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Learning the Post-Contact Reconfiguration of the Hand Object System for Adaptive Grasping Mechanisms

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***Abstract*— A new class of simple, adaptive, under-actuated and compliant robot hands has recently attracted the interest of the robotics community. The under-actuated mechanisms and the structural compliance used in these hands facilitate and robustify not only grasping but also the execution of dexterous, in-hand manipulation tasks. Another significant characteristic of the particular hands is that they are able to efficiently grasp a wide range of everyday life objects even under significant object pose uncertainties. However, these hands, are difficult to model due to kinematic constraints introduced by the under-actuation and the use of complex flexure joints. Moreover, adaptive hands tend to reconfigure upon contact with the object surface, imposing certain parasitic object motions. In this paper, we propose a learning scheme that uses the contact force measurements collected from tactile sensors to estimate the post-contact reconfiguration of the hand-object system and the imposed parasitic object motion. The learning scheme's estimates are compared with "ground truth" data that describe the actual motion of the object and that are collected using a vision based motion capture system. The proposed learning scheme can be used with any type of adaptive robot hand and its efficiency is experimentally validated using extensive paradigms involving different hand designs and various everyday life objects.**

I. Introduction

Over the last decade a new class of adaptive robot hands has been introduced [1]–[3]. The particular hands, are of low-complexity, compliant, under-actuated and have been designed for executing robust grasping and dexterous, in-hand manipulation tasks with everyday life objects. A significant characteristic of adaptive hands, is their ability to extract stable power and precision grasps even under significant object pose or other environmental uncertainties, taking advantage of the passive adaptability that is inherited to their design by the under-actuation (the use of less motors than degrees of freedom) and the structural compliance.

For all these reasons, adaptive hands are an excellent alternative to the fully actuated, multi-fingered, rigid and expensive robot hands that are typically considered for grasping and manipulation tasks and that require sophisticated sensing elements and complicated control laws, in order to operate in dynamic environments.

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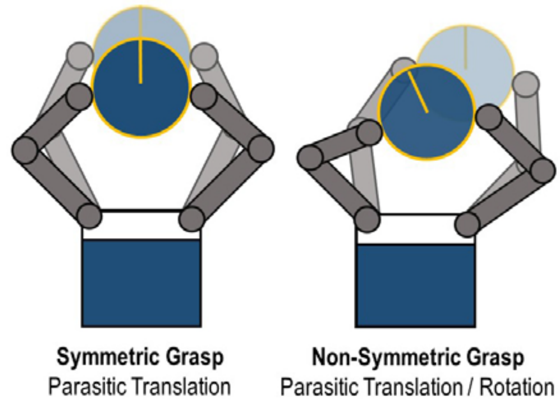

Fig. 1. Post-contact, parasitic object motion for symmetric and non-symmetric grasps with adaptive hands. The symmetric grasps produce a pure parasitic translation, while the non-symmetric grasps produce a coupled, parasitic translation and rotation of the object.

However, despite the promising performance of adaptive hands and their numerous applications, they have also certain disadvantages and limitations. For example, for many precision fingertip grasps their fingers tend to reconfigure towards an elastic equilibrium configuration determined by the contact forces exerted and the joint stiffness (see Fig. 1). The passive adaptability may facilitate grasping and may robustify dexterous, in-hand manipulation, but it complicates also the analysis and the modelling of these hands. In particular, their transmission is typically based on artificial tendons (cables) driven through low-friction tubes. These cables couple together different joints that are actuated by a single motor, introducing kinematic constraints. Moreover, the rerouting of the tendons causes phenomena like the capstan effect that introduce friction to the hand structure [4]. The joints of adaptive hands can be implemented either as spring loaded pin joints or as flexure joints based on urethane rubbers that complicate further the kinematics analysis, making the derivation of analytical models non-trivial.

All these phenomena become quite apparent during grasping and more precisely upon contact with the object surface. At this point, the hand is starting to squeeze the object and the forces exerted through the robot fingertips trigger a hand-object system reconfiguration that imposes a parasitic object motion that may be undesired. For example, when the hand is in the process of grasping a glass full of water such perturbations may cause the water to be spilt, or if the hand is used in order to grasp some part of the environment (e.g., a button / knob of a console, a handle of a door etc.) such hand object system reconfigurations may pull the grasped part towards the wrist and damage it.

