity has always been associated with the grasping and manipulation processes and people tended to characterize as dexterous those robot hands that have multiple fingers, multiple actuators, and DoF (mostly fully actuated devices). Such hands are typically rigid, heavy, and expensive and they require sophisticated sensing elements and complicated control laws in order to execute efficiently dexterous tasks. On the other hand, the new class of adaptive robot hands offers a simplified and affordable dexterity, as well as increased robustness and intuitiveness in the execution of stable grasping and dexterous, in-hand manipulation tasks.

Significant research effort has also been put into developing simple, minimalistic devices for robust grasping and dexterous, in-hand manipulation. In [7], it has been demonstrated that a reduction in the number of hand actuators and constraints can relax the control effort and simplify the execution of dexterous manipulation tasks. Odhner *et al.* [11] proposed an open-loop methodology for adaptive hands that is inspired by humans and that facilitates the execution of flip and pinch tasks facilitating picking up objects from a table surface. Mason *et al.* [12] proposed a learning scheme for performing object recognition, object in-hand localization, and grasp evaluation (e.g., using grasp rejection when needed), using a minimalistic approach that they call "grasp first—ask questions later." In [13], extrinsic dexterity was introduced as the ability of simple hands to perform dexterous manipulation tasks using extrinsic to the hand object system resources (e.g., resources like gravity and external contacts). The grasping and regrasping actions performed were open-loop yet surprisingly robust. Regarding grasping and dexterous manipulation planning, the traditional approach involves analytical methods and constrained optimization schemes for performing grasp synthesis, computation of the hand object system Jacobians, extracting stable but also minimal effort grasps, maintaining the force closure properties of the grasp, and respecting task specifications and constraints. Such a work can be found in [14]. In this paper, the authors propose a methodology for planning in-hand manipulation tasks with multifingered hands, considering task constraints and deriving stable grasp configurations. Similar approaches have also been used in the grasping literature [15]. Van Hoof *et al.* [16] proposed a reinforcement learning methodology for acquiring new dexterous, in-hand manipulation capabilities/skills for adaptive robot hands equipped with tactile sensors that does not rely on dynamic or kinematic models. Kojima *et al.* [17] proposed a machine learning scheme that predicts whether a grasp with a multifingered hand is stable or not. This scheme was later on used in a learning framework that facilitates dexterous, in-hand manipulation with a multifinger hand equipped with appropriate tactile sensors [18]. Regarding vision-based approaches, Hang *et al*. [19] presented a framework for grasp planning and in-hand grasp adaptation using a combination of visual, tactile, and proprioceptive feedback. The particular work facilitates robust fingertip grasping, accounting for the weight of the object, possible slipping, and external disturbances, and enabling the execution of finger gaiting tasks.

In [8], we presented preliminary results on the formulation of a methodology that combines constrained optimization schemes and machine learning techniques for deriving manipulation models that account for dynamic phenomena and that can simplify the execution of dexterous, in-hand manipulation tasks with adaptive hands, while in [20], we focused on the extraction of a representative set of manipulation primitives that offer an intuitive yet dexterous control of adaptive robot hands. In this paper, we combine all the work done in [8] and [20], in order to propose a unified, user-oriented methodology that facilitates the execution of dexterous manipulation tasks in an intuitive and simplified manner (see Fig. 2). To do so, we provide new results and analyses and we discuss in detail the role and the use of different components. It must be noted that the proposed methodology benefits from a synergistic interaction between the different submodules (e.g., dimensionality reduction and model training) that improves the overall efficiency of the system.

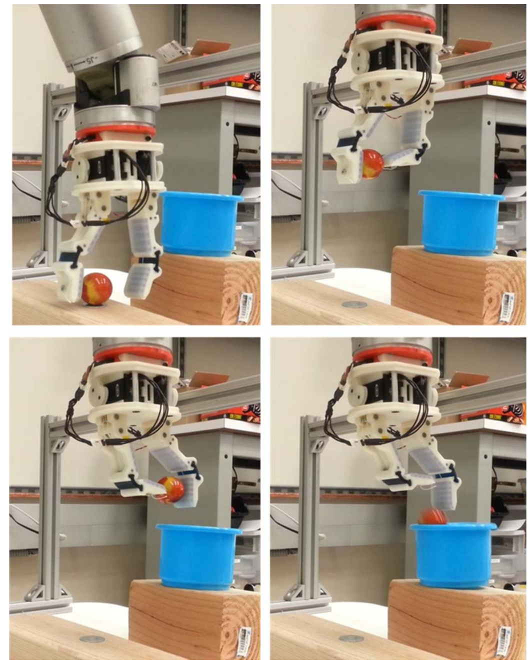

Fig. 2. Example of a dexterous manipulation task (equilibrium point manipulation) executed with the Yale Open Hand model T42PF. Four instances of the task are depicted. Such hand capabilities can extend the dexterous workspace of robot arms.

Regarding the extraction of motion primitives, several studies have focused on projecting the human or robot kinematics in lower dimensional manifolds where both the motion analysis of the human hand and the control of the robotic devices are simplified. Santello *et al.* [21] and Bicchi *et al.* [22] first demonstrated that the control of the human hand posture involves only a few postural synergies, concluding that the first two principal components (PCs) account for more than 80% of the total variance. In the robotics literature, motion primitives have been used for simplifying grasping [23]–[26] and dexterous manipulation [27], [28] but also for deriving new bioinspired hand designs [29].

III. METHODS

A. Methodology Overview

In this section, we present an overview of the proposed methodology. The proposed hybrid framework consists of two separate modules, the offline training phase and the online execution phase. For the offline training phase of the framework, the various steps are as follows.

1) The simulation module explores all the feasible manipulation paths for a given hand object combination, providing a good first guess to the autonomous experimental platform.
2) The feasible manipulation paths are executed by the autonomous data collection setup that gathers real manipulation data that will be used for model training and extraction of primitives. Such data include also dynamic, difficult to model phenomena like uncontrolled slipping and rolling.

