Vision-based Robot Manipulation Learning via Human Demonstrations

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Abstract—Vision-based learning methods provide promise for robots to learn complex manipulation tasks. However, how to generalize the learned manipulation skills to real-world interactions remains an open question. In this work, we study robotic manipulation skill learning from a single third-person view demonstration by using activity recognition and object detection in computer vision. To facilitate generalization across objects and environments, we propose to use a prior knowledge base in the form of a text corpus to infer the object to be interacted with in the context of a robot. We evaluate our approach in a real-world robot, using several simple and complex manipulation tasks commonly performed in daily life. The experimental results show that our approach achieves good generalization performance even from small amounts of training data.

I. INTRODUCTION

In order to accomplish tasks such as handing a cup of water, autonomous robots need to be able to perform more complex manipulation. Robotic manipulation is one of the central research areas in robotics, involving perception, planning, and control. Motion planning for complex manipulation remains a challenge, especially in unstructured dynamic real-world scenes. Among various existing techniques, imitation-from-observation offers considerable promise [17][7].

The idea behind imitation-from-observation is to build robots that learn to behave by observing the behavior of human beings. Benefiting from the power of deep learning, various learning based methods work well at generating manipulation actions [19][20][5]. However, generalization to new objects and situations is still a challenge and require further effort, since the contexts of robot executions differ from those of human demonstrations in most practical setting.

The difficulty with generalization lies in the fact that the manipulated objects matter a lot when performing a task. For example, consider a scenario in which an apple is put into a bowl by a human demonstrator. Then, we give the robot a banana and a plate and hope that the robot could perform the similar task. However, the demonstrations provide incomplete information necessary to interact with new objects because they never occur before. Especially, how can the robot know that it should place the banana in the plate, but not vice versa.

In this work, we propose a robotic manipulation skill learning approach facilitating generalization across objects and environments. Among all the solutions for learning from demonstration, of particular interest in this work is that only a single third-person view demonstration is used. This not only approximates the human way of learning behaviors, it also makes our approach salable in real world application. Our approach utilizes action recognition to learning manipulation behavior from human demonstration in the form of the sequence of actions so as to generalize across variations in context. In addition, object detection in computer vision is applied to produce the identity and pose of an object in the context of a robot. In contrast to previous methods, prior knowledge about the relationship between objects and actions is incorporated into previously learned manipulation action in order to reason about the object to be interacted with. Although we need collect data to train the manipulation learning model and object detecting model separately, training on real or simulated robots is avoided in our method. As we known, it is difficult and sometimes impossible to collect the sufficient data required by training in this situation. We validate our approach through real world experiments on UR5 robot and demonstrate its robustness and generalization over a wide variation in manipulation tasks and objects.

The main contributions of our work are as follows.

1) We propose a more general imitation-from-observation framework to improve generalization over objects and environments.

2) We implement our method on an industrial UR5 robot to validate our insight and framework.

3) We further conduct experiments using manipulation tasks common in daily life to evaluate the effectiveness of robot skill generation and the generalization performance.

The rest of this paper is organized as follows. Section II discusses the current state of robotic skill learning from visual observation. Section III presents the details of our approach. Section IV introduces system implementation in brief, followed by an experimental evaluation. Section V concludes the paper.

