Rapid Categorization of Object Properties from Incidental Contact with a Tactile Sensing Robot Arm

Tapomayukh Bhattacharjee*, Ariel Kapusta, James M. Rehg, and Charles C. Kemp

***Abstract*— We demonstrate that data-driven methods can be used to rapidly categorize objects encountered through incidental contact on a robot arm. Allowing incidental contact with surrounding objects has benefits during manipulation such as increasing the workspace during reaching tasks. The information obtained from such contact, if available online, can potentially be used to map the environment and help in manipulation tasks. In this paper, we address this problem of online categorization using incidental contact during goal-oriented motion. In cluttered environments, the detailed internal structure of clutter can be difficult to infer, but the environment type is often apparent. In a randomized cluttered environment of known object types and "outliers", our approach uses Hidden Markov Models to capture the dynamic robot-environment interactions and to categorize objects based on the interactions. We combined leaf and trunk objects to create artificial foliage as a test environment. We collected data using a skin-sensor on the robot's forearm while it reached into clutter. Our algorithm classifies the objects rapidly with low computation time and few data-samples. Using a taxel-by-taxel classification approach, we can successfully categorize simultaneous contacts with multiple objects and can also identify outlier objects in the environment based on the prior associated with an object's likelihood in the given environment.**

I. INTRODUCTION

Rapid identification of haptic properties of objects in unknown environments during exploration or navigation is a difficult problem. Our method extracts information from incidental contacts and simultaneously comprehends the incoming data. The information obtained from such contact can be used to map the environment by categorizing object properties from the robot-environment interactions. This can potentially help in manipulation tasks and in the exploration of unknown environments. Allowing incidental contact with surrounding objects while maneuvering through a cluttered environment has many benefits such as an increase in the robot's workspace. By '*incidental contact*', we mean any contact that occurs unintentionally while performing a goal-directed manipulation tasks. In this study, we address this issue of rapid categorization of objects conditioned on the environment.

Our approach uses hidden Markov models (HMMs) and considers the likelihood of finding particular object types in an environment to classify dynamic robot-environment interactions. We extend our previous work [1] on object classification by implementing HMMs to model these interactions for rapid online categorization. We generalize our algorithm to non-stereotyped motions. Our new algorithm allows multiple simultaneous contacts and has the capability to identify outlier objects. Inferences based on the likelihood of finding an object in a given environment use little training data for identifying specific objects and isolating outliers. For our experiments, we used the 7 DoF arm of the humanoid mobile manipulator, Cody, as shown in Fig. 1. As an example of a cluttered environment with known object types and unknown configuration, we created artificial foliage consisting of combinations of leaf and trunk objects. A common scenario is shown in Fig. 1 in which the robot is making simultaneous incidental contacts on its forearm (forearm skin sensor) and end-effector (our newly developed flipper with tactile sensing described in Section IV-A.1) with multiple objects. Only the forearm sensors are used to perform object categorization. We provided the robot-arm with goals in its workspace, and it used model-predictive control (MPC) [2] to limit contact forces while navigating towards the goals.

We organize the remainder of the paper as follows. In Section II, we review related work in this domain. Section III describes our approach of categorization of objects conditioned on the robots environment. In Section IV, we describe our experimental procedure in detail and in Section V, we present experimental results for this algorithm and analyze the accuracy in various conditions. In Section VI, we present the conclusions from our work.

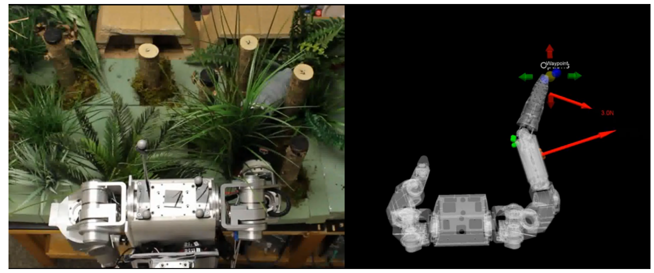

Fig. 1. *(Left) A mobile humanoid robot, Cody, reaching into clutter while making simultaneous contact with multiple objects; (Right) Rapid categorization of Leaf and Trunk categories while the robot is reaching into clutter. The taxels categorized as leaves are marked with green dots (on the left side of forearm) while the brown dots show the trunk (on the right side of forearm).*

II. RELATED WORK

Categorization of haptic properties of objects is an extensively explored field (refer [1] for a detailed literature

T. Bhattacharjee, A. Kapusta and C. C. Kemp are with the Healthcare Robotics Lab, Georgia Institute of Technology,

J. M. Rehg is with the Computational Perception Lab, Georgia Institute of Technology,

*T. Bhattacharjee is the corresponding author {tapomayukh@gatech.edu}.

