Robotic Applications of Pre-Trained Vision-Language Models to Various Recognition Behaviors

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Abstract-A number of models that learn the relations between vision and language from large datasets have been released. These models perform a variety of tasks, such as answering questions about images, retrieving sentences that best correspond to images, and finding regions in images that correspond to phrases. Although there are some examples, the connection between these pre-trained vision-language models and robotics is still weak. If they are directly connected to robot motions, they lose their versatility due to the embodiment of the robot and the difficulty of data collection, and become inapplicable to a wide range of bodies and situations. Therefore, in this study, we categorize and summarize the methods to utilize the pre-trained vision-language models flexibly and easily in a way that the robot can understand, without directly connecting them to robot motions. We discuss how to use these models for robot motion selection and motion planning without re-training the models. We consider five types of methods to extract information understandable for robots, and show the examples of state recognition, object recognition, affordance recognition, relation recognition, and anomaly detection based on the combination of these five methods. We expect that this study will add flexibility and ease-of-use, as well as new applications, to the recognition behavior of existing robots.

I. INTRODUCTION

With the advancement of neural network, various deep learning methods have been developed. The tasks include image recognition [1], image generation [2], etc. Modalities such as vision and language are well suited for deep learning due to the ease of large-scale data collection, and they have made great progress mainly in the fields of computer vision and natural language processing. In addition, the development of vision-language models that combine these two aspects has been gaining popularity in recent years. [3] has set forth a problem called Visual Question Answering (VQA) and released its dataset. [4] has successfully solved a zero-shot image classification problem by training the relations between images and phrases through contrastive learning. [5] has successfully solved various problems such as Visual Question Answering, Image Captioning, and Visual Grounding with a single model. Several methods to learn the relations among various modalities is being applied to robot behavior. [6] has set forth a problem called Embodied Question Answering, in which the robot performs path planning to search for the answer to a question in a 3D simulation space. On the actual robot, [7] has successfully achieved a picking task from object recognition and ambiguous verbal instructions. [8] has enabled a variety of pick-and-place



Fig. 1. The concept of this study. The mobile robot recognizes if the door is open, if the kitchen is clean, where the handles of the kettle and fork are, what number is shown on the display, and if the elevator door is open.

tasks using CLIP [4]. However, the data collection suddenly becomes difficult once the robot motion is used as data, and the number of data that can be contained in the dataset drops by a large order of magnitude. In most cases, the models trained using robots work only in the environment and robot body where the data is collected, resulting in a significant loss of versatility and adaptability. Note that there are efforts to solve this problem by collecting a large amount of data on a large number of embodiments [9].

From these points of view, we do not relate robot motions directly to vision and language in this study, but apply Pre-Trained Vision-Language Models (PTVLMs) in a form that can be understood by robots. The form of information understandable for robots is a continuous value with a few dimensions or a discrete value with a small number of choices. Depending on its usage, PTVLMs can significantly improve the recognition ability of existing robots, and lead to a variety of new recognition behaviors. We will categorize the extraction methods of information understandable for robots using PTVLMs, and experiment with various tasks that can be accomplished by combining the methods. Our policy is to take full advantage of the high versatility and adaptability of **PTVLMs** provided by the large datasets, so we do not perform any re-training using our own datasets that would reduce the versatility and adaptability.

We will first describe some possible applications of this study. For example, whether the door is open or closed has been previously recognized by the presence or absence of point cloud, but by using **PTVLMs**, its recognition is possible by simply asking the question "Is the door open?"

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Fig. 2. The overview of tasks using **Pre-Trained Vision-Language Models (PTVLMs)**, implementations of **PTVLMs**, information extraction understandable for robots using **PTVLMs**, and robotic applications of the information extractions.

for the current image. The door handle has been previously recognized using template matching or a trained model with a dataset created by human annotation, but with **PTVLMs**, the location of a door handle can be recognized by simply asking "Where is the door handle?". Also, anomaly detection has been previously performed by learning images in the normal state and calculating the rate of reconstruction [10], but with **PTVLMs**, it is possible to detect anomalies with verbal explanations by comparing the descriptions of the normal and current states. Although a very simple idea, we believe that this method of applying **PTVLMs** can easily and flexibly increase the recognition ability of robots.

