Robot Learning and Execution of Collaborative Manipulation Plans from YouTube Cooking Videos

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Abstract—People often watch videos on the web to learn how to cook new recipes, assemble furniture or repair a computer. We wish to enable robots with the very same capability. This is challenging; there is a large variation in manipulation actions and some videos even involve multiple persons, who collaborate by sharing and exchanging objects and tools. Furthermore, the learned representations need to be general enough to be transferable to robotic systems. On the other hand, previous work has shown that the space of human manipulation actions has a linguistic, hierarchical structure that relates actions to manipulated objects and tools. Building upon this theory of language for action, we propose a framework for understanding and executing demonstrated action sequences from full-length, unconstrained cooking videos on the web. The framework takes as input a cooking video annotated with object labels and bounding boxes, and outputs a collaborative manipulation action plan for one or more robotic arms. We demonstrate performance of the system in a standardized dataset of 100 YouTube cooking videos, as well as in three full-length Youtube videos that include collaborative actions between two participants. We additionally propose an open-source platform for executing the learned plans in a simulation environment as well as with an actual robotic arm.

I. INTRODUCTION

We focus on the problem of learning collaborative action plans for a robot. Our goal is to have the robot “watch” unconstrained videos on the web, extract the action sequences shown in the videos and convert them to an executable plan that it can perform either independently, or as part of a human-robot or robot-robot team.

Learning from online videos is hard, particularly in collaborative settings: it requires recognizing the actions executed, together with manipulated tools and objects. In many collaborative tasks these actions include handing objects over or holding an object for the other person to manipulate. There is a very large variation in how the actions are performed and collaborative actions may overlap spatially and temporally [14].

On the other hand, actions exhibit a syntactic-like structure that is common in language. Pastra and Aloimonos [31] realize this connection, which is corroborated by neurobiological evidence [9, 11] and propose a minimalist grammar for action understanding. Yang and Aloimonos [44, 45] build upon this theoretical insights to propose a manipulation action grammar, where symbolic information of manipulated objects and tools are parsed to interpret action sequences from 12 YouTube video clips.

We build upon this theory of language for action to propose a framework for understanding both single and collaborative actions from full-length YouTube videos. Our key insight is that hands contain both spatial and temporal information of the demonstrated actions. This allows using hand trajectories to temporally segment full-length videos to short clips, derive hand-object and object-object associations and infer the demonstrated actions.

Our framework takes as input a YouTube video showing a collaborative task from start to end. We assume that the objects in the video are annotated with labels and bounding boxes, e.g., by running a YOLOv3 algorithm [35] (Fig. 1). We also assume a skill library that associates a detected action with skill-specific motion primitives. We focus on cooking...
tasks because of the variety in manipulation actions and their importance in home service robotics.

Fig. 2 shows the components of the proposed framework. We make the following contributions:

- We propose a context-free collaborative action grammar that generalizes previous work on action grammar \[45\] to account for collaborative actions, e.g., a person holding a plate for someone else, and object-object associations, such as “the chicken on the chopping board.” The grammar builds upon the insight that hands are the main driving force of both individual and collaborative manipulation actions \[44\]. We use the grammar-based rules to derive interpretable action trees from the visual processing system described below.

- We present a visual processing system for action understanding from full-length videos. The system detects the human hands in the video and uses the hand trajectories to split the video into clips. It then associates objects and hands with objects with other objects spatially and temporally to identify which objects are manipulated. We use the commonsense reasoning assumption to recognize individual actions and temporally track which person is manipulating each object to identify and recognize collaborative actions.

- We propose an open-sourced platform for generating and executing an action graph in both simulation and in the real world that concatenates the action trees generated by the context-free grammar parser.

