Visually Grounding Instruction for History-Dependent Manipulation

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Abstract—This paper emphasizes the importance of robot's ability to refer its task history, when it executes a series of pick-and-place manipulations by following text instructions given one by one. The advantage of referring the manipulation history can be categorized into two folds: (1) the instructions omitting details or using co-referential expressions can be interpreted, and (2) the visual information of objects occluded by previous manipulations can be inferred. For this challenge, we introduce the task of history-dependent manipulation which is to visually ground a series of text instructions for proper manipulations depending on the task history. We also suggest a relevant dataset and a methodology based on the deep neural network, and show that our network trained with a synthetic dataset can be applied to the real world based on images transferred into synthetic-style based on the CycleGAN.

I. INTRODUCTION

The ability to refer to the past is essential for robots for their long-term interaction with humans. The goal of this paper is to validate the benefits of the history-aware robot, especially when it continuously receives the text instructions to perform a series of pick-and-place manipulations. We claim that robots can benefit by referring to one’s task history in terms of following aspects: (1) a robot can interpret the text instructions omitting details or using co-referential expressions, and (2) can infer the occluded visual information due to robot’s fixed point of view.

We propose a task of history-dependent manipulation, to present the advantage of the manipulation robot which can refer to its task history. Figure 1 shows an example of history-dependent manipulation task. In this task, a human who knows the shape of the target structure keeps instructing the robot to manipulate blocks. While the human observes the workspace from multiple perspectives, the robot can visually observe the workspace with an RGB camera at a fixed position. Under these conditions, it is required for the robot to refer its task history (1) for understanding the language expression assuming robot’s ability to recall the past, and (2) for overcoming the occlusion in its visual observation.

In Figure 1, the blue fonts of the text instruction show an example of the first case. After the robot manipulates ‘front green block’, the next instruction orders the robot to manipulate ‘another green block’. If the robot can recall that the object manipulated in the previous operation was ‘front green block’, it would understand what ‘another green block’ refers, which is the rear green block that has not been manipulated before. The red fonts of the text instruction show an example of the second case. After the robot stacks the front green block on the yellow block, the yellow block becomes invisible to the robot at the next stage. Since there is no limitation in human’s perspective, he/she can instruct the robot to place the next target object behind the yellow block, which is occluded in robot’s perspective. Although the yellow block is invisible to the robot, this problem can be solved only if the robot can recall the visual information obtained from the previous operation.

In this paper, we propose a synthetic dataset of various scenarios of the history-dependent manipulation task, and a deep neural network based methodology to solve the challenges of history-dependent manipulation. Our synthetic dataset provides 1200 scenarios of history-dependent manipulations, and each scenario is composed with a series of pick-and-place manipulations for building structures with given blocks. For each pick-and-place manipulation, a set of relevant instructions and an RGBD images observing the workspace before the operation are provided.

Note that our synthetic dataset does not include complex characteristic of images, natural languages, and robot motions. If the dataset contains such complex environmental factors, we concerned that the added complexity would increase the uncertainty of proposed model’s final prediction, which would be a hindrance to empirically show the benefits of history-aware robots. Therefore, we have focused on providing a benchmark dataset without such indispensable elements. Our synthetic dataset focuses solely on validating the effectiveness of the robot which can refer to the task.
history. We believe the scalability and feasibility issues can be discussed and resolved one by one, after forming a consensus among researchers about the importance of history-aware robots.

The remainder of this paper is structured as follows. The related works are introduced in Section II. Section III describes the proposed dataset regarding our history-dependent manipulation problem. Section IV shows the proposed method based on the attention-based deep neural networks, which would be a benchmark model for future researches. Section V discusses the qualitative and quantitative experimental results, as well as the real-world demonstration of the proposed approach based on the CycleGAN is presented.

