Interactive Learning-from-Observation through multimodal human demonstration

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Abstract—Learning-from-Observation (LfO) is a robot teaching framework for programming operations through few-shots human demonstration. While most previous LfO systems run with visual demonstration, recent research on robot teaching has shown the effectiveness of verbal instruction in making recognition robust and teaching interactive. To the best of our knowledge, however, few solutions have been proposed for LfO that utilizes verbal instruction, namely multimodal LfO. This paper aims to propose a practical pipeline for multimodal LfO. For input, an user temporally stops hand movements to match the granularity of human instructions with the granularity of robot execution. The pipeline recognizes tasks based on step-by-step verbal instructions accompanied by demonstrations. In addition, the recognition is made robust through interactions with the user. We test the pipeline on a real robot and show that the user can successfully teach multiple operations from multimodal demonstrations. The results suggest the utility of the proposed pipeline for multimodal LfO.

I. INTRODUCTION

Household robots with manipulation capabilities are increasingly being considered as an alternative labor force in various scenes, including nursing homes, restaurants, and home environments [1]. While typical robotic systems assume that the robot will perform specific operations in a fixed environment (e.g., on an assembly line), home systems need to provide the ability to program the robot to fit the user’s needs and environment. Learning-from-Observation (LfO) is a framework that aims to teach robot manipulative operations by on-site human demonstrations without coding and thus is one of the promising solutions for home robot control [2].

In LfO, a human demonstration is encoded into an intermediate representation of object manipulation, called as a task model (Fig. 1). The task model consists of a sequence of primitive robot actions, so-called tasks, and parameters to achieve the tasks, so-called skill parameters. Because the task model is an abstract representation of object operations, the encoded task model is theoretically applicable to multiple environments on arbitrary hardware.

While several studies have demonstrated that LfO systems successfully work in both industrial and home environments, LfO has been developed based on visual demonstration. For instance, vision-based LfO systems have been developed for part assembly [3]–[5], knot tying [6], grasping, and dancing [7]–[9]. On the other hand, studies have shown that human uses verbal instruction to make the teaching more interactive and efficient [10]–[12]. Inspired by the nature of language, we have developed an LfO system that utilizes both visual and verbal information, namely, multimodal LfO [13], [14]. However, the motivation for multimodal LfO has been limited to robust visual recognition and information enrichment, and applications that take advantage of interactivity have not yet been proposed.

This paper aims to present a practical pipeline of the task-model encoder that employ interaction (Fig. 1). To facilitate teaching at the task granularity, we employed one of the simplest teaching styles; stop-and-go demonstration. In stop-and-go demonstration, an user pauses the hand motions when tasks switch. At every pauses, the demonstrator gives a verbal instruction for the next task before resuming the hand movements. For a input of stop-and-go demonstration, the system encodes a task model through GUI-based interaction. We show that the proposed pipeline can encode task models that are operated by a real robot. The contributions of this paper are: (1) proposing a pipeline for multimodal LfO (2) proposing a pipeline that has interaction capability, and (3) showing the effectiveness of the LfO system using a real robot with a dexterous robot hand.

In what follows, Sec. II explains related studies and Sec. III explains assumptions for the proposed pipeline. Sec. IV explains the implementation. In Sec. V, we show several experiments where a variety of operations are taught to be executed by a real robot.

II. RELATED WORKS

A. Role of language in recognition

Many studies have shown that natural language can serve as useful information to guide the visual system. For ex-
ample, we have previously shown that the use of verbal input can guide the robot system to determine the timings and the location of grasping and releasing and thus make the LfO robust [13]. In addition, language include semantic constraints in manipulations that are not explicitly taught through visual demonstration [15].

Language can be applied not only to visual system guidance, but also to interactive education. Recent research has proposed interactive systems that utilize human language for remembering user’s previous input [16], operation in a new environment [17], and clarifying uncertain instructions [18]. However, to our knowledge, no multimodal LfO with user feedback has been proposed. In this study, we propose a system that implements a user-interaction feature to more effectively utilize verbal instructions for task recognition.