Fig. 2. *(Left) Trunk-only environment for training the HMM model for Trunk Category; (Middle) Leaf-only environment for training the HMM model for Leaf Category; (Right) Combined environment for testing*

review). Our focus in this study is online classification of objects from incidental contact, on which there are few related previous studies. Our previous work included categorization from incidental contact during goal-directed movements [1] but it was implemented for stereotyped motion of the robot-arm and was not generalized to multiple contacts. In addition, the categorization was done offline and the algorithm required extensive training data of equal sample-length to classify specific objects [1]. In our current study, we address these shortfalls by implementing an online categorization scheme using HMMs which can deal with time-series data of varied length. Some of the previous studies on online categorization used explicit exploration movements for object identification [3] and shape identification [4]. Soh *et. al.* [3] created a spatio-temporal online recursive kernel gaussian process to perform online object classification during gripping movements by a robot hand. They found that they could identify between objects based on signature tactile features. The tactile features were measured with a specific hand closing movement. Liu *et. al.* [4] used a naive Bayesian process to perform online classification of shape and pose of objects during an explicit exploration movement by a robot finger. They used an off-the-shelf tactile sensor array mounted on a robot finger and were able to rapidly identify object shape after exploration of the object by the finger. The objects were smaller than the sensor array, so complete exploration before identification was possible. Chitta *et. al.* [5] created a hybrid velocity-force controller that allows a robot gripper to hold objects and gather tactile and deformation data from the interaction. Using their gathered tactile and deformation data, they were able to distinguish between states of the objects (e.g. empty, full, open, closed) with recognition rates comparable to that of a human. Jamali and Sammut [6] used several machine learning algorithms to perform material classification based on surface texture during explicit exploration movements by a bio-inspired artificial finger. Vibrations measured by the tactile sensors in the finger while being run across the textured surface at a specified speed could be used to identify the material with some accuracy after minimal training data.

Work on online categorization has been performed in other fields as well, such as in 3D scene analysis, handwritten character recognition, human gait recognition, and in monitoring of bearings for abnormal behavior in industrial machinery. Hu *et. al.* [7] categorized 3D scenes into different object types from range data for use in robotics. They described the tradeoff between precise categorization at the cost of speed and fast categorization at the cost of increased misclassifications and used a simple but imprecise scene representation method to address the problem. Hu and Zanibbi [8] performed online recognition of handwritten mathematical symbols by creating an HMM for each symbol class and a segmental K-means to initialize the gaussian mixture models parameters. Garain and Chaudhuri [9] combines a nearest-neighbor classifier with an HMM to perform online recognition of handwritten mathematical symbols. Kale *et. al.* [10] used a continuous HMM to perform online identification of humans by gait. Starner *et. al.* [11] presented two real-time HMM systems to recognize continuous, sentence-level American sign language while Yamato *et. al.* [12] proposed a HMM-based method for recognizing human actions from a series of time-sequential images. Cartella *et. al.* [13] assessed bearing condition in industrial machinery using online adaptive learning of left-right continuous HMM. These studies use HMMs as a tool for rapid identification of object characteristics.

III. CATEGORIZATION METHOD

For our problem, the robot must classify each region of contact, R_i, according to the type of object, c_i, that resulted in the contact region. We assume that the robot is operating in a known environment, E, composed of T object types and that each contact region, R_i, results from one of these T object types or results from an anomalous object type that is not typically found in the environment, E. In this paper, we use hidden Markov models (HMMs) to perform the classification problem, and focus on the problem of an environment with different object types.

Hidden Markov model is a statistical tool to model systems using a state-based approach such that the current state is dependent only on the previous state. The states are hidden and are not directly observable. Instead, they are stochastically dependent on observations. The elements which constitute an HMM are (1) N, the number of states in the model; (2)

M, the number of distinct observation symbols per state; (3) A = $\{a_{ij}\}$, the state transition probability distribution; (4) B = $\{b_j(k)\}$, the observation symbol probability distribution; and (5) P = $\{\pi_i\}$, the initial state distribution [14], [15]. The model is represented as given in eq. (1), where the parameter λ describes the HMM model.

$$\lambda = (A, B, \pi) \tag{1}$$

For classification using HMMs, we need to train the HMM models first. We had different HMM models which we trained on environments composed of single object categories. We trained the HMMs by choosing the λ which locally maximizes $P(O|\lambda)$ iteratively using expectation-maximization (EM) techniques [14]. After training the models for the different categories, we evaluate a new observation sequence $O = \{O_1, O_2, ...O_n\}$ according to eq. (2) which gives us the model which best matches the observation sequence. The third step in eq. (2) leads to the fourth step, if all the models are equally likely, as is the case for the first part of this study.

$$\begin{aligned} c^* &= \underset{c \in [C]}{\arg\max}\, P(\lambda_c|O) \\ &= \underset{c \in [C]}{\arg\max}\, \frac{P(O|\lambda_c)\, P(\lambda_c)}{P(O)} \\ &= \underset{c \in [C]}{\arg\max}\, P(O|\lambda_c)\, P(\lambda_c) \\ &= \underset{c \in [C]}{\arg\max}\, P(O|\lambda_c) \end{aligned} \tag{2}$$

Later, we use HMMs to identify an outlier in the environment for which all the models are not equally likely. In this case, the conditional probability is given by eq. (3).

$$c^* = \underset{c \in [C]}{\arg\max}\, P(O|\lambda_c)\, P(\lambda_c) \tag{3}$$

IV. Experimental Procedure

For our experiments, we used a mobile humanoid robot Cody to reach into artificially created reconfigurable cluttered environments while rapidly classifying into various categories objects encountered through incidental contact. The details are given in the following subsections.

