2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)
Congress Center Hamburg
Sept 28 - Oct 2, 2015. Hamburg, Germany

Unplanned, Model-Free, Single Grasp Object Classification with Underactuated Hands and Force Sensors

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***Abstract*— In this paper we present a methodology for discriminating between different objects using only a single force closure grasp with an underactuated robot hand equipped with force sensors. The technique leverages the benefits of simple, adaptive robot grippers (which can grasp successfully without prior knowledge of the hand or the object model), with an advanced machine learning technique (Random Forests). Unlike prior work in literature, the proposed methodology does not require object exploration, release or re-grasping and works for arbitrary object positions and orientations within the reach of a grasp. A two-fingered compliant, underactuated robot hand is controlled in an open-loop fashion to grasp objects with various shapes, sizes and stiffness. The Random Forests classification technique is used in order to discriminate between different object classes. The feature space used consists only of the actuator positions and the force sensor measurements at two specific time instances of the grasping process. A feature variables importance calculation procedure facilitates the identification of the most crucial features, concluding to the minimum number of sensors required. The efficiency of the proposed method is validated with two experimental paradigms involving two sets of fabricated model objects with different shapes, sizes and stiffness and a set of everyday life objects.**

I. Introduction

Over the last decades many studies have focused on deriving object properties or discriminating between different everyday life objects, using vision or force / tactile sensor based methods. For robots operating in human-centric, dynamic environments, identifying object properties is an important but difficult task even for sophisticated vision algorithms. Moreover, in practical everyday tasks occlusion, poor lighting conditions, or camera workspaces limitations may render the use of vision based methodologies infeasible. For such cases a viable alternative is to perform object identification using tactile or force sensors. The tactile / force sensing based methodologies are able to derive different object properties like shape, texture, size, stiffness, weight [1]–[4] or to discriminate object's class [5]–[7]. Knowing object properties helps to optimize the manipulation action (e.g., by allowing minimization of forces required to achieve a stable grasp), whereas knowing the object class enables the execution of object-specific strategies or plans [8]. Specific object properties like shape and size may influence a grasp configuration, while others like friction, weight and stiffness may affect the amount of external forces that should be imposed on the object to guarantee stability of the grasp. Knowing object properties may facilitate: 1) the execution of object and task specific grasps, 2) the minimization of forces and effort required to guarantee stability of grasp, 3) a high level object-specific task planning.

Fig. 1. A robot hand equipped with force sensors grasping a plastic apple for classification purposes.

Roboticists have applied tactile sensing to robot hands for many decades, inspired by nature's most dexterous and versatile end-effector the human hand. The human hand has approximately 17,000 mechanoreceptive units that innervate it's skin and provide a highly sophisticated system for understanding the environment [8]. Touch and kinesthesis have been described as subtle senses that are critically important for human environmental interaction [9]. Humans rely on tactile information in daily life for identifying different objects and their properties (e.g., detecting the fullness of a cup, identifying objects in the dark etc.). Normally different exploratory procedures are used for different properties [10]. In medicine, touch based interaction, permits identification of tissue type and structure during palpation [9] while feedback during grasping, enables task optimization [11]. In the field of industrial robotics, object classification via open loop grasping could complement bin picking and blind grasping (e.g., within a warehouse or production line). Quality inspection may also be facilitated by such methods (deficiencies in the shape or weight of a manufactured object can be detected as it is picked up).

This work was supported by the NSF grant IIS-1317976.
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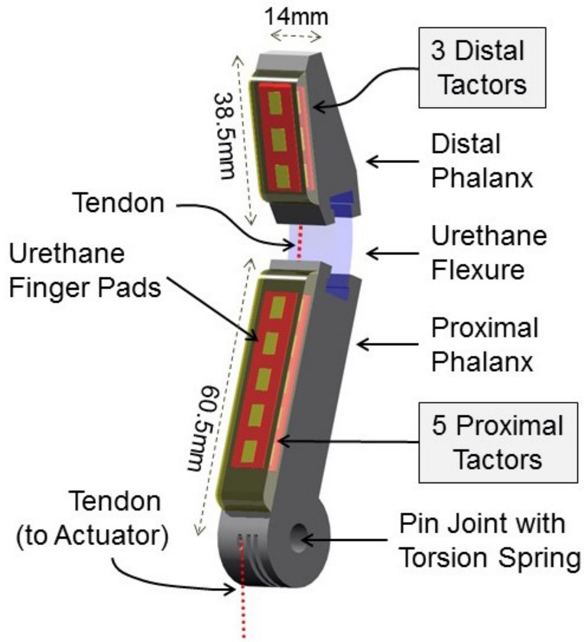

Fig. 2. The structure of an underactuated finger and the locations of the force sensors.

