Verbal Focus-of-Attention System for Learning-from-Demonstration

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Abstract—The Learning-from-Demonstration (LfD) framework aims to map human demonstrations to a robot to reduce programming effort. To this end, an LfD system encodes a human demonstration into a series of execution units for a robot, referred to as task models. Although previous research has proposed successful task-model encoders that analyze images and human body movements, the encoders have been designed in environments without noise. Therefore, there has been little discussion on how to guide a task-model encoder in a scene with spatio-temporal noises such as cluttered objects or unrelated human body movements. In human-to-human demonstrations, verbal instructions play a role in guiding an observer’s visual attention. Inspired by the function of verbal instructions, we propose a verbal focus-of-attention (FoA) system (i.e., spatio-temporal filters) to guide a task-model encoder.

For object manipulation, the encoder first recognizes a target-object name and its attributes from verbal instructions. The information serves as a where-to-look FoA filter to confine the areas where the target object existed in the demonstration. The encoder next detects the timings of grasp and release tasks that occur in the filtered area. The timings serve as a when-to-look FoA filter to confine the period when the demonstrator manipulated the object. Finally, the task-model encoder recognizes task models by employing the FoA filters. The contributions of this paper are: (1) to propose verbal FoA for LfD; (2) to design an algorithm to calculate FoA filters from verbal input; (3) to demonstrate the effectiveness of a verbal-driven FoA by testing an implemented LfD system in noisy environments.

I. INTRODUCTION

The demand for service robots to perform household manipulation operations for elderly people is increasing along with average age in many societies. A robot system that satisfies this demand needs to meet two requirements: (1) novice users can teach robots without special programming skills; (2) a learned operation can be interpreted by various robots in varied environments. Learning-from-Demonstration (LfD) is a framework that meets these requirements [1]-[4] (Fig. 1).

In a traditional LfD system, the task-model encoder first uses passive observation to encode human demonstrations into series of execution units for a robot, referred to as task models. A task model contains information about what-to-do and how-to-do for an execution, referred to as task and skill parameters, respectively. The task-model decoder next decodes the task models with on-site visual information to calculate appropriate motor commands for a robot in the real world. The advantages of LfD are the design for an intuitive robot teaching method and the scalability to various robots and on-site environments. However, applying an LfD system in practical environments faces the challenge of encoding a demonstration in noisy environments.

In this paper, we propose an LfD system that robustly encodes a noisy demonstration through active observation with spatio-temporal filters, referred to as focus-of-attention (FoA). We define the noise as any unrelated information presented to the task-model encoder. Specifically, we deal with two types of noises: spatial noise and temporal noise. We define spatial noise as unrelated objects in a demonstration. To address this noise, the task-model encoder needs to filter for an object of interest. We define temporal noise as unrelated human body movements before and after a manipulation operation. To address this noise, the task-model encoder needs to filter for the period of a manipulation operation.

In a human-to-human demonstration, verbal instructions are often used in conjunction with visual instructions to efficiently guide an observer’s visual attention [5]-[7]. Inspired by the function of the verbal instructions, we propose to apply a verbal FoA to reduce noise in a demonstration. For example, when a demonstrator says, “Open the fridge,” a system should reasonably pay attention to a fridge in the demonstration. In addition, the task-related human body movements should occur while the demonstrator holds the fridge door. Once the system knows “where and when to pay

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attention,” the task-model encoder can easily obtain skill parameters to substantiate the task models.

The role of FoA has a long history in computer vision. A research topic related to FoA is “active recognition” [8]. Active recognition is the processing of visual information in a cluttered scene by employing high-level knowledge about what a system needs to recognize. The idea of active recognition points out the importance of FoA for a recognition system to operate in a practical environment. However, previously proposed applications were limited in specific domains such as visual object search or rock sampling, outside the context of LfD [9], [10].

Another related research topic is to model a visual attention mechanism for image recognition, which is called “saliency” [11], [12]. However, this approach is different from our approach in two aspects. First, the saliency is vision-based FoA passively generated in response to an input image, whereas we aim to propose an active recognition by understanding the intention of a demonstrator from verbal instructions. Second, the design of saliency is based on a structure of bottom-up visual information, whereas the verbal FoA is based on top-down information from a standpoint that verbal instructions contribute to understanding intentions of the partner [13], [14].