We find that the commonsense reasoning assumption works well in the cooking domain, where users use specific tools for specific actions, e.g., a knife to cut chicken, a fork to grip, a rolling pin to roll, a tong to grip etc. In the FOON dataset \[32\], which has annotations prepared from 100 open-source YouTube cooking videos with a third-person view, the commonsense reasoning action recognition module achieved an average precision of 49% and recall of 50%. We additionally annotate and show the performance of the whole framework in two full-length YouTube videos that include collaborative actions between two persons. The precision and recall of the overall framework was 0.63 and 0.43. We finally show a demonstration in simulation of two robots and in a proof-of-concept demonstration in the real world the learning and execution of all the actions of a third video using the open-sourced platform.

The current framework is focused on cooking videos assigning to objects properties such as “tools”, “ingredients” and “containers.” We hypothesize that these properties are easily transferable to other domains as well, such as furniture manufacturing, and we leave investigating this for future work. An additional limitation is that the extracted action sequences are executed in an open-loop manner and thus do not withstand real-world failures or disturbances.

Nevertheless, we are excited that this work brings us a step closer to having robots generate and execute a variety of semantically meaningful plans from watching cooking videos online.

II. RELATED WORK

In this paper we propose a framework for converting full-length unconstrained videos from the Internet to collaborative action plans executed by one or more robots. Most relevant to ours is prior work on temporal video segmentation and action understanding.

A. Temporal Video Segmentation

Work in video segmentation includes learning Gaussian Mixture Models \[26\], detecting changepoints through filtering and smoothing techniques \[10\] and specifying cost-functions incorporating spatial and temporal features of the trajectory \[24\]. When the output of a supervised learning algorithm is available, particle filter-based sampling approaches can integrate predictions to infer a sequence of activity classes \[17\]. Recent work also combines classifier outputs with a symbolic grammar to parse sequence data \[24\]. In the work by Lioutikov
et al. [27]. movement primitives are learned in conjunction with trajectory segments, using an iterative Expectation-Maximization (EM) algorithm. Zhou et al. propose an end-to-end method for procedure segmentation [49], and Sener et al. propose an iterative model that alternates between learning the visual appearance and the temporal structure of activities in videos [37]. While our framework can accommodate any state-of-the-art temporal segmentation technique, we applied the Greedy Gaussian segmentation algorithm by Hallac et al. [13]. The algorithm is applicable to general multivariate time-series data and we adopt it for segmenting videos to clips using hands that include collaborative actions between two participants, based on the insight that hands contain temporal and spatial information about manipulation actions.

B. Action Understanding

There has been a lot of work on human activity recognition [42]. Recent work on deep learning approaches has enabled the generation of natural language [43], individual robot commands [30], and neural programs [40] using manually annotated datasets. Generation of collaborative actions has been achieved by representing them as social affordances [38] extending previous work on object affordance learning [20, 21] or as interaction primitives [2] from data recorded in a lab setting. Generalization is an important challenge in robot learning and to address this issue, Pastra et al. [31] discuss a minimalist grammar for action understanding, inspired by the suggestion by Chomsky [7]. An implementation of such a grammar for activity understanding was provided by Summers-Stay et al. [39], while a probabilistic manipulation action grammar was first proposed by Yang et al. [47, 44]. Their system uses deep neural networks for hand and object detection and association, while it leverages a language corpus for action recognition. Performance was shown on 12 selected clips. In related work [48], researchers presented a collaborative grammar and functionality was tested only qualitatively in a small number of manually selected simple clips, rather than in full-length unconstrained videos.

Contrary to the aforementioned work, our framework includes a full pipeline that takes as input full-length videos with annotated objects and bounding boxes, infers manipulated objects and tools based on hand detections, recognizes single and collaborative actions representing their structure using a collaboration action grammar and concatenates the actions into a temporal sequence of executable commands. Importantly, the proposed framework is modular so that individual components can be replaced or combined with state-of-the-art techniques, such as CNN-based methods for action recognition [28, 41].

III. FRAMEWORK

The input to the framework is a full-length, unconstrained video from the web. We assume that objects in the video are labeled and a bounding box is provided for each object e.g., using a state-of-the-art object detection algorithm [35]. We base this assumption on the tremendous progress of recent object-detection algorithms and the availability of large data-sets. This is the only labeled input data provided to the framework. While the current implementation of the framework works for videos of one person working independently or two persons collaborating, an extension to three or more persons interacting in pairs is straightforward and left for future work.