II. RELATED WORKS

Learning from demonstration has been studied extensively in the field of robotics for decades. Recent advances in deep learning have made learning from observation practical, by which robots learn to perform manipulation tasks from observing human behavior. Many researchers have explored the idea of observation learning and a number of different techniques have been developed in robotics and artificial intelligence. For a more complete review on recent work of the field, we recommend the reader refer to [1]. In this section, we discuss current work related to our approach in brief.
Behavior cloning is a classical way to learn robotic manipulation, in which a direct mapping from states to actions is learned to reproduce either the trajectories/joint configurations of a robot, or a sequence of actions to be executed by a robot. The latter situation is referred to as task level learning that are concerned in this work. In order to acquire more information associated with human demonstration, new techniques developed in computer vision are investigated in the field of robot learning. Hejia Zhang et al. [2] propose a framework for executing collaborative manipulation tasks learned from full-length videos on the website based on object recognition. A two phased approach is introduced by Lea et al. [3], in which features are extracted for each frame by using a Temporal Convolutional Network [4], and further used for action classification. In addition, action recognition combined with instance segmentation also provides an effective way for robot manipulation learning. The work by Wang He et al. [5] propose an approach using VGG-16 [6] network to take a pair of RGB and motion images as the input, thereby utilizing both spatial and temporal information [4] to generate action plots for robot task execution. In the work by Shuo Yang [7], a novel deep model based on grasp detection network and video captioning network is proposed to learn to reproduce stacking blocks and placing fruits tasks. Maria Koskinopoulou et al. [8] formulate a latent representation of demonstrated behaviors and associate the representation with the corresponding robotic actions. Cubek et al. [9] introduce a method to recognize human-demonstrated task on an object-relational abstraction layer. Our approach does not only take use of object detection and action recognition, but also incorporate human knowledge into action planning. In this way, the generalization capability is greatly improved.

Contrary to usual behavior cloning schemes, an alternative way is to learn perception and planning in an end-to-end fashion. In this setting, tasks are learned directly from raw videos of a human demonstration and a robots execution by using a cost function or a reward signal. However, this also poses a challenge for generating expected trajectories from samples in such a high dimensional input space. To this end, meta-learning based methods leverage demonstration data from a variety of meta-training tasks [10] [11] [17]. Moreover, domain-adaptive provides generalization over different objects and environments for some tasks [17]. In the research line inverse reinforcement learning, a lot of methods are proposed to improve the sample efficiency. For example, the context translation model that predicts what an expert would do in the robot context is used as reward function in the training of control policy [12]. The experts cost function is recovered with inverse reinforcement learning and then used to extract a policy [13]. Activity features obtained from the convolutional feature encoder of an activity classifier pre-trained on a large activity dataset are used to generate a reward signal for the learning algorithm [14].

III. PROPOSED METHODS

We present an approach that enables robots to learn vision-based manipulation skills from a third-person view demonstration. The framework of our approach is shown in Fig. composed with four modules: manipulation learner, object sensor, action planner and action executor. For a given demonstration video, manipulation learner extracts the sequence of action primitives (actions in short) by using deep activity recognition models. After that, the robot starts its manipulation task by capturing raw images produced by a camera. Object sensor processes raw images and reasons about the identities and poses of task-relevant objects in the workspace. To execute an action, the object being interacted with is inferred based on the current action and the likelihood distribution of which the object is relevant to the action. To this end, human knowledge about the relationship between objects and actions is introduced in action planner in the form of a text corpus. As a result, action planner outputs an action and the identity and pose of the object to be interacted with if necessary. It is worth note that actions are pre-programmed in action executor based on the basic robot operations, including moving and turning the end effector.
and opening and closing the gripper. Details of our method are discussed in the following subsections.

A. Manipulation Learning

Vision-based action recognition is a powerful tool for understanding image and video in computer video. The basic idea of action recognition is to describe human behavior as a sequence of basic actions occurring in time order by classifying where an action is present or not in videos. In this work, we are interested in enabling robots to learn manipulation skills used in daily life, such as picking up something, pouring water into a cup and so on. Based on observation of our daily living manipulations, we define seven action primitives (idle, move, pick, place, push, tilt, rotate), so as to represent human demonstration and control robots execution. For example, we could describe the manipulation task put object A into object B as a sequence of action primitives <idle, move, pick (object A), move, place (object B)>.

For a given demonstration, AP-CNN generates n action primitives, where n is the number of frames in video. To reduce the redundancy in consecutive frames, a window based filter is applied. With a window moving forward from the head to the end of action primitive sequence, continuously identical primitives are considered as a single action primitive. The specific procedure of window filter is shown in Algorithm 1.

