

Autonomously Acquiring Models of Objects for Instance-Based Manipulation and Mapping

Author Names Omitted for Anonymous Review. Paper-ID [add your ID here]

Abstract—Manipulating and reasoning about objects is an important task for robots that help people in the home, in factories, and in hospitals. General-purpose object manipulation requires object recognition, pose estimation, and grasp planning; existing solutions cannot reliably recognize or pick up an object the robot has never encountered before, while existing category-based computer vision approaches run much slower than real time and encounter many false positives and negatives. However in many applications, general-purpose object detection or manipulation is not required: the robot would be useful if it could adapt itself to recognize, localize, and manipulate the small set of objects most important in that application, but do so with very high reliability. To address this problem, we convert the task of *category recognition* (pick up any mug) to *instance recognition* (pick up this mug) by autonomously acquiring visual models for specific objects by using a range scan (which is slow) to provide supervision for a simple and efficient vision-based system for detection and servoing. Using our algorithm, a robot can interact with an object for ten minutes, and then reliably localize it with vision and robustly manipulate it with closed-loop visual servoing. We demonstrate our learned model can enable efficient closed-loop grasping with high reliability, follow natural language pick-and-place commands, and enable vision-based semantic mapping using learned detectors.

I. INTRODUCTION

Robotic assistants will assist us at childcare, help us cook, and provide service to doctors, nurses, and patients in hospitals. Many tasks require a robot to robustly perceive and manipulate objects. Some systems require training by a human operator on an object to object basis, which is time consuming and can be difficult for a non-expert to perform [19, 23, 24]. There do exist some systems which do not require training on a per object basis, but they are computationally expensive and do not enjoy the highest accuracy or precision and have not been demonstrated for grasping [32]. Existing approaches to learn 3d object models still require expensive ICP-based methods to localize objects, which are susceptible to local minima.

To address these issues, we present an approach for enabling a robot to train itself to recognize and manipulate the specific objects it will need to use during future collaborations with humans. Our system is powerful because it learns to identify and grasp on a per object basis. Our system is portable, convenient, and general because the expert knowledge it employs is built into the algorithms which it uses to train itself, requiring only basic interaction from a non-technical human collaborator. Our contribution is an algorithm which allows a robot to autonomously train its subsystems by using slower, more expensive sensing approaches to provide supervision for faster, simpler methods that excel with large amounts of training data.

It works because our experiments tell us so. This is how well they work: . Thus we see an improvement over expert trained systems (cite usability results), and is an improvement over un-annotated systems (cite success rates, the ability to generalize, and the low computational overhead since we don't crunch expensive features or do heavy classification at run time).

II. OBJECT DETECTION AND POSE ESTIMATION

We first describe our instance-based object detection and pose estimation pipeline, which uses standard computer vision algorithms combined to achieve a simple software architecture, a high frame rate, and high accuracy at recognition and pose estimation. This pipeline can be manually trained by an expert to reliably detect and grasp objects. Additionally, section III describes our approach to enabling a robot to autonomously train this pipeline by actively collecting images and training data from the environment.

A. Object Recognition

JGO: Cover BING, SIFT, BoW, typical training pipelines, and RGB-D approaches popular in the robotics community.

Our recognition pipeline takes RGB-D video from the robot, proposes a small number of candidate object bounding boxes in each frame, and classifies each candidate bounding box as belonging to a previously encountered object class. Our object classes consist of object instances rather than pure object categories. Using instance recognition means we cannot reliably detect categories, such as “mugs,” but the system will be able to detect, localize, and grasp the specific instances for which it has models with much higher speed and accuracy.