B. Robot task planning from language

Starting with the work of the SHRDLU [19], the problem of task planning based on language instructions has been studied for decades. Before the development of Natural language processing (NLP) technology, the dominant method of understanding sentences was by parsing verbs and syntax (e.g., [20], [21]). In recent years, the use of NLP technology has become more common, and systems have been proposed to analyze abstract instructions [22] and complex instructions, including conditional branching [23]. For example, the authors in [22] propose a framework that decompose abstract instruction into step-by-step procedures using large language models.

While multimodal robot teaching is often employed in end-to-end methods based on large models [22], [24]–[28], multimodal teaching has also been studied in symbolic robot teaching systems [29], [30] Multimodal LfO systems are also classified as symbolic AI systems, and specific implementation methods have recently been proposed [14]. However, the system used a simple knowledge base that maps tasks to verbs in a single sentence, which limits the length of task sequences that can be taught and the flexibility of input texts. Therefore, in this paper, we propose a system for teaching tasks of arbitrary length using less restrictive linguistic sentences by utilizing a step-by-step teaching method and a task recognition model based on NLP. The proposed system addresses this problem by requiring the user to give step-by-step language instructions that are broken down into task granularity.

III. TEACHING STRATEGY FOR MULTIMODAL LfO

The aim of the task-model encoder is “given a visual and speech demonstration, recognize the sequence of tasks and their temporal correspondence with the visual demonstration.” This section defines the inputs and outputs of the encoder and describes the difference between human demonstration and task execution granularity. We propose a teaching method to bridge this difference in granularity.

A. Unit of human demonstration

In this paper, we define that an input to the multimodal LfO starts with grasping an object followed by several manipulative tasks, and ends with releasing the object. We call this unit a grasp-manipulation-release (GMR) operation. Note that we assume a single object is being manipulated in a GMR operation. GMR operation can sometimes involve both hands (such as carrying a hot pot with both hands).

In this paper, we focus on an operation where each one of the hands operates dominantly, while the other hand is not involved or operates as a supportive action, such as holding (e.g., cutting vegetables with a knife in the right hand while holding the vegetables in the left hand).

Although it seems that LfO for a single GMR operation limits the application of the system, we believe that many manipulative household tasks can be achieved as a result of multiple GMR operations. For example, cleaning the table after a meal can be broken down into the GMR of a plate for clearing dishes and the GMR of a sponge for wiping the table; LfO can be applied to a wide range of household tasks by being able to learn the units of GMR.

B. Unit of robot execution

On the other hand, the unit of robot execution, task, can be finer than GMR operations. In a typical LfO, a task is defined as a transition of a target object’s state. An example is a contact state between polyhedral objects for part assembly [2] or topology of a string for knot tying [6]. We have previously defined a set of states for manipulative operations based on the types of motion constraints imposed on the object [15]. As the result, a GMR operation is divided when the motion constraints to the object change. For example, a GMR operation of “picking up a cup and carrying it on the same table” is divided into the tasks of picking up the object (PTG11) bringing it (PTG12), and placing it (PTG13) (symbols in parentheses are from [15]). We also include grasp and release in the task set because these actions are accompanied by a transition in the contact state between the robot hand and the object. Table.1 shows examples of GMR operations and their task components.

### Table I: Examples of GMR operations (modified from [31])

| GMR operation                          | Explanation                             |
|---------------------------------------|-----------------------------------------|
| Grasp-PTG11-PTG12-PTG13-Release       | pick, bring, and place something        |
| Grasp-PTG31-Release                   | slide something open                     |
| Grasp-PTG33-Release                   | slide something close                    |
| Grasp-PTG51-Release                   | rotate something open                    |
| Grasp-PTG33-Release                   | rotate something close                   |

![Fig. 2. The different granularity of manipulative operation.](image)
C. Stop-and-go demonstration to resolve differences in granularity

Many variations exist in how to give multimodal demonstrations. We designed a teaching methodology that allows users to effectively teach tasks at robot granularity.

First, to allow users to teach multiple tasks in a GMR operation at once, we employed a method that implicitly informs the system of the task switching by momentarily stopping the hand (i.e., stop-and-go teaching). For an example of pick-place an object, the demonstrator should stop the hand motion when it approached the object, when the hand grasped the object when the hand lifted the object off the table when the hand carried the object above the table when the object was placed on the table, when the hand released the object, and when the hand moved to a home position.