Algorithm 1 Action Primitive Window Filter

| Input: Action primitive sequence, S_n; Window width, w |
| Output: Key action primitives, K |

1: i ← 0
2: K ← ∅
3: repeat
4: find the most frequent $S_M$ in $\{S_i, S_{i+1}, ..., S_{i+w}\}$
5: if $S_M$ is not the last one in $K$ then
6: append $S_M$ to $K$
7: end if
8: i ← i + 1
9: until $i == n - w$
10: return $K$

B. Object Sensing

The object sensor module plays a sensor-like role in our framework, through which object information including object category and object pose is computed from raw RGB images obtained by a robot camera. Its worth noting that the workspace of a robot is constrained to a tabletop in this work. Constrained workspace could allow us to focus on more important aspects of our framework.

As shown in Fig. 1, a popular object detection deep network Mask R-CNN [16] is applied to detect the category of objects and their corresponding masks from raw RGB image input. It works in two steps. The first is to recognize
candidate object bounding boxes using Region Proposal Network (RPN) [15]. Then it is to predict the class, box offset and a binary mask for each region of interest (RoI). For presentation purposes, the result of Mask R-CNN is defined as follow:

\[ C = \{c_1, c_2, ..., c_n\} \]  
\[ M = \{m_1, m_2, ..., m_n\} \]

where \( C \) is the set of types of objects recognized, \( M \) is the set of masks on the detected objects, and \( n \) indicates how many objects are recognized in total. Furthermore, the set of pixel points \( m_i \) is expressed as follow, representing the mask that covers the corresponding object.

\[ m_i = \{(x_1, y_1), (x_2, y_2), ..., (x_j, y_j)\} \]

where \( j \) is the number of pixel points in mask \( m_i \). Therefore, for each detected object, 3d object pose is represented as follow:

\[
m = \{x, y, \theta, c\} \tag{4}
\]

where, \((x, y)\) is the center of a detected object, \(\theta\) is the orientation of the mask relative to the horizontal axis, and \(c\) denotes the object class. To estimate the object pose, we utilize a principle component analysis (PCA) based algorithm, in which, \((x, y)\) is the mean point of \(n\) pixel points in \(m_i\) and \(\theta\) is the main direction with the largest variance. The example results of Mask R-CNN and the PCA are visualized in Fig. 4.

C. Action Planning

Action planner is an intelligent part in our framework for adapting to changing environments. In this work, we consider the situation where a robot works under the circumstances with a varied configuration, instead of a constrained one. It means that robots have to plan and execute tasks in new scenes that are different from those in the human demonstration. To achieve this, both world knowledge and some reasoning ability are required to match object instances to the sequence of actions learned.

To incorporate our prior knowledge about action, we construct a knowledge base in the form of text corpus. Our knowledge base is made up of sentences in English which describe how human users act for a given object. For example, pick the apple or push the pear to the white plate and etc. In total, we manually collect 1340 sentences according to the tasks in our experiment. However, it is also possible to collect sentences through learning method such as video caption. Theoretically, the ability of action planner can be greatly improved with more knowledge about human behavior.

Furthermore, we refer the work [2] to combine objects with actions using a probability model as follow:

\[ o = \arg \max_{o_i \in \mathcal{O}} P(o_i | A = a) \]  
\[ \mathcal{O} = \text{the detected objects set from Mask R-CNN}, \ a \ is \ the \ current \ planning \ action \ primitive \ from \ the \ task. \ Based \ on \ the \ corpus, \ we \ first \lye filter \ all \ the \ sentences \ related \ with \ the \ current \ action \ primitive \ \( a \) \ and \ then \ find \ the \ object \ \( o \) \ with \ the
highest probability in these filtered sentences. Depending on
the interaction property of an action, the number of objects
that action planner generates varies. For example, pick, place
and rotate are actions involving one manipulation object, and
push and tilt are related with two objects. In the case of one
manipulation object, the object in the detected set with the
highest frequency is chosen the target object. In other cases,
all the objects in the knowledge base are sorted by their
frequency and checked in order if these objects are in the
detected set.