II. RELATED WORK

A. History-Dependent Robot Behavior

For enabling a robot to understand human’s utterances based on the history and to eventually perform a goal task, various studies have been conducted. In the field of visual navigation, the task of vision-and-dialog navigation has emerged recently [1], [2]. Their goal is to enable a robot to successfully reach the target by continuously communicating with humans based on language. In this task, a robot needs to keep asking a human how to navigate until reaching a target, and a human would respond to the robot. Since the language expression may refer to past conversations or robot’s past trajectory, the robot needs to perceive the dialog and navigation history to follow the given instruction properly.

In the field of manipulation, [3] suggested a system related to challenges when grounding a given language instruction to proper manipulation depending on the environment and task context. In their work, understanding anaphoric references based on history (i.e., Pick up the snack, and microwave it). [4] proposed a probabilistic model, which is able to accumulate knowledge based on past visual and language information, and employ that knowledge to ground the current language command. These works have highlighted the importance of understanding history by enabling robots to perceive language expressions based on the human assumption of robot’s ability to recall the past. In addition to this, our study further suggests that understanding history can also help robots to infer the information about invisible objects due to occlusion, which is another crucial aspect not covered by previous relevant studies.

B. Visually Grounding Referring Expressions

Since our robot needs to ground the given language instructions in the input RGBD image, our history-dependent manipulation task has a similarity with studies in computer vision research field, whose objective is to comprehend the referring expressions describing a target object existing in the input image [5]–[11]. After several studies that can be categorized by whether the proposed model finds the target object based on a detection box [5], [6] or segmentation map [7], [8], the recent models are able to both locate and segment the referred target object [10], [11].

The task of visually grounding referring expressions have been also related to the object manipulation [12], [13], for enabling robots to find the target object to manipulate. [12] proposed a dataset that can be used to train a robot or agent that can pick up the target object referred by human language instructions. [13] developed a system which can distinguish the target object referred by human language instruction when multiple objects belonging to the same class are given.

These studies are similar with ours in that their models can retrieve the object referred by a given language expression. However, since they do not assume that a human can instruct an agent over times, their objective does not include enabling agents to understand the historical information accrued through the past.

C. Visual Dialog

Since our robot needs to infer the historical information accumulated through the past to understand the current language instruction, our study shares in common with the study of visual dialog agents. The task of visual dialog focuses on developing an agent which has an ability to have a natural language based communication with humans about the visual content in a given image [14].

The objective of the visual dialog agent is to solve the classification problem to choose the correct answer to the question related to the input image when the dialog history for the image is also provided as input. To acquire the correct answer, the agent needs to ground the question in the image and infer the contextual information from the dialog history. [14] was a pioneer in this research field by proposing a relevant dataset and benchmark model, and as a result, related studies are still actively being conducted [15]–[17].

This task is related to our study since the visual dialog agent interacts with humans multiple times, perceiving the historical information. However, our research is distinguished from the task of visual dialog since the visual information provided to our robot changes each time after the robot manipulates the object by following the given language instruction. In other words, our task requires the robot to track not only the history of linguistic interactions, but also the history of how the objects in the workspace have been manipulated so far.

III. SYNTHETIC IMAGE-AND-TEXT DATASET

A. Task Scenario

We focus on a situation where the text instructions ordering the robot to move blocks are given one by one. Each task of history-dependent manipulation starts with a workspace with several blocks of various colors scattered in random locations. The task ends when all the given blocks are moved to build structures. During the task, the robot observes the given workspace vertically from above using an RGBD camera, and executes the given instruction one by one. Since robot’s camera is fixed at a specific location, there can be blocks that are invisible due to occlusion.
With our simulator based on the CoppeliaSim (previously known as V-REP) [18], a dataset reflecting this task scenario has been collected. Our dataset consists of 1200 tasks of history-dependent manipulation (1000 for training, 200 for test), where each task is a series of pick-and-place manipulations to build structures as shown in Figure 2. For each pick-and-place, an RGBD image of the workspace before the manipulation, a set of language instructions, a bounding box information of ground truth target object and position, and time index of the past pick-and-place manipulation that needs to be referred, are provided. For each RGBD image, 3 to 12 corresponding text instructions are provided, and each history-dependent manipulation task consists of 4 to 8 pick-and-place manipulations. In total, the dataset comprises 6092 RGBD images and 43194 text instructions.