A. *Experimental Setup*

Cody, as shown in Fig. 1, is a mobile humanoid robot weighing approximately 160 kg. It has two Meka A1 arms, a Segway omni-directional base and a Festo 1 DoF (degree of freedom) vertical linear actuator for changing its height. The two 7 DoF anthropomorphic arms contain series elastic actuators for compliance and torque control ability. When we control these arms, each joint simulates a low-stiffness, visco-elastic, torsional spring. We control the robot's arms by changing the equilibrium angles of these simulated springs over time [1].

Cody has a force-sensitive high-resolution skin across its forearm. Meka Robotics and the Georgia Tech Healthcare Robotics Lab developed the forearm tactile skin sensor, which is based on Stanford's capacitive sensing technology, as described by Ulmen *et. al.* [16]. This skin has a capacitive pressure-sensor array and each sensing element is called a taxel (tactile pixel). The skin has 384 taxels in total arranged in a 24 X 16 pattern. Each taxel is of 9 mm X 9 mm size and it can measure applied force at 100 Hz. [1].

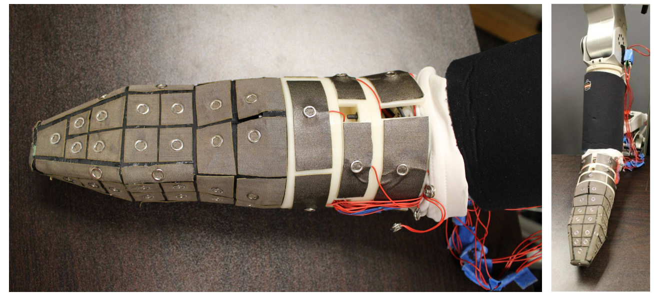

Fig. 3. *Our newly developed flipper with tactile sensing based on fabric based sensing technology. It has 69 taxels in total. It is used to navigate clutter.*

We created an artificial cluttered foliage environment using leaf and trunk objects as shown in Fig. 2. The clutter is reconfigurable so we can create a large set of environments by rearranging the relative position of the leaf and the trunks. It is made reconfigurable by a ground platform made of a combination of wet and dry foams as shown in Fig. 2. The leaves can be stuck stably inside these foams and can be removed at will. The trunks are fixed to the table beneath the foam platform with flanges to provide stability. Each foam block is a 25 cm X 10 cm sized rectangular block. We can move the foam blocks and the trunks and we can place leaves in different relative positions to reconfigure the environment and create a variety of cluttered environments with which the robot can interact.

1) Whole-Arm Tactile Sensing with Flipper: While reaching into clutter, contact can occur at any point of the arm including the end-effector. By using only the forearm skin sensor, we would lose contact information used for haptic navigation. Without an end-effector, we would also lose the degrees of freedom afforded by Cody's wrist joint. Hence, we created a wedge-shaped end-effector (referred to as a 'flipper', see Fig. 3) for Cody, on which we mounted tactile sensors based on our fabric-based tactile sensor technology [17]. We put 69 taxels ranging from 1 cm^2 to 15 cm^2 in a pattern fixed to the 25 cm long flipper's surface. We used haptic signals from the flipper to navigate in the foliage environment.

B. *Collecting Training Data*

The purpose of our classification is to categorize between leaf and trunk in a foliage environment. Hence, we need a model for the trunk and the leaf categories. To train the model for the trunk category, we made the robot reach into a trunk-only environment as shown in Fig. 2 (Left). To train another model for the leaf category, we made the robot reach into a leaf-only environment as shown in Fig. 2 (Middle). The test

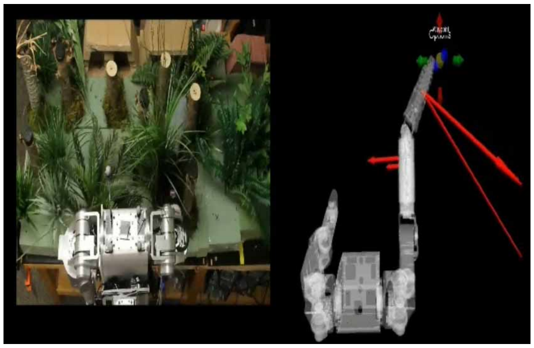

Fig. 4. *(Left) Cody reaching into clutter while making contact with multiple objects on forearm and flipper; (Right) The contact forces on the forearm and flipper skins are shown in Rviz with the goal provided by the interactive marker*

environment was a combination of trunk and leaf objects as shown in Fig. 2 (Right).