Next, we employed a method in which visual demonstration and verbal instruction were taught separately. This is because simultaneous teaching is considered a form of dual tasking that requires a higher cognitive load for the user. Such teaching methods may not be suitable for unskilled users, especially the elderly [32]. Furthermore, to efficiently teach the correspondence between verbal instructions and actions, we adopted a method in which the demonstrator gives a verbal instruction for the next task at the timing of each hand stop, rather than giving verbal instructions all at once before/after visual demonstrations (i.e., step-by-step instructions).

IV. IMPLEMENTATIONS OF TASK-MODEL ENCODER

This section explains the pipeline that we implemented to recognize tasks from the stop-and-go multimodal demonstration. Fig. 3 shows the overview of the pipeline. The pipeline is composed of two steps. In the first stage, the encoder detects segmenting timings based on the stopping motion and splits the video and speech based on the timings. It transcribes the speech using a third-party speech recognizer. The result of segmentation and speech recognition was previewed so that the user modify the result if necessary. After the confirmation, a task sequence is recognized from the verbal input using an NLP-based recognizer, and skill parameters are extracted for each task to compile a task model.

A. System input

We used Azure Kinect sensor [33] to record RGB-D images and a speech input during the demonstration. The sensor is placed in positions that could capture the entire demonstration. The image resolution is 1280x720, and the nominal sampling rate for the video and speech is 30 Hz and 48000 Hz, respectively.

B. Video segmentation and speech recognition

For a stop-and-go demonstration, the pipeline splits the video and audio at the times when a manipulating hand stopped. To detect the times, we characterized the intensity of hand motion based on the changes in luminance of images [34]. For the calculation, RGB images are converted into YUV images and the Y channel is extracted as the luminance. The luminance images are spatially filtered using a moving average of 50x50 window, and the pixel-wise absolute difference is taken between adjacent frames (Fig. 4(a)). The mean of the difference is taken as the luminance change at each time. After the removal of outliers and low-pass filtering of 0.5 Hz, the local minimum of the time series is extracted as the stop timings (Fig. 4(b)). After the confirmation of the split timings (in Sec. IV-C), the RGB-D video and the audio are split based on the detected timings. The split speech is transcribed using a third-party cloud speech recognition service [35] and previewed to the user for additional confirmation.

C. Previewing for the user modification

Since the speech content and the correspondence between video and audio are critical to task recognition and the extraction of skill parameters, we implement the feature to ask for users’ modifications on the computation result of video splitting and speech recognition. After the luminance-based video splitting, the user is prompted for each split video. The user can ignore videos unrelated to the teaching (e.g., movements before and after a GMR operation) and merge over-split videos through a button-based GUI (Fig. 5). Note that we assume that the user can give the demonstration again when the under-segmentation occurred instead of manually segmenting the video through the GUI.

After confirming the video segmentation, the video and audio are re-partitioned and the split audios are transcribed.
using the speech recognition service of Sec. [V-B]. The transcribed text is displayed to the user in order so that the user can modify using a GUI (Fig. 5).

D. Task recognition

After splitting the demonstration, the system recognizes each task based on the transcribed instruction. To this end, we trained a language-based recognition model. We first collected a dataset of textual instructions for videos of a single task. We annotated an existing video dataset of preparing a breakfast [36]. We chose the cooking domain because cooking needs the use of a variety of foods and tools with manipulation. We labeled the video with task labels and prepared the video dataset of a single task using a third-party video annotation tool. The dataset contained 12 task classes with a total of 1340 videos. Table II shows the task classes and the number of data.

For those videos, we collect the instruction that explains the motion using a crowd sourcing service, called Amazon Mechanical Turk. We collected 100 sentences for each task. Finally, a recognition model was trained to associate each instruction and corresponding tasks. This model was a random forest model trained on top of a fixed BERT model [37]. Note that we used egocentric videos for the data collection because the demonstrator is assumed to give demonstrations while teaching, rather than while observing the demonstration from a third-person perspective. Table III shows the examples of sentences collected by different cloud workers. We observed variation in the verbs and nouns that appear in the instructions.