II. ROBOTIC APPLICATIONS OF PRE-TRAINED VISION-LANGUAGE MODELS

A. Overview of Pre-Trained Vision-Language Models

The overall structure of this study is shown in Fig. 2. There are various tasks in the vision-language model, and [11] has classified them into four categories: generation task, understanding task, retrieval task, and grounding task. The generation task includes Image Captioning (IC), which generates captions of images, and Text-to-Image Generation (TIG), which generates images from texts. The understanding task includes Visual Question Answering (VQA), which answers questions about images, Visual Dialog, which answers questions based on images and dialog history, Visual Reasoning, which requires justification to the answer of VQA, and Visual Entailment (VE), which verifies the semantic validity of image-text pairs. The retrieval task includes Image-to-Text Retrieval (ITR) and Text-to-Image Retrieval (TIR), which retrieve the relationship between image and text from predefined choices. The grounding task includes Phrase Grounding and Reference Expression Comprehension, which extract the bounding box of the corresponding location in the image from the text.

Considering the simplicity of use for robots, we only handle tasks that use direct vision-language relations. In other words, we do not deal with Visual Dialog which includes dialog history and Visual Reasoning which requires reasoning. To summarize, the tasks we handle in this study are IC, TIG, VQA, VE, ITR, TIR, and VG (since Phrase Grounding and Reference Expression Comprehension are almost the same, we unify them as Visual Grounding, VG). In this study, we treat OFA [5] and CLIP [4] as **PTVLMs** that cover these tasks. OFA is a method that unifies IC, TIG, VQA, VE, and VG with a single model. CLIP is a model that can acquire the relationship between images and texts through contrastive learning, and is capable of ITR and TIR. Note that the model itself is not limited to OFA or CLIP, as long as it can perform these tasks.

B. Information Extraction from Pre-Trained Vision-Language Models for Robotics

Discrete values with multiple choices (e.g. language) are difficult to handle in a robot, which operates by human programming. Also, multi-dimensional continuous values (e.g. vision) are difficult to incorporate directly into a program, and some kind of information extraction is necessary. In other words, it is necessary to extract information as discrete values in a predefined small number of choices, or as continuous values in a small number of dimensions. In this study, we classify the methods to extract information from **PTVLMs** in a way that robots can understand into the following five categories.

- **Binary VQA (BVQA)**: binary information is extracted by asking questions such as "Is -?" and "Do -?" in VQA.
- Matching with VQA (MVQA): discrete values in a small number of choices are obtained by asking questions such as "What kind of -?" and "How much -?" in VQA and by matching the answers to the phrases prepared in advance.
- Image-to-Text Retrieval (ITR): discrete values in a small number of choices are obtained by searching for the phrase that best matches the image among the predefined choices.
- Visual Grounding (VG): continuous values in a small number of dimensions are obtained by selecting the bounding box in the image that best matches the phrase.
- **Difference of Image Captioning (DIC)**: binary information is obtained by quantifying the difference between the descriptions output by IC.

It is difficult to extract information directly from images in a form understandable by robots, so it is difficult to use Text-to-Image Generation (TIG) and Text-to-Image Retrieval (TIR). If the output of VQA is a sentence, it is not possible to extract information directly in a form understandable by robots, so we ask "Is -?" or "Do -?" questions that return a binary answer of Yes or No (BVQA), ask "What kind of -?" or "How much -?" questions that output simple and short answers that match predefined choices (MVQA), or calculate the difference in descriptions output by Image Captioning using Sentence-BERT [12] (DIC). ITR and VG can directly output the answers in a form understandable by robots. Visual Entailment (VE) is considered to be included in BVQA.

The details of the models to be used for the five types of information extraction are described below.