To generate candidate bounding boxes, we first apply the BING objectness detector [8] to the image, which returns a set $\{B_i\}$ of thousands of approximate object bounding boxes in the image. This process substantially reduces the number of bounding boxes we need to consider but is still too large for us to process in real time. Besides, even good bounding boxes from BING are typically not aligned to the degree that we require. Therefore, we use integral images to efficiently compute the per-pixel map:

$$J(p) = \sum_{B \in \{B_i\} \text{ s.t. } p \in B} \frac{1}{\text{Area}(B)}. \quad (1)$$

We then apply the Canny edge detector with hysteresis [] to find the connected components of bright regions in the map $J(p)$, which correspond with high probability to objects in the image. We form our candidate object bounding boxes

by taking the smallest bounding box which surrounds each connected component. These bounding boxes make it easy to gather training data and to perform inference in real time, but at the expense of poorly handling occlusion as overlapping objects are fused into the same bounding box. It is possible to search within the proposed bounding boxes to better handle occlusion.

For each object c we wish to classify, we gather a set of example crops E_c which are candidate bounding boxes (derived as above) which contain c . We extract dense SIFT features \mathbf{f} from all boxes of all classes and use k-means to extract a visual vocabulary of SIFT features \mathbf{V} . We then construct a BoW feature vector for each image and augment it with a histogram of colors which appear in that image. The augmented feature vector is incorporated into a k-nearest-neighbors model which we use to classify objects at inference \square .

The use of SIFT features is motivated by the instance level nature of our task. State-of-the-art vision methods typically use HOG \square or CNN \square features, but that choice is motivated by category level recognition. **ST: What about category level recognition motivates HOG or CNN? Can you be more specific?**

We use kNN because it is easy to rebuild online, which is a key property a classifier should enjoy if it is to interact with our framework in real time. State-of-the-art computer vision classifiers currently employ SVM's \square or other models which require expensive training. Using such a model would introduce a training step in the inside loop of our data collection process, which would be costly in either engineering or time. It is possible to use kNN during the online collection process and then train a stronger classifier in the background at higher latency, essentially introducing a cascading step in the data collection process.

B. Pose Estimation

JGO: Computer vision approaches, geometry and point cloud based approaches. Dieter Fox's automatic training pipeline (how well developed is it? we may need to sell our approach as being a general algorithm for allowing a robot to train arbitrary subsystems in order to differentiate ourselves.) We tackle the pose estimation problem using the same classification pipeline that we use for object recognition. We train a separate pose classifier for each object class. This time, the class assigned to each training example is the orientation from which the object is viewed in that example. During inference, we first determine the object class of a candidate bounding box, and once the class is known we apply the corresponding pose classifier to determine the orientation from which we are viewing the object. We combine this orientation with position information from the point cloud information derived from the D channel of the RGB-D video to form a full pose estimate.

TABLE I
THE LIST OF SYMBOLS WE USE IN THE DEFINITION OF GRATA.

Symbol	Meaning
X	Ground Truth Labels
Y	Observations
$D \subset X \times Y$	Universe of Observable Data
$\{T_i\}_{i \in \mathbb{N}}$	Sequence of Training Sets
$\mathcal{T} = 2^D$	All Possible Training Sets
$O : \mathcal{T} \rightarrow \mathbb{R}$	Objective Function
$S : \mathbb{N} \rightarrow \mathbb{R}$	Objective Function History
$\mathcal{S} = \{S : \mathbb{N} \rightarrow \mathbb{R}\}$	All Possible Objective Function Histories
$H : \mathcal{S} \times \mathbb{N} \rightarrow \{0, 1\}$	Help Criterion
$\mathcal{C} = \mathcal{T} \times \mathcal{S} \times \mathbb{N}$	Complete Training Set
$G : \mathcal{C}$	Help Request
$P : \mathcal{C} \rightarrow \{0, 1\}$	Stopping Criterion
$L : \mathcal{C} \rightarrow D$	Sample Proposal

III. GENERAL ROBOTIC AUTONOMOUS TRAINING ALGORITHM

We teach the system by finding its weaknesses and training it to overcome them.

Our framework structures the training in a way that scales.

When the robot asks for help, we can ground ambiguous object examples to the right class and retrain the models online.