IV. EXPERIMENTS

We implement our framework on a real world robot for
empirical validation by studying the effectiveness of human
demonstration based manipulation learning on vision-based
tasks. In particular, five simple tasks and two complex
tasks are designed to evaluate the ability to learn manipu-
lation skills and generalization over objects and situations.
Each trial starts with the demonstrator performing a spec-
ified task. After observing human behavior, the robot is
to adapt manipulation learned to the objects in its own
context. A test is successful if the robot performs equally
as well as demonstrator. The video results are available at:
https://youtu.be/2zDHKNMdOFo.

A. Implement Details

The AP-CNN is implemented on top of Resnet50 [24], a
deep network pre-trained on Imagenet for object recognition.
We reuse the convolutional part of Resnet50, which takes a
240 × 360 images with three channels as input and outputs
a 2048 dimension vector to the LSTM. AP-CNN ends with
fully connected layer interleaved with ReLU and a softmax
layer for action classification.

To collect data for training AP-CNN, we record human
demonstrations involving not only simple manipulation tasks
but also complex tasks. Specifically, 100 demonstration
videos are made for each simple task, and 50 videos for each
complex task. Finally, 600 videos in our dataset are randomly
partitioned into a training set with 90% of the data, and a test
set with the remaining data. Adam optimization [23] with a
learning rate of 1e-4 is used to train AP-CNN. It took about
11 hours to train the AP-CNN on a single desktop PC with
64 GB RAM and a RTX 2080ti GPU.

The implementation of Mask R-CNN is based on [16].
To train Mask R-CNN, we collect 1782 images involving 28
different kinds of objects taken by the RealSense [21] camera
and resize the RGB images in the dataset into 600 × 600.
All these images are labeled manually by LabelMe [22].

Our hardware platform is an industrial UR5 robot arm
equipped with an RG2 gripper. The RealSense camera is
located 100 cm above the work surface, producing images
at a resolution of 600 × 600 pixels. A laptop with a RTX
2080 GPU acceleration is used for real-time robotic control
and communication with UR5 via TCP/IP protocol.

Fig. 5. The example results of robot learning from demonstrations. (a): a
pick-place task executed by the robot, learned from Fig. 3(a). (b): a pushing
task executed by robot, learned from Fig. 3(b). (c): an opening bottle task
learnt from Fig. 3(c). (d): a pouring bottle task learnt from Fig. 3(d). (e): a
delivering task learnt from the demonstration in Fig. 3(e). Note that the
objects that the robot faces when executing tasks are different from those
in the demonstrations.

B. Simple Task Learning

We first evaluate our approach on simple manipulation
tasks. To this end, the following five operations commonly
used in our daily life are chosen.

- Pick-place task: picking up an object and placing it into
  a container.
- Pushing task: pushing an object toward a goal position.
- Opening task: turning the cap to open an object.
- Pouring task: grasping an object and tilting it to pour
  something into a container.
- Delivering task: picking up an object and handing it to
  someone.

The video pictures of each operation performed by human
are shown in Fig. 3 respectively. For each task, human demonstration is performed once, while 10 trials of the robots task execution are conducted with objects unseen in human demonstration. Moreover, to introduce uncertainty in robotic execution, the objects are randomly placed on the work surface for each trial. The example video pictures of robots execution on five simple tasks are shown in Fig. 5 respectively. The success rates and objects used in human demonstration and the robots executions are shown in Table I. The overall success of our approach across all simple tasks is over 90% in the circumstance of novel objects and changing situations.