1) **Binary VQA:** BVQA is a task that asks questions Q such as "Is the door open?" or "Does the image describe a person running?" for the current image V to extract binary answers A of Yes or No. We can express BVQA as $f_{BVQA}(V,Q) = A$ ($A \in \{Yes, No\}$). Binary values are easy to use with the robot programming of "if-else". Multiple V with noise and multiple Q with rephrased expressions of the same content are prepared, and A is determined based on the ratio of Yes and No. In this study, five V are prepared by RGBShift, which adds randomly selected values from a uniform distribution within the range of [-0.1, 0.1] to each RGB value. We prepare four types of Q by changing the article to $\{a, the, this, that\}$, and integrate a total of 20 results which are the combinations of these V and Q. Since OFA is trained by combining five multimodal tasks including IC and VQA, A does not always become Yes or No. Therefore, if a value other than Yes or No is obtained, the answer is considered as Invalid.

2) Matching with VQA: MVQA is a task to select the matching answer A to questions Q such as "What object is included in this image?", "What color is the apple?", and "How big is this apple?" from the predefined choices C. We can express MVQA as $f_{MVQA}(V,Q,C_{\{1,\dots,N_C\}}) = A$ $(A \in C_{\{1,\dots,N_C\}})$, where N_C expresses the number of predefined choices). The robot behavior is described for each C, and conditional branching is possible depending on the selected C. Similar to BVQA, multiple V with noise and multiple Q about the same state are prepared, and A is determined based on the percentage of matches. Since the C are not always output as the answers, the answers are considered Invalid if they do not match.

3) Image-to-Text Retrieval: ITR calculates the degree of matching between the current image V and each of the predefined phrase choices C, and selects the choice A with the highest degree of matching. We can express ITR as $f_{ITR}(V, C_{\{1, \dots, N_C\}}) = A$ ($A \in C_{\{1, \dots, N_C\}}$, where N_C expresses the number of the predefined choices). Similarly to MVQA, the actions are described for each C, and conditional branching is possible depending on the selected C. In the original CLIP to conduct ITR, a sentence similar to the current sentence is selected from a large amount of textual datasets. However, in this study, a small number of C are given in advance and the robot selects its answer among them, so that it is understandable for robots. Compared to MVQA, it is likely to be able to select a more precise answer than MVQA, since it can output the probability for each C.

4) Visual Grounding: VG is a task to determine a target phrase Q such as "a refrigerator" to ask the question "Which

region does the text 'a refrigerator' describe?", and to get the bounding box A of the relevant part. We can express VG as $f_{VG}(V,Q) = A$ (A expresses the coordinates of the bounding box). This method is compatible with various controls because it can obtain the location of an object in V based on an arbitrary Q. Note that there are many methods to perform only VG, such as ViLD [13] and LSeg [14].

5) Difference of Image Captioning: DIC computes the difference A of the situational descriptions obtained from the question Q "What does the image describe?" for two images $V_{\{1,2\}}$. We can express DIC as $f_{DIC}(V_{\{1,2\}},Q) = A \ (-1 \le A \le 1)$. The two sets of the situational descriptions obtained at a certain location are vectorized by Sentence-BERT [12], etc. By calculating the cosine similarity A between these vectors and cutting them by a threshold value, it is possible to obtain a binary result of whether or not a change has occurred. In addition, since the language is given, it is easy for humans to understand the change intuitively. Also, by using GPT-3 [15] and asking questions such as "What is the difference between 'text1' and 'text2'?" (where 'text1' and 'text2' refer to each situational description), it is possible to directly output what the difference between them is as sentences.

C. Robotic Applications of Information Extraction from Pre-Trained Vision-Language Models

Using the five information extraction methods described so far, we categorize the specific tasks that can be performed. Here, we consider the following five tasks: object recognition, state recognition, affordance recognition, relation recognition, and anomaly detection.

1) **Object Recognition:** Among object recognition, we can mainly perform class recognition, feature recognition, and location recognition of objects. Class recognition can be achieved by making a binary judgment of whether a particular object exists or not using BVQA, or by making a multiple-choice judgment using MVQA or ITR. This method can be used to determine whether or not an object is correctly grasped and to make a transition to the next action.

Feature recognition can be achieved by a multiple-choice judgment using MVQA or ITR. Q of "How big is -?" or "What color is -?" in MVQA can extract information such as color, shape, and size of an object. Regarding ITR, feature recognition is also possible by defining C such as "a {large, medium, small} egg".