A robot may also discriminate between different objects using haptic properties when vision is not available, or when it needs additional information e.g., an unripe fruit feels different to a ripe fruit, though they may visually appear the same.

In this paper we present a complete methodology for discriminating between different objects while grasping them, using an underactuated compliant robot hand (Fig. 1) equipped with force sensors. The underactuated robot hand comprises of two fingers, each equipped with 8 force sensors (Fig. 2). The proposed approach can be used with any type of robot hand[1] and is essentially model free as it does not require any prior information about the object or the robot hand model. This is particularly beneficial for grippers with complex kinematic and dynamic models that are difficult to be derived and when complexity of the analytic methods gets high (e.g., upon contact with the object, for the underactuated, compliant fingers used in this study). Moreover, our approach does not require calibration of force sensors, since raw sensor values and their inter-object variation can be used for classification.

Regarding the experiments, the robot hand is controlled in an open-loop fashion to close to a predefined configuration (at the motor space) and grasp objects with various: shapes, sizes and stiffness located in arbitrary poses (positions and orientations). Upon contact with the object, the actuator positions lead to flexure joint deformations that enable the hand to comply to object geometries and adjust normal forces at the contact points. The open-loop, passive adaptation nature of the underactuated grippers gives us two significant advantages for tactile based object classification. First, it provides robustness to large position and orientation differences in object pose, removing the necessity of accurate grasp planning. Second, it eliminates the effect of the controller parameters on the classification process.

In this work we discriminate between different 'model' and everyday life objects using advanced machine learning techniques for classification (Random Forests) and a feature space that consists of the actuator positions and the force sensor measurements at two different time instances of the grasping process. It must be noted that although the proposed methodology can be used with any classifier desired, we employ the Random Forests technique in order to achieve high classification accuracy (see Section V for details) and determine what the most important features are, using its inherent feature variables importance calculation procedure. Features importance scores are necessary in order to optimize our experimental set and conclude to the minimum number of sensors required. The efficiency of the proposed methods is experimentally validated for discrimination between both 'model' objects with various shapes, sizes and stiffness and everyday life objects (groceries).

The rest of the paper is organized as follows: Section II summarizes the related work, Section III explains the methods used to discriminate between the different objects, Section IV presents the experimental setup and the experiments conducted, Section V reports and discusses the classification results, compares different classifiers and provides guidelines for the optimization of the experimental setup, while Section VI concludes the paper.

II. Related Work

The advances in sensor technology provided a boost in the field of tactile based object classification in recent years. The majority of the methods presented in literature, employ data driven approaches due to the complexity of analyzing tactile sensor data. In contrast to our work, all of these methods use expensive grippers and force sensors. Also, some of these methods necessitate sophisticated control methods and exploratory procedures. The data driven methods are used either for deriving object properties such as rigidity, material and texture of the object or for deciding the object class.

For identifying object properties, piezo-resistive pressure sensors are utilized in [12] to classify three rigidity levels by grasping the objects. In this work, mean, variance and maximum force values are used as features and a Decision Tree classifier is employed. In [13], a 6-axis force/torque sensor is attached to the finger of the robot and the material of the objects is

[1] It may require additional control laws depending on the hand type (e.g., for rigid hands to avoid breaking the objects).

classified by sliding the finger on object surface. A texture recognition method is presented in [14] which uses a multimodal sensor that provides force, vibration and temperature data. These data are collected by sliding the finger on the object surface with a predefined trajectory. A more 'subjective' classification is presented in [15] where the system is trained for 34 adjectives to describe the objects with characterizations like absorbent, compact, cool, metallic, unpleasant etc. In this work a biomimetic sensor is used, which gives pressure, temperature and deformation information of contact surfaces.

