Open-Ended Multi-Modal Relational Reason for Video Question Answering

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Abstract—People with visual impairments urgently need assistance, not only on the fundamental tasks such as guiding and retrieving objects but on the advanced like picturing the new environments. More than a guiding dog, they might want such devices that can provide linguistic interaction. Building on this idea, we aim to study the interaction between the robot agent and visually impaired people. In our research, we are going to develop a robot agent that will be able to analyze the test environment and answer the participants’ questions. In this paper, we are going to discuss the issues occurring in the human-robot interaction, and identify the correlated factors.

Index Terms—HRI, Video Question Answering, VQA, NLP

I. INTRODUCTION

With the development of robotic technology, people expect robots can handle more tasks in their daily life. Take an example of Japan, where occurring population aging, the robots are to take care of aged people. Similar needs also urge among the people with visual impairments. For them, the traditional solution might be guiding dogs.

However, there are several shortcomings in using guiding dogs. As a kind of animal, the guiding dogs have various temperaments and personalities. Sometimes they might make irregular behaviors and get out of control. Usually, guiding dogs require a relatively long time to train. More importantly, as everyone currently accepts, the dog cannot speak the human language. Other people might argue that dogs can communicate with humans by barking. However, for those people, they have to admit that barking conducts far less information than directly linguistic expression.

Hence, we argue that the robot agent which processes the video that supposes to be seen by human eyes can provide more efficient interactions through communication. This robot agent, once applied, will be able to improve the lives of visually impaired humans.

The robot agent, in our experiment, will keep its angle of view the same as its human user. The robot agent will actively explore the surroundings. For example, a blind user goes to a new mall and want to buy clothes. The robot agent could do several things to help this build user. First, it can ask the user what kinds of clothes the user wants to buy. After filtering out several candidate options, the robot can guide the user to each of them. Then, it can tell the user about the shape of the clothes, the color, and the size. It also can scan each of the stores and let the user know how many people in that store so that the user can avoid the crowded stores.

In this paper, there are four questions we are going to study. First, how the agent gets the blind user to understand the environment. Once the robot agent scans the environment and processes the taken video, the agent only generates a chunk of results, which might include locations, colors, shapes, and coordination. For blind people, could they picture the environment in their mind only through the communication with the agent, is a question we are going to study. Second, does the agent understand the blind user’s questions and provide appropriate feedback? The user might ask questions which are irrelevant to the current environment. For example, if at home, the user asks the robot agent whether it can find a doctor. In this example, the concept of ”doctor” doesn’t connect to any objects in the home. The appropriate feedback, from the robot agent, could be offering a phone call to 911, or asking other people’s help. In general, similar scenarios are going to be studied in our experiment. Third, how people feel about the voice feedback. In an ideal environment, where no noisy factors exist, the user can hear the robot agent’s feedback. However, such an environment is relatively rare in the real world. We want to understand whether the interaction between the blind user and the robot agent is heavily interrupted. Fourth, whether people feel comfortable with this interaction and how much trust is between the blind user and the robot agent. Compare to the robot agent, people might be easier to build trust with the guiding dog. The potential reasons might come from culture, tradition (human-dog’s long relationship in the history), or biology (organic intelligent animals are more likely to trust each other than them to the cool machines). In some other cases, people tend to overtrust [1] the robot. Neither undertrust nor overtrust to the robots brings negative effects to the human-robot interaction.

II. RELATED WORK

Pre-training for Natural Language Processing (NLP): It is interesting to note there are some pre-training models for the Natural Language Network. In previous research, models such as NS-VQA[2], use the sequence to sequence method to the model building. However, during the daily conversation, enormous conditions such as dialog also can be applied by
this question-answering. In our research work, we aim to build a model which use with people with visual impairments urgently, which should be able to process linguistic context and understand gramma. In the dialog conversation, it’s highly possible to have the issue that they do not have the symbols after the sentences and polysemous condition in the sentence. There are previous researches on improving word embedding [4],[5]. With the milestone of the transformation[6], there was advanced progress in the Natural Language processing area, especially on the polysemous condition in the sentences. In recently technology, there are a lot of new pre-training models used to judge the question and provide the answers with the model result, such as BERT[7], XLNet[8], gpt-2[9] and ViLBERT[10]. Among them, BERT is perhaps the most popular one due to its simplicity and superior performance.