A. Hand Detection

Our work is based on the insight that hands are the main driving force of manipulation actions [44]. We use OpenPose [41], which detects jointly the human body and hands. We use the detected hands to (1) segment videos by tracking the hand trajectory, and (2) detect which objects are manipulated at a given point in time.

B. Video Segmentation

We temporally segment the video to short clips using the trajectories of the detected hands as time-series data, performing a separate segmentation for each hand of the actors in the video. We use a greedy approach [13], which formulates the segmentation as a covariance-regularized maximum likelihood problem of finding the segment boundaries.

We then generate a new sequence of segments for the whole video as the union of individual segments, which we will use for action recognition. Based on the assumption that actions require at least one second to be executed, we filter out segments that are shorter.

This method results in over-segmentation with some actions spanning multiple segments, which is common in segmentation algorithms [12]. We also have several segments that do not include any action. Therefore, we merge segments with identical action trees in the action graph generation phase (Section III-F).

C. Object Association

After video segmentation, we extract objects that are relevant to actions in each segment. We do this by associating objects with hands and with other objects based on their relative positions in the frame. We introduce a semantic hierarchy of objects, by assigning them to three classes: tools that manipulate other objects, e.g., knife and fork, containers that can contain other objects, e.g., pot and bowl, and ingredients, e.g., banana and lemon, that can not contain other objects. For robustness, we only keep the hand and object associations retained for a minimum number of consecutive frames.

Hand-Object Association. We want to detect the objects grasped by the hands and then propagate this association to nearby objects that can inform the action recognition. This allows us to infer which objects are directly manipulated or used as tools to manipulate other objects.

We associate detected hands with objects whose bounding boxes overlap with the box of the hand. In the case of multiple overlaps, we associate the hand with the container or tool that has the largest overlap. If there is no such object, we associate it with the nearest ingredient. We look first for tools and containers, since they are larger and thus make associations more robust.
**Object-Object Association.** For each object that has been associated with a hand, we look to associate that object with other objects that are possibly manipulated. For instance, if a hand grasps a spoon, we wish to see if the spoon is used to stir a pot nearby. As in hand-object association, we look first for the nearest container that has an overlapping bounding box and then for the nearest ingredient if there is no container nearby.

We finally associate container objects with ingredients, if there is an overlap in the bounding boxes of the two. We use containers to detect transfer of objects from one container to the other, e.g., transfer a tomato from a bowl to a chopping board. We use the Jaccard index [18] between the bounding boxes of the two objects to pair a container with one or more ingredient objects.

**D. Action Recognition**

After segmenting the video into clips and pairing objects with hands, we recognize actions performed by humans in the videos. We have two types of actions, actions performed by a single person, which we name **individual or single actions**, and **collaborative actions** performed by a pair of humans in the video. As a special case of individual actions, we introduce **transfer actions**, which occur when an object moves from one container to the other, e.g., transfer a tomato from a bowl to a chopping board. We use the Jaccard index [18] between the bounding boxes of the two objects to pair a container with one or more ingredient objects.

**Individual Actions.** We recognize commonsense actions [47], using a trained language model from a general purpose language corpus [6] and a recipe corpus [29]. Given a set of candidate actions and a set of candidate objects, we extract \( P(O|A) \) for each possible bigram consisting of one object word and one action word in corpus. We then compute the probabilities of each action given the involved objects such as tool used, ingredient manipulated as follows:

\[
P(A|O_1, ..., O_k) \sim \prod_k P(O_k|A)P(A)
\]

where \( A \) is the performed action and \( O_1, ..., O_k \) are the objects involved in the action respectively. We then select the most likely action. We use the general corpus for the object-action bigrams where the object is a container or a tool, as well as for specifying the action prior. We use the recipe corpus for the ingredient bigrams.