For identifying object class, [16] adapts the popular vision based object recognition technique 'bag-of-features', to the tactile based classification problem. In this method, a 'vocabulary' of tactile images is formed by grasping a set of objects from several local regions. Histograms are then generated for objects classes. While classifying an object, the method necessitates multiple grasping actions, creates a new histogram from the observations and compares it with the histograms obtained by the training. In [17], object classification is achieved by using the time series of tactile-array images during squeezing and 'de-squeezing' (releasing) of the object with a k Nearest Neighbors classifier. It is important to note that, due to the data necessary to be collected in the de-squeezing phase, the grip on the object is lost. In our case, we use a single stable grasp and we do not necessitate a de-squeezing motion, so we can maintain our grasp during and after the classification. However, in these experiments, there are only very slight orientation and position variations, whereas our system is able to handle arbitrary positions and orientations of objects. The method in [18] identifies mobility and rigidity information of the object together with its class. This is achieved by sliding a tactile array on the object surface and utilizing a k Nearest Neighbors classifier.

Unsupervised learning techniques are utilized to cluster raw sensors data for a tactile based object classification problem [7], [19]. In [19], time series of sensor measurements are used and feature hierarchies are constructed using spatio-temporal hierarchical matching pursuit (STHMP) on raw data. In this work a 1-vs-all classifier is obtained. The technique is implemented with 3 different hands (Schunk Dextrous Hand, Schunk Parallel Hand and iCub hand) using 10 household objects. The authors in [7] utilize joint position information together with the tactile data and report increased success rates. In that work, authors present an incremental learning technique which allows online improvement of the classifier. In [20], a multimodal tactile sensor which provides force, vibration and temperature information is attached to a Shadow Dexterous Hand. The system goes through a series of exploratory movements to extract the rigidity, texture and thermal properties of the object. Reinforcement learning techniques are utilized to process the collected data. Recently, Deep Learning was utilized for multimodal object recognition using a four finger hand [21]. The hand was equipped with force sensor arrays, 6 axis force/torque sensors for each fingertip and joint encoders. In that work, the role of each sensor on the recognition performance is examined in detail.

The closest work to ours is presented in [22]. Like in our method, the classification is made based on a single grasp and instead of using time series data like some of the aforementioned methods, this method forms a feature vector with data collected upon events (when first contact of the fingers is detected, and in steady state). During the experiments, the gripper of PR2 robot was used which was equipped with a capacitive sensor array. In these experiments the internal state (fullness) of the containers is recognized. Different from our method, all the objects used in the experiments have radial symmetry, therefore the data do not have orientation variance. Moreover, the method uses a hybrid control scheme which switches between velocity and force control whereas our procedure is completely open loop. It is very important to know that in [22] the authors report that the parameters of the controller significantly affect the classification performance and therefore a thorough control design was required. This shows an important advantage of our open-loop scheme which uses an underactuated, adaptive robot gripper.

III. Methods

A. An Ensemble Classifier based on Random Forests

In this paper we use a Random Forests classifier in order to discriminate between different object classes. The Random Forests technique was originally proposed by Tin Kam Ho [23] and Leo Breiman [24] and is an ensemble classifier based on decision trees. In statistics and machine learning, ensemble classifiers are called the methods that combine a set of independent classifiers, to obtain better predictive performance. The classifier's output, is the class which is the mode of individual trees' decisions. Each decision tree of the random forest, casts a vote for the most popular class at the input variables. Some of the advantages of the Random Forests technique are:

- It runs efficiently and fast on large databases.
- Provides high classification accuracy.
- Provides an inherent feature variables importance calculation procedure.
- Can handle thousands of input variables.
- Can easily handle multiclass problems (like the problem we address).

In this work we deal with a multiclass problem since we have to discriminate between a wide range of objects with various properties. Thus, we use a Random Forest classifier for two main reasons: 1) to achieve high classification accuracy and 2) to calculate feature variables importance and optimize our experimental setup, keeping the minimum number of sensors required to achieve a certain level of accuracy. In Section V we also compare the random forests technique with other classifiers.