A. GRATA Definition

In the following algorithm design pattern, X is the set of ground truth labels for the specified problem, Y is the set of all possible observations for the specified problem, $D \subset X \times Y$ is the set of all possible training pairs observable in our problem instance, $\{T_i\}_{i \in \mathbb{N}}$ is a sequence of curated sets of training examples (where $\forall i \in \mathbb{N}, T_i \subset D$), \mathcal{T} is the power set of D , $O : \mathcal{T} \rightarrow \mathbb{R}$ is the objective function that we are trying to optimize (which includes the implementation of the physical actions the robot must take to evaluate it), $S : \mathbb{N} \rightarrow \mathbb{R}$ is the objective function history (i.e. $S(i) = O(T_i)$), \mathcal{S} is the set of all possible objective function histories, $H : \mathcal{S} \times \mathbb{N} \rightarrow \{0, 1\}$ is a function which decides whether to ask for help at a specified time step, $\mathcal{C} = \mathcal{T} \times \mathcal{S} \times \mathbb{N}$ is the complete training state, $G : \mathcal{C}$ is a function which implements asking for and receiving help (e.g. auditing and grounding data under bad conditions or asking for a new collections strategy or a crucial example), $P : \mathcal{C} \rightarrow \{0, 1\}$ is a function that evaluates a stopping criterion and decides whether to continue training, and $L : \mathcal{C} \rightarrow D$ a function that proposes a new ground truth $x \in X$ and collects a corresponding observation $y \in Y$ to form a new training example $(x, y) = d \in D$.

Applying GRATA to a problem involves defining the above quantities and implementing the high level algorithm in the figure \square .

B. GRATA Simulation

Understanding the behavior of GRATA requires running the system many times. This would be impractical to do on the actual robot. It is necessary use a simulator for the process so that we can dramatically shorten the experimental iteration

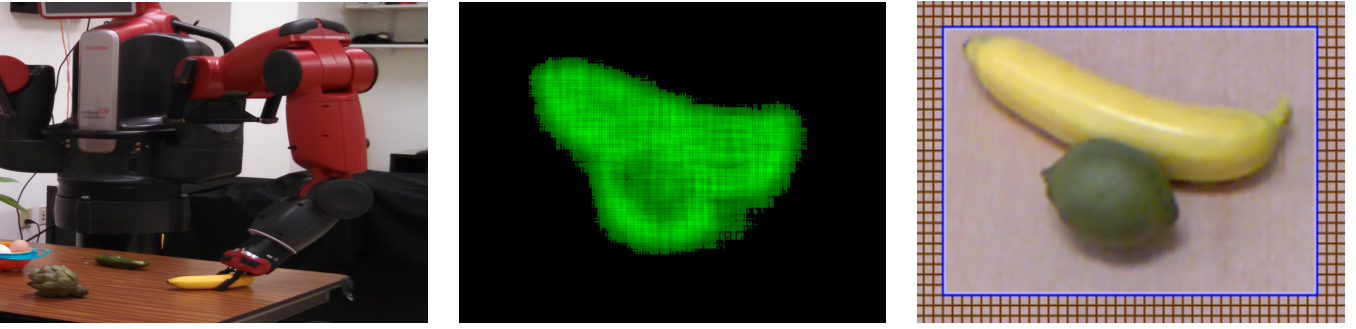


Fig. 1. The Object Detection Pipeline. Left: The raw image as viewed through the kinect. Center: The computed objectness map J . Right: Labeled object detections. **ST: Use subfigure**

GRATA

```

 $t \leftarrow 1$ 
 $c \leftarrow 1$ 
 $T_1 = \emptyset$ 
 $S(1) \leftarrow 0$ 
 $i \leftarrow 1$ 
while  $c$  do
  if  $H(S, i) == 1$  then
     $G(T_i, S, i)$ 
  else
     $d \leftarrow L(T_i, S, i)$ 
     $T_{i+1} \leftarrow T_i \cup \{d\}$ 
  end if
   $i \leftarrow i + 1$ 
   $S(i) \leftarrow O(T_i)$ 
   $c \leftarrow P(T_i, S, i)$ 
end while

```

Fig. 2. The high-level generalized robotic automatic training algorithm (GRATA) which we employ.

time. A dense sampling strategy is a good baseline and the data collected can be queried by an active learning technique to simulate the process of data collection.