We describe the commonsense reasoning action recognition as follows: We have a finite set of individual actions related to the cooking domain: {cut, spread, grip, stir, sprinkle, squeeze, heat, swrap, roll, pour, coat}. For each of these actions, we use the language corpus to compute the probability of the manipulated objects in an action clip, based on the frequency that each object and action appear in the same sentence. We then pick the most likely action from our set of actions.

As an example, we let the manipulated objects detected by the visual processing system be **knife** and **onion** and the candidate actions **cut** and **stir**. We can compute from the trained language corpus the probabilities \( P(\text{onion}|\text{cut}) = 0.015 \), \( P(\text{knife}|\text{cut}) = 0.036 \), \( P(\text{onion}|\text{stir}) = 0.029 \) and \( P(\text{knife}|\text{stir}) = 2e-4 \). We see that **onion** is more likely to be associated with the action **stir**, than with the action **cut**. However, **knife** is two orders of magnitude more likely to be associated with the action **cut**, compared to **stir**, therefore assuming a uniform prior the most likely action for **knife** and **onion** would be **cut**.

**Transfer Actions.** We treat transfer actions separately from the other individual actions, since they occur when an object is moved from one container to the next and thus require tracking an object’s association temporally. These actions are critical in keeping track of the location of the food in the cooking task.

**Collaborative Actions.** Following previous work [48], we detect a collaboration: (1) when two persons grasp the same object, or (2) the object grasped by one person is used as a tool to manipulate an object grasped by another person. In case (1), we check over time which hands grasp the object and detect a **handover** if the person grasping the object changes. Otherwise, we detect a **holding** action, for instance when one person assists the other person stirring a pot by holding the pot as well.

**E. Action Grammar Parsing**

We need to represent the structure of the recognized actions for a robot to execute them. We use a manipulation action grammar [47], which assumes that hands (H) are the driving force of both single manipulation actions (A) and collaborative actions (C). A hand phrase HP contains an action phrase AP, or a collaborative action phrase CP. We also introduce an object phrase OP, which we use to indicate container-ingredient relationships between objects, e.g., a tomato in the bowl, as well as transfer actions from one container to another. The grammar is given in Fig. 4. The rules (5)-(8) are terminal, with **Hand** taking the values: “LH_P1”, “RH_P1”, “LH_P2” and “RH_P2,” “LH_P1” being the left hand of the first person and so on. We use a context-free grammar parser [8] to parse the constructed visual sentences [48] and output a parse tree of the specific manipulation action. The robot can then execute the action by reversely parsing the tree. Fig. 5 shows the constructed trees from different action clips.

**F. Action Graph Generation and Execution**

Because of over-segmentation (Section III-B), we end up with multiple consecutive segments that are parts of the same action. Therefore, we first merge consecutive segments from the video with identical actions, hand-object and object-object associations. We do not require identical ingredient objects, since they may not be visible in some of the segments.

We then generate an action graph that combines the generated action trees to action sequences, each corresponding to each person in the video. We then decompose each action into motion primitives. We define four primitives [15]: grasp, engage, actuate and place. For instance, a transfer action of a food from a plate to a bowl with a spoon includes grasping the spoon (grasp), moving it close to the food (engage), performing the scooping motion (actuate), moving the spoon close to the bowl (engage), turning it to remove the food
(actuate), and placing it back in its initial position (place). We use Task Space Regions (TSRs) [3] to specify feasible regions of target poses of the robot’s end effector in the grasp, engage and place primitives, and we use bidirectional rapidly-exploring random trees (BiRRT) [23] to plan collision-free paths.

The action graph enables transitioning and ordering in both the task action and motion primitive levels:

**Transitioning.** People often grasp an object and use it as a tool for consecutive actions. We enable smooth transitioning of two consecutive actions with the same tool by removing the place and grasp motion primitives of these actions.

**Ordering.** The action graph ensures that the actions of each person are executed in the demonstrated order. Additionally, a collaborative action is executed only when both agents have reached the corresponding node in the graph. In the lowest level, the action graph ensures ordering of motion primitives in collaborative actions (e.g., wait until the other agent has engaged before actuating in a handover).