In this paper, we propose a learning methodology for estimating based on the contact forces exerted on the object, the imposed parasitic object motions. To do so, we use advanced Machine Learning techniques (Random Forests regression) to predict from the contact forces exerted the post-contact, parasitic object motions and the hand object system reconfiguration. The learning estimates are compared with "ground truth" data provided by a vision based motion capture system. The efficiency of the proposed methods is experimentally validated through a series of reconfiguration paradigms, involving different adaptive robot hand designs as well as various everyday life objects.

The rest of the paper is organized as follows. Section II discusses the related work on grasping and manipulation with adaptive hands, Section III, focuses on the methods used in order to control the robot hands in grasping tasks and formulate the proposed methodology, Section IV presents the apparatus used and Section V presents an extensive set of experimental paradigms. Finally, Section VI compares the proposed methodology with similar previous work that uses a constrained optimization scheme and Section VII concludes the paper and discusses some possible future directions.

II. Related Work

Adaptive hands have received an increased attention from the robotics community over the last decade, with most studies focusing on new hand designs [5]–[7], robust grasping [8], [9] and dexterous, in-hand manipulation [10], [11]. Nowadays, most researchers control adaptive hands in an open-loop fashion [12], [13]. However, in order to formulate efficient grasping or manipulation planning schemes with these hands, their behavior and their kinematics should first be accurately modelled.

Regarding the modelling of adaptive hands, Odhner et al. introduced the smooth curvature model [14], [15], an efficient representation of complex planar flexure joints that approximates them as elastic beams that bend smoothly. More precisely, a set of low-order polynomials were used to characterize the joint curvatures even for large deformations. The proposed models extract a set of homogeneous transformation matrices that describe the configurations of the rigid hand phalanges / links, as well as their derivatives (e.g., Jacobians and Hessian matrices).

Regarding grasp quality and stability, a series of studies have focused on under-actuated hands. In [9], a constrained optimization scheme was proposed that uses the soft synergy model proposed by Bicchi et al [16] and the grasp compatibility index proposed by Chiu et al [17], in order to derive task-specific force closure grasps for synergistically controlled, under-actuated robot hands. Ciocarlie et al [18], [19], formulated a constrained optimization framework for compliant, under-actuated robot hands that uses a quasistatic equilibrium formulation in order to derive design parameters that optimize stability across a set of grasps. All these studies focused either on a higher, grasp planning level or on providing a scheme for design optimization, without taking into consideration the imposed post-contact, parasitic object motions and the hand object system reconfiguration.

Furthermore, Su et al [20], proposed a robust grasp planning scheme for under-actuated hands that works even under object pose uncertainties, employing a contact-force based grasp adaptation that allows the extraction of stable grasps with a single trial (no re-grasping is required). Chen et al [21], proposed an adaptive methodology for reaching and grasping with multi-fingered hands, improving their performance under object pose uncertainties. To do so, they employed a spatial virtual spring framework and they formulated an adaptive grasping control scheme that achieves local in-hand adjustments (of the fingers that are not yet in contact with the object surface) without resorting to the arm motion. Prattichizzo et al [22], studied the structural conditions required in order to design an internal force controller decoupled from the object motions and they proposed a controller that achieves stable grasping with compliant, multi-fingered robot hands, while Malvezzi et al [23] proposed an internal forces controller that guarantees that the object will not be perturbed. All these studies focused either on deriving stable grasps or on eliminating object motions for compliant robot hands, without dealing with under-actuated pinch grasps that impose certain post-contact parasitic object motions and without considering the hand object system reconfiguration.

Recently, we proposed a methodology based on analytical models and constrained optimization methods, for deriving stable, symmetrical, minimal effort grasps with adaptive hands and compensating for post-contact, parasitic object motions using the Barrett WAM robot arm [24], [25]. The methodology used a grasping force optimization scheme and a force decomposition model to compute an appropriate set of contact forces and estimate the post-contact, parasitic object motion that these forces will trigger. More precisely, in [24] we focused only on the simple case of symmetric grasps of model objects, while in [25] we focused on both symmetric and non-symmetric grasps, considering also a set of everyday life objects. The contact forces were derived from the displacements of the robot fingers and no tactile sensing was available to measure the actual contact forces. The efficiency of the proposed methods was validated using various simulated and experimental paradigms involving different robot arm hand systems.