This paper deals with the design of the task-model encoder to overcome the spatio-temporal noises in an object manipulation demonstration. To address this issue, we propose a verbal FoA to guide the task-model encoder. The encoder first recognizes a task-related verb (e.g., pick) and the target-object name with its attribute (e.g., a red cup) from verbal instructions. The information serves as a where-to-look FoA filter to confine the areas where the target object existed in the demonstration. The encoder next detects the timings of grasp and release tasks that occur in the filtered area by analyzing the time-series distances of the object to both hands. The timings serve as a when-to-look FoA filter to confine the period when the demonstrator manipulated the object. Finally, the task-model encoder recognizes task models by employing the FoA filters. We demonstrated the effectiveness of the verbal FoA by testing an implemented LfD system with a real humanoid robot. The contributions of this paper are: (1) to propose verbal FoA for LfD; (2) to design an algorithm to calculate FoA filters from verbal input; (3) to demonstrate the effectiveness of a verbal FoA by testing an implemented LfD system in noisy environments.

II. RELATED WORKS

This paper aims to employ verbal FoA toward LfD that operates in household environments. In this section, we explain how in the related studies our proposed LfD approach and our verbal FoA are positioned.

A. Learning-from-Demonstration (LfD)

Representative work of LfD is included in excellent surveys [2]–[4]. Most of the work tries to mimic a trajectory of a demonstrator’s motion in a robot end effector. This approach, “trajectory-based LfD,” has achieved promising results in laboratory environments. However, a learned demonstration through trajectory-based LfD cannot be transferred to arbitrary robot hardware nor be applied in an even slightly different environment. Although the characteristic might be trivial for industrial applications, it is generally a problem for household applications where various robots need to operate in a varied environment.

Task-based LfD, in contrast, is an approach to map a human demonstration to a robot via an internal representation of the demonstration, a task model [1] (Fig. 1). This approach provides solutions to the problem of trajectory-based LfD because theoretically, various robots with adequate hardware can operate by decoding a task model with on-site visual information. However, the previous task-based LfD systems were designed in laboratory environments without noise [1], [15]–[22]. Therefore, there has been little discussion on how to guide a task-model encoder in a scene with spatio-temporal noises such as cluttered objects or human body movements unrelated to the essence of the demonstration.

Overall, our proposed verbal-driven FoA is positioned as a solution for task-based LfD to overcome the spatio-temporal noises in a practical environment including household environments.

B. Focus-of-Attention (FoA)

In the context of computer vision, a methodology to improve image recognition by FoA is called active recognition [8]. Active recognition requires agents to know what they are going to recognize based on the purpose of the task. For example, Ikeuchi et al. proposed a task-oriented cognitive system that systematically modifies the architecture of the vision system depending on the specification of each task [10]. Previous work has demonstrated the effectiveness of FoA to improve the robustness and the computational efficiency of image recognition [8].

The idea of FoA to improve image recognition is also supported by neuroscience work. Studies have shown that top-down information flow from higher-order brain regions modulates information processing at early stages in the visual neural pathway [23]. In particular, verbal information has been suggested to play a critical role in the top-down modulation. For example, verbal information is known to affect visual attention and perceptual sensitivity [5]–[7]. It has also been shown that not only visual information but also verbal communication is effectively used in human-to-human demonstrations [24], [25]. Therefore, verbal instructions during demonstrations should contain useful information to help image recognition. However, most of the work on robot active recognition has utilized vision-based FoA based on range data and RGB-D images. Applications with verbal-driven FoA were, if any, limited in specific domains such as visual object search [9].

Image recognition by multi-modal learning of language and vision is also an active topic of research in the deep learning community in recent years. However, as Tsotsos notes [8], most of the studies do not fit the definition of active recognition because they do not aim to design a framework that contextually selects how, where, and when to recognize depending on the purpose of the task.

Overall, our proposed verbal-driven FoA is positioned as an extension of vision-based active recognition by leveraging
the nature of demonstration where verbal instructions co-occur with visual demonstration.