Fig. 5 shows shows the confusion matrix of the task recognition where 10% of the sentences were used for the testing. We conducted ten-fold cross-validation to validate the result. The averaged performance was 83%. This result suggests that the tasks can be robustly recognized from natural verbal instructions with variations.

E. Skill parameter extraction

Every task requires skill parameters for robots to decode. [13], [14]. Once a task is determined, processes called daemon run to extract the parameters by analyzing the corresponding video. Here we explain the examples of skill parameters and computation for extracting the parameters.

1) The name of the target object: The name of the target object is used to help recognize other skill parameters. We assume that the name is specified in the verbal input, and extract it through a third-party language parser [38]. In the current pipeline, we define a set of object names applicable to the LfO system and prepared an object detector for detecting the objects.

2) Hand laterality: Information on the laterality of hands used for the manipulation is important because the information should be consistent with other skill parameters such as grip type, and approach direction to the target object. Hand laterality is extracted by analyzing the video of grasping the object, which starts with approaching the hand to the object and ends with grasping it.

Assuming that the object location does not change during the grasping task, a daemon extracts the object’s 2D location applying the object detector to the first RGB image of the video. Because the last frame corresponds to the timing of grasping the object, a hand detector detects the 2D locations of both hands in the last frame. The laterality of the manipulating hand is then determined as the hand closer to the object.

3) Grasp type: Grasp type is important for not only grasping an object but also for successfully operating a

| Task label       | Count | Mean length (S.E.) (sec) |
|------------------|-------|--------------------------|
| Picking (PTG11)  | 127   | 0.43 (0.13)              |
| Bringing (PTG12)| 108   | 1.46 (0.20)              |
| Placing (PTG13)  | 113   | 0.73 (0.05)              |
| Rotating_Jingle| 38    | 1.14 (0.14)              |
| Rotating_Jingle| 72    | 0.73 (0.11)              |
| Feeling (STG3)   | 24    | 3.53 (0.90)              |
| Pouring (STG5)   | 42    | 2.26 (0.54)              |
| Holding (STG6)   | 239   | 3.50 (0.32)              |
| Calling (MTG1)   | 22    | 4.52 (0.75)              |
| Grasping         | 464   | 0.56 (0.02)              |
| Releasing        | 392   | 0.37 (0.01)              |

TABLE II: Statics of the labeled tasks. Task symbols in [15] are indicated in parentheses.

| Task label | Count | Mean length (S.E.) (sec) |
|------------|-------|--------------------------|
| Pouring oil from a bottle | 5.59 (1.42) |
| Cutting potatoes | 3.55 (0.90) |
Fig. 6. Confusion matrix for recognizing tasks from texts.

Fig. 7. (a) Extracted hand positions and (b) the estimation of rotating_hinge task.

sequence of tasks [39]. The pipeline detect a grasp type that is based on robot grasp theory using an image classifier model. The image of the manipulating hand at the last frame of the grasping video is fed into the model, and a grasp type is determined after correcting the model output with the likelihood of the grasp types tied to the object name [40], [41].

4) Hand positions and hand trajectory: How a demonstrator moved the manipulating hand is important because it contains the knowledge of successfully achieving a task without collision with an environment and how to manipulate an articulated object such as a shelf or a door. The 3D hand positions during the teaching are extracted by using the 2D hand detector and the depth images (Fig. 7(a)). For a rotating_hinge task, the hand trajectory is parameterized by applying a circular fitting to the hand positions during the corresponding video (Fig. 7(b)).

5) Human pose: Human pose during the operation is shown to give a robot system implicit knowledge required to achieve tasks efficiently [42]. Based on the design of task models that we previously proposed [14], we encode the human arm posture at the beginning and the end of each task video. Briefly, the 3D poses of the demonstrator are estimated using a third-party 3D pose estimator [43] and each of the body parts (upper/lower arms of left and right arms) is encoded into spatially digitized 26-point directions on the unit sphere.

6) 3D Object positions: The 3D object position at the moment of grasping is calculated from the RGB-D image at the start of grasping. Our LfO system assumes that the object position may slightly differ from the one at the demonstration, and re-calculates the object position at the timing of robot execution through an on-site visual input (see Fig. 1). Note that positional information including the human hand is represented relative to an AR marker set on the environment first and offset against the position of the target object before the manipulation. That is, the location of the object is the origin of the coordinate in task models.