Location recognition can be achieved by outputting the location of a specific object in the image using VG. The obtained locations can be used for grasping control by masking the point cloud within the location, or for wheeled-base control by measuring the distance to the location.

By combining these methods, stepwise refinement of object recognition is also possible. The presence of the target object is confirmed by BVQA, MVQA or ITR, and its bounding box is cropped by VG. After that, class recognition for another target object against the cropped image is performed, and these process are executed iteratively. This method is useful for object recognition in a refrigerator, object recognition on a desk at a distance, and so on.

2) State Recognition: State recognition mainly uses BVQA or ITR to check the binary state of the current environment, objects, etc. For example, in BVQA, the state of a door can be recognized by asking "Is this door open?". Regarding ITR, the same result can be obtained by preparing C of "an open door" and "a closed door". Another benefit of this state recognition is that it can recognize ambiguous and qualitative states based on the knowledge obtained from a large-scale dataset. For example, it can make human-like judgments for Q such as "Is this kitchen clean?".

In addition, it can recognize a character state by asking Q such as "What is written on this bottle?". Moreover, this state recognition is likely to make it possible to write conditional expressions such as "if-else" and "assert" in robot programming using the spoken language.

3) <u>Affordance Recognition</u>: Affordance refers to the role of each part of a tool or object; for example, the place to grasp or the effector that exerts the action. **PTVLMs** enable implicit affordance recognition, whereas in most cases, a dedicated network for affordance recognition has been set up so far [16]. For example, by running VG on Q such as "handle of the scissors" or "handle of the kettle", it is possible to recognize the parts of tools and objects with meaning related to their operations. The recognized parts can be used for grasping, tilting the spout of the kettle toward the cup, and so on.

4) **Relation Recognition:** MVQA and ITR allow us to recognize relationships between objects. In MVQA, by asking Q "What is the relative relationship between the mouse and keyboard?", we can extract the relationship in terms of position, such as "next to", "in front of", "on", and "under". By recognizing the relations based on which prepositions are included in the sentences, we can generate the next robot movements. This can also be used for segmentation of motions. By recognizing not only changes in relationships between objects but also relationships between the robot and objects, the robot can detect the changing point as an anomaly by using DIC.

5) <u>Anomaly Detection</u>: DIC can be used for anomaly detection. Until now, anomaly detection has usually been performed by collecting and learning images in normal conditions, and then using the degree of reconstruction of the images [10]. Here, in the normal state, the robot takes pictures at a certain location and records them. Next, we generate captions for the current images taken at the same location and for the images taken in the normal state, and output the difference between them using DIC. If the difference is large, it is assumed to be abnormal, and humans can understand the change linguistically from the difference between the captions.

III. PRELIMINARY EXPERIMENTS

We will experimentally describe specific use cases for the five recognition behaviors described in Section II-C. The purpose of this study is to classify the usage of **PTVLMs** and its possible applications for easily and flexibly generating recognition behaviors of robots. The experiments are mainly qualitative as the comprehensiveness of the applications is most important. On the other hand, the reliability of each experimental application is ensured by adding noise to the images or changing the angle of view to compute the mean and variance.

A. Object Recognition

Although object recognition is partially a common problem setup, it is described for the sake of comprehensiveness. The essence of this study lies in the next section and thereafter.