In this paper, we substitute: a) the force decomposition model with tactile sensors that measure the actual contact forces exerted (relaxing the uncertainties) and b) the constrained optimization scheme with a machine learning methodology. More precisely, a Random Forests regressor is used to estimate from the exerted contact forces the post-contact, parasitic object motion in both symmetric and non-symmetric grasps.

III. Methods

In this section, we present the methods that are used to: a) control and plan the motion of adaptive hands in grasping tasks and b) estimate the post-contact, parasitic object motion (that is caused by the reconfiguration of the hand object system) from the exerted contact forces.

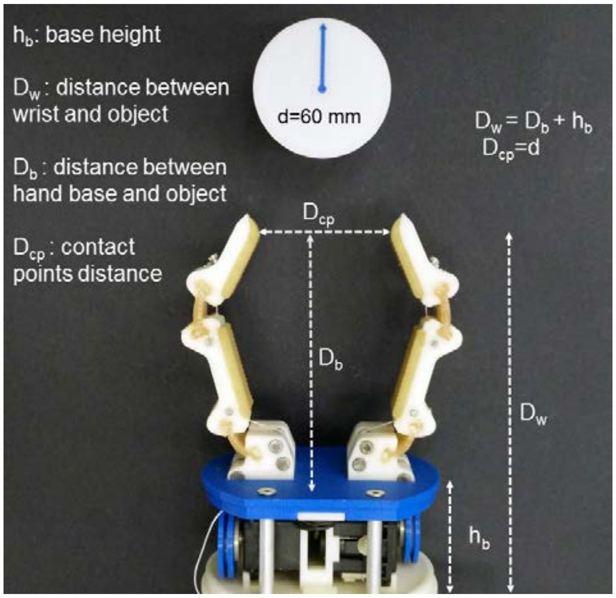

Fig. 2. An illustration of the wrist offset calculation procedure for the T42FF while grasping a sphere with a diameter of 60 mm. The distances are depicted with white dashed lines.

A. Planning Stable Grasps

In order to preposition the objects so as to secure stable initial grasps, we compute an appropriate wrist offset from the object. To do so, we optimize a specific grasp quality metric [26]. The metric chosen in this work, is the distance between the contact centroid ($\mathbf{o}_{cc}$) and the object geometric centroid ($\mathbf{o}_{gc}$) similarly to [27] and [28] that is given by:

$$Q_{DC} = \|\mathbf{o}_{cc} - \mathbf{o}_{gc}\| \quad (1)$$

In order to minimize this distance and derive an optimal initial grasp, we flex the fingers by applying an increasing motor load until the distance between the two fingertip positions is equal to the object dimensions (e.g., the diameter of a sphere). All the parameters of the object are considered known. The forward kinematics of the fingers are solved using the models provided in [15]. Having computed the finger poses at which the distance between the fingertips equals the object dimension, we can now easily compute the wrist offset. Details are provided in Fig. 2.

B. Modelling Adaptive Hands

Adaptive hands may either be developed with spring loaded pin joints or with flexure joints. In the case of spring loaded pin joints, the potential energy of the hand is expressed as:

$$V(\mathbf{q}) = \tfrac{1}{2}\mathbf{q}^{\mathrm{T}}\mathbf{K}\mathbf{q} \quad (2)$$

where $\mathbf{q}$ is the vector of the joint angles and $\mathbf{K}$ is the stiffness matrix that represents the pin joint compliances. In the case of flexure joints, the smooth curvature model [14], [15] can be used to provide estimations of the hand kinematics. The particular model is based on the assumption that flexure joints behave as elastic beams that bend smoothly and can therefore be approximated by low-order polynomials (Legendre polynomials). The configuration of the flexure joints is described with three generalized coordinates instead of one that is used for pin joints. The potential energy of the hand $V(\boldsymbol{q})$, is computed as reported in [15] and [27]. The smooth curvature model, derives the finger poses relatively to the tendon displacements or the tendon loads. Thus, the problem of finding the hand configuration, is a constrained energy minimization. The equilibrium configuration of the hand-object system can be found by minimizing the function:

$$E(\boldsymbol{\tau}) = -\nabla_q V(\mathbf{q}) + \mathbf{J}_{\mathbf{p}}^{\mathbf{T}}\mathbf{f} \quad (3)$$

where $\boldsymbol{\tau}$ denotes the forces acting on the system, $\mathbf{f}$ is the vector of the contact forces applied at a specific point $\mathbf{p}$, $\mathbf{J}_{\mathrm{p}}^{\mathrm{T}}$ is the Jacobian of the particular point and $\nabla_q V$ is the gradient of the total internal energy of the system. Given the contact forces exerted on the object, the scheme can estimate the parasitic object motion and the reconfiguration of the hand object system using equation (3). More specifically, the problem, can be formulated as:

$$\boldsymbol{\tau}^* = arg \min_{\boldsymbol{\tau}} E(\boldsymbol{\tau}) \quad (4)$$

s.t.