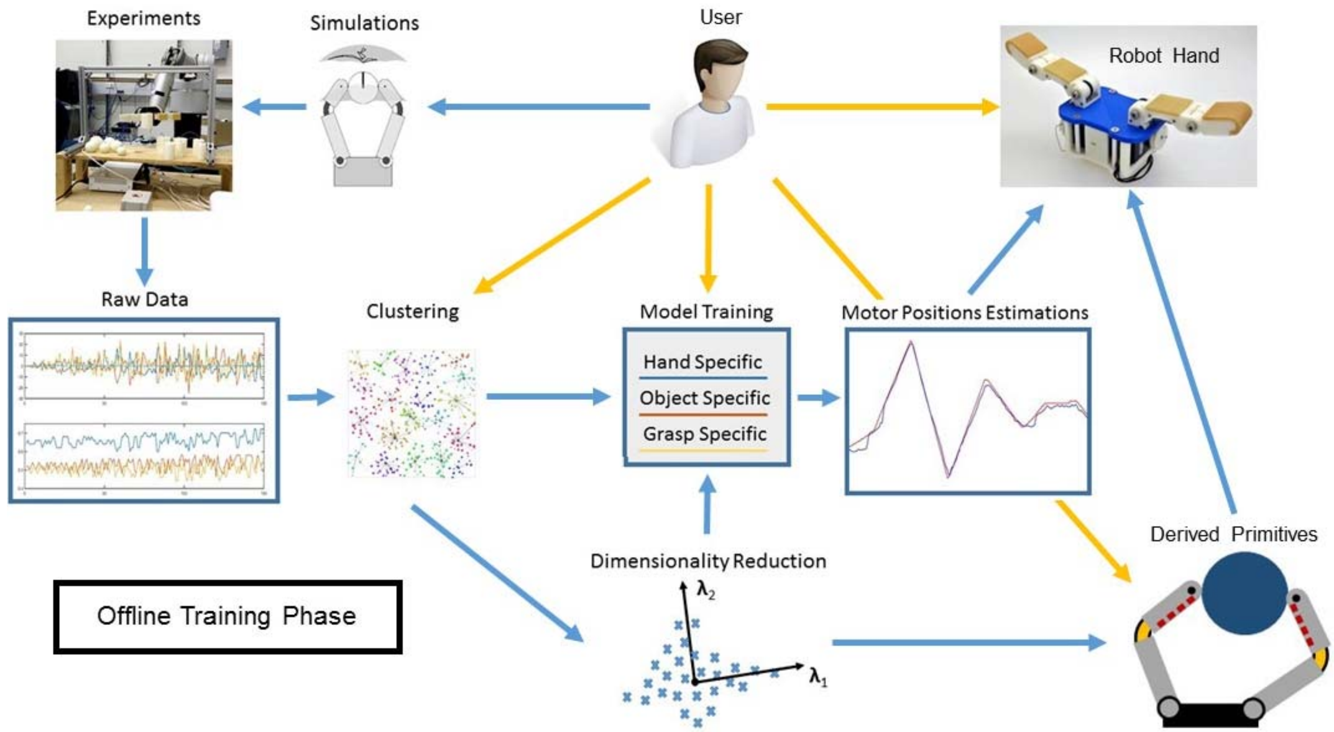

Fig. 3. Simplified representation/visualization of the structure of the proposed methodology. Blue arrows are used to denote the direction of the offline, training process, while orange arrows are used to denote the interactions of the expert user with the different submodules of the methodology. The expert user assesses the "behavior"/efficiency of the dexterous manipulation models and primitives and the results of the clustering technique, refining the selections when needed. Regarding the training process, the simulations module provides a good first guess of the feasible manipulation paths to the autonomous experimental setup that conducts the experiments in an unsupervised manner. The raw manipulation data are clustered using the K-means clustering algorithm into groups of similar manipulation strategies that can be then used for model training or for dimensionality reduction. The model training results to task-specific (hand-specific, object-specific, and grasp-specific) dexterous manipulation models that map desired object trajectories (input) to the corresponding motor trajectories that guarantee the execution of the desired task (output). The dimensionality reduction results to representative manipulation primitives that represent some primitive manipulation capabilities of the adaptive gripper/hand and that facilitate the execution of dexterous tasks in an intuitive and simplified manner. Both approaches can be used to control a wide variety of adaptive robot hands and the expert user is then again responsible for assessing the capabilities of the system and refining the training process (e.g., retraining the manipulation models to achieve better generalization to new tasks) to achieve better results.

3) The raw object and motor position trajectories (manipulation data) are clustered to similar manipulation strategies that are task specific (hand specific, object specific, and grasp specific).
4) The random forests regression technique is employed to train dexterous manipulation models for all possible tasks. Such models are equivalent to the inverse of the hand object system Jacobian, so for a given/desired object trajectory, they provide the required motor trajectories that will lead to an efficient execution of the task.
5) PC analysis (PCA) is used in order to project high-dimensional data to low-d manifolds where the analysis is simplified and the extraction of simple and intuitive manipulation models and primitives is facilitated.

It must be noted that dimensionality reduction is not always required as for simple grippers (e.g., model T42) that have only a 2-D control space, the problem is already simple. This process may be required for hands that have a high-dimensional control space (e.g., model O). For the online execution phase of the framework, the various steps are as follows.

1) The user provides either a desired object position trajectory or a desired object pose or high-level task specifications (e.g., object motion around an axis). Alternatively, the input can be provided by a perception system that recognizes new objects in the environment and identifies their affordances.
2) The user input is classified to the most similar task. In the case of a desired object position trajectory, a random forests regression model is used to map input object trajectories to output motor trajectories that will execute the desired object motion. In the case of a desired object position, the current object pose and the desired object pose are classified to the most proximal, feasible manipulation path (connecting path), and the corresponding random forest regression model is used to generate the appropriate motor trajectory that will move the object from one to the other. In the case of a desired object motion (high-level specification), the most similar manipulation primitive is triggered and the robot hand is controlled in a low-d manifold (object space).