Using a dense sampling strategy, we approximate the set D and can then run offline experiments using other sampling strategies. However, the numbers we report are on actual executions of the system where the robot gathers the data online.

IV. APPLICATIONS OF GRATA

A. Recognition Training

B. Pose Estimation Training

C. Grasp Training

4. Once aiming is complete, save the image in the reticle, try to grasp, and save whether that grasp completed. This can be ascertained by the gripper position.
5. Calculate a density map for this

V. EXPERIMENTAL SETUP

JGO: This is where we describe the experiments we performed. We are not trying to extend the state-of-the-art on our individual tasks. Rather, we are providing an interactive framework which will raise the maximum automated vision available to the average user.

Our system can be evaluated in two important ways. Firstly, how effective is the system at the tasks for which it is trained? Secondly, how accessible to users is the system? For now we evaluate system performance, and leave user studies for future work.

A. Object Detection and Pose Estimation

For object Detection and pose estimation, we constructed data sets on which we could evaluate our models. This involved hand annotating the ground truth for the images in the sets, which is a costly procedure which we are attempting to eliminate for future tasks. However, we cannot evaluate our system in a principled fashion without such a data set.

We demonstrate our method's success in this setting where we pay the cost to acquire the data so that we can trust our method and that cost need not be paid during future applications.

Probably uses confusion rates as the objective function.

Expert viewpoint collection (uses at least hard negatives)

Super dense sampling

uniform hard negative sampling with stopping criterion

B. Grasp Experiments

For grasp experiments, we conducted online trials in order to compute success rates. This uses grasp success rate as an objective function.

Expert annotation of grasps

Uniform grasp sampling

Thompson sampling

C. PID Control Experiments

For PID experiments, we conducted online trials in order to compute success rates. We use the time to convergence as the objective function

TABLE II
PERFORMANCE OF OUR SYSTEM ON THE OBJECT DETECTION TASK.

Data Collection Method	Success Rate
Expert Annotation	0.0
Dense Sampling	0.0
Hard Negatives Auto-Stopping	0.0

TABLE III
PERFORMANCE OF OUR SYSTEM ON OFFLINE DATA.

Data Set	
Expert Curated	0.0
Expert (noisy)	0.0
Automatic (curated)	0.0
Automatic (noisy)	0.0

VI. EVALUATION AND DISCUSSION

We could report the performance of the system as a function of user interactions.

We could report the performance of the system as a function of program lifetime.

Our representative set could consist of a block, a spoon, a bowl, a diaper, and a sippy cup. A *single cut video* showing multiple grasps of all objects is available here.

A. Object Detection

We establish a baseline for performance by training the system in a representative domain specific setting, which tells us how well it can perform on laboratory objects when trained by an expert. This represents the best that the system could be expected to perform.

B. Pose Estimation

C. Grasping

D. PID Control

VII. RELATED WORK

Ude et al. [37] described an approach for detecting and manipulating objects to learn models. It uses a bag of words

Grasp Sampling Method	Success Rate
Expert Annotation	0.0
Uniform Sampling	0.0
Thompson Sampling	0.0

Fig. 3. Performance of our system on the grasping task.

Parameter Learning Method	Average Convergence Time
Expert Annotation	0.0
Constant Learning Rate	0.0
Decaying Learning Rate	0.0
Wide Scale Random Noise	0.0

Fig. 4. Performance of our system on the PID control task.

model and learns to detect the objects. It does not learn a model for grasping. Schiebener et al. [34] describes an extension that also does model learning. The robot pushes the object and then trains an object recognition system. It does not use a camera that move and does not grasp. Schiebener et al. [33] discovers and grasps unknown objects.