### B. Text Instruction

The process of generating instructions for each pick-and-place manipulation can be divided into three sub-processes: (1) generating phrases for target objects, (2) generating phrases for target locations, and (3) combining them into a complete sentence. We neglected ambiguous instructions, so that generated instructions can only indicate a single pick-and-place manipulation.

1) **Phrase Generation for Target Objects:** In our dataset, a target block can be described based on the color, position, nearby blocks, and task history. Regarding the color, our dataset mentions it in an explicit way (i.e., the red block). But if another block with the same color needs to be mentioned in the same sentence, the color information can be annotated such as ‘Stack the left red block above the another same colored block’. The block position is described based on its \( xyz \) position when observed from human (simulator) perspective, such as ‘the block on the left side’. In addition, the relative position with respect to other blocks is also used to describe the block as ‘the foremost block’. If the target block cannot be annotated based on its color and position, it is referred by its adjacent blocks such as ‘the block closest to the red block’. For blocks that have been manipulated before, expressions such as ‘the block that you just moved’ can also be mentioned based on the task history. For example, when all blocks except for the current target block have been manipulated to build a structure, the current target block can be referred as ‘the last remaining block’.

2) **Phrase Generation for Target Positions:** After generating phrases for the target object to move, our simulator generates phrases that describe where the object should be placed. In our task, target positions can be categorized into two types. First, there are positions within the workspace that can be clearly described such as ‘center’, ‘left side’, ‘right front corner’. Second, there are positions adjacent to other blocks, which can be described as ‘on the left side of the yellow block’. In this case, a set of phrases of the block (‘the yellow block’), which is a reference object to describe a target position, is generated based on the object phrase generation method mentioned above, and some words for annotating the nearby location (‘on the left side’) are properly appended to the generated phrases for the reference object.

3) **Sentence Generation:** Let \( (V) \) denote the verb representing ‘pick-up’, \( (V) \)\( ^2 \) denote the verb representing ‘place’, \( (T) \) denote the phrases for target object, \( (P) \) denote the phrases for target position. Based on this, a complete sentence can be generated by assembling these elements as below:

- \( (V) + (T) + \text{‘and’} + (V) ^2 + \text{‘it’} + (P) \)
  - i.e., Take the red block and place it on the left side of yellow block.
- \( (V) ^2 + (T) + (P) \)
  - i.e., Place the red block on the left side of the yellow block.

### C. History Dependency Annotation

1) **History Dependency Types:** After the first pick-and-place manipulation, some text instructions needs to be interpreted by referring the history of how blocks have been manipulated. Situations where the robot needs to understand its task history can be categorized as follows:

- When a given instruction explicitly requires to recall how blocks have been moved.

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**Fig. 2.** An example of the proposed synthetic dataset for the single history-dependent manipulation task. Depth images are neglected due to the space limit. History time index denotes the time indices of the past manipulations that needs to be referred. The difference between current time index and the history time index becomes the history dependency distance.
When a block occluded by others needs to be recalled to interpret the instruction. We will call the first type of dependency as *explicit history dependency* (blue fonts in Figure 2), and the second type as *implicit history dependency* (red fonts in Figure 2). For the explicit annotation, it is examined whether the instruction contains expressions that need to be interpreted by referring to the task history. For the implicit annotation, it is examined whether the instruction mentions the occluded block. The type of history dependency can be annotated based on the phrases for the target object (‘pick-up’), and phrases for the object used as a reference to describe the target position (‘place’). Thus, our dataset provides annotations on what type of history dependency is required to understand each ‘pick-up’ and ‘place’ operation from the current instruction.