A visualization of the offline training phase of the proposed framework is depicted in Fig. 3, while a visualization of the proposed online execution phase is depicted in Fig. 4. It must be noted that the role of the expert user that assesses the behavior of the models and the results of the clustering and dimensionality reduction techniques is of paramount importance, for the following two reasons:

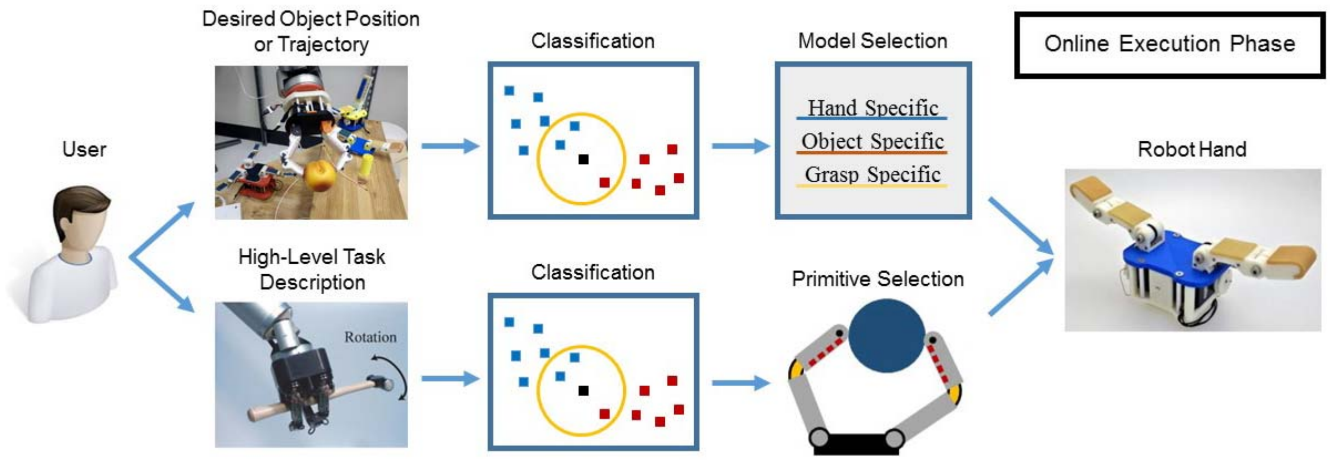

Fig. 4. Simplified representation/visualization of the structure of the proposed methodology for the online execution phase. Blue arrows are used to denote the direction of the online execution process. The user may provide as input to the system: 1) a desired object position; 2) a desired object trajectory; or 3) a high-level task description that corresponds to an appropriate manipulation primitive. A random forest classifier is used in order to decide based on the user provided input, which manipulation primitive or model to trigger.

1) guarantees the generalization capabilities of the framework (e.g., avoiding overfitting of the proposed manipulation models);
2) can lead to a locally optimized behavior of the framework and to an excellent task-specific performance.

B. Simulation Module

The simulation module combines analytical models and a constrained optimization scheme to describe the behavior of adaptive hands and explore the feasible manipulation paths for the examined robot hand design without conducting time-consuming experiments. The module is based on the constrained optimization (energy minimization framework) methods that were introduced in [8] and [30].

More precisely, given the potential energy of the hand $V(\mathbf{q})$ that can be denoted by $V(\mathbf{q}) = 1/2)\mathbf{q}^{\mathrm{T}}\mathbf{K}\mathbf{q}$ 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 $E(\boldsymbol{\tau}) = -\nabla_q V(\mathbf{q}) + \mathbf{J}_p^T \mathbf{f}$, where $\mathbf{f}$ are the imposed forces (e.g., contact forces) subject to the robot hand and task constraints. The proposed scheme predicts the hand configurations and the fingertips velocities. From the derived fingertip velocities, we can easily compute the object velocity using the grasp matrix $\mathbf{G}$.

An example of the efficiency of the simulation module is presented in Fig. 5, where we compare the execution of an equilibrium point manipulation task in simulation and in the real world with the same adaptive robot hand. The task focuses on following a predefined trajectory in the object space and the hand used is the Yale Open Hand model T42PP. Three different object poses of the trajectory are depicted (initial, middle, and final). It must be noted that the simulation module closely matches the real system behavior but it cannot account for uncontrolled slipping and rolling that sometimes appear unexpectedly during the execution of dexterous, in-hand manipulation tasks. Another potential source of differences between the simulated system and the real system is the friction of the tendon routing system of the real hand, since such phenomena are not included in the simulation module and are not taken into consideration during the exploration of the feasible manipulation paths. The simulation module needs to be further improved to include also such phenomena.

C. Grouping Together Similar Manipulation Strategies

The K-means clustering technique [31] is used to examine the collected manipulation data and group together similar manipulation strategies/trajectories. The vector of the input variables consists of the final object pose (three variables for 2-D tasks and six variables for 3-D tasks) and the equivalent motor positions, at the beginning and the end of the manipulation task (two time instances). The K-means is a vector quantization methodology that partitions n observations into k clusters. After clustering each observation belongs to the cluster with the nearest mean. Different values of k have been considered and results have been evaluated by an expert. The role of the expert was to evaluate the quality of the data that the clustering algorithm uses (e.g., to reject noisy data) and assess any physical meaning of the structure of the extracted clusters. The extracted clusters are used by the random forest regression technique to train manipulation models and by a dimensionality reduction technique to project the robot kinematics to a lower dimensional manifold where analysis is simplified.

D. Projection of Robot Data to Low-D Manifolds

The dimensionality reduction method used is the PCA [32] that employs orthogonal transformations in order to convert the possibly correlated input variables into a set of linearly uncorrelated variables, the PC. Given an initial n-dimensional space, a number of PCs available are always equal to n and they can be used to project the initial data to manifolds of