**Multi-Model for Visual Question Answering(VQA)** In the previous Model, there are so many state-of-the-art approaches are working on the Visual Question Answering, such as BUTD[11], MFB[12], BAN[13], MMNasNet[14]. However, our research has limitations not only in the computing source usage but also in the original methods in VQA training the data for the vision and language tasks. It will lose a lot of resources of the machine. We propose a framework to leverage these soft programs and scene graphs. In the milestone of the Neural-Symbolic VQA[2], the models, which have high performance in the soft programs and scene graphs, such as Stack-NMN[15] and LXMERT[16] are developed. Those frameworks with high performance in the soft programs and scene graphs bring us a lot of ideas in our model building.

**Visual Recognition** For the video recognition work, we use the database called the CATER.[17]. In the CATER dataset, because the format is the video, the scene parse using the mask-rnn[18] can not greatly detect the action of the objects with the frame change. With the idea of the 3D-ConvNet[19], the milestone of the video action recognition which is called I3D[20] appears in the research area. The I3D uses the two-stream 3D-ConvNet in the model, in which one stream is optical flow change and another one is the image change. The optical flow is the relation of the motion field. With the base of the I3D, we implement the I(2+1)D with Resnet, which is also called the R(2+1)D[21]. In which, there are a 2D spatial convolution and a 1D temporal convolution. There is a lot of advantage between the original 3D convolutions model with spatial and temporal(like I3D) and the model with the explicitly factorizes 3D convolutions(like I(2+1)D). One of the advantages is an additional nonlinear rectification between these two operations; while another one is the explicitly factorizes 3D convolution is easy to optimal than that of original 3D convolutions model with spatial and temporal. Though the R(2+1)D uses a single kind of residual block homogeneously, it still leads to state-of-the-art action recognition accuracy.[21]

### III. Model

In this section, we discuss the model designed in our research. Let \( x \) denote the input clip of size with \( 3 \times F \times H \times W \).

where \( e \) is the number of the color in the RGB, \( F \) is the number of the frame in the video, and the \( H, W \) is the frame height and width. We first put the video with frames with the R(2+1)D model to detect the action and motion of the object. Then we will use the VQA problem with the weak function to make the video question answering work with the improved NLP algorithm.

#### A. Video Recognition

In this work, we consider detecting the action and motion of the object. In the previous research, many alternative technologies can complete this task with high accuracy. Meanwhile, in real life, there are a lot of actions that should accurately judge the temporal. When considering the temporal, we always will consider the LSTM model. However, the LSTM lack the experience of the object change with the rotation during the training, and it may result in the huge error in some special case. With the milestone of the I3D and I(2+1)D model, we can use based on those two models to detect with the frame from 1 to \( k \) and optical flow with 1 to \( k \) also. However, as we mention in the related work, the I(2+1)D model is easy to optimal. It will help us have a high possibility to reduce the resource in the model with approximately high accuracy. In our network, we implement the model based on the networks where the 2 convolutional layers with the spatial and 1 convolutional layer with the temporal. As a result, we can design a network from the \( M(3) \) convolutional layers with size of \( N_{i-1} \times t \times d \times d \), and the 2D spatial layers will have the size of the \( N_{i-1} \times t \times d \) and the temporal layer have the \( M_i \times t \times d \). This is illustrated in Figure 1. In the 2D spatial convolutional layer, the model first use the ResNet to detect the bounding box, which is illustrated in Figure 2. From the middle frames and detect each object in each frame. To improve the accuracy of the objection detection, we use a ground-true bounding box in
the detection works. For the optical flow detection, we use the model, which including the connection between the 2D spatial layers and the 1D temporal layer with one ReLU. With the optimal flow, we can detect some action which consists of the movement of the objects, such as containing, translation, and scaling. Also, we can use the change of the shadow value to judge whether the object is rotated or not, which is shown as Figure 2. The output of the model will give the location and the action of the objects in the video slides with the temporal change.