III. OVERVIEW OF THE TASK-MODEL ENCODER

This section describes the overview of the task-model encoder employing our proposed verbal FoA (Fig. 2). The task-model encoder is formed in two steps. First, it initiates the verbal FoA from verbal input, consisting of several spatio-temporal FoA filters. Next, several daemon processes, corresponding to skill parameters, are invoked based on a recognized task type and obtain the parameters from the sensor data by employing the FoA filters. In this section, we first state the problem to solve by using the verbal FoA and explain the algorithm. The detailed implementation of the verbal FoA is described in the following section. Next in this section, we explain the task model, skill parameters, and the algorithms of daemons implemented in this paper. Further detailed designs of the task model and daemon are described in related work [26].

A. Verbal-driven focus-of-attention

Task-model encoders proposed in previous studies analyze a target object before and after a manipulation operation or the trajectory of a manipulating hand [1], [15]–[22]. Therefore, the studies postulate the encoder can access the position of the target object or the timings when the manipulation occurred. Here, we define the problem to solve by the verbal-driven FoA as “given a demonstration with spatio-temporal noises, output the information about where and when a manipulation operation occurs.” We define spatial noise as unrelated objects in a demonstration and temporal noise as unrelated human body movements before and after a manipulation operation.

In the proposed verbal FoA, we made several assumptions:

- A demonstrated manipulation operation shall be associated with verbs.
- A target object shall not move spontaneously without human interventions.

Fig. 3 illustrates the pipeline to calculate the verbal FoA. The verbal FoA is composed of several FoA filters shown in the circles. The input data are transcribed human verbal instructions, RGB-D images, and human skeleton poses during a demonstration. The modules shown in boxes calculate the FoA filters using the following steps:

1. The language parser extracts task-related verbs (i.e., the task-candidate-FoA filter), a target-object name of the verbs (i.e., the target-name-FoA filter), and an attribute of the target object such as color (i.e., the attribute-FoA filter).
2. The object selector calculates the time-series of the target-object position (i.e., the target-object-position FoA filter) by analyzing the target-name-FoA filter, the attribute-FoA filter, and all the detected object positions through the generic object detector.

3. The grasp-release detector collects the timings when grasp and release tasks occur with the laterality of a manipulating hand (i.e., the grasp-release-FoA filter) by analyzing the time-series distances of the target object to both hands.

Among the FoA filters, the target-object-position FoA filter and the grasp-release-FoA filter correspond to the information about where and when a manipulation operation occurs, respectively.

B. Task model and skill parameters

1) Definition of task

In traditional task-based LfD, 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 [1] or a topology of a string for knot tying [17]. In this study, we defined a state as a contact-state between a target object and an environment (Fig. 2(a)). The definition was based on a motion taxonomy of household operations [27] and Mason’s definition of basic states for mechanical linkages [28], [29]. (Fig. 4). The defined states include non-contact (NC), planar contact (PC), prismatic contact (PR), one-way prismatic contact (OP), revolute contact (RV), and one-way revolute contact (OR). We also included grasp and release in the task set because they are accompanied by a transition of contact state between a robot end effector and a target object. The state set is independent of the verbal FoA and other tasks may be added if desired.

2) Design of skill parameters

We categorized the tasks into three classes from the viewpoint of robot controls [30]:

- Position goal task: a task to achieve a desired state by applying a positional shift $p$ to a target object.
- Force goal task: a task to achieve a desired state by applying force $f$ to a target object.
- Hybrid goal task: a task to achieve a desired state by applying positional shift $p$ and force $f$ to a target object.

We categorized skill parameters to follow this categorization: (1) position parameters that are needed for applying positional shift $p$; (2) force parameters that are needed for applying force $f$. In addition to these parameters, we included (3) body

| TABLE I | SKILL PARAMETERS OF MANIPULATION TASKS |
|--------------------------|----------------------------------------|
| tasks | Position parameters | Force parameters |
| NC-NC | Waypoints | - |
| NC-PC | - | Detaching axis direction |
| OP-PR | - | Force on the axis |
| OR-RV | - | Attaching axis direction |
| PC-NC | - | Force on the axis |
| PR-OP | Trajectory on maintaining dimension (2D plane) | Surface normal axis direction |
| RV/OB | - | Force on the axis |
| PC-PC | Trajectory on maintaining dimension (1D distance) | Plane orthogonal to trajectory |
| PR-PR | - | Force in the plane dimension |
| RV/RV | Trajectory on maintaining dimension (Angle and radius) | Axis direction to rotation center |
| | | Force on the axis |
parameters that are needed to mimic human motion characteristics. Detailed explanations are described in related work [26].