$$\mathbf{J}_{\mathbf{h}}^{\mathbf{T}}\mathbf{f} = \boldsymbol{\tau} \quad (5)$$

$$\mathbf{G}\mathbf{f} = -\mathbf{f}_{\mathrm{ext}} \quad (6)$$

$$\sqrt{f_{s_i}^2 + f_{t_i}^2} \le \mu f_{n_i}, i = 1, \dots, n_c \quad (7)$$

$$\mathbf{q}^- \le \mathbf{q} \le \mathbf{q}^+ \quad (8)$$

$$\mathbf{c}_i \in \partial\mathbf{O}, i = 1,2 \quad (9)$$

$$S_h \notin \mathbf{O} \quad (10)$$

where $\mathbf{J}_{\mathbf{h}}^{\mathbf{T}}$ is the hand Jacobian, $\mathbf{G}$ is the grasp matrix, $\mathbf{q}^-$and $\mathbf{q}^+$are the lower and upper joint limits, $\mathbf{O}$ is the space occupied by the object, $\mathbf{c}_i$ is the vector containing the i-th fingertip coordinates (that must lie on the object surface $\partial\mathbf{O}$) and $S_{h,}$ is a set of discrete points lying on the robot hand phalanges that should never penetrate the object. The constrained optimization scheme can predict the hand configurations and the fingertip velocities. The velocity of the object can be extracted from the fingertip velocities using the grasp matrix $\mathbf{G}$.

It must be noted, that most of these parameters and constraints are hard to derive and compute and they cannot encapsulate the complete mechanics of the problem, since they do not account for several hard to model phenomena (e.g., kinetic friction forces). Thus, in this paper we choose to use these models only in the grasp planning phase and to formulate a learning scheme for estimating the post-contact reconfiguration of the hand object system.

C. A Learning Scheme based on Random Forests

In this section, we formulate a machine learning scheme that is able to predict the post-contact parasitic object motion of the object, based on the contact forces exerted during grasping. The problem is formulated as a regression problem and we choose as a predictor, the Random Forests regression method that is an ensemble method based on multiple decision trees.

The Random Forests were originally proposed by Tin Kam Ho of Bell Labs [29] and Leo Breiman [30] and can be used either for classification or for regression. Random Forests run efficiently and fast on large databases, they can be parallelized, they provide excellent estimation accuracy,

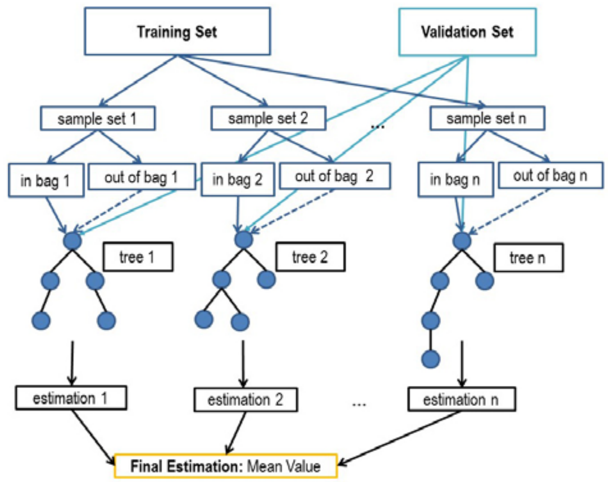

Fig. 4. Structure of the Random Forests regressor. The final estimation of the forest is the mean value of the individual tree estimations.

they do not overfit by design (they have a built-in cross validation procedure), they are resistant to outliers, they provide a comprehensive metric of the feature variables importance and they are an ideal technique for multidimensional spaces. In the regression case, the random forest predictor is formed similarly to the classification case by taking instead of the most popular class, the mean estimation value over the individual estimations of the *n* decision trees of the forest. An exemplar structure of a Random Forests regressor, is depicted in Fig. 4. The out of bag data are one-third of the total samples that is left out of the training set and is used to get a running unbiased estimate of the classification or regression error as new trees are added to the forest.