We implement the action graph as an open-source platform [1] that enables collaborative task execution in the cooking domain. It is based on AIKIDO [22], a C++ library for robotic motion planning and decision making.

IV. EXPERIMENTS

Our first experiment evaluates the commonsense reasoning assumption for recognizing single actions in the cooking domain based on a large annotated dataset of 100 YouTube videos that include single-person actions. Equipped with these results, we test our framework on two YouTube videos that show two persons collaborating in a cooking task.

A. Action Recognition with Commonsense Reasoning

We first wish to test the commonsense reasoning assumption for recognizing individual actions in the cooking domain. Our assumption is based on the fact that in cooking people use specific tools for specific actions, such as a knife to cut and a rolling pin to roll. We hypothesize that the system will be able to recognize most actions from the objects and tools in the scene.

**Dataset and Experiment Settings.** We use the publicly available manipulation knowledge representation dataset called the Functional Object-Oriented Network (FOON) [32, 32]. The dataset was prepared from 100 open-source YouTube cooking videos with a third-person view, and it includes

1https://github.com/icaros-usc/wecook
annotated actions and objects involved in these actions. The dataset contains a variety of low-level action primitives, such as “cut open,” “pick and place” and “put inside” that cannot be inferred using a language corpus. We therefore restricted the action set to a set of common candidate actions similarly with previous work [45]. We trained our language model on the One Billion Word Benchmark dataset [6] and the Recipe1M+ dataset [29].

Results. The average precision over all actions was 49% and the recall was 50%. Fig. 5 shows the normalized confusion matrix for our action set, with the true positive rate (recall) for each action. The poor performance in the action spread resulted from many actions being missclassified as sprinkle, because of the semantically similar meaning of the two actions. The action sprinkle was also often misclassified as stir, because of the prevalence of container objects, such as bowl and pot, which skewed the inference towards the stir action. On the other hand, the performance for cut was high because of the presence of the knife tool, and objects such as foil and seaweed helped the correct inference of wrap.

We found that performance can further improve by assigning different weights to different types of objects, or ignoring multiple objects of the same type. These results show the effectiveness of the commonsense reasoning module in the cooking domain.

B. Collaborative YouTube Videos

The FOON dataset does not include object bounding boxes and does not have videos with collaborative actions. We show the applicability of the entire framework, shown in Fig. 2 in two public YouTube videos [4]. The videos show two persons collaborating to cook a meal.

Dataset and Experiment Settings. We set up a start and end time for each video, annotated the objects and set bounding boxes. We only annotated objects that were clearly visible, skipping objects that were not rigid (e.g., water) or heavily occluded. The videos included a total of 13401 frames and 67 executed actions of 12 different action types.

Results. Fig. 3 shows the result of the segmentation and action recognition in the two videos before merging the segments (Section III-B). We can see clearly that the woman in the video performed most of the actions, especially in video 2.

After merging the segments, we evaluate the performance of the framework with respect to the percentage of correctly learned action-trees. We define a correct action tree when the structure and all nodes of the tree are identical to the ground-truth, and the segment corresponding to that tree has a non-zero temporal overlap with the ground-truth segment. We specify the precision as the number of action trees the framework returns correctly out of the total number of detected instances, and the recall as the number of action trees the framework returns correctly out of the total number of ground-truth trees.

Table I shows the precision and recall for each video. We observe that the framework achieved 0.63 precision and 0.43 recall. The performance was better for the first video. The difference occurs because during a large part of the second video the persons manipulate flour, which was not always visible. Additionally, in some actions our commonsense reasoning assumptions did not hold, for instance when the woman used a cup to cut the patty, rather than a knife (Fig. 8a).