To collect training data, we made Cody reach into the leaf training environment and into the trunk training environment multiple times. For each of these reaches, we commanded multiple goal positions for the robot end-effector using the interactive markers in Rviz as shown in Fig. 4. The 7 DoF robot arm moves towards the goal using model predictive control [2] while limiting contact forces across its whole arm. Fig. 4 shows the sensed forces from the forearm and flipper skin sensors while the robot is making contact with the environment. During each of the reaching attempts, we provided multiple goals to make the arm contact various parts of the clutter with various configurations. Between each reach, we changed the configuration of the environment using our reconfigurable cluttered environment setup to create multiple environment situations. We used both the forearm and flipper tactile sensors for haptic navigation and used the data from the forearm for object classification. The next two subsections detail the methods for extracting features from the data collected during the experiments.

C. Connected Component based Categorization

Our first method of extracting features relies on connected components. We represented the data from the forearm skin sensor as a gray-scale image with a 24 X 16 array pattern. We converted this image to a binary image representing the taxels in contact by applying a threshold to each taxel. We computed connected components on this array pattern to segment the contact regions. For each of these connected components, we computed the maximum force and the contact motion at every time-instant. We expected these two features to be informative about the characteristics which distinguishes a leaf from a trunk because we would expect the 3D position of the contact area to travel more when the robot is bending a soft leaf and the maximum force to rise faster when making contact with a trunk.

During each of the reaching attempts in the cluttered environments, the robot frequently came into contact with multiple objects simultaneously. We tracked the motion for each of these connected components using their estimated 3D positions in the world frame. We assumed that the robot's torso did not move throughout the trials and used the forward kinematics from the robot's torso to the center of each associated contact region to estimate these positions. We associated connected components between time steps based on the distances between their estimated 3D positions.

For data management purposes, we name each period between when the robot makes contact with an object and when the robot breaks contact with that object as one trial. There were varied numbers of trials during each reaching attempt depending on the number of times the robot initiated and broke contact with objects in the environment. Based on the connected component based segmentation, there were 288 such trials for the leaf environment over 10 reaches and 324 trials for the trunk environment over 25 reaches which form our training data for this approach.

D. Taxel based Categorization

Our second method of extracting features is taxel-based. We consider data from each of the 384 taxels separately, nullifying the need for segmentation and tracking. This method is inherently high resolution but may contain redundant information when multiple taxels contacting the same object measure similar information content. We collect the same force and motion features as described in Section IV-C. In the taxel-based approach, the maximum force is the force acting on the taxel as there is only one force per taxel at each time-instant. In this approach, we name each period between when each taxel in the robot's forearm skin sensor makes contact with an object and when that taxel breaks contact as one trial. There were varied number of trials during each reaching attempt depending on the number of times each taxel initiated and broke contact with objects in the environment. Based on the taxel-based approach, there were 496 trials for the leaf environment over 10 reaches and 582 trials for the trunk environment over 25 reaches which form our training data for this approach. The features collected from a sample reaching experiment are shown in Fig. 5.

V. RESULTS AND DISCUSSION

In this section, we present an experimental evaluation of algorithm using cross-validation, and present an assessment of online categorization performance.

A. Cross-Validation Performance of HMMs

We used two-fold cross-validation to characterize the performance of our HMM classifiers. The data was collected through various reaches in the leaf and trunk environments as discussed in Section IV-B. We applied both component-based (Section IV-C) and taxel-based (Section IV-D) categorization methods to the data to compare their performance. To analyze the effect of states and the effect of different features used in our algorithm, we compared the performance of our algorithm with varying numbers of hidden states (5, 10, and 20 states) and when using only force as a feature vs. both force and motion as features. The results are given in Table I.

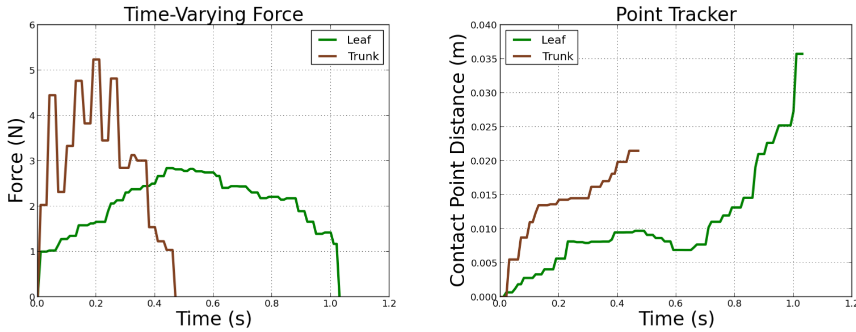

Fig. 5. *The force (Left) and motion (Right) features collected from a taxel using taxel-based approach while the robot was reaching into a clutter. The figure shows a trial in which the robot came into contact with leaf (in green) and another trial in which it came into contact with a trunk (in brown). The left figure shows that as the robot pushes against the object, the force increases at first and then the MPC controller tries to decrease it while moving towards the goal. The right figure shows the motion of the taxel in contact. Clearly, the rate of increase of force as well the magnitude is higher for trunk contact. Also, the motion is larger for leaf as the robot can push and bend the leaf easily.*