2) History Dependency Distances: Not only the type of history dependency, our dataset also provides annotations of time indices of the past manipulations that need to be referred, which we call as ‘history time index’. In the case of explicit history dependency, the time index of the previous pick-and-place manipulation which is referred by the current instruction is labelled. For the implicit history dependency, the time indices of when the occluded object moved to its current location, and when it was occluded are labelled. We denote the difference between the current time index and the history time as ‘history dependency distance’, which is a criterion for how far the model can refer to the past.

Figure 2 shows an example of history dependency distance. In the stage 1, the yellow block that moved in the stage 0 is referred by the phrase ‘the block which you moved’. In this case, the history time index for this phrase would be \(\{0\}\), and corresponding history dependency distance would be \(\{1-0\} = \{1\}\) since the current time index is \(\{1\}\). After stage 1, the yellow block become invisible to the robot since the red block has been stacked on that block. When this yellow block is mentioned in the stage 2, the history time index would be \(\{0, 1\}\) since the time indices of when it moved and when it was occluded need to be considered. Corresponding history dependency distance will be computed based on this, such that \(\{2 - 0, 2 - 1\} = \{2, 1\}\), since the current time index is \(\{2\}\).

IV. METHODOLOGY

To solve history-dependent manipulation, we propose a model based on a deep neural neural networks as shown in Figure 3. It takes an RGBD image and a text instruction as inputs, and locates two bounding boxes for target object and position. The model is composed of modules which are responsible for encoding valuable features from image, language, and task history. Based on extracted features from image, language, and history modules, its classification module predicts two bounding boxes for target object and position. After the prediction, the latent vector obtained from its first fully connected layer is saved as a task history vector for the current manipulation, if it contributed most for the current prediction.

Fig. 3. The proposed model for task of history-dependent manipulation. Best viewed in color.

A. Attention Module

Before describing main modules consisting our model, we would explain the attention module first, which is a sub-module frequently employed in image, language, and history modules. Let us assume that feature vectors encoded from image, language and task history can be represented as a set of vectors such that \(X = \{x_1, \ldots, x_N\}\), where \(x_i \in \mathbb{R}^{D_x}\). Based on the query-key-value-style attention mechanism proposed in [19], our attention module determines where to attend on the information in \(X\). Let \(q \in \mathbb{R}^{D_{kv}}\) denotes the given query vector, and denote \(W_k, W_v \in \mathbb{R}^{D_{kv} \times D_x}\) as matrices for projecting \(x_i\) into key and value vectors as \(W_kx_i, W_vx_i \in \mathbb{R}^{D_{kv}}\). Based on this, a feature vector \(f_X\) representing \(X\) is obtained by a weighted sum of values, where the weight for the \(i\)-th value \(W_vx_i\) is a score of the \(i\)-th key \(W_kx_i\), computed based on the cosine similarity between \(q\) as follows:

\[
f_X = \text{Attention}(q, X; W_k, W_v) = \sum_{i=1}^{N} A_i(W_vx_i),
\]

\[
A_i = \frac{\text{score}(q, W_kx_i)}{\sum_{j=1}^{N} \text{score}(q, W_kx_j)}, \quad \text{score}(a, b) = \frac{a^Tb}{\|a\|\|b\|}
\]