Table 1 illustrates the skill parameters of each task. A position goal task (i.e., NC-NC) requires position parameters; a force goal task (e.g., NC-PC) requires force parameters; a hybrid goal task (e.g., PC-PC) requires position and force parameters. In addition to these parameters, each task has the body parameters. In this way, the task class determines the content of skill parameters, which are obtained by daemons.

Table 2 illustrates the skill parameters of the grasp and release tasks. We divided the skill parameters into two classes. The skill parameters in the first class are obtained by a daemon and the skill parameters in the second class are obtained at the time of robot execution. For example, a grasp position is classified as the second class because a target-object position is not invariant.

C. Obtaining skill parameters by a daemon

Depending on a recognized task type, daemons collect necessary skill parameters, summarized in Table 1 and 2 by employing the verbal FoA. In the current implementation, we assume that a demonstrated manipulation operation shall occur between the grasp and release timings.

1) Task type recognition

The task-model encoder recognizes tasks included in a demonstration by analyzing the task-candidate-FoA filter. In the current implementation, the FoA contains one or more candidates for a sequence of tasks associated with a verb. For example, the verb “open” is associated with two candidates: OP-PR-PR and OR-RV-RV. When there are multiple candidates, the daemon selects the candidate by analyzing the trajectory of the manipulating hand during a manipulation operation. Depending on the decided sequence of tasks, the task-model encoder invokes daemons to obtain the necessary skill parameters.

2) Position parameters

A daemon extracts the manipulating-hand trajectory from the human skeleton poses between the grasp and release task timings (i.e., the grasp-release-FoA filter). In the case multiple tasks are recognized, the daemon segments the trajectory accordingly into sub-trajectories corresponding to each task by using temporal information such as the timings when verbs were uttered and the timings at a local minimum of the hand velocity. The extracted trajectories are analyzed to obtain the position parameters.

For NC-NC tasks, the position parameter is obtained as a spatially discretized manipulating-hand trajectory. For PC-PC, PR-PR, and RV-RV tasks, the position parameter is obtained as parameters of 2D plane fitting, line fitting, and circle fitting of the manipulating-hand trajectory, respectively.

3) Force parameters

In the case of the force goal task, the detaching and attaching axes are obtained as the axes on which the acceleration and deceleration of the manipulating hand occurred around the timings when the grasp and release tasks occurred (i.e., the grasp-release-FoA filter). In the case of the hybrid goal task, the axes on which the force is applied are obtained as the axes orthogonal to the axes on which the positional shifts are applied. In both cases, the magnitude of the force is left as an empty value because of the difficulty to obtain the value from verbal and visual information.

Table II. Skill Parameters of the Grasp and Release

| tasks    | Parameters filled by daemon            | Parameters filled on-site |
|----------|----------------------------------------|---------------------------|
| grasp    | Object name, Object attribute          | Grasp type, manipulating hand, Grasp position |
| release  | Release location                        | Release position          |

Figure 3. Overview of the verbal-driven focus-of-attention (FoA).

Figure 4. Definition of states and the possible state transitions. (a) Three basic states originally defined by Mason and three augmented states. The grey object is a target object. (b) Possible state transitions.
4) **Body parameter**
A daemon obtains the body parameters as a spatially discretized human posture. We used 26 point orientations on the unit sphere as an implementation of the discretization inspired by Labanotation dance scores, which has previously been applied in several robot studies [15], [31].

5) **Skill parameters of the grasp and release**
Several skill parameters of the grasp and release are directly obtained from the output of the verbal FoA. Here we explain the strategy to obtain the remaining skill parameters: grasp type, grasp location, and release location.

A grasp type is appropriately selected by a demonstrator according to the purpose of the task. For example, in the case of placing a cup on a shelf with narrow space up and down, it is reasonable to grasp the side surface of the cup. On the other hand, in the case of placing a cup on top of a tray of other cups, it is reasonable to grasp the top surface of the cup. Based on a human grasp taxonomy [32], [33], a daemon detects a grasp type by a rule-based image analysis at the time when the grasp occurred (i.e., the grasp-release-FoA filter).