IV. Apparatus

In this section, we present the experimental setup that we used in order to experimentally validate the effectiveness of the proposed methods. The experiments included symmetric and non-symmetric grasps of different everyday life objects. The post-contact parasitic object motion was captured using a standard web camera. The kinematic models of the examined adaptive hands were prepared using the freeform manipulator toolbox [15], the SynGrasp toolbox [31] and the Robotics Toolbox [32], in MATLAB (MathWorks).

A. Robot Hands Examined

In this paper, we examine the post-contact reconfiguration and the imposed parasitic object motion, for two different adaptive robot grippers / hands. Model T42 is an open-source, two-fingered, compliant and underactuated robot gripper. Each finger of the T42 has a dedicated actuator (Dynamixel MX 64) and two phalanges. The possible versions of the T42 hand are the FF, PP and PF, where the P stands for spring loaded pin joints and the F stands for flexure joints implemented with elastomer materials (Smooth-On, PMC 780 urethane rubber). In this work, we used a T42PF and a T42PP that are both equipped with tactile sensors. The hands are depicted in Fig. 5.

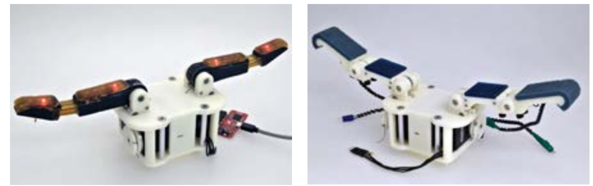

Fig. 5. The models T42PF and T42PP that are used in the experiments. The T42PF consists of a custom base and two fingers of the RightHand Robotics ReFlex hand [38] that are equipped with 8 tactile sensors. The T42PP consists of a custom base and two fingers with two spring loaded pin joints. Each distal phalanx is equipped with 5 tactile sensors.

Fig. 6. The setup used for data collection. The frame is created with a set of T-slotted profiles of the Industrial Erector Set (80/20). A blue 3D printed base is used in order to hold both the web camera and a pulley for repositioning the object (using the dedicated motor at the top right side of the image). The red base of the hand is a 3D printed wrist coupling of the Yale Open Hand project [33].

B. Experimental Setup

The data collection setup, was prepared using a set of T-slotted profiles of the Industrial Erector Set (80/20) to create a frame that supports both the camera (using a 3D printed base) and the wrist coupling that is used for attaching the hands (a dovetail coupling of the Yale Open Hand project [33]). The data collection setup is depicted in Fig. 6. In order to compensate for the post-contact parasitic object motions, we use the Barrett WAM 7 DoF redundant robotic manipulator. More details regarding the Barrett WAM can be found in [34].

The camera used in order to track the motion of the object is the Creative Senz3D that shoots RGB video with an HD 720p resolution (1280x720). For the object tracking algorithm, a fiducial markers based tracking using the Aruco library [35], was used. All scripts required, were developed in Python and they were included in our grasp planning framework. The experiments were performed with everyday life objects, in order to test our methodology in realistic scenarios. The objects used, have different shapes, sizes and weights and can be found in the YCB object set [36].