B. Image Module

Given an RGBD image observing the workspace, the image module firstly extract the spatial feature based on the backbone network from [20]. Note that our model needs to understand object’s positional information, to perceive the relationship between the language and image when a phrase such as ‘rightmost purple block’ is given as input. Regarding this, spatial coordinates, whose width and height is same as the generated spatial feature, containing positional information of the each spatial location, is concatenated to the generated spatial feature. The implementation of the spatial coordinate is same as the approach proposed in [21].
Let $F_I = \{f_I(1,1), \ldots, f_I(W,H)\}$ denote the obtained spatial feature and coordinates, where $W$ and $H$ denote its width and height, and $F_I(i,j) \in \mathbb{R}^{D_I}$ denote a feature from a spatial location $(i,j)$. Based on $F_I$, the image module obtains image patches of candidate objects to pick up, and candidate positions to place it down. In this regard, we employ approaches that have been widely used in works related to object detection [22]. Based on $F_I$, a region proposal network (RPN) generates proposals, which are candidate bounding boxes of where ‘pick-up’ or ‘place’ can be performed. Afterwards, a proposal feature $F_P \in \mathbb{R}^{N_P \times D_P}$ (dark blue rectangle in Figure 3), the feature of visual information contained in the $N_P$ proposals, is obtained by region-of-interest (RoI) pooling layer. Here, $F_P(i) \in \mathbb{R}^{D_P}$ denotes the feature for the $i$-th proposal. Although it is neglected in the Figure 3, $F_P$ is also fed into a box-regression layer, to more accurately adjust the size of generated bounding boxes as [22] did. In Figure 3, the box-regression layer is neglected due to the space limit.

In addition, the image module obtains a feature vector which can represent the visual information about all objects observed on the input image. Regarding this, the attention module is used to obtain the objectness feature $f_{obj}$ (purple rectangle in Figure 3), by focusing more on the spatial location containing the object. Let $q_{obj} \in \mathbb{R}^{D_{qkv}}$ denote the query vector for capturing the objectness of each feature vector in $F_I$. Note that $q_{obj}$ is also one of model’s trainable parameters. Then, the objectness feature is obtained as follows:

$$f_{obj} = \text{Attention}(q_{obj}, F_I; W^f_{k}, W^v_{v}),$$  \hspace{1cm} (3)

where $W^f_{k}, W^v_{v} \in \mathbb{R}^{D_{qkv} \times D_I}$ denote the matrices for projecting each $F_I(i,j)$ to key and value vectors.

### C. Language Module

Let $L = \{w_i\}_{i=1 \ldots N_L}$ denote a given text instruction consisting of $N_L$ words, where $w_i$ denotes the $i$-th word in the sentence $L$. The language module encodes the given sentence $L$ into a set of word embedding vectors, such that $E = \{e_i\}_{i=1 \ldots N}$, where $e_i \in \mathbb{R}^{D_E}$ denotes the word embedding vector of $w_i$. After encoding $E$ based on the bi-directional LSTM [23], a set of vectors $F_L = \{\text{Bi-LSTM}(e_i)\}_{i=1 \ldots N_L}$ is obtained. Here, $F_L(i) \in \mathbb{R}^{D_L}$ denotes the encoded vector of the $i$-th word.

Since $L$ contains all information about which object to pick up and where to place it, rather than representing a given sentence with a single feature, our language module encodes the information for ‘pick-up’ and ‘place’ separately based on the attention module. To extract language information about the target object to ‘pick-up’, our model has a query vector $q_{pick} \in \mathbb{R}^{D_{qkv}}$, which is a trainable parameter to capture the language information related to ‘pick-up’. For obtaining key and value vectors of $F_L$, the projection matrices $W^L_{k}, W^L_{v} \in \mathbb{R}^{D_{qkv} \times D_L}$ are used. Based on these, the language feature of ‘pick-up’ and ‘place’ can be obtained as follows (dark green rectangles in Figure 3):

$$f^L_{pick} = \text{Attention}(q^L_{pick}, F_L; W^L_{k}, W^L_{v})$$ \hspace{1cm} (4)

$$f^L_{place} = \text{Attention}(q^L_{place}, F_L; W^L_{k}, W^L_{v})$$ \hspace{1cm} (5)

### D. History Module

Assume that the model has a set of vectors representing the task history as $H = \{h_i\}_{i=1 \ldots N_H}$, where $h_i \in \mathbb{R}^{D_H}$ denotes a vector encoding the history of the $i$-th operation. In our model, the information related to ‘pick-up’ and ‘place’ are stored separately (i.e., $h_0$ for the first ‘pick-up’, $h_1$ for the first ‘place’, $h_2$ for the second ‘pick-up’...). How $h_i$ is obtained will be represented in the Section IV-E.