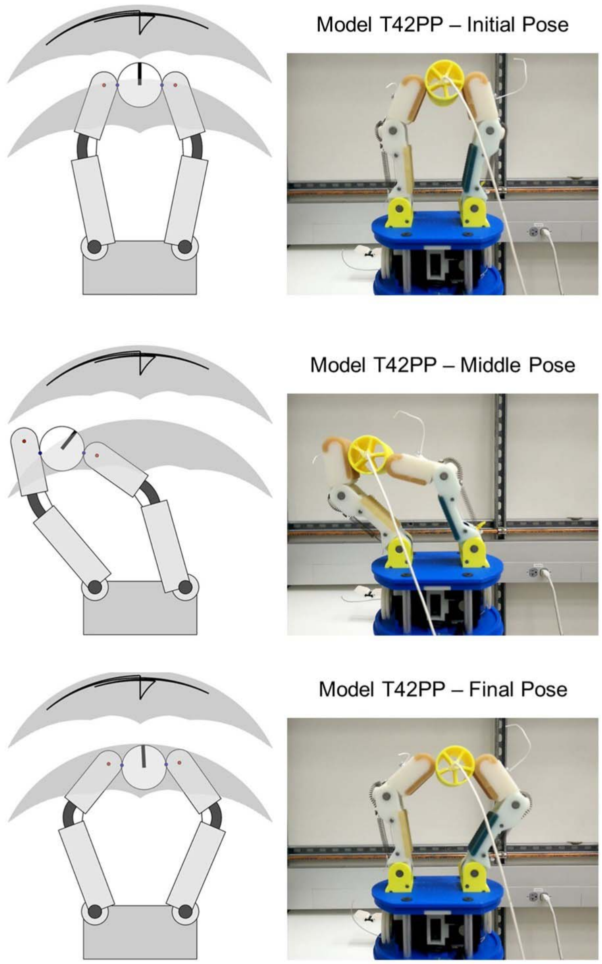

Fig. 5. Comparison of simulated and real-life execution of a dexterous manipulation task (equilibrium point manipulation) with the Yale Open Hand model T42PP. The two hands follow a predefined trajectory in the object space depicted with a black line. Three different object poses of the path are depicted. The simulated hand closely matches the behavior of the real hand.

fewer dimensions. The first PC accumulates always most of the data variance. The second PC is always orthogonal to the first, the third to the second, and so on. Thus, every succeeding PC has as much of the remaining variance as possible. In this paper, the PCA method is used to project the collected manipulation data to low-d manifolds, where control is simplified and manipulation planning becomes more intuitive for the user. The low-d space can be used either to extract a representative set (synergy set) of manipulation primitives or to solve the regression problem that will derive task-specific, in-hand manipulation models (equivalent to the hand object system Jacobian) [8]. The interactions of the dimensionality reduction technique with the other modules are provided in Fig. 3, where the structure of the proposed methodology is thoroughly discussed.

In this paper, we use the term synergy set (S) to denote the representative set of manipulation primitives and the term PC to denote each manipulation primitive of the set. It should also be noted that in the case of manipulation primitives extraction, if we do not split the manipulation data with the clustering technique, grouping together the similar manipulation strategies and we choose instead to project all the data to a common low-d space, then the primitives derived will be limited (e.g., as many as the dimensionality of the original space) and will represent some sort of average behavior of the hand during the execution of dexterous manipulation tasks, neglecting other meaningful and potentially useful behaviors. Thus, by using the clustering methods and splitting the collected data into groups of similar manipulation strategies, we allow a mechanism with a limited number of actuators to have several manipulation primitives instead of the limited number of primitives that would be typically derived. Regarding manipulation models, the regression problem can be solved in the low-d space of the robot kinematics where the analysis is simplified and the models can be trained in a task-specific way (see Figs. 3 and 4). It must be noted that dimensionality reduction is not always required as for simple grippers (e.g., model T42) that have only a 2-D control space, the problem is already simple. This process is of paramount importance for hands that have a high-dimensional control space (e.g., model O).

E. Task-Specific Manipulation Models Training

To account for the first type of user-provided input presented in Fig. 1, we use the random forests regression method and we train all the possible dexterous, in-hand manipulation models, in a task-specific manner, using the data of each group of similar manipulation strategies as they were derived by the clustering algorithm.

The random forests classification and regression techniques were proposed by Ho [33] and Breiman [34]. Random forests are ensemble classification and regression methods based on a combination of multiple decision trees. The final classification decision of a forest is always the most popular class among the individual classifiers. The final regression estimation of a forest is the mean value of the independent estimations of various trees. In this paper, the random forest regression technique is used to train all the identified, task-specific manipulation models and the random forest classifier is used to trigger the appropriate task-specific manipulation model based on the user-provided input (*a priori* knowledge of the task specifications), or alternatively based on features received from a perception system (e.g., in the case of new objects and tasks encountered during the autonomous operation of the system).

IV. Experiments

In this section, we present the experiments conducted to validate the efficiency of the proposed methods and we describe the apparatus used.

A. Robot Arm and Hands

The robot arm used during the experiments is the 7-DoF Barrett WAM [35]. The WAM is a research oriented, redundant, cable-driven, compliant robotic manipulator that has anthropomorphic kinematics. An appropriate, 3-D printed wrist coupling of the Yale Open Hand project [36] was used to attach the hands at the robot arm's end-effector. The robot

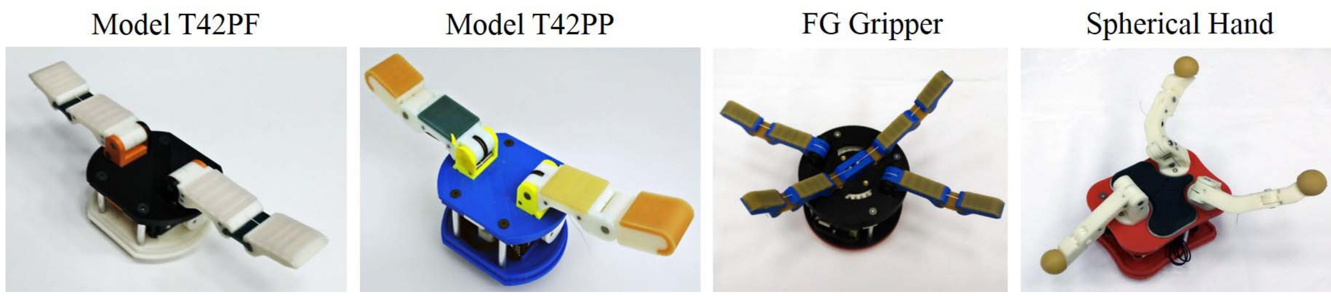

Fig. 6. Robot hands examined are depicted. All hands have been developed by the GRAB Lab at Yale University. The two-fingered model T42 and the three-fingered model O are freely distributed through the Yale Open Hand project website [36].