The grasp and release locations are defined as locations where the grasp and release occurred in an environment model (i.e., the target-object-position FoA filter). The location is obtained as a label of a semantically segmented 3D area such as “above-a-shelf area” by matching the model with the positions of the manipulating hand when the grasp and release occurred. At the time of robot execution, the task-model decoder calculates the grasp and release positions inside the locations.

IV. IMPLEMENTATION OF THE VERBAL FOCUS-OF-ATTENTION

In this section, we describe detailed implementations of the verbal FoA (Fig. 3). All the modules are implemented on Robot Operating System (ROS), which is a commonly used middleware for robot systems. The system is composed of four modules: language parser, generic object detector, object selector, and grasp-release detector.

A. **Language parser**
The language parser analyzes transcribed human verbal instructions to output task candidates (i.e., the task-candidate FoA filter), a target-object name (i.e., the target-name-FoA filter), and an attribute of the target object (i.e., the attribute-FoA filter). For example, for an input of “Pick up a red cup and place it on the shelf,” this module outputs a task candidate “PC-NC-NC,” a target-object name “cup,” an attribute “red.” The input data is obtained by sequentially applying an ego-noise reduction filter [34], a voice activity detection based on signal power, and a cloud speech recognition service [35] to an audio signal acquired through a wireless microphone.

Based on the word classes and the word dependencies detected by a Stanford language parser [36], the module extracts task-related verbs, a target-object name of the verbs, and an attribute of the target object. The algorithm follows the steps below:

1. The module filters task-related verbs by referring a knowledge database (Table 3), which associates each task with a predefined representative verb set. The current implementation limits the teachable tasks to the set of associations. Ideas to ease the limitation are discussed in the Discussion section.

2. The module searches a target object that is labeled as the accusative object of the filtered verbs.

3. The module searches adjectives that are labeled as an adjectival modifier of the object. The current implementation supports color as an attribute. Therefore, the module detects the color attribute, if any, by string-matching the found adjectives with a predefined color name set (e.g., red, blue).

B. **Generic object detector**
The generic object detector analyzes time-series RGB-D images to output the time-series of the 3D position of the detected objects. We used an Azure Kinect sensor [37] mounted on a robot’s head to capture the images. The nominal sampling rate was five hertz.

The module detects objects in a demonstration by a generic object detection CNN [38] (Fig. 5 (a), left pane). The CNN detects 42 household-object classes such as dish, cup, and plastic bottle. The module crops the RGB-D images using the detected bounding boxes and converts them into point clouds represented by environment coordinates. For each cropped image, the module calculates the object position as the mean value of the point cloud positions (Fig. 5 (a), right pane).

C. **Object selector**
The object selector outputs the time-series of the target-object positions (i.e., the target-object-position FoA filter) by analyzing the target-name-FoA filter, the attribute-FoA filter, and all the detected object positions. This module first filters objects by matching the detected object names and the target-name-FoA filter (Fig. 5 (b), left pane). Next, the module filters objects by matching object colors and the attribute-FoA filter (Fig. 5 (b), right pane). An object color is decided as the dominant pixel-color inside the detected bounding box in the HSV color space. In the case an attribute-FoA filter is not detected by the language parser, only the target-name-FoA filter is applied.

The filtered target objects are mapped to a 3D voxel space. In the current implementation, a voxel is a regular polygon with 0.15 m length. Note that the module does not verify identities between the target objects. The target objects

| Representative verbs          | Candidate of task sequences |
|------------------------------|----------------------------|
| pick, pluck, get, grab       | PC-NC-NC                   |
| put, place, set, attach, stow, latch, hang, load | NC-NC-PC                  |
| wipe, sweep, align, erase, drag, roll, haul | PC-PC                     |
| open, pull                   | OP-PR-PR or OR-RV-RV      |
| close, shut                  | PR-PR-OP or RV-RV-OR      |
| widen, slide, broaden rotate, turn, wheel, slue | PR-PR or RV-RV            |
represented in the voxel space are sent to the grasp-release detector as the target-object-position FoA filter.