First, Fig. 3 shows the results of object class and feature recognition using MVQA or ITR. We set up problems of class recognition "class", shape recognition "shape", and color recognition "color", and applied them to three object images: (1) yellow round cup, (2) clear round glass, and (3) blue rectangular box. The questions Q with four different articles in MVQA, the choices C that takes the match, and the choices C in ITR are prepared. MVQA shows the percentage of each C and Invalid (invalid answer other than the predefined C) for the 20 trials described in Section II-B, and ITR shows the probability of each C for a single trial. Note that for each object, V from five different angles of view are prepared, and the mean μ and standard deviation σ are also shown for the percentage of correct responses. Regarding class recognition, both MVQA and ITR correctly recognize (1) as "cup", (2) as "glass", and (3) as "box". As for MVQA, for example, various answers such as "yellow cup" and "coffee cup on the desk" are output for (1), so if a word of each C is included in the answer, we judge that the output matches it. Next, regarding shape recognition, we prepared two C: "round" and "rectangular". (1) and (2) are correctly recognized as "round", and (3) as "rectangular". In MVQA, even if there are many invalid cases, the recognition accuracy becomes 100% by ignoring them. On the other hand, especially for (1), the answer of MVQA is often invalid, and ITR is able to give a clearer answer. Finally, for color recognition, MVQA and ITR correctly identify (1) as "yellow", (2) as "clear", and (3) as "blue", except for (3) in ITR, almost the same as class and shape recognition. However, there are many invalid answers for (2) in MVOA, and the answers for (3) in ITR are highly scattered. In the former, the answer is often "white" because it has assimilated into the desk. In the latter, the white part of the box seems to be transparent, and the probability of "clear" is considered to be higher. Although color and shape recognition is uncommon, class recognition is a common problem. In [17], class recognition using ITR is used in a robot competition because it is possible to improve the recognition accuracy subsequently without re-training by just tuning the text of the choices (called prompt tuning).

Next, Fig. 4 shows the results of the object location recognition using VG. Not only phrases for the class recognition such as "cup", "glass", and "box", but also phrases for the feature recognition such as "round object" and "clear object" can be used to extract the location of the corresponding object. As exactly the same results can be obtained from the



Fig. 3. The results of the object class, shape, and color recognition using MVQA or ITR for three examples.



Fig. 4. The results of object location recognition with the information of the object class, shape, and color using VG.



Fig. 5. The results of stepwise refinement of object recognition using $\ensuremath{\mathsf{MVQA}}$ and VG, in order.

class recognition and feature recognition phrases, the results represented by the green bounding boxes have overlapped. Note that since OFA outputs only one bounding box that matches best, only object (1) is recognized as "round object".

Finally, Fig. 5 shows the results of stepwise refinement of object recognition. Two situations, (1) and (2), were prepared, and object recognition of the target object was performed in the order of MVQA, VG, and MVQA. For example, in (1), the recognition is initially limited to a room with a TV on the wall, but by extracting the location of the TV and performing MVQA on the image, it is possible to recognize that a mountain is displayed on the TV. More detailed object recognition is possible by stepwise refinement of the target object.

B. State Recognition

Fig. 6 shows the results of binary state recognition using BVQA or ITR. Regarding BVQA, we describe four types of O with different articles, and regarding ITR, we describe two C. BVQA shows the percentages of Yes, No, and Invalid (answers other than Yes or No) for the 20 trials described in Section II-B, and ITR shows the probabilities of Yes (the first choice) and No (the second choice) for one trial. Note that for each state, V from five different angles of view are prepared, and the mean μ and standard deviation σ are also shown for the percentage of correct responses. Three examples (1)–(3)are provided, where all the answers should be Yes for the left image and No for the right image. From the figures, BVQA correctly outputs Yes or No in all cases. On the other hand, the ratio of Yes and No for ITR is close to 50% and 50%, and it is not as clearly recognized as BVQA. As for (3), the answer is reversed. BVOA is easier to use to describe the state of the environment and objects than ITR, because BVQA allows more flexible question phrases and clearer answers than ITR. Note that in (1) and (2), Q is asked in the form of "Is -?" but by asking Q of "Does this image look like -?" as in (3), it is possible to make the percentage of invalid answers almost zero. For (3), if we ask Q of "Is -?", 20/20 cases are invalid. On the other hand, it has been experimentally found that the answers to Q of "Does this image look like -?" is not very accurate compared to "Is -?".

Of course, it is possible to build state recognizers with almost 100% accuracy by collecting training data or by manually programming for the specific environment. However, an important contribution of this study is that it can be easily applied to a wide variety of environments and robots,



Fig. 6. The results of state recognition using $\ensuremath{\mathsf{BVQA}}$ and $\ensuremath{\mathsf{ITR}}$ for three situations.

without any programming or model training specific to each environment and robot.