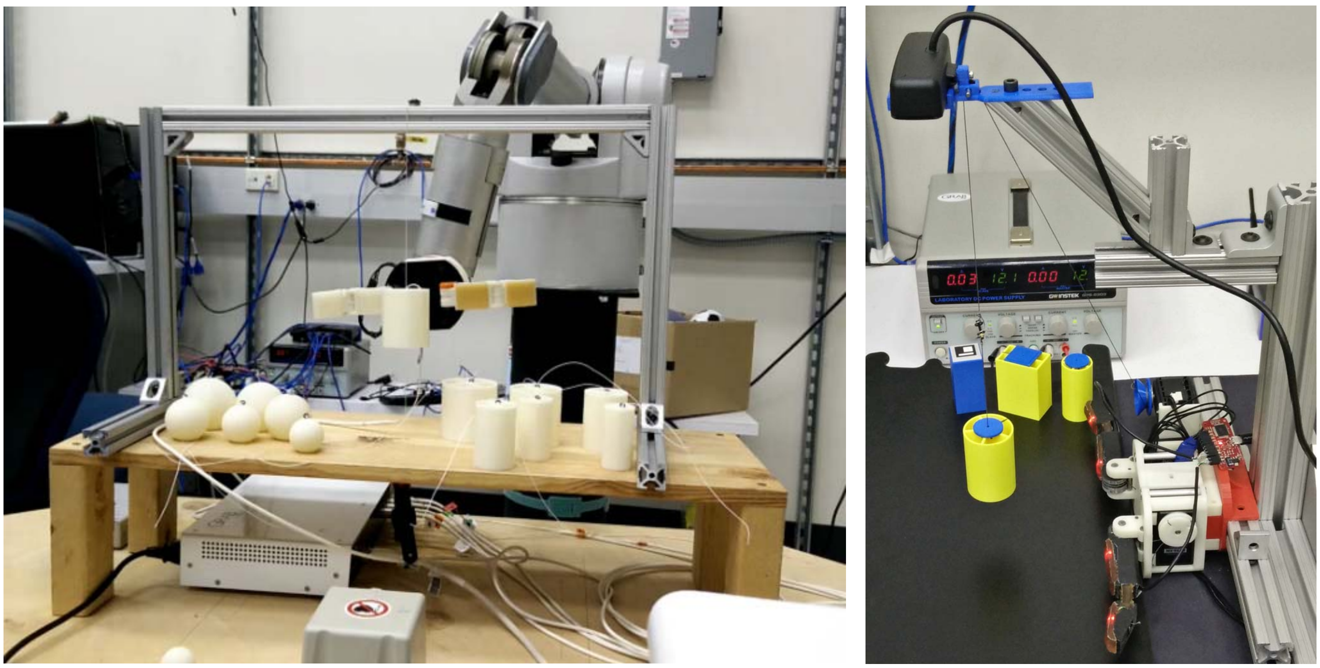

Fig. 7. Experimental setups that were developed to automate the data collection procedure for 2-D and 3-D tasks. The experimental setup for the 3-D tasks (left) and the 2-D tasks (right).

hands examined are the Yale Open Hand model T42, the Yale Open Hand model O, and the Yale FG gripper. All the hands have been developed by the GRAB Lab at Yale University.

The Yale Open Hand models are disseminated in an open-source fashion through the website of the initiative [36]. All the hands examined are depicted in Fig. 6. The model T42 is a two-fingered, compliant, underactuated, robot gripper that has two phalanges and a dedicated actuator per finger. The T42 robot hand can be developed with either spring-loaded pin joints (denoted with P) or flexure joints based on urethane rubber (denoted with F). For example, a T42FF refers to a version with two flexure joints per finger. The spherical hand/model O is a three-fingered robot hand that has two phalanges and a dedicated motor per finger, as well as a dedicated motor for the coupled abduction/adduction of two of the three fingers. Finally, the model FG is a four-fingered robot hand that has two pairs of underactuated fingers with two phalanges per finger. The two pairs of fingers are kept decoupled by an independent, central, rotating axis that facilitates finger gaiting. The hand can also perform equilibrium manipulation tasks [37]. The elastomer material used for the development of the flexure joints in all hands is urethane rubber (Smooth-On—PMC 780).

B. Automated Data Collection

For planar, 2-D manipulation tasks the experimental setup consists of a frame based on T-slotted profiles of the industrial erector set, a dedicated actuator that repositions the object to its initial pose, and a vision-based system that tracks the object using fiducial markers and a simple web camera. The examined hands are attached to the frame using a wrist coupling mechanism of the Yale Open Hand project [36], while the camera is mounted on the frame using a 3-D printed holder. The camera holder has also a pulley incorporated that facilitates the repositioning of the objects at the center of the camera field of view (initial pose), using a dedicated motor.

For the execution of 3-D in-hand manipulation tasks, the examined robot hand is attached at the end-effector of the 7-DoF Barrett WAM robot arm (see Fig. 7). The arm prepositions the examined hands to reach a precomputed, optimal configuration that has a certain wrist offset from the examined object. From this configuration, the adaptive robot hands (that tend to move on specific submanifolds of 3-D space during unconstrained flexion) are able to achieve the desired contact points that maximize the stability of the initial grasp. The frame developed is once again used for repositioning the objects to their initial pose, after each manipulation trial. Upon grasping, the hand starts exploring the feasible manipulation paths for a specific object, based on the initial estimates (first guess) provided by the simulation module. All the steps described are repeated continuously until all feasible manipulation paths for a given hand, object and initial grasp combination, have been sufficiently explored.

C. Object Motion Tracking

In planar manipulation tasks, the object tracking is accomplished using a simple web camera (Creative Senz3D). The vision-based motion tracking scheme was implemented using fiducial markers of the Aruco library [38] and the OpenCV library [39]. To capture the object motion in 3-D tasks, we used the trakSTAR (Ascension Technologies) magnetic motion capture system. The trakSTAR is equipped with a medium range transmitter (MRT), eight model-180 2-mm-diameter magnetic sensors, is characterized by high accuracy in both position (1.4 mm) and orientation (0.5°), provides a sampling rate of 80 Hz, and derives the sensors poses in terms of homogeneous transformation matrices. Unstable grasps or the loss of a grasp can be detected by sudden accelerations of the object motion tracking measurements and the task execution can be terminated. All the scripts and the code required for object detection were developed in Python and were incorporated in our grasp planning framework implemented in Robotics Operating System. The objects used in the experiments conducted in this paper are 3-D printed cylinders of diameters of 30, 50, 70, and 90 mm, a plastic pear that has an irregular geometry, and a 40-mm sphere.