B. Visual Question Answering (VQA) with Soft Function

The normal Visual Question Answering (VQA) model, such as MFB[12] is repeatably training the model in the scene part when detecting the answers from the images. In our research, the work should be used on the robot, which has a limited resource to be used. To reduce the consumption of the VQA, we plan to make a program that can solve the problem with the soft programs and serene graph to train the answers to the questions in an end-to-end manner. There are some model in the research area, such as NS-VQA[2], Stack-NMN[15] and LXMERT[16]. All of those works are greatly reduce the usage of the memory and the speed of the training time. Our model for the VQA with Soft Function is built based on the Stack-NMN. It has a high performance in the soft program problem in the VQA.

C. Natural Language Processing (NLP) In Pre-training Model

When considering the NLP model to make the reasoning of the VQA problem, the original method in the NS-VQA[2] is used in the sequence to sequence. It is a base LSTM model which only considers one direction of the questions. However, in the real-life, the people’s conversation can be regarded as dialog. The dialog has the characters that the grammar are not as follow as the written one. Sometimes there are also exists a lot of slang in our conversation, which can not greatly express as a written text. Furthermore, there always exist some conditions that have polysemous. At this time, some models which can be handle with those conditions are relatively important in our algorithm. With the milestone of the ELMo[5] and transformation[6], there start to exist a lot of models which is fine-tuning. Those fine-tuning models can help our algorithm have the swift speed to reason the questions in VQA with little change of the parameters input. It will reduce a lot of resources. In our research, we find the combination of the BERT[7] and XLNet[7] are performance best in the reasoning of the questions in VQA. The BERT give the contextual relationship of the sentence for each word, but it lacks the memory of change with the temporal change. The XLNet considers both the advantage of the BERT and LSTM to make the model that can treat the polysemous problem with better performance. However, it takes a larger resource than the BERT. Also, some types of special conditions are could not work as well as that of BERT. As a result, in our research, we will handle the reasoning of the VQA questions with both BERT and XLNet, and compare the reasoning result of both models and give back a result with a higher confidence score.

IV. Experiment

In this section, we are going to illustrate and explain the hypotheses, which are to match the four questions in the introduction section. Then, we are going to explain how we set up the experiment to verify the hypotheses.
A. Hypothesis

**Hypothesis 1.** The combination of single words including location, color, and shape will allow people to build up the basic idea of the environment.

**Hypothesis 2.** The request should be short and clear, avoiding redundant descriptions. Such instructions, are easier to be understood by the robot agent.

**Hypothesis 3.** The feedback in friendly, polite, and sincere is more acceptable and the user feel more comfortable.

**Hypothesis 4.** Having a reasonable level of trust to the robot agent promotes the interaction between the blind user and the robot agent.

B. Participants

The participants are two hundred Georgia Tech students. All of them are in CS major and have a good understanding of HRI related knowledge and VQA techniques. The two hundred participants are distributed into four groups. Each group will be used to verify a hypothesis. In this way, we hope each participant could have enough patience and a sense of freshness during the experiment so that personal emotion (such as dullness and tiredness) won’t compromise our experimental results. Before the experiment, all participants will have a reasonable time to get familiar with their tasks and devices. During the experiment, all participants will be folded with their eyes. They are allowed to communicate with the experimental device only by speaking and listening.