In robot on-site recognition, the estimated object position is set as the origin of the coordinate.

V. EXPERIMENTS

We tested the proposed task-model encoder based on the performance of multimodal LfO. To this end, we connected the encoder to a task-model decoder we have previously implemented. The decoder generated robot commands from the task model and on-site visual images using a set of policies trained by reinforcement learning [39], [44], while imitating the human poses during teaching [45]. Since our LfO system is intended to be generalized to various home environments, the system was qualitatively examined from three aspects: (1) if the system applies to a wide variety of GMR operations by combining tasks, (2) if the system is flexible in modifying a GMR operation according to scenes.

To check the (1) system applicability, we tested three GMR operations commonly observed in household situations: “pick-carry-place a box-shaped object from one,” “open a fridge,” and “open a drawer.” To test the (2) system flexibility, we considered a case of a pick-carry-place operation that accompanies multiple bring (PTG12) tasks to avoid obstacles. We tested the system with a humanoid robot, Nextage [46] and a dexterous robot hand with four fingers [47].

A. GMR of pick-bring-place an object

Fig. 8 shows the overview teaching a “pick, carry, and place a box” operation. This GMR operation consists of grasp, pick (PTG11), bring from one location to another (PTG12), place (PTG13), and release tasks.

The taught verbal input and the visual demonstration are shown at the top. The robot completed the operation. Importantly, To test the system flexibility, we tested the same “pick-carry-place a box-shaped object from one,” operation when multiple bring (PTG12) tasks are inserted in-between the pick (PTG11) and place (PTG13) tasks. Such a case happens when several way points are required to avoid collision with the environment. Fig. 8 shows that the multiple bring tasks can be taught through the stop-and-go demonstration,
example, an occluded human hand caused the failure of recognition. Such misrecognition was typically caused by occlusion. For recognition of hands, objects, grasp types, and human poses, when skill-parameter extraction failed due to the incorrect stop-and-go motion. In addition, we observed several cases timing of task switching due to inefficient pausing during the experiment. We observed several failure cases. During the experiment, we observed several failure cases. One is the case where video splitting was not detected at the location to another (PTG12), and release tasks. The opening operation consists of grasp, open to a certain range (PTG5), and release tasks. Those operations were completed by the robot, suggesting that the proposed LfO system can operate variable operations by composing the task models.

C. Failure cases of task-model recognition

During the experiment, we observed several failure cases. One is the case where video splitting was not detected at the timing of task switching due to inefficient pausing during the stop-and-go motion. In addition, we observed several cases when skill-parameter extraction failed due to the incorrect recognition of hands, objects, grasp types, and human poses. Such misrecognition was typically caused by occlusion. For example, an occluded human hand caused the failure of extracting hand position and trajectory. In those cases, the user needed to discard the demonstration and repeat it.

VI. DISCUSSION

In this paper, we proposed a pipeline for task-model encoder for multimodal LfO system, assuming stop-and-go teaching with step-by-step instruction. This assumption allow the user to teach GMR operations at the granularity of task and to take correspondence between visual and verbal input. Furthermore, the encoder implemented a function to preview the processing result to allow the user to modify it on-the-fly (Fig. 6). Experiments tested the feasibility of the proposed pipeline for multiple types of GMR operations, and the encoded task models were successfully operated by a robot. In addition, we confirmed that these task models are operated by another robot that has different degrees of freedom (results are shown in [44]). These results suggest the utility of the system.

Because the proposed pipeline relies on several recognition modules for extracting task-model encoder, the overall recognition performance depends on the performance of these modules. Although we addressed this issue by implementing the preview function in recognizing task sequences, the instability remains in skill-parameter extraction. Adding another GUI for visualizing and correcting the task models would facilitate the robustness of the pipeline as a future study.

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Fig. 8. Results of Multimodal LfO for the GMR operation of pick-carry-place a box.

Fig. 9. Results of Multimodal LfO for the GMR operation of pick-carry-place a cup with multiple bringing tasks in-between.

Fig. 10. Results of Multimodal LfO for the GMR operation of disposing a cup (a) and (b) opening a door.