V. RESULTS

In this section, we present the manipulation models and primitives derived, the performance of the manipulation models, as well as results from the experiments conducted.

A. Task-Specific Manipulation Models

In this section, we evaluate the efficiency of the task-specific manipulation models, in predicting accurate motor positions for executing desired, 3-D in-hand manipulation tasks. The manipulation task considered involved random, multidirectional equilibrium point manipulations of a 3-D printed sphere. Results for model O are presented in Fig. 8. Fig. 8(a) depicts the results of a model trained using the original, high-d space manipulation data, while Fig. 8(b) depicts the results for a manipulation model that was trained in the low-d space of the manipulation data (derived using the PCA technique). For the low-d case, the model estimations were backprojected in the high-d space to control the actual robot hand. As it can be noticed, the low-d case results are slightly worse than the results of the original data. It must be noted that the similarity scores are the average values over the multiple rounds of the 10-fold cross-validation procedure. The training data contained 10 manipulation trials with the same object. The manipulation model achieved an accuracy of 96.01% for the original data, 93.86% for the low-d representations, and 82.64% for uncontrolled slipping not previously seen during training. All results are reported in Table I. The estimation accuracies are computed using the PRMSE, as described in [8].

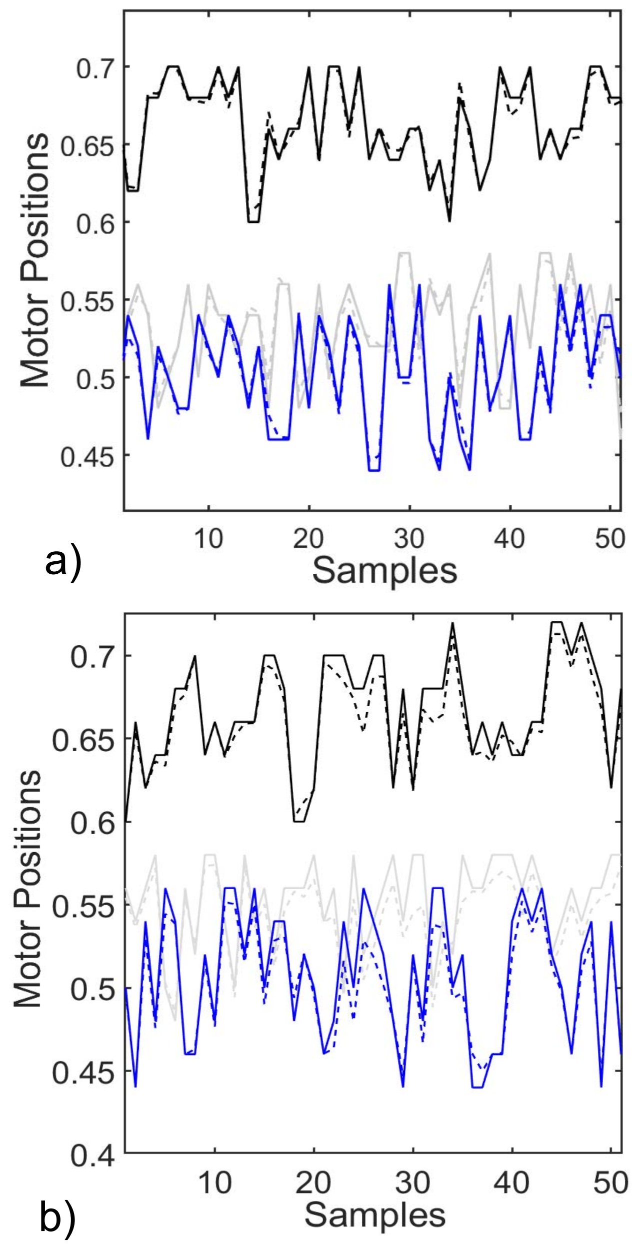

Fig. 8. Estimation results for the model O performing a 3-D in-hand manipulation task with a sphere that has a diameter of 40 mm. Different colors denote the different finger motors (the abduction/adduction DoF was kept locked). Continuous lines: actual motor positions. Dashed lines: estimated motor positions. Data for a single trial are presented. (a) Manipulation model was trained using the original, high-d space manipulation data. (b) Manipulation model was trained in the low-d space of the data (derived using the PCA technique). The estimations were backprojected in the high-d space to control the actual robot hand.

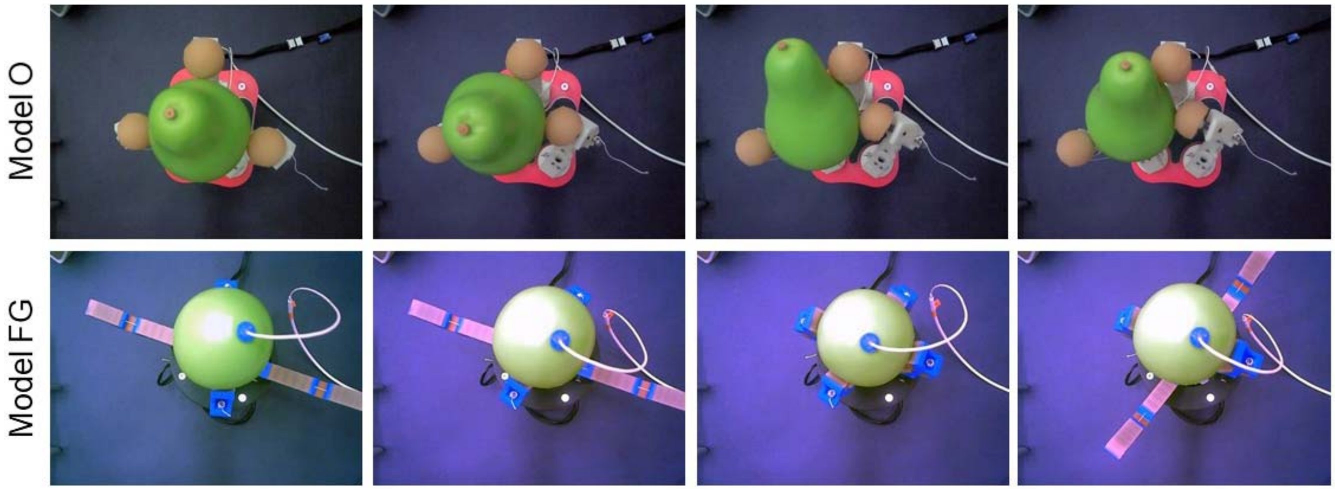

Fig. 9. Examples of 3-D in-hand manipulation tasks executed with the model O and the model FG robot hands. The first row of images contains instances of the execution of equilibrium point manipulation tasks with a plastic pear. The second row presents a finger gaiting manipulation task executed with the same plastic pear.