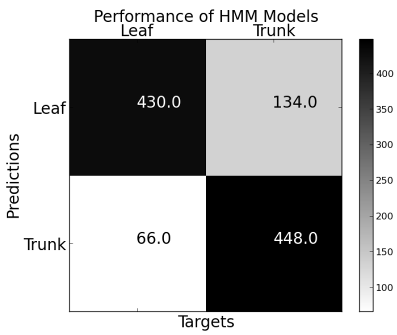

Fig. 6. *Cross-validation performance of taxel-based categorization using a 20-state HMM with force as the feature.*

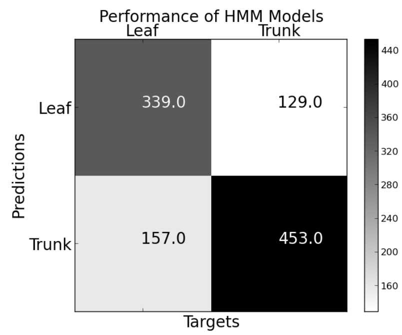

Fig. 7. *Cross-validation performance of taxel-based categorization using a 20-state HMM with force and motion as the features.*

The taxel-based methods consistently performed better than component-based methods both for one-feature and for two-feature based classification methods, irrespective of the number of states used. This may be due to the presence of higher resolution data in taxel-based methods which captures the characteristics of dynamic interactions more effectively than in component-based methods: in a connected component, there are multiple taxels interacting with the same object that may each capture different aspects of the dynamic interaction when considered individually. The confusion matrices for the results of the cross-validation study for the taxel-based method with 20 states are shown in Fig. 6 with force as the sole feature and in Fig. 7 with both force and motion as features. Note that cross-validation results using force as the sole feature gives consistently equivalent or better results than using two features. It can be seen from Table I that our algorithm consistently performs better using 10 or 20 hidden states than using 5 states. This implies that 5 state transitions may be insufficient to characterize and distinguish models of leaf and trunk categories.

B. Online Categorization Performance

In this section, we describe the implementation of our algorithm for online rapid categorization as the robot reaches into clutter. Based on results from Section V-A, we used taxel-based methods for categorization. The robot used both the forces sensed from forearm tactile sensing skin and flipper to reach into clutter by moving towards commanded goal while minimizing these forces using MPC [2]. We classified the taxels in contact into 3 categories: trunk, leaf and uncertain. The uncertain category was for those taxels which cannot be classified into either trunk or leaf with confidence. We implemented this classification scheme by using a threshold on the log-likelihood values of the HMM below which the taxel was categorized as uncertain. This helped in reducing the number of misclassifications and in improving the false-positive accuracy of our algorithm.

To analyze the performance of our algorithm, we computed metrics of computation time, and amount of data samples required for classification for one of the reaching tasks. The results are given in Figs. 8, 9, and 10. From Fig. 8, we see that the algorithm can categorize rapidly taking on average 0.83 s per 100 taxels in contact for inference using a 10-state univariate HMM. This computation was performed on a system which runs Ubuntu 12.04 32-bit OS with a 3.2.0-45-generic-pae linux kernel. It has 4 GB RAM and an Intel® Core^{TM} i5-2410M CPU @ 2.30 GHz X 4 processor. The number of data-samples used for classification varies over time as seen in Fig. 9, with an average around 12

TABLE I

CROSS-VALIDATION PERFORMANCE.

Type	Features Used	5 Hidden States	10 Hidden States	20 Hidden States
Component-Based Categorization	Max. Force	61.76%	72.22%	70.75%
	Max. Force and Contact Motion	54.41%	55.55%	58.50%
Taxel-Based Categorization	Force	72.91%	**80.24%**	**81.40%**
	Force and Contact Motion	70.22%	**71.98%**	**73.47%**

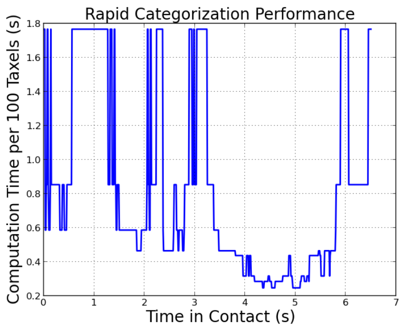

Fig. 8. *Computation time per 100 taxels in contact during a reaching task for two category classification using 10-state univariate HMM.*