B. Features Selection

The feature space used consists of the actuator positions and the force sensor readings at two different time instances. More precisely, the feature vector contains 2 sets of 2 motor positions (1 motor for each finger) and 2 sets of 16 force sensors (8 for each finger), having a total of 36 variables (see Fig. 3). This choice makes the proposed methodology essentially model-free, as no a-priori information regarding the robot model or the actual joint angles is required. This is especially important for applications with underactuated, compliant robot hands, since for the majority of these hands, the calculation of their kinematics gets complicated especially after contact with an object, where passive compliance takes place. Moreover, the force sensor readings do not have to be calibrated since we only care about the differentiation of their values among the different classes (so their raw values can be efficiently used). At this point it must be noted that although our methodology does not require advanced sensor calibrations, we do acknowledge that our experiments were conducted within a relatively short time period and that over longer periods of time the classifier may require re-training due to changes in sensor output (e.g., caused by sensor drifts).

As we have already noted the proposed features are collected at two different instances of the open-loop grasping process. The first instance occurs when both robot fingers are in contact with the object surface. The second instance occurs when the actuators motion has stopped. In order to automatically extract these two instances we compare the actual and desired actuator positions. When their differences reach a predefined threshold, a contact with the object is identified and the time of the first instance is recorded. Finally, when the hand is in steady state (i.e., when the grasping motion has stopped) the second time instance is recorded. Moreover, we have experimentally verified that the use of a third time instance provides marginally better results and that the use of time series increases the computational complexity of the methodology, without a significant increase of the accuracy.

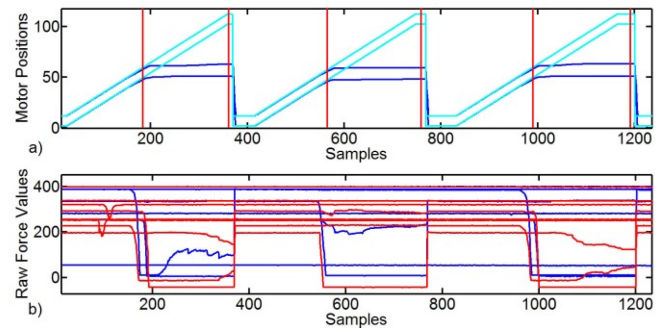

Fig. 3. Automatic contact detection for three trials. Subfigure a) presents the desired (cyan lines) and the actual (blue lines) motor positions, while the red lines denote the instances detected. Subfigure b) presents the force measurements for the left (blue lines) and the right finger (red lines).

C. Calculating Feature Importance

A reasonable goal for such a setup, is to select the most important sensors and minimize the number of sensors required to achieve similar classification accuracy. In this respect, we use the Random forests inherent capability to compute the importance scores of the feature variables and assess their relative importance. More precisely, the Random Forests methodology uses for each tree, a different bootstrap sample set from the original data. One-third of the samples are left out of this set (they are called out-of-bag samples) and are not used in the construction of the *n*-th tree. For every tree in the forest, we use the out-of-bag samples and count the number of votes cast for the correct class. Then the values of the variable *m* are randomly permuted in the out-of-bag samples and the votes are computed and counted again. Subtracting the number of votes casted for the correct class in the permuted out-of-bag data from the number of votes casted for the correct class in the untouched out-of-bag data, we get the importance score of a feature variable *m,* for each tree. The raw importance score for each feature variable, is computed as the average importance score of all trees of the random forest.

IV. Experimental Setup

In order to assess the performance of the proposed methodology, we have designed three sets of experiments. The first set assesses the efficiency of the classifier for discriminating objects with different shapes and sizes, the second set focuses on the discrimination of objects with different shapes and stiffness and the third set focuses on the discrimination between different everyday life objects. In this section, we present the objects selected for these experiments, the apparatus used and we provide a description of the experiments conducted.

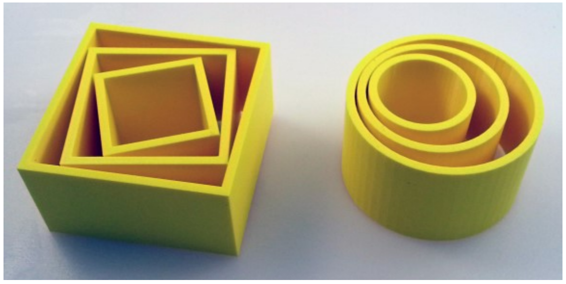

Fig. 4. The model objects of the first set. The boxes and cylinders have side lengths / diameters of 50, 70 and 90 mm.