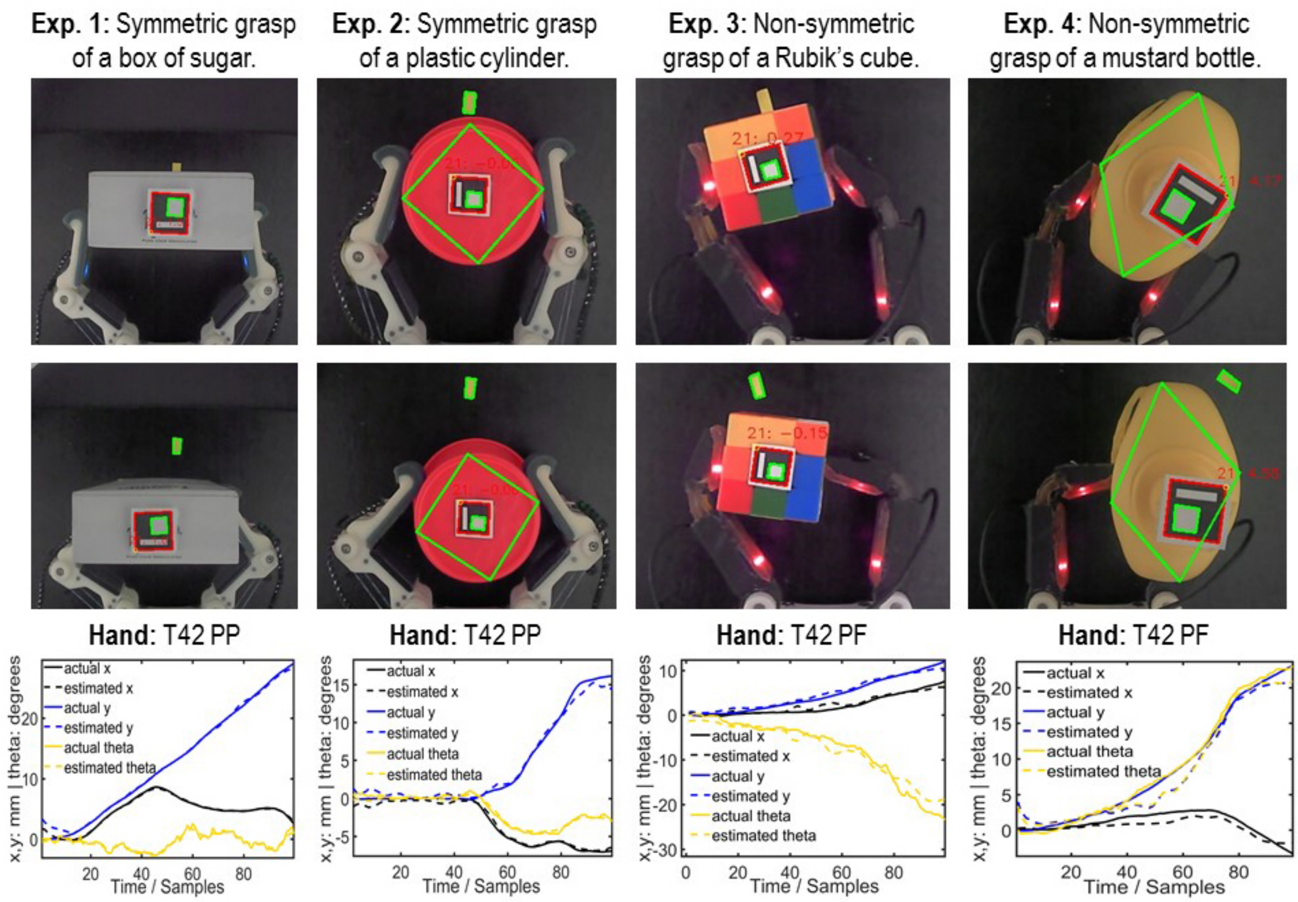

Fig. 7. Screenshots of the conducted experiments. Two symmetric and two non-symmetric grasps are depicted. The objects grasped are a box of sugar, a plastic cylinder, a toy cube (Rubik's cube) and a bottle of mustard. The trajectories of the objects are estimated and provided in the third row.

C. *Force Sensing*

In order to capture the forces exerted by the robot fingertips we used the TakkStrip tactile sensors (RightHand Robotics) that were originally created by the Takktile team [37]. More specifically, the Model T42PF has two RightHand Robotics fingers attached that are equipped with two Takkstrip modules with 8 sensors per finger (5 located on the proximal and 3 on the distal phalanx). More details regarding the RightHand Robotics fingers can be found in [38]. For the development of the Model T42PP we used two TakkStrip 2 modules that were incorporated in an appropriately designed version of the T42 distal phalanx. After installing the tactile sensors, we covered them with finger-pads implemented with elastomer materials (Smooth-On, Vytaflex 40 liquid urethane rubber). For data collection, we used the TakkFast high-speed USB interface (RightHand Robotics) that transfers data from I2C to USB at high speeds (100 Hz).

V. Experimental Results

In this section we present a set of experimental results that validate the efficiency of the proposed methods. The experiments included capturing and estimation of the post-contact, parasitic object motions for different adaptive robot hands and different grasp types (symmetric and non-symmetric grasps).