Next, Fig. 7 shows the results of binary state recognition using BVQA for qualitative states that are more difficult to judge. The percentages of Yes, No, and Invalid are shown for Q of (1) whether the trash can is full and (2) whether the kitchen is clean. Although the results are not as clear as those of Fig. 6, answers are generated in a manner consistent with human intuition. It can be applied to tasks such as robot patrolling.

Finally, Fig. 8 shows the results of character state recognition using MVQA. The robot can recognize various character shapes such as numbers on an elevator display, letters on a cardboard box, room numbers, and so on, by devising questions. This can be applied to robots checking mail, recognizing the floor number in an elevator, and entering a certain room based on the room number.

C. Affordance Recognition

Fig. 9 shows the results of the affordance recognition

BVQA: Q. Is {a, the, this, that} trash can full?



Fig. 7. The results of qualitative state recognition using $\ensuremath{\mathsf{BVQA}}$ for two situations.



Fig. 8. The results of character state recognition using MVQA.

using VG. First, the handle and the spout of the kettle are recognized in the top row of Fig. 9. This means that the robot can grasp the kettle, bring the spout close to the cup, and pour hot water into the cup. In addition, the robot can recognize the grasping positions of various objects such as a door, cup, spray, shelf, oven, toaster, scissors, hammer, and umbrella.

D. Relation Recognition

Fig. 10 shows the results of relation recognition using **MVQA**. We prepared V where the keyboard and mug are in front-back, left-right, and top-bottom positional relationships, and asked Q of "What is the relative relationship between the mug and the keyboard?". Each relationship is expressed by the prepositions "in front of", "next to", or "on top of". By matching these prepositions with predefined C, we can recognize the relationship and apply it to robotic manipulation.

E. Anomaly Detection

Fig. 11 shows the results of anomaly detection using DIC. We take "original" as an original V, and prepare a set of V that are almost the same ("same") or different ("different") with the original V. We show the description of those images output by IC and the cosine similarity between "original" and "same", or "original" and "different". Note that five images applied with RGBShift are prepared for each V, and the



Fig. 10. The results of relation recognition using MVQA for three situations.

average μ and standard deviation σ of the similarity are described. Three examples (1)–(3) are given, all of which show high similarity between "original" and "same", and low similarity between "original" and "different". Opening the door of the shelf or placing objects on the desk increases the number of descriptions about the objects in the shelf or the newly placed objects. Although the results output by IC change slightly when the angle of view and lighting conditions change, the similarity does not decrease much because the descriptions are similar. This similarity enables the robot to detect anomalies and to communicate them to the surrounding people through spoken language.

IV. DISCUSSION

The experimental results are summarized and discussed in terms of their performance, limitations, and development. First, object recognition was possible using either MVQA or ITR. In MVQA, there are some cases where the answer becomes invalid, but this can be improved by preparing multiple questions and images, ignoring the invalid answers, and obtaining the answer with the highest probability. While shape and color recognition of objects can be performed in the same way, there were some cases where recognition does not work well with ITR. It was also possible to recognize



Fig. 11. The results of anomaly detection using DIC for three situations. The original image and the images that are "same" as or "different" from it are shown, along with the similarity scores.

the location of an object not only by its class, but also by its shape and color. Furthermore, the combination of VG and MVQA enables stepwise refinement of object recognition.

Second, state recognition was possible using either BVQA or ITR, and BVQA was able to output clearer answers compared to ITR. In ITR, information regarding the object (e.g. door) is strong, while the information regarding the state (e.g. open) is weak, making it difficult to judge the state. As for BVQA, there may be many invalid answers depending on the question, but this can be avoided by adjusting the question. This state recognition can also answer to qualitative questions such as whether the kitchen is clean or dirty, which is less clear compared to whether the door is open or closed. Of course, this is a concept averaged from a large dataset, but it is possible that the robot can acquire a general human sense. In addition, the robot can recognize the character state on a display or on paper, and these can greatly expand the range of executable tasks without any re-training.