### C. Complex Tasks Learning

Furthermore, we test our approach in a more complicated configuration. In this setting, two complex tasks composed of two or more simple tasks are designed. As shown in Fig. 6(a), in the first complex task, the demonstrator puts all items on the table into a white box and delivers the box to another person. In the second complex task, as shown in Fig. 6(c), the demonstrator grasps and tilts a black bottle to pour something into a white box and then delivers the box to another person. Video pictures of the robots execution are shown in Fig. 6(b)(d), respectively. Similarly to, the robot executes the tasks with novel objects and their changing positions. We perform 10 runs for each task and record success rates of the results. Success rate and the objects used in human demonstration and the robots executions are shown in Table II.

In our experiments, failure cases occur in both simple and complex task execution. Some failures are blamed on object detection, where no object was discovered or where the discovery is wrong or incomplete. The other cases are related to manipulation learner, where the sequence of action primitives extracted is partially inconsistent, possibly leading to conflicting action choices in action planner. In general, these failures could be prevented by increasing training data.

### V. CONCLUSIONS

In this work, we propose a robotic learning system capable of learning manipulation skills from visual observations alone. Our approach to imitation learning relies on third-person demonstrations, which makes our approach applicable in more general scenarios. To achieve the goal, we present how action recognition and objection detection are combined with action planning to give a general solution for robot learning. Overall, the results show that our combination of techniques is effective and efficient to generate robot skills. Experimental evaluation on complex manipulation tasks from the household domain demonstrates the generalization performance of our framework. Thus, we believe that our approach offers a promising way to design autonomous robotic systems with human-like manipulation skills. However, failure occurred in our experiments still leave room for improvement, especially for action planning. A general and robust action planner is an important area for future work.

### ACKNOWLEDGMENT

This work was supported by State Key Laboratory of Software Development Environment under Grant No SKLSDE-2019ZX-03.

### REFERENCES

[1] Osa, Takayuki, Joni Pajarinen, Gerhard Neumann, J. Andrew Bagnell, Pieter Abbeel and Jan Peters. "An Algorithmic Perspective on Imitation Learning. Foundations and Trends in Robotics 7 (2018): 1-179.
[2] Zhang, Hejia , and S. Nikolaidis . "Robot Learning and Execution of Collaborative Manipulation Plans from YouTube Videos." arXiv preprint arXiv:1911.10686 (2019).
[3] Lea, Colin, Ren Vidal, and Gregory D. Hager. “Learning convolutional action primitives for fine-grained action recognition.” 2016 IEEE international conference on robotics and automation (ICRA). IEEE, 2016.
[4] Lea, Colin, et al. “Temporal convolutional networks: A unified approach to action segmentation.” European Conference on Computer Vision. Springer, Cham, 2016.
[5] Wang, He, et al. “Learning a Generative Model for MultiStep HumanObject Interactions from Videos.” Computer Graphics Forum. Vol. 38. No. 2. 2019.
[6] Simonyan, Karen, and Andrew Zisserman. “Very deep convolutional networks for large-scale image recognition.” arXiv preprint arXiv:1409.1556 (2014).
[7] Shuo, Yang, et al. “Learning Actions from Human Demonstration Video for Robotic Manipulation.” 2019 IEEE International Conference on Intelligent Robots systems(IROS). IEEE, 2019.
[8] Koskinopoulou, Maria, Stylianos Piperakis and Panos E. Trahanias. Learning from Demonstration facilitates Human-Robot Collaborative task execution. 2016 11th ACM/IEEE International Conference on Human-Robot Interaction (HRI) (2016): 59-66.
[9] Cubek, Richard, Wolfgang Ertel and Gmitter Palm. “High-level learning from demonstration with conceptual spaces and subspace clustering.” 2015 IEEE International Conference on Robotics and Automation (ICRA) (2015): 2592-2597.