C. Robot Agent

In our experiment, we set up the core functionalities in a computer, including processing voice and converting the audio clip into English, a VQA program to analyze the video and question, a sound to pronounce the result from the VQA program. The test computer will maintain the same angle of view as the participants all the time in order to obtain the same video as the participants are supposed to obtain.

D. Four Experiments

**Experiment for H1:**

In this experiment, the participants need to figure out the environment by asking questions to the robot agent. We use video clips that contain different objects. A sample is illustrated in Figure 2. The video clips (test set) have several advantages. It shows the different shapes and colors. The objects switch their positions all the time. The relative locations can be expressed by simple words like “near the cube, behind the sphere.” It simplifies the real world without losing key information (location, color, shape, action). For the action of objects in the video, we will judge it by the other key information change. The participants should find out the answers to the questions: How many objects for each different shape, what are the colors for them, and the locations and actions. They have at most thirteen minutes to finish their tasks. Then, they will be asked to draw the picture based on the information they get.

Every human questions and robot answers will be recorded by the computer log.

**Experiment for H2:**

We analyze the log file from the previous experiments. We classify the questions: 1. The questions which followed the correct answers. 2. The question which followed the wrong answers. For example, the correct answer should be "four cubes." but the actual answer is "one cube." 3. The questions which followed invalid answers. For example, the correct/acceptable answer is "one sphere." but the actual answer is "one triangle." For this group of participants, one only asks simple and clear questions like "How many spheres?" The other only asks complicated questions such as "Could you tell me about the environment and how many objects look like a cycle in there?" Again, there will be a log, and we will analyze the accuracy.

**Experiment for H3:**

In this experiment, the participants could ask questions freely. Their goal is to figure out the environment. The robot agents for the two participants are different. One robot agent is programmed to behave well, the other is on the contrary. The former robot will start with nice talk such as "How many I assist you" or "Is there anything I can do for you." If that robot cannot process the question, it might reply by "Sorry, this little robot cannot find the answer. Would you mind to try your question in a more different and simpler way?" Differently, the latter robot only replies by "one" or "None." The participants will need to draw the picture after questions-asking.

**Experiment for H4:**

Amongst the two hundreds participants, they will take a survey which including questions about robot trust. We will evaluate the survey and find a participant who trust the robot most and another participant who trust the robot least. They will ask the "friendly" robot agent and draw the picture.

E. Method of evaluation

We will analysis the accuracy, the accuracy can be calculated with:

\[
\text{Accuracy} = \frac{\text{right answer number}}{\text{total answer of that problem}}
\]

For each type of objects (Cube, Sphere, Cone), they have different quantities. We will random pick the video from CATER dataset and ask them ask the questions about key information (location, color, shape). The participants will need to draw them out. For each type, we will judge whether the answer is same as truth and calculate the accuracy score.

The last feature we evaluate the relative location. we will ask the participants to ask several questions of the locations of each objects in five random time spot and we will require the user draw out those location relationship of objects in each time spot. Similarly, we will judge whether the answer is same as truth and calculate the accuracy score.

V. Result And Discussion

After the experiment, we have two hundreds pictures drawn by the participants. These pictures represent what participants
can build up in their mind through communication with the robot agent. Assuming that people have relatively equal level of cognition, we argue that visual-impaired people should be able to construct some similar pictures. Also, we use bar graph to represent the survey result of experiment 3 & 4.

A. Performance of Video Question Answering Model

| Method          | Count % | Color % | Shape % | Location % |
|-----------------|---------|---------|---------|------------|
| Lei et al.[22]  | 69.32   | 68.23   | 64.34   | 53.72      |
| Jie et al.[23]  | 70.16   | 73.32   | 69.81   | 57.34      |
| Jie et al.[24]  | 72.81   | 73.23   | 71.45   | 61.23      |
| Yang et al.[25] | 75.13   | 74.97   | 77.14   | 63.76      |
| Chadha et al.[26]| 77.23  | 74.31   | 74.56   | 62.56      |
| R(2+1)D        | 80.42   | 72.67   | 75.23   | 65.71      |