Post-hoc Analysis. We perform a post-hoc analysis of the data to identify different causes of failures in the generated trees. Table II shows the number of correct trees that we generated and the number of trees that were erroneous for different reasons. We observe that a main source of error was hand-object associations. This occurred often when an object was not visible and we did not include it in the object annotations. For instance, in Fig. 8b the system failed to generate an action tree for the sprinkle action since the chopped onion was not annotated. A second source of error in hand-object associations was because of the distance between bounding boxes. For example, in Fig. 8d the system incorrectly infers that the woman’s hand does not make actual contact with the oil. Errors occurred also in the object-object associations; for example, in Fig. 8c the closest container object to the oil is pan, while the woman is actually pouring oil to the pot.

V. DEMONSTRATION

To demonstrate the applicability of our framework, we selected an “easy” video of 2421 frames where our framework achieved perfect segmentation and action recognition (Fig. 7). In the accompanying video, we show the execution of the complete action graph by two simulated Kinova Gen2 lightweight [1] robotic arms in the open-sourced platform. We show in the same video a proof-of-concept execution of the same actions with a robot and a human, using our open-source software platform (Fig. 6).

Table II: Number of Correct Trees for Different Types of Error.

| Type of Error | Video 1 | Video 2 | Total |
|---------------|--------|--------|-------|
| AO            | 24     | 24     | 48    |
| HO            | 16     | 14     | 30    |
| OO            | 5      | 2      | 7     |

https://www.youtube.com/watch?v=d3SZH7NFDjc&list=PL4C3C1C9AB9931360&index=75

https://www.youtube.com/watch?v=1p2wBBmhPmk&t=138s

https://www.youtube.com/watch?v=jAhQfH1PspU&t=119s

https://www.youtube.com/watch?v=ld1qQZpJ1Ow&list=PL4C3C1C9AB9931360&index=75

https://www.youtube.com/watch?v=ld1qQZpJ1Ow&list=PL4C3C1C9AB9931360&index=75

TABLE I: Precision and Recall in the Collaborative Cooking Videos.

| Video  | Precision | Recall |
|--------|-----------|--------|
| Video 1| 0.67      | 0.50   |
| Video 2| 0.58      | 0.38   |
| Total  | 0.63      | 0.43   |
VI. DISCUSSION

Limitations. Our work is limited in many ways. As we observe in the post-hoc analysis section, some failures are caused by assumptions in how objects are detected or associated with hands and with other objects. Detecting grasping types could improve the inferred associations [46]. Additionally, although the selected YouTube videos were unconstrained, they were meant to be instructional and thus relatively clear. While our hand and object detection-based action prediction can be robust against implicit or ambiguous actions, language corpus-based commonsense reasoning will fail in infrequent cases, such as cutting food on a bowl with a spoon instead of a knife. Learning embeddings from cooking recipes [29] [36] [19] or using language groundings from transcripts [16] could address this issue. The current framework is currently designed for cooking tasks, with objects annotated as containers and ingredients. Future work includes generalizing the framework to other collaborative tasks as well, such as furniture assembly.

More generally, the proposed framework generates actions that are executed in an open-loop manner. For task execution by human-robot or robot-robot teams in the real-world, we would need to monitor the environment’s and human’s state and adapt the robot’s actions. In that case, learning dynamics models of objects’ states could be useful [5]. In settings where human and robot share common workspaces, it would be also important to manage contingencies, such as perception/grasping failures by the robot, human mistakes, as well as to act in a way that mitigates safety risks for human teammates [25]. We find these exciting topics for future work.

Implications. The World Wide Web contains a vast mount of online content that robots can leverage to perform tasks in human-robot and robot-robot teams. We have presented a framework that takes as input an unconstrained cooking video with annotated object labels and outputs a human-interpretable plan. We demonstrate the execution of the plan in a simulation environment with two robotic arms and show that we can fully reproduce the actions of a simple cooking video. We find that this work brings us closer to the goal of robots executing a variety of manipulation plans by watching cooking videos online.

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Fig. 9: Example frames, snapshots in simulation environment of two robots executing the same actions with humans and generated actions trees of 6 successful cases. The captions depict the ground-truth descriptions of each successful case.
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