Third, affordance recognition was possible by the textual innovations in VG. The concept of affordance is obtained implicitly from a large dataset without using a specialized neural network. Affordance recognition is possible for a wide variety of objects and tools.

Fourth, relation recognition was possible by taking prepositional matches with predefined choices using MVQA. By knowing the relation between specified objects, the robot can manipulate them to change to the target relation. In the future, it is expected to be applied to motion segmentation, human motion understanding, imitation learning, and so on, based on the change of relations between objects and bodies.

Finally, anomaly detection was possible by vectorization and differencing of sentences output by IC (DIC). Although the outputs of IC change slightly with changes in the angle of view or with noise, the differences in the descriptions are not large, resulting in a high degree of similarity in the outputs. On the other hand, when the images change significantly, the outputs of IC also change significantly and the similarity score drops, thus enabling anomaly detection with the threshold value. Using sentences to detect differences is compatible with the use of chat tools and conversation to report anomalies, and further applications are expected.

In this study, we have comprehensively described the innovativeness of this idea through preliminary experiments. The vision-language model is still in the process of significant development, and it is necessary to keep an eye on its trend, create further applications, and incorporate them into actual robots. As one example, we show a simple experiment in a supplementary video. We have performed an automatic patrol experiment using state recognition on the mobile robot Fetch. The robot can close the refrigerator door by ITR if it is open, turn off the faucet by BVQA if water is running, and exit the room by ITR if the door is open. On the other hand, more detailed performance checks are needed for each example when incorporating PTVLMs into actual robots, which will be addressed in the future. In particular, it is important to discuss how to prepare the question phrases, predefined choices, and thresholds for determining the output. Although we have adjusted them manually in the preliminary experiments, it would be better to automatically acquire them from the data of actual tasks. [18] has proposed a method to create multiple questions by changing the articles, state expressions, forms, and wordings, and to select the best combination of questions by a genetic algorithm. In the future, we would like to generalize the process of choosing questions and predefined choices for the best performance.

V. CONCLUSION

In this study, we comprehensively and experimentally show that a pre-trained vision-language model can be used for various recognition behaviors in robots. The model is used to extract discrete values of a few choices or continuous values of a few dimensions, without directly connecting them to the action of robots. We classify the information extraction into five methods: binary state recognition using VQA (BVQA), matching with predefined textual choices after VQA (MVQA), retrieval of matching textual choices from images (ITR), extraction of locations in images that match the text (VG), and difference computation of outputs by IC (DIC). Using these five methods, robots are able to perform object recognition including class, shape, and color, as well as location recognition of objects, state recognition including qualitative states, affordance recognition of objects and tools, relation recognition of objects, and anomaly detection. Although the idea is very simple, the appropriate combination of vision and language can improve the flexibility and usability of recognition systems that have been trained or programmed for specific robot bodies and environments. The robot can figure out whether the door is open or closed and where to grasp the tool using spoken language, and detect anomalies in a descriptive manner.