A. *Model Objects and Everyday Life Objects*

In this work we use three sets of model and everyday life objects with different sizes, shapes and stiffness, in order to test the efficiency of the proposed classifier, to discriminate between objects with different properties.

The solid objects were 3D printed, while the compliant objects were created with standard machining tools using foam sheets of different stiffness levels. The first set involves 6 rigid model objects (3 rectangles and 3 cylinders) with different shapes and sizes. The rigid model objects are depicted in Fig. 4 and their characteristics (sizes and stiffness) are reported in Table I. Object stiffness were measured via perturbations by a load cell mounted on a linear actuator. The linear actuator position accuracy was 0.01 mm and the load cell force resolution was 0.01 N.

It must be noted that the stiffness of the rigid rectangles was measured in the center of a face, where their geometry allows for a greater deformation.

Table I: Characteristics of model objects of the first set.

Objects	*Cylinders*	*Rectangles*
Sizes	50, 70, 90 mm (diameter)	50, 70, 90 mm (side)
Stiffness	97 kN/m	51 kN/m

The second set of objects consists of four rectangles and four cylinders with same size and different stiffness. The second set objects are depicted in Fig. 5, while their characteristics are reported in Table II.

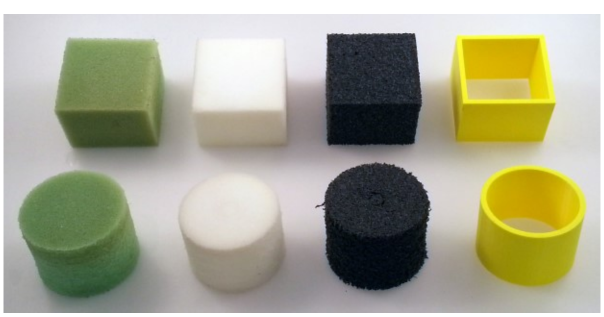

Fig. 5. The model objects of the second set. The first row depicts rectangles with same side length and different stiffness. The second row depicts four different cylinders with same diameter and different stiffness.

Fig. 6. The everyday life objects used for the experiments. These objects are contained in the YCB object set [25].

Table II: Stiffness of the objects of the second set.

Objects	*Green*	*White*	*Black*	*Yellow*
Cylinders	156 N/m	346 N/m	2.1 kN/m	97.2 kN/m
Rectangles	156 N/m	346 N/m	2.1 kN/m	51.1 kN/m

The third set contains a wide set of everyday life objects. The objects used are contained in the YCB object set [25] to facilitate replication of the results by other groups and benchmarking of the proposed techniques. These objects are depicted in Fig. 6 and their characteristics are reported in Table III.

Table III: Characteristics of everyday life objects. All food package items are unopened and contain original products.

Objects	*Dimensions (mm)*	*Stiffness Side 1 (kN/m)*	*Stiffness Side 2 (kN/m)*
Coffee Can	102x139	67.2	N/A
Soup Can	66x101	49.4	N/A
Sugar Box	38x89x175	4.73	26.87
Apple (toy)	75	10.6	N/A
Peach (toy)	59	8.79	N/A
Windex Bottle	80x105x270	9.87	5.0
Mustard Bottle	50x85x 175	4.69	2.98
Bleach Bottle	50x93x250	3.2	3.2
Gelatin Box	28x85x73	3.1	4.7
Cracker Box	60x160x230	2.6	3.0

B. *Experimental Setup*

1) *A Two-Fingered Underactuated Hand:*

The robot hand used in this study uses the base of the Model T42 of the Yale OpenHand project [26] and the fingers of the ReFlex hand (Right Hand Robotics). The robot hand has two underactuated fingers with two phalanges per finger. Each finger has one pin joint and one flexure joint. An image of the robot hand can be found in Fig. 1, while the parameters and the structure of each robot finger are reported in Fig. 2. Each finger has a dedicated actuator (Dynamixel MX 28).