A. *Data Collection and Training*

To train the Random Forests models, we used a training dataset that included multiple trials for every hand, grasp and object combination. The raw values of the tactile sensors were used for training and no calibration or sensor selection was performed as the absence of force readings from particular sensors (that are not in contact with the object surface) does not deteriorate the performance of the methodology. The poses of the objects were captured with the vision system, as described in Section IV. The Random Forests models were trained in a task / grasp specific way similarly to [39], as the behavior of adaptive hands during grasping depends on the initial grasp and on the contact forces exerted by the fingers. The models were grown with ten decision trees in order to increase speed of execution and computational efficiency and since the difference in terms of estimation accuracy between the 10 and the 100 trees was not significant. All results reported are the average values over the different rounds of 5-fold cross-validation procedure.

B. *Estimating the Post-Contact Parasitic Object Motions*

To validate the efficacy of the proposed methods in estimating the post-contact parasitic object motions, we compared the estimated motions with actual object motions.

Table I. Estimation accuracy for different hands, grasp types and everyday life objects.

Hand	Experiment	Score
T42PP	Symmetric grasp of a box of sugar (Domino sugar).	95.64%
	Symmetric grasp of a plastic cylinder (a plastic cup).	97.67%
T42PF	Non-symmetric grasp of a plastic cube (a Rubik's cube).	94.36%
	Non-symmetric grasp of mustard bottle (Domino sugar).	89.82%

Results of the post-contact, parasitic object motion estimation are depicted in Fig. 7, while the scores of the estimations accuracy are reported in Table I. In order to represent the similarity between the actual and the estimated post-contact, parasitic object motions as a percentage, we used as a metric the percentage of the normalized mean square error (NMSE).

In Fig. 7, it is evident that symmetric grasps are easier to model and that we can estimate their parasitic object motions more accurately. The estimated motions are not entirely accurate as they do not include difficult to incorporate, dynamic parameters (e.g., tendon routing friction) and possible asymmetries and/or design inaccuracies in the robot hand structure. The theoretical results of the constrained optimization scheme dictate that the post-contact parasitic object motion for a symmetric grasp should be a pure translation of the object, while the parasitic object motion for non-symmetric grasps should have also rotational components. The first finding is not observed in the real experiments, mainly due to friction. However, although it is not zero, the parasitic rotation of the objects is not significant in the symmetric grasps depicted in the first two plots of the third row of Fig. 7.

VI. Discussion

In this section we discuss the advantages and the disadvantages of the constrained optimization schemes proposed in [24], [25] and the hereby proposed learning methodology. The constrained optimization scheme requires extensive knowledge of the hand and object parameters (e.g., joint and fingertip stiffness etc.) as their values affect the estimations and the scheme is especially prone to errors from modelling inaccuracies. Moreover, even the tactile sensor values need to be calibrated and scaled to the appropriate units, in order to be used. However, the constrained optimization scheme provides intuition about the problem mechanics and can be particularly useful for testing the significance and the effect of different hand and object parameters or to provide insight and inspiration for new design iterations. Finally, the constrained optimization scheme can be used for new robot hands or special objects that have not been seen during training and that can be described analytically. On the other hand, the machine learning scheme trains a Random Forests regression model that is actually a "black box" model and does not provide any insight about the problem mechanics. However, the particular model does not require any knowledge about the hand parameters and it can efficiently use the raw values of the tactile sensors without any calibration, scaling or sensor selection. It should also be noted that the Random Forests regressor relies on the availability of good training data to perform efficiently.

VII. Conclusions

In this paper, we presented a learning methodology that can estimate the post-contact reconfiguration of the hand object system for adaptive grasping mechanisms. The methodology is based on machine learning methods for regression, does not require any a-priori knowledge of the hand-object system parameters and can predict the imposed post-contact, parasitic object motion, using the contact forces exerted on the object. These contact forces are captured with appropriate tactile sensors that are installed on the robot finger-pads and they are used as input to a Random Forests regression model. To validate the efficiency of the proposed methods, we used a variety of experimental paradigms involving different robot hand designs and various everyday life objects in both symmetric and non-symmetric grasps.

Regarding future directions, we plan to focus on a synergistic collaboration of a machine learning and a constrained optimization scheme, to generalize them for complex objects and to assess the effect of multiple contact points, external disturbances and modeling inaccuracies on their performance.

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