Based on the bi-directional LSTM, the history module encodes $H$ into $F_H = \text{Bi-LSTM}(H)$ first, where $F_H(i) \in \mathbb{R}^{D_H}$ represents a vector encoding the $i$-th history. Based on the attention module, the history module encodes $F_H$ with respect to ‘pick-up’ and ‘place’, to understand $H$ with respect to each sub-task. Based on this, if the input $L$ is “Take the last block and stack it above the block that you just moved”, the model needs to focus on the whole history to understand what to pick up, but focus only on the latest history to understand where to place it.

To capture the history information related to current ‘pick-up’ task, the relevant language feature $f^L_{pick}$ and time information of the current ‘pick-up’ is employed to construct a query vector $q^H_{pick} \in \mathbb{R}^{D_{qkv}}$. Regarding the time information, let $T_{pick}, T_{place} \in \mathbb{R}^{T_{max}}$ denote the one-hot encoded time indexes of when current pick-and-place would happen, and $W_T \in \mathbb{R}^{D_T \times T_{max}}$ denote the matrix for projecting them into a high-dimensional space. For example, for the first pick-and-place manipulation, time indexes would be $T_{pick} = [1,0,0,\ldots]^T$ and $T_{place} = [0,1,0,\ldots]^T$.

Based on language and time information for each ‘pick-up’ and ‘place’, the query vector for each sub-task are generated, and the history feature of ‘pick-up’ and ‘place’ are obtained as follows (brown rectangles in Figure 3):

$$f^H_{pick} = \text{Attention}(q^H_{pick}, F_H; W^H_{k}, W^H_{v})$$ \hspace{1cm} (6)

$$f^H_{place} = \text{Attention}(q^H_{place}, F_H; W^H_{k}, W^H_{v})$$ \hspace{1cm} (7)

$$q^H_{pick} = W^H_{q} [f^L_{pick}; W_T T_{pick}]$$ \hspace{1cm} (8)

$$q^H_{place} = W^H_{q} [f^L_{place}; W_T T_{place}]$$ \hspace{1cm} (9)

where $W^H_{q} \in \mathbb{R}^{D_{qkv} \times (D_{qkv} + D_T)}$ and $W^H_{k}, W^H_{v} \in \mathbb{R}^{D_H \times D_{qkv}}$ are projection matrices for query, key, and value vectors.

### E. Classification Module

The classification module predicts which proposal is most suitable for ‘pick-up’ or ‘place’. To estimate whether the object in the $i$-th proposal is proper for ‘pick-up’ or ‘place’, the classification module consists its input vectors $I_{pick}$ and $I_{place}$ based on the features of $i$-th proposal, objectness, language, and time, such that:

$$I_{pick}(i) = [F_P(i); f_{obj}; f^L_{pick}; W_T T_{pick}]$$ \hspace{1cm} (10)

$$I_{place}(i) = [F_P(i); f_{obj}; f^L_{place}; W_T T_{place}]$$ \hspace{1cm} (11)
After passing each $I_{\text{pick}}(i), I_{\text{place}}(i)$ to a fully connected and a leaky ReLU layer, intermediate features $H_{\text{pick}}(i), H_{\text{place}}(i)$ are obtained. Then, the score $s_{\text{pick}}(i)$ and $s_{\text{place}}(i)$ representing how much the $i$-th proposal would be suitable for ‘pick-up’ or ‘place’ are obtained after passing each $[H_{\text{pick}}(i); f^H_{\text{pick}}], [H_{\text{pick}}(i); f^H_{\text{place}}]$ to its last fully connected layer.

Among $N_P$ proposals, assume that the $p_1$-th proposal with the maximum $s_{\text{pick}}$ value is chosen for ‘pick-up’, and the $p_2$-th proposal with the maximum $s_{\text{place}}$ value is chosen for ‘place’. Then, $H_{\text{pick}}(p_1)$ and $H_{\text{place}}(p_2)$, which represent the meaningful visual, language, and time information used to solve the current manipulation task, are appended to the set of history vectors $H$.