2) *Embedded Force Sensors:*

'Takktile' force sensors are embedded in the grip pad of each phalanx. These robust and inexpensive sensors are based on MEMS barometers mounted on printed circuit boards [27]. Each robot finger accommodates a total of 8 sensors: 3 sensors on the distal phalanx and 5 sensors on the proximal phalanx. An Arduino platform is used to interface the sensors with the planner PC.

C. Experiments Conducted

Three experiments were conducted with the different object sets. In all experiments, the objects were placed in arbitrary positions and orientations within the grasping workspace of the robot hand (Fig. 7). Objects were placed on a table on which the robot hand rested while grasping, leading to a consistent grasp height from the base of each object. We chose to use arbitrary positions and orientations, in order to demonstrate that our methodology: 1) does not depend on the object pose and is robust to object pose uncertainties, 2) works in a direct manner (no re-grasping or other repetitive procedures are required), 3) can deal with asymmetric finger trajectories, resting positions, contact times and contact locations (which result from the adaptive nature of the gripper), 4) can deal with fingers 'pushing' the objects during grasp. For each of the 22 objects, 20 grasps were performed.

V. RESULTS

In this section we present the classification results, a comparison between different classification methods and the identification of the most importance features (e.g., force sensors) using the Random Forests inherent feature variables importance calculation procedure. For the training of the classifiers, we use the 10-fold cross-validation method [28]. The classification accuracies we averaged over the multiple rounds.

A. Classification Results for Model Objects

At first we present classification results for the model objects contained in object sets 1 and 2. Table IV reports the classification accuracy. The classifier is slightly better at discriminating between objects with different shapes and sizes rather than between objects with different shapes and stiffness.

Table IV: Classification results for model objects.

Case	*Object Set 1: Size and Shape Discrimination*	*Object Set 2: Shapes and Stiffness Discrimination*
Accuracy	93.57% (SD: 3.25%)	93.01% (SD: 3.02%)

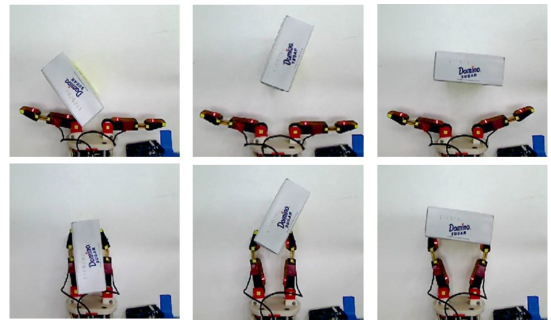

Fig. 7. Examples of different arbitrary positions used while collecting the training and the test data.

B. Classification Results for Everyday Life Objects

The second classification problem that is being solved concerns a discrimination between a wide range of everyday life objects. The classification accuracies are reported in Table V for two different cases: 1) for constrained orientations, 2) for free orientations. In the constrained orientations case objects were positioned in an arbitrary manner with the orientations limited within ±45 degrees of the principal axis. The second case included experiments with any arbitrary orientation (±360 degrees). As was expected for the constrained orientations case the classification accuracy is much higher.

Table V: Classification results for everyday life objects.

Case	*Constraint Orientations*	*Free Orientations*
Accuracy	100%	94.32% (SD: 3.09%)

C. Comparison of Classification Methods

In this subsection we compare some standard classification methods against the random forests classifier. More specifically, the methods used are: 1) Linear Discriminant Analysis (LDA), 2) Neural Networks (NN), 3) Support Vector Machines (SVM) and 4) Random Forests (RF). Regarding the training of the different methods, we performed SVM based classification using different kernels and keeping the best scores (linear, RBF etc.) and we constructed a single hidden layer Neural Network with fifteen hidden units (after trial and error to select the most appropriate number of units), which was trained with the Levenberg-Marquardt back-propagation algorithm. The Random forests were grown with ten trees for processing speed (two times faster) and one hundred trees for accuracy. The classifiers were compared for the task of discriminating between everyday life objects with constrained orientations. Classification accuracies for the different methods, are reported in Table VI. Random forests outperformed all other methods but all achieved high classification accuracies.