D. Grasp-release detector

The timings when the grasp and release occur helps a daemon to obtain a grasp type, human postures to grasp and release, and the trajectory of a manipulating hand during an operation. However, because of occlusion due to the hand, RGB-D image processing often fails to detect the exact timings. Here, the grasp-release detector analyzes the human skeleton poses and output of the object selector to detect the timings when the grasp or release occurred (Fig. 6). The human skeleton poses were obtained through an Azure Kinect sensor with a nominal sampling rate of 15 hertz. The positions labeled as hand-tip of the human skeleton poses were analyzed as human hand positions.

Assuming that the grasp and release occur when a human hand approaches and leaves a target object, the module first calculates the candidates of the timings by using the equation

$$T_i = \text{Argmin}(\text{Distance}(H_t, \text{Obj}_i)),$$

where $i$ indicates an index of a 3D spatial voxel and $H_t$ indicates a hand position at time $t$, $\text{Obj}_i$ indicates the object position defined as the median of the target-object positions in a voxel $i$. $\text{Argmin}$ indicates an operation to obtain the index of the global minimum along the time, and $\text{Distance}$ indicates an operation to obtain the Euclidean distance between two positions. $T_i$ is calculated for the left and the right hand for all the voxels containing more than one target object. We ignored the voxels where the distance between $H_t$ and $\text{Obj}_i$ at $T_i$ is more than 0.2 m assuming that the grasp and release occur when the manipulating hand is close to the target object.

The module next decides whether a candidate of the timing, $T_i$, corresponds to the grasp or release. To this end, the module analyses the averaged existence probabilities of the target object before and after $T_i$. Depending on a characteristic of the existence probabilities, the module classifies $T_i$ into one of the following three types. In the case the target object exists before $T_i$ and does not exist after $T_i$, the $T_i$ is classified as a grasp timing (Fig. 6 (b)). In the case the target object does not exist before $T_i$ and exists after $T_i$, the $T_i$ is classified as a release timing (Fig. 6 (c)). Otherwise, the $T_i$ is classified as an unrelated timing. In the current implementation, we set the criteria of existence probability as 0.5. Here, we assume that voxel resolution is fine enough that any grasp release does not occur in the same voxel. The $T_i$s that are classified as grasp or release are sent to a daemon with the index $i$ of the voxels and the laterality of the manipulating hand.

V. EXPERIMENT

We have tested an implemented LfD system and verified the effectiveness of the proposed verbal-driven FoA. To save space, this section covers two representative cases. We used a humanoid robot, Seednoid [39], as the LfD agent. The robot was selected because it has a pair of 7-DOF arms as well as a movable waist to enable a wide variety of manipulations.

![Figure 6. Processing of the grasp-release detector. (a) (left) Human demonstration of open-a-fridge operation. (a) (right) The trajectory of the right-hand during the demonstration. Colored points indicate the filtered positions by the grasp-release FoA. Gray points indicate temporal noises. Daemons analyze the filtered points to obtain skill parameters such as a grasp type, human postures to grasp and release, and the hand trajectory during the operation. (b, c) A voxel where grasp and release were detected, respectively. The red dash lines indicate the detected timings when the grasp or release occurred (i.e., grasp-release FoA). (top) Euclidean distance between the target object (i.e., fridge) and the right hand. (bottom) Existence probability of the target object smoothed with a time window with a duration corresponding to 10% of the period of the whole demonstration.](Image)

Figure 5. Processing of the generic object detector and the object selector. (a) (Left) Detected objects in a demonstration of pick-place-a-red-cup operation. (Right) All the detected object positions overlaid on a 3D environment model depicted as gray lines. Each color depicts a different object class. (b) Object selection from all the detected positions by the target-name-FoA filter followed by the attribute-FoA filter. Black points depict the filtered positions by the FoA filters. Gray points depict spatial noises.