V. EXPERIMENTS

A. Network Training

Based on the training dataset composed of 1000 tasks of history-dependent manipulation, our model is trained by an end-to-end way. Note that a task consists of a series of pick-and-place manipulations, and our dataset provides several instructions describing each manipulation. Therefore, to iterate over one task, one sentence is randomly sampled as an input for each manipulation. For the word embedding vector, we used pretrained model from [24].

For each manipulation, after the network generates the scores of $s_{\text{pick}}$ and $s_{\text{place}}$ for generated proposals, a binary cross-entropy function is used to compute the loss for each sub-task, such that $\mathcal{L}_{\text{pick}}$ and $\mathcal{L}_{\text{place}}$. Here, at the beginning of the training phase, a ground truth bounding box information is given to the network to generate history vectors $H$. After that, we gradually increase the ratio of feeding the estimated bounding box information to the network to generate $H$, so that the network can be gradually exposed to its own generation errors. This method is based on the existing study related to the scheduled sampling [25].

In addition to the classification losses, the losses from the RPN and box-regression layer of the image module, which are denoted as $\mathcal{L}_{\text{RPN}}$ and $\mathcal{L}_{\text{reg}}$, are computed as the same way proposed from [22]. Then, the final loss for a single pick-and-place manipulation becomes

$$\mathcal{L} = \lambda_1(\mathcal{L}_{\text{pick}} + \mathcal{L}_{\text{place}}) + \lambda_2\mathcal{L}_{\text{RPN}} + \lambda_3\mathcal{L}_{\text{reg}},$$

where $\lambda_1$ is a balancing hyper-parameter. In real experiment, we used $\lambda_1=0.5, \lambda_2=0.05, \lambda_3=1.0$. After averaging $\mathcal{L}$ from all manipulations composing a task, it is minimized by the Adam optimizer [26] with the learning rate of 0.0001.

B. Qualitative Result

Figure 4 shows an example of the qualitative result, when the trained network estimates the target object and position based on the series of input image and language pairs in our test dataset, orders from top to bottom. For the input text instruction, please refer to the $x$-axis values of language attentions. The generated objectness attention, where the yellow area indicates the higher value of attention, shows that the image module has successfully learned how to focus on the area where the object is located. Regarding the generated attentions for text instruction, it is shown that the proper attention has been given to the phrases related to ‘pick-up’ or ‘place’.

However, the attention generated for the task history does not seem to be sufficient to explain our model’s inference results. When we examined other cases from the test dataset, it is observed that the history attention tends to be generated more evenly than the language attention, so that the entire task history can be considered. To generate the history attention which is more suitable for explaining the reasoning process of the model, we claim that the separate agent to generate the corresponding attention is necessary, and this would be our future work.

C. Quantitative Result

To demonstrate the effectiveness of referring the task history, we conducted an ablation study, which compares the task accuracy of our network when it has a history module or not. To verify the performance, the accuracy of single pick-and-place manipulation has been measured. If the IoU (Intersection over Union) between the ground truth and predicted bounding boxes is greater than 0.5, the result is counted as correct. For measuring the performance of the proposed model with the history module, we have referred the studies of visual dialog [14], and measured the accuracy of the $n$-th manipulation by allowing the model to encode the history correctly based on the ground truth bounding box information of ‘pick-up’ and ‘place’ until the $(n-1)$-th manipulation. When training the proposed model without a history module, since it does not have the ability to understand the task history, the training data of pick-and-place manipulations without the history dependency were employed.

Table I shows the measured accuracy for each model. To subdivide the results, the accuracy of PICK, PLACE, BOTH are shown. Here, PICK or PLACE refer to the accuracy of classifying the target object or position, and BOTH refers to the accuracy of classifying both target object and position. ‘Existence of history dependency in instructions’ denotes whether the task history needs to be referred to interpret the phrases related to a target object (phrase of pick) or position (phrase of place). Here, ‘None’ denotes that the instruction does not require to understand the history, and ‘Phrase of Both’ denotes that the history needs to be perceived to understand phrases of target object and position.