TABLE I
SCORES BETWEEN THE ACTUAL AND THE ESTIMATED MOTOR POSITION TRAJECTORIES FOR MODEL O FOR THREE CASES: 1) ORIGINAL DATA; 2) LOW-D DATA; AND 3) SLIPPING

Model O	Model O (Low-D)	Model O (Slipping)
96.01% SD: 1.35%	93.86% SD: 2.05%	82.64% SD: 5.34%

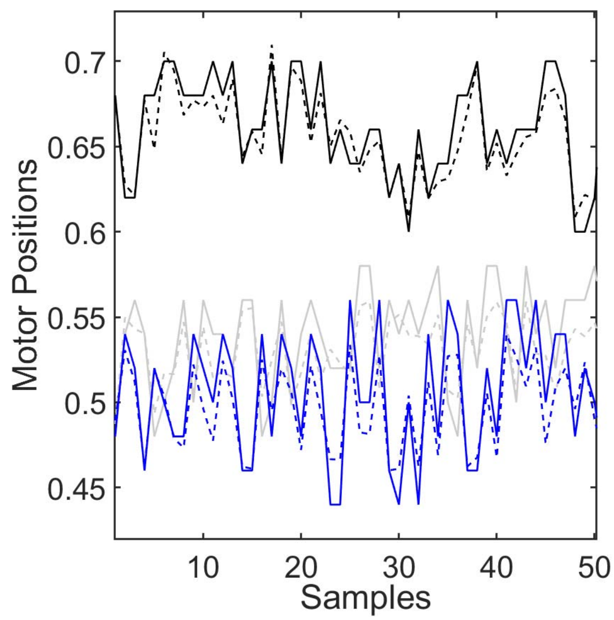

Fig. 10. Estimation results for the model O performing a 3-D in-hand manipulation task with a sphere that has a diameter of 40 mm. The effect of "unseen" slipping in the motor positions estimation accuracy is evident. As it can be noticed, there is a significant drop in the motor positions estimation accuracy. Continuous lines: actual motor position trajectories. Dashed lines: corresponding motor positions estimations.

Images from the 3-D manipulation tasks conducted with the model O and model FG robot hands are presented in Fig. 9. As it can be noticed, the estimation accuracy is quite high and it can only be affected by an uncontrolled slipping as presented in Fig. 10. The uncontrolled slipping can lead to a drop in the estimation accuracy of 10%–15%.

For a similar methodology to be used with fully actuated, rigid robot hands, appropriate control and planning schemes of significant complexity should be developed. These schemes are needed to compute stable initial grasps, to avoid intrafinger, object or environmental collisions, to compute a set of minimal contact forces that will lead the robot fingertips to grasp the object gently (without crushing it) but also firmly, and to plan the execution of the desired manipulation tasks. All these prerequisites are taken care by design in the case of adaptive robot hands, simplifying considerably the execution of dexterous manipulation tasks. It should also be noted that in the case of fully actuated, multifingered hands, the control space is high dimensional and the extraction of a representative set of primitives becomes much more challenging.

B. Manipulation Primitives

In this paper, we use the term synergy set to describe the primitive matrices derived by the dimensionality reduction methods. The manipulation primitives derived for T42PP Takktile with the PCA method are depicted in Fig. 11. The first primitive focuses on equilibrium point manipulation, while the second primitive pulls the object inside the grasp. The model O or spherical hand and the FG gripper have four primitives per synergy set, as they have four actuators. The first synergy set implements finger gaiting in the FG case and equilibrium point manipulation in the model O case. The second synergy sets use only two of the opposing fingers for both models and replicate once again equilibrium point manipulation tasks (see Fig. 9).

TABLE II

OBJECT RANGES OF MOTION (PERTURBATIONS) FOR EACH OBJECT SIZE PER PRIMITIVE OF THE T42 PP TAKKTILE. OBJECT TRANSLATIONS ARE REPORTED IN MILLIMETERS AND ROTATIONS IN DEGREES

Cylinder 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

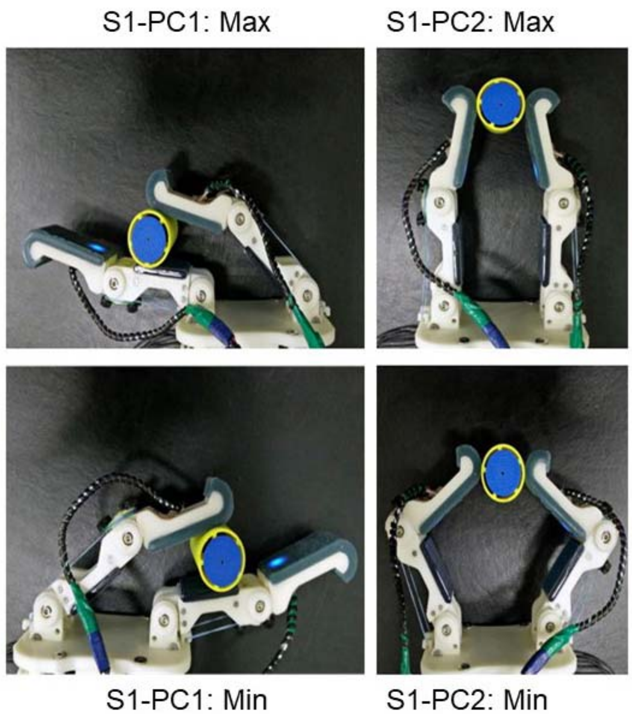

Fig. 11. Derived manipulation primitives for the T42PP Takktile gripper. The first primitive focuses on equilibrium point manipulation of the smallest cylinder. The second primitive pulls the objects toward the wrist. The letter S is used to denote a "synergy set" derived from different groups of similar manipulation strategies.