Summary:

People doing SLAM. Wang et al. [39], Gallagher et al. [11],

People doing 3d reconstruction. Krainin et al. [21], Banta et al. [2]

People doing big databases for category recognition. Kent et al. [18], Kent and Chernova [17], Lai et al. [24], Goldfeder et al. [12]

Object tracking in vision (typically surveillance).

POMDPs for grasping. Platt et al. [29], Hsiao et al. [14]

People doing systems. Hudson et al. [15], Ciocarlie et al. [9]

Crowd-sourced and web robotics have created large databases of objects and grasps using human supervision on the web [18, 17]. These approaches outperform automatically inferred grasps but still require humans in the loop. Our approach enables a robot to acquire a model fully autonomously, once the object has been placed on the table.

Zhu et al. [40] created a system for detecting objects and estimating pose from single images of cluttered objects. They use KinectFusion to construct 3d object models from depth measurements with a turn-table rather than automatically acquiring models.

Chang et al. [6] created a system for picking out objects from a pile for sorting and arranging but did not learn object models.

next-best view planning [22]

Nguyen and Kemp [28] learn to manipulate objects such as a light switch or drawer with a similar self-training approach. Our work learns visual models for objects for autonomous pick-and-place rather than to manipulate objects.

Developmental/cognitive robotics [26?]

Banta et al. [2] constructs a prototype 3d model from a minimum number of range images of the object. It terminates reconstruction when it reaches a minimum threshold of accuracy. It uses methods based on the occluded regions of the reconstructed surface to decide where to place the camera and evaluates based on the reconstruction rather than pick up success. Krainin et al. [21] present an approach for autonomous object modeling using a depth camera observing the robot's hand as it moves the object. This system provides a 3d construction of the object autonomously. Our approach uses vision-based features and evaluates based on grasp success. Eye-in-hand laser sensor. [?]

ST: Need to find the instance-based work that Erik mentioned when he said it was a "solved problem."

Velez et al. [38] created a mobile robot that explores the environment and actively plans paths to acquire views of objects such as doors. However it uses a fixed model of the

object being detected rather than updating its model based on the data it has acquired from the environment.

Methods for planning in information space [13, 1, 30] have been applied to enable mobile robots to plan trajectories that avoid failures due to inability to accurately estimate positions. Our approach is focused instead on object detection and manipulation, actively acquiring data for use later in localizing and picking up objects. **ST: May need to say more here depending on what GRATA actually is.**

Early models for pick-and-place rely on has been studied since the early days of robotics [5, 25]. These systems relied on models of object pose and end effector pose being provided to the algorithm, and simply planned a motion for the arm to grasp. Modern approaches use object recognition systems to estimate pose and object type, then libraries of grasps either annotated or learned from data [32, 12, 27]. These approaches attempt to create systems that can grasp arbitrary objects based on learned visual features or known 3d configuration. Collecting these training sets is an expensive process and is not accessible to the average user in a non-robotics setting. If the system does not work for the user's particular application, there is no easy way for it to adapt or relearn. Our approach, instead, enables the robot to autonomously acquire more information to increase robustness at detecting and manipulating the specific object that is important to the user at the current moment.

Visual-servoing based methods [7] **ST: Need a whole paragraph about that.**

ST: Ciocarlie et al. [9] seems highly relevant, could not read from the train's wifi. Existing work has collected large database of object models for pose estimation, typically curated by an expert [23]. Kasper et al. [16] created a semiautomatic system that fuses 2d and 3d data, but the setup requires a special rig including a turntable and a pair of cameras. Our approach requires an active camera mounted on a robot arm, but no additional equipment, so that a robot in the home can autonomously acquire new models.