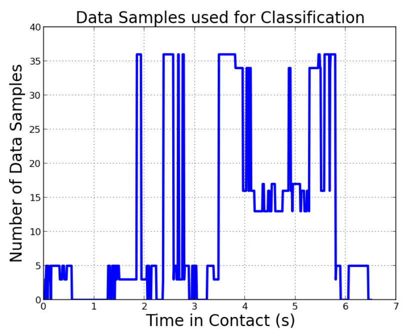

Fig. 9. *Number of Data Samples used to classify the objects in clutter using HMMs during a reaching experiment. The data-samples are zero when the classification is uncertain. Please note that the number of data samples is proportional to time with the data-sample rate at 100 Hz.*

(exactly 11.9). Fig. 10 shows that the number of correctly classified taxels is higher than the misclassified taxels and the number of uncertain taxels is low.

To compare our results against ground-truth, we conducted 10 reaching experiments in the artificial foliage environment and designed them such that 5 of them contacted only leaves while the other 5 only trunks. The results are shown in Fig. 11. The results for the reaching trials in which the robot contacted only leaves, are shaded in green while the results for trunk contacts are shaded in brown. The number of misclassifications was reduced, with the tradeoff that our algorithm is more conservative. We prefer a conservative approach as this allows us to choose environment-based manipulation strategies with higher confidence.

After these experiments, we did a general reaching experiment in which the robot reached into clutter while making contact with trunk and leaf at different times or simultaneously. *The video of the reaching trials is submitted along with this manuscript. It shows our approach for rapid categorization with simultaneous contacts and multiple objects.* Fig. 12 shows a snapshot of the robot reaching into the clutter while it is making contact with leaves. The rapid categorization algorithm classifies the taxels in contact as leaves and marks them with green dots as shown in Fig. 12. *Link to the video is given in [18]*

C. Effect of Data-Sample Length

Based on results from Fig. 9 in Section V-B, we analyzed the effect of the data-sample length on the algorithm performance. We varied the training-data sample length by truncating the remaining data such that the maximum number of data samples varied from 200 to 50 in intervals of 50. We performed a two-fold cross-validation and the results are shown in Fig. 13. We do not see significant effect of the data sample length on the algorithm performance. This result encourages us to believe that we can achieve faster categorization without reduction in performance by using fewer training samples.

D. Identifying an Outlier in the Environment

We conducted an experiment to show that our algorithm can be used to identify an outlier object in the environment without explicitly modeling an outlier category. An outlier object is an object which does not normally belong to the environment in question and has distinct physical properties from the expected object types. If we had a model for the outlier category, we could use eq. (3) as is, for computing the conditional probability. However, in our implementation, without explicitly modeling the outlier, we identify an outlier by using a threshold on the log-likelihood values of HMM. We selected the threshold by considering the likelihood of finding an outlier object in the environment.

Our setup consisted of a foam roll embedded in the artificial foliage environment as shown in Fig. 14. The experiment was designed to compare the algorithm performance against ground-truth. The robot would make contact with the outlier first and then would come into contact with leaf or trunk.

For our task, c^* (computed using eq. (3)) is the maximum of ${c^*}_T$ (for trunk) and ${c^*}_L$ (for leaf). We computed the difference between the log-likelihood values of ${c^*}_T$ and ${c^*}_L$ which is an indicator of how confident the model is in its inference. If the model (c^*) was either ${c^*}_T$ or ${c^*}_L$ and the difference was greater than a threshold chosen (80 for our

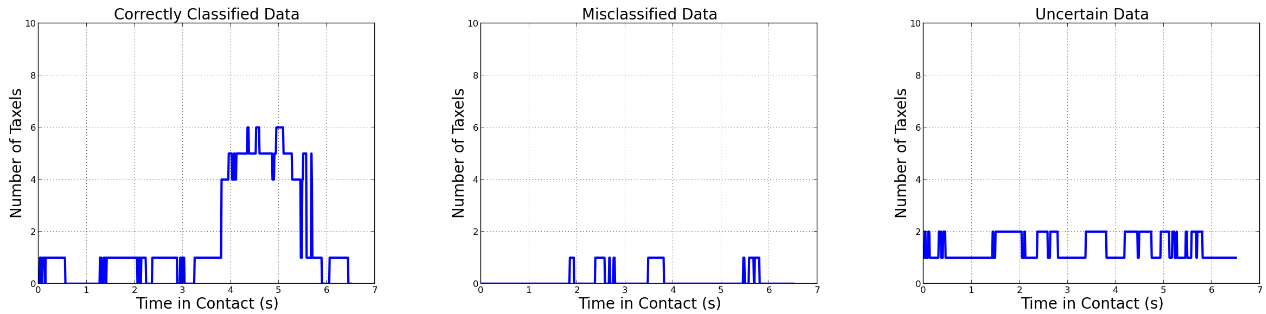

Fig. 10. *(Left) Number of correctly classified taxels; (Middle) Number of misclassified taxels; (Right) Number of Taxels which are not strongly classified into one of the two categories, they are put into an uncertain category. We have this uncertain category to be able to reduce misclassifications while rapidly categorizing the environment*