It must be noted that the efficiency of methods like the SVM and the NN, is highly affected by the tuning of their parameters or the selection of an appropriate kernel. Random Forests outperform all the other methods even for the simplest case of 10 grown trees and without requiring any additional tuning. It is possible that after excessive tuning, other classifiers may achieve similar or slightly better results but the RF will still be a simple and highly effective solution.

Table VI: Comparison of different classifiers.

Classifier	*Accuracy*
Linear Discriminant Analysis	89.74%
Neural Networks	95.65%
Support Vector Machines	92.30%
Random Forests (10 trees)	98.04%
Random Forests (100 trees)	100%

D. Optimizing the Experimental Setup

In this subsection we perform a calculation of the feature variables importance and we employ the outcomes in minimizing the number of sensors required to achieve a certain level of classification accuracy. The importance bar plots of the different feature variables for the cases of everyday life objects with constrained and free orientations, are presented in Fig. 8. The x axis presents the sets derived from 10 different separations of the training data. As it can be noticed the feature variable importance scores are robust along the different separations. The classification results for the reduced number of feature variables are reported in Table VII.

Table VII: Effect of feature variables selection in the classification accuracy for everyday life objects with free and constrained orientations.

Orientations	*All (36) Features (16 force sensors)*	*12 Features (4 force sensors)*
Free	100%	98.48%
Constrained	94.32%	92.43%

For the case of the constrained orientations when we train the classifier with the 12 most important feature variables we get a drop of the classification accuracy of only 1.52%, while for the case of the free orientations, the use of the 12 most important features leads to a classification accuracy drop of only 1.89%. The fact that we achieve similar classification accuracy with a reduced number of features dictates that we have a redundancy in the feature space. The redundant features can be removed without affecting the efficiency of the proposed methodology. Thus, we are able to redesign the experimental setup, concluding to a simplified version that requires a minimum of 2 force sensors per finger instead of the original 8.

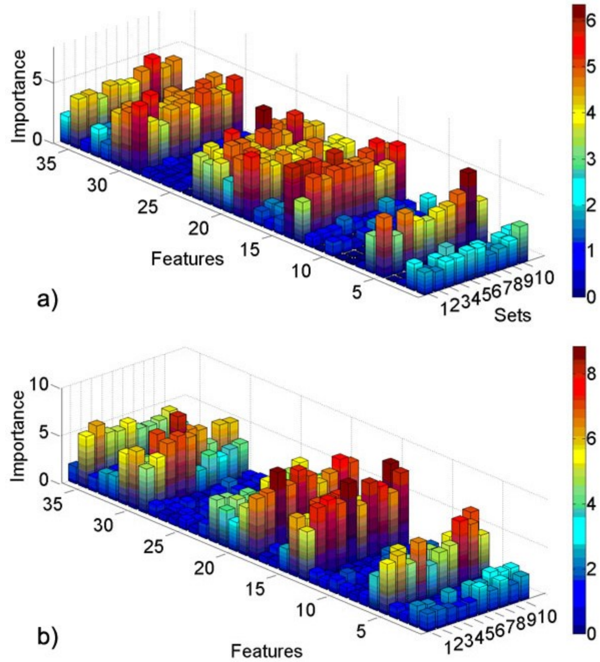

Fig. 8. Feature variables importance bar plots for discrimination of everyday life objects with constrained (subplot a) and free orientations (subplot b). The height of the different bars represents the importance scores of the different feature variables. The sets of data used for the computation of the feature variables importances, are ten different / random separations of the training data.

VI. Conclusion

In this paper we formulated a complete methodology for performing object classification in an interactive manner, using an underactuated hand and force sensors. For doing so we grasped a wide range of objects with different shapes, sizes and stiffness positioned in arbitrary poses in front of the robot hand. A Random Forrest classifier was employed in order to discriminate between the different classes of objects. The feature space used consists of the servo motor positions and the force measurements, at two different instances of the grasping process. The experiments were performed with an underactuated compliant robot hand which was controlled in an open-loop fashion. A feature variables importance calculation procedure (inherent in the Random Forests classifiers) was used in order to identify the most important features, and it was concluded that the number of force sensors can be reduced from 8 to 2 per finger, without significant loss of classification accuracy.

Acknowledgment

We would like to thank Raymond R. Ma for providing his expertise in robot hand design and Kevin Gemmell for helping us measure the objects stiffness.

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