### TABLE I

| Task      | Demonstration Objects | Workspace Objects | Success Rate  |
|-----------|-----------------------|-------------------|---------------|
| pick-place| plate, apple   | plastic-box banana| 100%(10/10)   |
| push away | carrot      | grape croissant   | 100%(10/10)   |
| open bottle| black-bottle plastic-box | paper-box blue-bottle | 90%(9/10) |
| pour water | paper-box banana black-bottle | paper-box blue-bottle | 90%(9/10) |

### TABLE II

| Task      | Demonstration Objects | Workspace Objects | Success Rate  |
|-----------|-----------------------|-------------------|---------------|
| 1         | carambol, croissant, cake, paper-box | plastic-box apple toy-train corn | 90%(9/10) |
| 2         | black-bottle paper-box | blue-bottle paper-box | 90%(9/10) |
Fig. 6. The examples of robot execution on combined tasks. (a) shows a demonstration of clearing up the table and delivering the white box to human’s hand. (b) shows the robot’s execution of this kind of task in a new environment. In subfigure (c), the pictures show a demonstration of opening the bottle, pouring in the box and delivering the box to human’s hand. (d) shows the robot’s execution of this complex task in a new environment.

[10] Duan, Yan, Marcin Andrychowicz, Bradly C. Stadie, Jonathan Ho, Jonas Schneider, Ilya Sutskever, Pieter Abbeel and Wojciech Zaremba. “One-Shot Imitation Learning. NIPS (2017).
[11] Finn, Chelsea, Tianhe Yu, Tianhao Zhang, Pieter Abbeel and Sergey Levine. “One-Shot Visual Imitation Learning via Meta-Learning. ArXiv abs/1709.04905 (2017): n. pag.
[12] Liu, Yuxuan et al. “Imitation from Observation: Learning to Imitate Behaviors from Raw Video via Context Translation. 2018 IEEE International Conference on Robotics and Automation (ICRA) (2017): 1118-1125.
[13] Ho, Jonathan and Stefano Ermon. “Generative Adversarial Imitation Learning. NIPS (2016).
[14] Pauly, Leo, Wisdom C. Agboh, Mohamed Abdellatif and David C. Hogg. “One-Shot Observation Learning Using Visual Activity Features. (2018).
[15] Ren, Shaoqing, et al. “Faster r-cnn: Towards real-time object detection with region proposal networks.” Advances in neural information processing systems. 2015.
[16] He, Kaiming, Georgia Gkioxari, Piotr DollÃ© and Ross B. Girshick. “Mask R-CNN. 2017 IEEE International Conference on Computer Vision (ICCV) (2017): 2980-2988.
[17] Yu, Tianhe, Chelsea Finn, Annie Xie, Sudeep Dasari, Tianhao Zhang, Pieter Abbeel and Sergey Levine. “One-Shot Imitation from Observing Humans via Domain-Adaptive Meta-Learning. ArXiv abs/1802.01557 (2018): n. pag.
[18] Hatori, Jun et al. “Interactively Picking Real-World Objects with Unconstrained Spoken Language Instructions. 2018 IEEE International Conference on Robotics and Automation (ICRA) (2017): 3774-3781.
[19] Feichtenhofer, Christoph , A. Pinz , and A. Zisserman . “Convolutional Two-Stream Network Fusion for Video Action Recognition.” 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) IEEE, 2016.
[20] Donahue, Jeff, Lisa Anne Hendricks, Marcus Rohrbach, Subhashini Venugopalan, Sergio Guadarrama, et al. “Long-term recurrent convolutional networks for visual recognition and description. 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2014): 2625-2634.
[21] Keselman, Leonid, et al. “Intel realsense stereoscopic depth cameras,” Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops. 2017.
[22] Russell, Bryan C., Antonio Torralba, Kevin P. Murphy and William T. Freeman. “LabelMe: A Database and Web-Based Tool for Image
[23] Kingma, Diederik P., and Jimmy Ba. “Adam: A method for stochastic optimization.” arXiv preprint arXiv:1412.6980 (2014).
[24] He, Kaiming et al. “Deep Residual Learning for Image Recognition.” 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2015): 770-778.