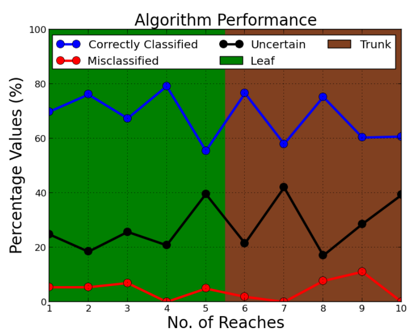

Fig. 11. *Rapid categorization performance for 10 reaches in clutter. The figure shows the percentage of correctly classified, misclassified, and uncertain taxels. To compare the algorithm performance with ground truth, the first 5 reaches were engineered to have contacts only with leaves while the next 5 reaches had contacts only with trunks as represented by their respective colors.*

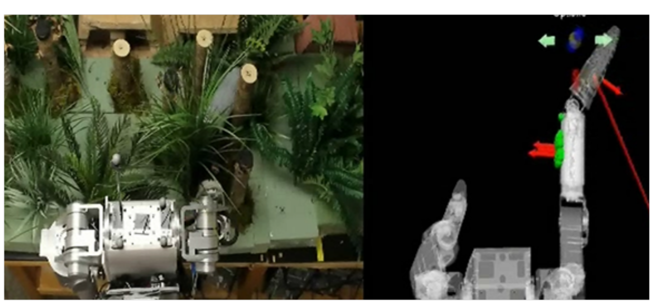

Fig. 12. *Successful categorization of leaves using taxel-based approach (green dots corresponding to the taxels in contact) as the robot reaches into clutter. The classification algorithm uses data from the forearm skin sensor only. The MPC controller uses the forces from both the forearm and flipper skin sensor to reach into clutter.*

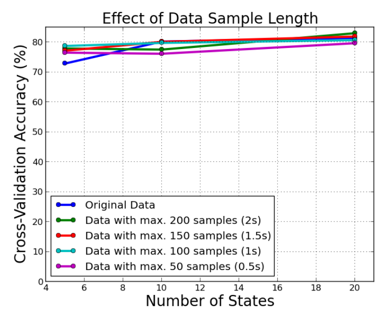

Fig. 13. *Effect of changing the data-sample length. The original data has trials with variable length. To analyze the effect of data-sample length on the cross-validation performance, we truncated the remaining data such that the maximum number of data samples in the trials are varied from 200 to 50 in intervals of 50. The sampling rate was 100 Hz.*

Fig. 14. *Experimental setup showing an outlier (foam roll) in an artificial foliage environment.*

task), we classified it as a trunk or a leaf respectively with high confidence. However, if the difference was between 80 and 15, we classified it as an outlier. Note that this is equivalent to having a model for an outlier in eq. (3) with a low prior. If the difference was less than 15, we classified it as uncertain because we do not have strong confidence in our inference. The results are shown in Fig. 15. The algorithm successfully identified the outlier during both contact events, although there were some uncertain contact data as well. This method shows the potential of identifying outliers in the environment without the need of an explicit model.

One limitation of this algorithm is the need to choose a threshold to identify the outlier. A wiser choice of features might help in easily distinguishing the different object properties and make the algorithm more robust. Also, we used a specific artificial environment for testing and some carefully chosen environments for training which limits its practical usage. The information content in the haptic data is dense and visually promising but we might require more elaborate processing techniques to achieve more confident estimates

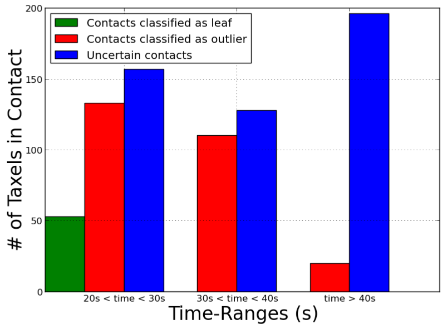

Fig. 15. *Successful detection of the outlier object (red) during a reaching experiment. There were three distinct phases of contact, the first two were with the outlier object while the last was with leaves. The algorithm successfully detected the outlier in the first two phases of contact while some of the taxels were uncertain (blue). There were few misclassified taxels (green). For the last phase of the contact, the taxels were uncertain about the contact.*

about the categories. In addition, the recognition performance depends on the task chosen and the MPC controller used in this study, and it remains to be seen how well it can generalize to other controllers.