?] describes an approach for lifelong robotic object discovery, which infers object candidates from the robot's perceptual data. This system does not learn grasping models and does not actively acquire more data to recognize, localize, and grasp the object with high reliability. It could be used as a first-pass to our system, after which the robot uses an active method to acquire additional data enablin it to grasp the object. Approaches that integrate SLAM and moving object tracking estimate pose of objects over time but have not been extended to manipulation [39, 11, 31, 35].

Our approach is similar to the philosophy adopted by Rethink Robotic's Baxter robot, and indeed, we use Baxter as our test platform [10]. **ST: Haven't actually read this paper, just making stuff up based on Rod's talks. Should read the paper and confirm.** Baxter's manufacturing platform is designed to be easily learned and trained by workers on the factory floor. The difference between this system and our approach is we rely on the robot to autonomously collect the training information it needs to grasp the object, rather than

requiring this training information to be provided by the user.

Robot systems for cooking [4, 3] or furniture assembly [20] use many simplifying assumptions, including pre-trained object locations or using VICON to solve the perceptual system. We envision vision or RGB-D based sensors mounted on the robot, so that a person can train a robot to recognize and manipulate objects wherever the robot finds itself.

Approaches to plan grasps under pose uncertainty [36] or collect information from tactile sensors [14] using POMDPs. ?] describe new algorithms for solving POMDPs by tracking belief state with a high-fidelity particle filter, but using a lower-fidelity representation of belief for planning, and tracking the KL divergence.

Hudson et al. [15] used active perception to create a grasping system capable of carrying out a variety of complex tasks. Using feedback is critical for good performance, but the model cannot adapt itself to new objects.

VIII. CONCLUSION

ST: First paragraph: contributions. What are the things this paper has done to advance the state of the art?

ST: Next paragraphs: future work, spiraling upward to more and more ambitious extensions.

Right now, NODE runs on Baxter. We will port NODE to PR2 and other AH systems. GRATA could be applied in other domains as well. What are some examples?

REFERENCES

- [1] Nikolay Atanasov, Jerome Le Ny, Kostas Daniilidis, and George J Pappas. Information acquisition with sensing robots: Algorithms and error bounds. *arXiv preprint arXiv:1309.5390*, 2013.
- [2] Joseph E Banta, LR Wong, Christophe Dumont, and Mongi A Abidi. A next-best-view system for autonomous 3-d object reconstruction. *Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on*, 30(5):589–598, 2000.
- [3] Michael Beetz, Ulrich Klank, Ingo Kresse, Alexis Maldonado, L Mosenlechner, Dejan Pangercic, Thomas Ruhr, and Moritz Tenorth. Robotic roommates making pancakes. In *Humanoid Robots (Humanoids), 2011 11th IEEE-RAS International Conference on*, pages 529–536. IEEE, 2011.
- [4] Mario Bollini, Stefanie Tellex, Tyler Thompson, Nicholas Roy, and Daniela Rus. Interpreting and executing recipes with a cooking robot. In *Proceedings of International Symposium on Experimental Robotics (ISER)*, 2012.
- [5] Rodney A Brooks. Planning collision-free motions for pick-and-place operations. *The International Journal of Robotics Research*, 2(4):19–44, 1983.
- [6] Lillian Chang, Joshua R Smith, and Dieter Fox. Interactive singulation of objects from a pile. In *Robotics and Automation (ICRA), 2012 IEEE International Conference on*, pages 3875–3882. IEEE, 2012.