Figure 6. Processing of the grasp-release detector. (a) (left) Human demonstration of open-a-fridge operation. (a) (right) The trajectory of the right-hand during the demonstration. Colored points indicate the filtered positions by the grasp-release FoA. Gray points indicate temporal noises. Daemons analyze the filtered points to obtain skill parameters such as a grasp type, human postures to grasp and release, and the hand trajectory during the operation. (b, c) A voxel where grasp and release were detected, respectively. The red dash lines indicate the detected timings when the grasp or release occurred (i.e., grasp-release FoA). (top) Euclidean distance between the target object (i.e., fridge) and the right hand. (bottom) Existence probability of the target object smoothed with a time window with a duration corresponding to 10% of the period of the whole demonstration.
1) **Experiment 1: “Pick-place a cup” operation**

In this experiment, we verified that the task-model encoder substantiates a task model by reducing a spatial noise in a demonstration. A demonstrator picked up a red cup with the right hand and place the cup on a shelf with a verbal instruction of “Pick up a red cup and place it on the shelf.” The demonstration contained a blue cup as a spatial noise. However, the verb FoA recognized the color attribute and the timings when the grasp and release occurred. The result indicates that the verbal FoA reduced the spatial noise in the demonstration. In addition, we verified that the task model is executable by the real robot Fig. 7 (b).

Fig. 7 (a) shows a part of the substantiated task models. The system recognized the color attribute and the timings when the grasp and release occurred. The result indicates that the verbal FoA reduced the spatial noise in the demonstration. In addition, we verified that the task model is executable by the real robot Fig. 7 (b).

2) **Experiment 2: “Open a fridge” operation**

In this experiment, we verified the task-model encoder substantiates a task model by reducing a temporal noise in a demonstration. A demonstrator opened a fridge with the right hand with a verbal instruction of “Open the fridge.” The demonstration contained unrelated body movements before and after the open-related movements as a temporal noise.

Fig. 8 (a) shows a part of the substantiated task models. The system recognized the trajectory of the revolute movement by extracting the timings when the grasp and release occurred. The result indicates that the verbal FoA reduced the temporal noise in the demonstration. In addition, we verified that the task model is executable by the real robot Fig. 8 (b).

### VI. DISCUSSION

**A. Dual hand manipulation**

The verbal FoA algorithm detects the time when the grasp and release occurred for both arms independently. Therefore, the FoA can be applied to a demonstration of dual hand manipulation [30].

**B. Language-to-task mapping**

In this paper, we prepared a knowledge database associating verb sets with task candidates (Table. 3). Such association helps to avoid ambiguity of verbal instruction in terms of robot control. However, the verb-based association may not be sufficient as a practical application. The association for some verbs could change depending on the target object. For example, “use a mop” suggests a PC-PC task while “use a knife” suggests a NC-PC task. This issue has recently been addressed by Paulius et al. [40]. To address this issue, we are currently in the process of investigating a relationship of task similarities based on the task category and those based on an embedding space of a sentence.

### C. Attributes of the target object

In the current implementation, the verbal FoA supports color attributes. Considering that attribute can contribute to ensuring the identity and homogeneity to reduce ambiguities of the target object, supporting other attribute FoA filters could more efficiently guide the task-model encoder. To the best of our knowledge, there is no agreement as to a practically sufficient set of attributes. As a potential baseline, Beetz et al. proposed to use color, size, position, and shape for a robot perception system operating in a household environment [42].

### D. Toward a robust task model encoding

In this paper, the verbal FoA was tested with a demonstration with perfect information to substantiate a task model. However, the FoA could fail when the demonstration lacks essential information. For example, for an input of “Pick up this.,” the implemented FoA fails because it cannot resolve the pronoun. In a human-to-human demonstration, questioning is often used to compensate for the lacking information. The role of verbal communication for disambiguation is also supported by LfD research [43]. Toward a robust task model encoding, the verbal FoA can be combined with a questioning module to compensate for any lacking information, such as an unknown verb, additional attributes to confine a target object, or a pronoun.

### VII. CONCLUSION

In this paper, in the context of Learning-from-Demonstration (LfD), we dealt with a problem to encode human demonstrations into a series of execution units for a robot in the presence of spatio-temporal noises. Inspired by a function of verbal instructions to guide an observer’s visual attention, we proposed a verbal-driven focus-of-attention...
(FoA) system to reduce the noises, specifically unrelated objects in a demonstration environment and human body movements before and after a demonstrated manipulation operation. We demonstrated the effectiveness of the verbal FoA by testing an implemented LfD system with a real humanoid robot. The contributions of this paper are: (1) to propose verbal FoA for LfD; (2) to design an algorithm to calculate FoA filters from verbal input; (3) to demonstrate the effectiveness of a verbal FoA by testing an implemented LfD system in noisy environments.

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