REFERENCES

- A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in *Proceedings of the 2012 Neural Information Processing Systems*, 2012, pp. 1097–1105.
- [2] I. J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, "Generative Adversarial Nets," in *Proceedings of the 2014 Neural Information Processing Systems*, 2014, pp. 2672–2680.
- [3] S. Antol, A. Agrawal, J. Lu, M. Mitchell, D. Batra, C. L. Zitnick, and D. Parikh, "VQA: Visual Question Answering," in *Proceedings of the* 2015 IEEE/CVF International Conference on Computer Vision, 2015, pp. 2425–2433.
- [4] A. Radford, J. W. Kim, C. Hallacy, A. Ramesh, G. Goh, S. Agarwal, G. Sastry, A. Askell, P. Mishkin, J. Clark, G. Krueger, and I. Sutskever, "Learning Transferable Visual Models From Natural Language Supervision," arXiv preprint arXiv:2103.00020, 2021.
- [5] P. Wang, A. Yang, R. Men, J. Lin, S. Bai, Z. Li, J. Ma, C. Zhou, J. Zhou, and H. Yang, "OFA: Unifying Architectures, Tasks, and Modalities Through a Simple Sequence-to-Sequence Learning Framework," arXiv preprint arXiv:2202.03052, 2022.
- [6] A. Das, S. Datta, G. Gkioxari, S. Lee, D. Parikh, and D. Batra, "Embodied Question Answering," in *Proceedings of the 2018 IEEE/CVF International Conference on Computer Vision and Pattern Recognition*, 2018.
- [7] J. Hatori, Y. Kikuchi, S. Kobayashi, K. Takahashi, Y. Tsuboi, Y. Unno, W. Ko, and J. Tan, "Interactively Picking Real-World Objects with Unconstrained Spoken Language Instructions," in *Proceedings of the* 2018 IEEE International Conference on Robotics and Automation, 2018, pp. 3774–3781.
- [8] M. Shridhar, L. Manuelli, and D. Fox, "CLIPort: What and Where Pathways for Robotic Manipulation," in *Proceedings of the 2021 Conference on Robot Learning*, 2021, pp. 1–13.
- [9] Open X-Embodiment Collaboration, "Open X-Embodiment: Robotic Learning Datasets and RT-X Models," https://robotics-transformer-x. github.io, 2023.
- [10] D. Park, Y. Hoshi, and C. C. Kemp, "A Multimodal Anomaly Detector for Robot-Assisted Feeding Using an LSTM-Based Variational Autoencoder," *IEEE Robotics and Automation Letters*, vol. 3, no. 3, pp. 1544–1551, 2018.
- [11] F. Li, H. Zhang, Y. Zhang, S. Liu, J. Guo, L. M. Ni, P. Zhang, and L. Zhang, "Vision-Language Intelligence: Tasks, Representation Learning, and Large Models," arXiv preprint arXiv:2203.01922, 2022.
- [12] N. Reimers and I. Gurevych, "Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks," in *Proceedings of the 2019 Confer*ence on Empirical Methods in Natural Language Processing, 2019.
- [13] X. Gu, T. Lin, W. Kuo, and Y. Cui, "Open-vocabulary Object Detection via Vision and Language Knowledge Distillation," in *Proceedings of the 10th International Conference on Learning Representations*, 2022, pp. 1–20.
- [14] B. Li, K. Q. Weinberger, S. Belongie, V. Koltun, and R. Ranftl, "Language-driven Semantic Segmentation," in *Proceedings of the 10th International Conference on Learning Representations*, 2022, pp. 1–13.
- [15] T. B. Brown, B. Mann, N. Ryder, M. Subbiah, J. Kaplan, P. Dhariwal, A. Neelakantan, P. Shyam, G. Sastry, A. Askell, S. Agarwal, A. Herbert-Voss, G. Krueger, T. Henighan, R. Child, A. Ramesh, D. M. Ziegler, J. Wu, C. Winter, C. Hesse, M. Chen, E. Sigler, M. Litwin, S. Gray, B. Chess, J. Clark, C. Berner, S. McCandlish, A. Radford, I. Sutskever, and D. Amodei, "Language Models are Few-Shot Learners," arXiv preprint arXiv:2005.14165, 2020.
- [16] A. Myers, C. L. Teo, C. Fermüller, and Y. Aloimonos, "Affordance detection of tool parts from geometric features," in *Proceedings of the 2015 IEEE International Conference on Robotics and Automation*, 2015, pp. 1374–1381.
- [17] T. Matsushima, Y. Noguchi, J. Arima, T. Aoki, Y. Okita, Y. Ikeda, K. Ishimoto, S. Taniguchi, Y. Yamashita, S. Seto, S. S. Gu, Y. Iwasawa, and Y. Matsuo, "World Robot Challenge 2020 – Partner Robot: A Data-Driven Approach for Room Tidying with Mobile Manipulator," arXiv preprint arXiv:2207.10106, 2022.
- [18] K. Kawaharazuka, Y. Obinata, N. Kanazawa, K. Okada, and M. Inaba, "VQA-based Robotic State Recognition Optimized with Genetic Algorithm," in *Proceedings of the 2023 IEEE International Conference* on Robotics and Automation, 2023, pp. 8306–8311.