C. Applicability of Primitives to Different Objects

Regarding generalization of manipulation primitives among different object sizes, in [20], we report results on the effect of the object size on the values of the primitive coefficients. Even for large differences in the object sizes, the primitives do not change significantly. However, different object sizes lead to completely different object ranges of motion (object perturbations during in-hand manipulation). In Table II and Fig. 12, we report results on the relationship between the object sizes and the object ranges of motion, for the T42PP Takktile robot gripper. It appears that the hand manipulation capabilities depend highly on the object parameters. For example, for the S1-PC1 of the T42PP Takktile, the theta value for a cylinder with a diameter of 30 mm has a range from $-46°$ to $46°$, while for a cylinder with a diameter of 90 mm, the rotation component diminishes (the value is 0). Regarding generalization of the manipulation primitives, to a certain extent, it is safe to use for larger objects manipulation primitives extracted for smaller objects, as the motion that they will generate will squeeze the objects harder but without crushing them (due to the structural compliance and the underactuation of adaptive robot hands). On the other hand, primitives extracted for large objects cannot be used for smaller objects since the imposed behavior will not lead to stable grasps (the resulting hand/gripper aperture will be bigger than required).

D. Limitations

Although the proposed framework has provided some interesting results, it also suffers from some major drawbacks and shortcomings that need to be addressed in order to make it practically applicable in everyday life dynamic and unstructured environments. These limitations are as follows.

1) The models cannot account for uncontrolled, unpredictable slipping and rolling. If the training set does not contain similar behaviors, the models will not be able to perform satisfactorily. This is evident in Fig. 10, where we discuss the effect of slipping.
2) The framework relies on a human expert in the "loop" that will appropriately select the k value for the clustering algorithm and will check if the results of the dimensionality reduction of the derived representative groups of similar manipulation strategies are indeed representative of a primitive behavior that demonstrates the capabilities of the examined robot gripper/hand.
3) The simulation module does not take into consideration complex phenomena like the friction in the tendon routing of the real robot hand and approximates other complex phenomena like the bending of the flexure joints. Thus, additional modeling efforts are needed in order to optimize the behavior of the proposed framework.

It must also be noted that the objects used in this paper are simple 3-D printed and everyday objects. Some more complicated types of objects could lead to low success rates. Examples of such objects are: 1) objects of highly irregular shape; 2) very heavy objects; 3) object made out of materials that do not offer good friction coefficients between the robot fingertips and the object surface; and 4) articulated objects.

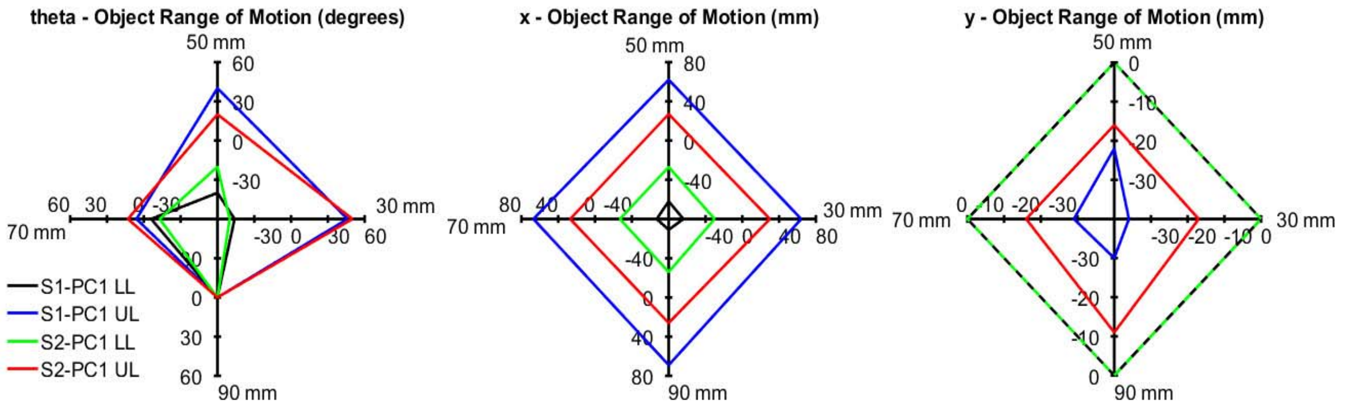

Fig. 12. Graphical representation of the ranges of object motions during manipulation with the T42 PP Takktile robot hand and cylinders of various diameters (30–90 mm). Each axis corresponds to a cylinder of different sizes. Only the first PC of each synergy set is depicted. LL stands for lower limit and UL stands for upper limit.

E. DexRep

In this section, we present DexRep, a scientific repository that aims at simplifying dexterous, in-hand manipulation, allowing an intuitive operation of adaptive robot hands, like the Yale Open Hand project devices. We created DexRep to facilitate the replication of our research by other research groups and continue improving the derived dexterous manipulation primitives and models, disseminating them online. The DexRep data repository can be found at the following URL: http://www.newdexterity.org/dexrep.

VI. Conclusion

In this paper, we focused on the formulation of a hybrid methodology that simplifies the execution of dexterous, in-hand manipulation tasks using adaptive robot hands. The proposed framework combines analytical models, a constrained optimization scheme, and machine learning techniques in a synergistic fashion. More precisely, the constrained optimization scheme is used to describe the kinematics of adaptive hands during the grasping and manipulation processes synthesizing a simulation module that can explore all the feasible manipulation paths easily and without requiring time-consuming experiments. The machine learning module consists of a clustering process that is used to group together similar manipulation strategies, a dimensionality reduction technique that is used to either extract a set of representative manipulation primitives or to provide low-d data for the training of a representative set of task-specific manipulation models, and a regression process that is used to train all possible task-specific, manipulation models that act in an equivalent manner to the hand object system Jacobian mapping the desired object trajectory (input) to the required motor trajectories (output). The methodology takes advantage of data collected using an automated experimental setup in an unsupervised manner. In this paper, we also assess the generalization capabilities of the derived manipulation models and primitives for both model and everyday objects. The efficiency of the proposed methods is validated through an extensive set of experimental paradigms involving various adaptive robot hands. The particular work has led to the development of the DexRep scientific repository that aims to provide a representative set of dexterous manipulation models that will allow an intuitive operation of adaptive robot hands in dexterous, in-hand manipulation tasks.

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