- [7] François Chaumette and Seth Hutchinson. Visual servo control. i. basic approaches. *Robotics & Automation Magazine, IEEE*, 13(4):82–90, 2006.
- [8] Ming-Ming Cheng, Ziming Zhang, Wen-Yan Lin, and Philip Torr. Bing: Binarized normed gradients for objectness estimation at 300fps. In *IEEE CVPR*, 2014.
- [9] Matei Ciocarlie, Kaijen Hsiao, Edward Gil Jones, Sachin Chitta, Radu Bogdan Rusu, and Ioan A Şucan. Towards reliable grasping and manipulation in household environments. In *Experimental Robotics*, pages 241–252. Springer, 2014.
- [10] C Fitzgerald. Developing baxter. In *Technologies for Practical Robot Applications (TePRA), 2013 IEEE International Conference on*, pages 1–6. IEEE, 2013.
- [11] Garratt Gallagher, Siddhartha S Srinivasa, J Andrew Bagnell, and Dave Ferguson. Gatmo: A generalized approach to tracking movable objects. In *Robotics and Automation, 2009. ICRA’09. IEEE International Conference on*, pages 2043–2048. IEEE, 2009.
- [12] Corey Goldfeder, Matei Ciocarlie, Hao Dang, and Peter K Allen. The columbia grasp database. In *Robotics and Automation, 2009. ICRA’09. IEEE International Conference on*, pages 1710–1716. IEEE, 2009.
- [13] Ruijie He, Sam Prentice, and Nicholas Roy. Planning in information space for a quadrotor helicopter in a gps-denied environment. In *Robotics and Automation, 2008. ICRA 2008. IEEE International Conference on*, pages 1814–1820. IEEE, 2008.
- [14] Kaijen Hsiao, Leslie Pack Kaelbling, and Tomás Lozano-Pérez. Task-driven tactile exploration. *Robotics: Science and Systems Conference*, 2010.
- [15] Nicolas Hudson, Thomas Howard, Jeremy Ma, Abhinandan Jain, Max Bajracharya, Steven Myint, Calvin Kuo, Larry Matthies, Paul Backes, Paul Hebert, et al. End-to-end dexterous manipulation with deliberate interactive estimation. In *Robotics and Automation (ICRA), 2012 IEEE International Conference on*, pages 2371–2378. IEEE, 2012.
- [16] Alexander Kasper, Zhixing Xue, and Rüdiger Dillmann. The kit object models database: An object model database for object recognition, localization and manipulation in service robotics. *The International Journal of Robotics Research*, 31(8):927–934, 2012.
- [17] David Kent and Sonia Chernova. Construction of an object manipulation database from grasp demonstrations. In *Intelligent Robots and Systems (IROS 2014), 2014 IEEE/RSJ International Conference on*, pages 3347–3352. IEEE, 2014.
- [18] David Kent, Morteza Behrooz, and Sonia Chernova. Crowdsourcing the construction of a 3d object recognition database for robotic grasping. In *Robotics and Automation (ICRA), 2014 IEEE International Conference on*, pages 4526–4531. IEEE, 2014.
- [19] Object Recognition Kitchen. http://wg-perception.github.io/object_recognition_core/, 2014.
- [20] Ross A. Knepper, Stefanie Tellex, Adrian Li, Nicholas Roy, and Daniela Rus. Single assembly robot in search of human partner: Versatile grounded language generation. In *Proceedings of the HRI 2013 Workshop on Collaborative Manipulation*, 2013.
- [21] Michael Krainin, Peter Henry, Xiaofeng Ren, and Dieter Fox. Manipulator and object tracking for in-hand 3d object modeling. *The International Journal of Robotics Research*, 30(11):1311–1327, 2011.
- [22] Simon Kriegel, T Bodenmiller, Michael Suppa, and Gerd Hirzinger. A surface-based next-best-view approach for automated 3d model completion of unknown objects. In *Robotics and Automation (ICRA), 2011 IEEE International Conference on*, pages 4869–4874. IEEE, 2011.
- [23] Kevin Lai, Liefeng Bo, Xiaofeng Ren, and Dieter Fox. A large-scale hierarchical multi-view rgb-d object dataset. In *Robotics and Automation (ICRA), 2011 IEEE International Conference on*, pages 1817–1824. IEEE, 2011.
- [24] Kevin Lai, Liefeng Bo, Xiaofeng Ren, and Dieter Fox. A scalable tree-based approach for joint object and pose recognition. In *Twenty-Fifth Conference on Artificial Intelligence (AAAI)*, August 2011.
- [25] Tomás Lozano-Pérez, Joseph L. Jones, Emmanuel Mazer, and Patrick A. O’Donnell. Task-level planning of pick-and-place robot motions. *IEEE Computer*, 22(3):21–29, 1989.
- [26] Natalia Lyubova, David Filliat, and Serena Ivaldi. Improving object learning through manipulation and robot self-identification. In *Robotics and Biomimetics (RO-BIO), 2013 IEEE International Conference on*, pages 1365–1370. IEEE, 2013.
- [27] Antonio Morales, Eris Chinellato, Andrew H Fagg, and Angel Pasqual del Pobil. Experimental prediction of the performance of grasp tasks from visual features. In *Intelligent Robots and Systems, 2003.(IROS 2003). Proceedings. 2003 IEEE/RSJ International Conference on*, volume 4, pages 3423–3428. IEEE, 2003.
- [28] Hai Nguyen and Charles C Kemp. Autonomously learning to visually detect where manipulation will succeed. *Autonomous Robots*, 36(1-2):137–152, 2014.
- [29] Robert Platt, Leslie Kaelbling, Tomas Lozano-Perez, and Russ Tedrake. Simultaneous localization and grasping as a belief space control problem. In *International Symposium on Robotics Research*, volume 2, 2011.
- [30] Samuel Prentice and Nicholas Roy. The belief roadmap: Efficient planning in belief space by factoring the covariance. *The International Journal of Robotics Research*, 2009.
- [31] Renato F Salas-Moreno, Richard A Newcombe, Hauke Strasdat, Paul HJ Kelly, and Andrew J Davison. Slam++: Simultaneous localisation and mapping at the level of objects. In *Computer Vision and Pattern Recognition (CVPR), 2013 IEEE Conference on*, pages 1352–1359. IEEE, 2013.
- [32] Ashutosh Saxena, Justin Driemeyer, and Andrew Y Ng. Robotic grasping of novel objects using vision. *The International Journal of Robotics Research*, 27(2):157–