Based on the result, we would like to emphasize that the performance of the proposed model with a history module has a better performance when understanding instructions with a history dependency. However, the result also shows that the proposed model without a history module can perform better in understanding instructions which does not require the history dependency. We claim that it is because the model with a history module always refers to the task
TABLE I  
| Existence of History Dependency in Instructions | None | Phrase of Pick | Phrase of Place | Phrase of Both |
|-----------------------------------------------|------|---------------|---------------|---------------|
| w/ History Module                             | 89.2 / 80.7 / 73.0 | 95.5 / 63.5 / 62.2 | 89.0 / 62.7 / 57.3 | 97.5 / 49.2 / 49.2 |
| w/o History Module                            | 91.5 / 86.5 / 79.5 | 82.7 / 69.2 / 56.4 | 85.5 / 52.2 / 44.3 | 90.7 / 36.4 / 34.7 |

Fig. 4. An example of the qualitative result. The task proceeded from top to bottom. Input depth images are neglected due to the lack of space, and more results can be found in the supplementary material. For input instructions, please refer to the x-axis values of language attentions. In the x-axis label of generated attentions for history vectors, pick\_i and place\_i denote the history vector stored after the i-th manipulation. Note that in the 3rd manipulation, the ‘left purple block’ exists but is occluded due to the yellow block which was manipulated in the 2nd operation.

Fig. 5. The accuracy result with respect to the history dependency distance of pick-and-place manipulation. Note that the larger value of the history dependency distance means that the instruction can be understood by perceiving the task history longer ago.

history. In other words, we suspect that the obtained history feature would have been a hindrance when the model tried to understand the text instructions that do not require the history dependency.

It is shown that the overall accuracy of PLACE is low. We claim that it is because the phrases describing the target position have much more linguistic complexity than the ones describing the target object. Meanwhile, the performance of the model without a history module is not bad when the history needs to be understood to interpret the phrase describing the target object. We suspect that the model has cheated on the characteristic of target object candidates, which tend to be placed in a random orientation, while the objects that are already manipulated tend to be placed upright.

Figure 5 shows how the accuracy of each model changes with respect to the history dependency distances of the instructions. Based on this result, we claim that the proposed model with a history module is more robust than the one without a history module, since its accuracy tends to be more stable even if the older task history needs to be perceived. Even if the overall performance is not very remarkable, we claim that the result shows that the proposed model with a history module could perform better on tasks that require reference to the task history, and we believe that our model can be employed as a baseline for future studies.

D. Real World Experiment

Our network trained based on the synthetic data has been also applied to the real-world. As shown in Figure 6, we attached a RealSense camera to Baxter robot’s right hand, and enabled a robot to place its arm at a fixed position to observe the workspace. To bridge the gap between RGBD
images from the real-world and simulator, we employed CycleGAN [27], which is able to transfer images from different domains. To train CycleGAN, we have collected 800 RGBD images of real-world workspace, and employed simulator-based images from our training dataset. As shown in Figure 6, the trained CycleGAN transforms the new real-world RGBD images to look like the ones from the simulator, so that our model can execute the task based on the transferred image.

VI. CONCLUSION

In this paper, we introduce a task of history-dependent manipulation, which aims to enable a robot to refer to its task history when executing a series of manipulation tasks instructed by text instructions. For solving challenges of this task, we have proposed a synthetic dataset and methodology based on the deep neural networks, which can provide a baseline for relevant future studies. In experiments, it is shown that our network has learned how to interpret the image, text, and task history based on the attention mechanism determining which part of the information needs to be focused on. Based on the CycleGAN, our network trained with the synthetic dataset has been applied to the real world, suggesting the scalability of our work.

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