VI. CONCLUSION

This paper describes our approach for rapid categorization of objects conditioned on the environment. Our approach uses hidden Markov models to model the dynamic interactions of the objects with a robot-arm. Using our newly developed flipper with tactile skin and the forearm skin sensor, the robot can haptically navigate through a cluttered environment while rapidly categorizing objects encountered through incidental contact. We created an artificial foliage as a test environment and trained two HMM models for categorizing trunk vs. leaf. Our algorithm consistently performed with cross-validation accuracy as high as 81%. For our tests, the highest performance was achieved when the categorization was done on a taxel-by-taxel basis with force as the sole feature and using 20 states. The computation time and data sample length were appropriate for online categorization. Results showed that our algorithm can be used to classify multiple objects with multiple simultaneous contacts. In addition, our initial tests suggest that outlier detection may be achievable.

VII. ACKNOWLEDGMENTS

We gratefully acknowledge the support from DARPA's Maximum Mobility and Manipulation (M3) program, Contract W911NF-11-1-603. Portions of this work were supported by NSF Award 1016772. We would like to thank Mark Cutkosky and the Stanford Biomimetics and Dexterous Manipulation Lab for their contributions to the forearm tactile skin sensor.

REFERENCES

[1] T. Bhattacharjee, J. M. Rehg, and C. C. Kemp, "Haptic classification and recognition of objects using a tactile sensing forearm," in *IEEE International Conference on Intelligent Robots and Systems (IROS)*, October 2012.

[2] A. Jain, M. D. Killpack, A. Edsinger, and C. C. Kemp, "Reaching in clutter with whole-arm tactile sensing," *International Journal of Robotics Research (IJRR)*, vol. 32, no. 4, pp. 458–482, April 2013.

[3] H. Soh, Y. Su, and Y. Demiris, "Online spatio-temporal gaussian process experts with application to tactile classification," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2012, pp. 4489–4496.

[4] H. Liu, X. Song, T. Nanayakkara, L. D. Seneviratne, and K. Althoefer, "A computationally fast algorithm for local contact shape and pose classification using a tactile array sensor," in *IEEE International Conference on Robotics and Automation (ICRA)*, 2012, pp. 1410–1415.

[5] S. Chitta, J. Sturm, M. Piccoli, and W. Burgard, "Tactile sensing for mobile manipulation," *IEEE Transactions on Robotics*, vol. 27, no. 3, pp. 558–568, 2011.

[6] N. Jamali and C. Sammut, "Majority voting: Material classification by tactile sensing using surface texture," *IEEE Transactions on Robotics*, vol. 27, no. 3, pp. 508–521, 2011.

[7] H. Hu, D. Munoz, J. A. Bagnell, and M. Hebert, "Efficient 3-d scene analysis from streaming data," in *IEEE International Conference on Robotics and Automation (ICRA)*, 2013.

[8] L. Hu and R. Zanibbi, "Hmm-based recognition of online handwritten mathematical symbols using segmental k-means initialization and a modified pen-up/down feature," in *International Conference on Document Analysis and Recognition (ICDAR)*, 2011, pp. 457–462.

[9] U. Garain and B. Chaudhuri, "Recognition of online handwritten mathematical expressions," *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, vol. 34, no. 6, pp. 2366–2376, 2004.

[10] A. Kale, A. N. Rajagopalan, N. Cuntoor, and V. Kruger, "Gait-based recognition of humans using continuous hmms," in *in Proceedings of 5th IEEE International Conference onAutomatic Face and Gesture Recognition*, 2002, pp. 336–341.

[11] T. Starner, J. Weaver, and A. Pentland, "Real-time american sign language recognition using desk and wearable computer based video," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 20, no. 12, pp. 1371–1375, 1998.

[12] J. Yamato, J. Ohya, and K. Ishii, "Recognizing human action in time-sequential images using hidden markov model," in *in Proceedings of IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR)*, 1992, pp. 379–385.

[13] F. Cartella, T. Liu, S. Meganck, J. Lemeire, and H. Sahli, "Online adaptive learning of left-right continuous hmm for bearings condition assessment," *Journal of Physics: Conference Series*, vol. 364, no. 1, pp. 12–31, 2012.

[14] L. R. Rabiner, "A tutorial on hidden markov models and selected applications in speech recognition," in *Readings in Speech Recognition*, A. Waibel and K. F. Lee, Eds., Kaufmann, San Mateo, CA, 1990, pp. 267–296.

[15] W. Chai and B. Vercoe, "Folk music classification using hidden markov models," in *Proceedings of International Conference on Artificial Intelligence*, vol. 6, no. 6.4. Citeseer, 2001.

[16] J. Ulmen, A. Edsinger, and M. Cutkosky, "A highly sensitive, manufacturable, low-cost tactile sensor for responsive robots," in *submitted to IEEE International Conference on Robotics and Automation (ICRA)*, 2012.

[17] T. Bhattacharjee, A. Jain, S. Vaish, M. D. Killpack, and C. C. Kemp, "Tactile sensing over articulated joints with stretchable sensors," in *IEEE World Haptics Conference (WHC), The 5th Joint EuroHaptics Conference and IEEE Haptics Symposium*, April 2013.

[18] "Rapid Categorization Online Video," http://youtu.be/AvuKeXXpP1U.