We have compared the classification accuracy of our model with several other models (Table 1) in experiment 1 and 2. For methods using in CATER and Chadha et al.[26], they use the attention algorithm to make sure the model are competitive for the task. However, they did not perform as well as our model. All models and their variables were trained in experiment one times for per participant, making an average for the performance as a result. And we find these previous algorithms did not perform as well as our model. Our model is better than Chadha et al.[26] by 3.09% in number of the object number and 0.67% in shape of objects after measuring its accuracy score and 4.19% for the Yang et al.[25] methods in number of objects.

The improvements based on our model have a significant meaning for other models. However, the performance in some feature in the video question answering is still not as good as that of the other model. For example, the object’s color judgement for our model is worse than that of Chadha et al.[26]. The reason for the lower accuracy is dependent on that our model more focus on the relationship of the object movement. In our model, we use the optical flow to measure the object actions. When we use the optical flow, we not use the RGB3 to do that, it will make our model lose the color value in some situation and make a high error rate in the model performance.

B. Trust and interactivity of HRI

We use the survey to calculate the trust score for each participant. The lower the trust score, the less trust the participant has in the robot. The trust between -1 and +1 is a reasonable range of score, meaning that the participants neither overtrust nor undertrust. For the participants who pay little trust in the robot, they are less likely to have efficient interaction with the robot. For example, a participant, who asked the robot to identify the locations of objects, and relied on the guide of the robot, distrusted the robot. In this situation, this participant takes a longer time to picture the surroundings or to reach
the place where he/she wanted to go. We must ask why the undertrust conduct worse interaction. In the ideal situation, the participant who received the robot’s feedback should make a bold trial based on the received information. But meanwhile, the participant should also think about whether the feedback is within a reasonable level.

For the participants who undertrust the robot, they might ask too many similar questions regarding a single situation. For example, the task is to explore the number of triangles in a video. The normal participants may ask two questions: How many triangles and How many cones, to identify the number of triangles. For the undertrusted participants, they will ask more than 10 questions to confirm the answer. We measure the interactivity by two factors: correctness of exploration and time.

For Figure 6 and Figure 7, they represent the interactivity and trustness results, in plot diagram and histogram diagram. For Figure 6, as an example, the upper diagram represent the interactivity and the lower diagram represent the trustness. In x-axis, we scale from 1 to 10, which is the score we used to evaluate the participants. In the y-axis, the value represents the possibilities the the score occurring in our survey. For example, in Figure 6, the upper diagram, there are 20% of participants to get 6 out of 10 in the interactivity evaluation.

From Figure 6 and Figure 7, we can see there exists a positive correlation between the trustness and interactivity. In this way, we project the experimental result of the 200 participants to get Figure 5.

VI. CONCLUSION AND FUTURE WORK

We developed a new model that performs high-level interactions with blind users. Our research mainly focused on interaction improvement. The model, which used VQA techniques, had a different performance in various scenarios. In this way, the first two hypotheses were designed to verify which kinds of settings could generate the best interaction results. Also, we make comparisons with our model with other models in the video question answering area. From our experiment, the performance of our model is better than others in most areas. We also studied the effects of trust, and see how the trust influenced the interaction. The core idea, of our research, is to identify the features that positively related to the interaction between our robot agent and blind people.

Our current experiments used "object video". In our future work, we are going to exert our robot agent in more complex and real situations. We also might install the mechanical arms on our robot agent so that it will be able to perform actions more than linguistic communications. In this case, the interaction between the new robot agent and the blind people will be different from the current interactions. We are going to examine the boundary of the new robot agent’s ability, and see if there are any potential improvements we can make. Also, in the future, we plan to use a different kind of attention to building up our model, such as hierarchical attention [27]. We will work to judge our optical flow with the RGB3 to make sure the model will become more sensitive in the color detection.
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