173, 2008.

- [33] David Schiebener, Julian Schill, and Tamim Asfour. Discovery, segmentation and reactive grasping of unknown objects. In *Humanoids*, pages 71–77, 2012.
- [34] David Schiebener, Jun Morimoto, Tamim Asfour, and Aleš Ude. Integrating visual perception and manipulation for autonomous learning of object representations. *Adaptive Behavior*, 21(5):328–345, 2013.
- [35] Antonio HP Selvatici and Anna HR Costa. Object-based visual slam: How object identity informs geometry. 2008.
- [36] Freek Stulp, Evangelos Theodorou, Jonas Buchli, and Stefan Schaal. Learning to grasp under uncertainty. In *Robotics and Automation (ICRA), 2011 IEEE International Conference on*, pages 5703–5708. IEEE, 2011.
- [37] Ales Ude, David Schiebener, Norikazu Sugimoto, and Jun Morimoto. Integrating surface-based hypotheses and manipulation for autonomous segmentation and learning of object representations. In *Robotics and Automation (ICRA), 2012 IEEE International Conference on*, pages 1709–1715. IEEE, 2012.
- [38] Javier Velez, Garrett Hemann, Albert S Huang, Ingmar Posner, and Nicholas Roy. Active exploration for robust object detection. In *IJCAI Proceedings-International Joint Conference on Artificial Intelligence*, volume 22, page 2752, 2011.
- [39] Chieh-Chih Wang, Charles Thorpe, Sebastian Thrun, Martial Hebert, and Hugh Durrant-Whyte. Simultaneous localization, mapping and moving object tracking. *The International Journal of Robotics Research*, 26(9):889–916, 2007.
- [40] M. Zhu, N. Atanasov, G. Pappas, and K. Daniilidis. Active Deformable Part Models Inference. In *European Conference on Computer Vision (ECCV)*, 2014.