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# Continuous Object State Recognition for Cooking Robots Using Pre-Trained Vision-Language Models and Black-box Optimization

Kento Kawaharazuka<sup>1</sup>, Naoaki Kanazawa<sup>1</sup>, Yoshiki Obinata<sup>1</sup>, Kei Okada<sup>1</sup>, and Masayuki Inaba<sup>1</sup>

Abstract-The state recognition of the environment and objects by robots is generally based on the judgement of the current state as a classification problem. On the other hand, state changes of food in cooking happen continuously and need to be captured not only at a certain time point but also continuously over time. In addition, the state changes of food are complex and cannot be easily described by manual programming. Therefore, we propose a method to recognize the continuous state changes of food for cooking robots through the spoken language using pre-trained large-scale vision-language models. By using models that can compute the similarity between images and texts continuously over time, we can capture the state changes of food while cooking. We also show that by adjusting the weighting of each text prompt based on fitting the similarity changes to a sigmoid function and then performing black-box optimization, more accurate and robust continuous state recognition can be achieved. We demonstrate the effectiveness and limitations of this method by performing the recognition of water boiling, butter melting, egg cooking, and onion stir-frying.

### I. INTRODUCTION

State recognition of the environment and objects by robots is essential for various tasks such as daily life support. security, and disaster response. This includes recognition of the open/closed state of doors, the on/off state of lights, and the relationships among objects, all of which determine the state of objects at a certain time [1]–[3]. On the other hand, changes in the state of food, as represented by cooking, happen continuously and need to be captured not only at a certain time point but also continuously over time. In addition, the state changes are complex and cannot be easily described by manual programming. Even if each state recognition is trained by a neural network, it is difficult to cover the wide variety of state changes that occur in food, and it is necessary to prepare datasets, models, and programs for each state recognition, which also creates problems in managing source codes and computational resources.

Various cooking robots have been developed to handle changes in the state of food. [4] has developed a system where two robots cook pancakes from a recipe. [5] has developed a system to optimize the quality of omelette cooking by batch bayesian optimization. However, these two systems do not capture the state changes of food directly, and the cooking is based on the time of applying heat. Although this has a certain effect, it is important to capture changes in the state of food directly, taking into account the individual

### **Continuous State Recognition**



Fig. 1. The concept of this study. We propose a continuous object state recognition method for cooking robots by using pre-trained large-scale vision-language models and black-box optimization.

differences of the food, the differences in heat power, and cooking with unknown recipes. On the other hand, there have been some studies that capture changes in the state of food by using images [6]–[9]. However, these all deal with classification problems based on convolutional neural networks, which determine whether the vegetable is sliced, shredded, chopped, etc., and cannot capture continuous changes in the state of food. At the same time, since the recognition is based on a predefined classification, it is difficult to respond to changes in states that are not included in the classification. It is also difficult to understand the degree of change.

Therefore, we propose a method to continuously recognize changes in the state of food for cooking robots through the spoken language using pre-trained large-scale visionlanguage models (VLMs) [10], [11] as shown in Fig. 1. In this study, we utilize VLMs that have learned the semantic correspondences between images and the spoken language through a large dataset [12], [13]. By using the spoken language, the proposed method can appropriately capture diverse and ambiguous state changes in the cooking process. Due to the semantic training of correspondences, VLMs are also robust to changes in images. Moreover, by using pre-trained VLMs, the method does not require any manual programming or training of neural networks. Using only a single VLM makes it easy to manage the source codes and computational resources for each state to be recognized. We prepare a set of various texts about the state of the food to be recognized, and capture the state changes as continuous changes in the similarity between the texts and the current image. We also show that by adjusting the weighting of each text prompt based on fitting the similarity changes to a sigmoid function and then performing black-box optimization, more accurate and robust continuous state recognition can be achieved. The sigmoid function is capable of representing

<sup>&</sup>lt;sup>1</sup> The authors are with the Department of Mechano-Informatics, Graduate School of Information Science and Technology, The University of Tokyo, 7-3-1 Hongo, Bunkyo-ku, Tokyo, 113-8656, Japan. [kawaharazuka, kanazawa, obinata, k-okada, inaba]@jsk.t.u-tokyo.ac.jp

the basic patterns of continuous state changes through its parameter variations and is well-suited for continuous state recognition. Our method corresponds to obtaining a value that changes more significantly in synchronization with the state change. It is important to note that no annotation of images is required since only the degree of change is captured. We demonstrate the effectiveness and limitations of our method through experiments on water boiling, butter melting, egg cooking, and onion stir-frying. Our contributions are summarized as follows:

- New Continuous State Recognition Task: Proposing a continuous recognition task for the state changes of food for cooking robots.
- Capturing Cooking State Changes: Capturing diverse and ambiguous state changes during the cooking process through spoken language analysis.
- **Simplified Implementation**: Eliminating the need for manual programming or neural network training, and ensuring easy code management and efficient resource use with a single pre-trained vision-language model.
- Improved Performance: Achieving accurate continuous state recognition by adjusting text prompt weights using a sigmoid function and black-box optimization.
- II. ROBOTIC CONTINUOUS STATE RECOGNITION USING PRE-TRAINED VISION-LANGUAGE MODELS AND BLACK-BOX OPTIMIZATION

# A. Pre-Trained Vision-Language Models for Robotic Continuous State Recognition

There are various types of pre-trained VLMs. Among them, it is necessary to obtain the results as continuous values rather than discrete ones for continuous state recognition. [10] has classified the tasks that VLMs can handle into four categories: Generation Task, Understanding Task, Retrieval Task, and Grounding Task. Generation Task includes Image Captioning (IC) and Text-to-Image Generation (TIG). Understanding Task includes Visual Question Answering (VQA), Visual Dialog (VD), Visual Reasoning (VR), and Visual Entailment (VE). Retrieval Task includes Image-to-Text Retrieval (ITR) and Text-to-Image Retrieval (TIR), which retrieve the correspondence between images and texts from alternatives using similarity. Grounding Task includes Visual Grounding (VG), which extracts the corresponding regions in the image from the text. Among these tasks, only ITR and VG output continuous numerical values, while the others output sentences or images. Between the two, only ITR, which can compute the similarity between the current image and the texts describing the change in the state of food, is consistent with our purpose.

In this study, we conduct experiments using CLIP [12] and ImageBind [13] as models that are capable of ITR. CLIP is a model that can calculate the cosine similarity between images and texts by vectorizing them into latent space. ImageBind is a model that can compute similarity not only for images and texts, but also for many other modalities including audio, depth images, heatmaps, and inertial sensors. Note that it is



Fig. 2. The overview of the proposed method: we obtain time series of images *D*, prepare a variety of text prompts, calculate the continuous similarity changes with pre-trained vision-language models and text weight, fit the similarity changes to a sigmoid function, compute the evaluation value, and iteratively optimize the text weight with black-box optimization.

necessary to extract the target region for state recognition, which can be done by using VG provided in [14].

# B. Robotic Continuous State Recognition Using Pre-Trained Vision-Language Models

Continuous state recognition is performed using VLMs capable of ITR. The method is simple. First, we prepare a text prompt Q for the state to be recognized. For example, "boiled water" to recognize water boiling and "melted butter" to recognize butter melting. Image V is continuously acquired (at 10 Hz in this study), V and Q are vectorized into v and q using ITR, respectively, and the cosine similarity  $v^T q$  is calculated. By plotting them continuously over time, we can quantify continuous state changes. In the case of water boiling recognition, the similarity of the current image to the text "boiled water" gradually increases. If we obtain the moving average of the similarity, we can recognize the beginning of the state change when the slope of the value with respect to time becomes large, or we can recognize the end of the state change when the slope becomes small. It is also possible to set a certain threshold and recognize that a state change has started or ended when the value exceeds the threshold.

The text input to VLMs does not have to be a single text, but can be multiple synonyms and antonyms (in the case of antonyms, it is necessary to add a minus sign,  $-v^T q$ ). It is also possible to add noise to the current image and take the average, or to use multiple models. In [15], we have experimented with the case where a set of antonyms is prepared and one model is used.

# C. Robotic Continuous State Recognition Using Black-Box Optimization

There are several challenges with the previously described method. First, preliminary experiments show that



Fig. 3. Types of continuous state changes. All of these changes can be represented by a sigmoid function.

the recognition performance varies greatly depending on the choice of texts. By using a variety of texts, we can absorb the differences in recognition performance among texts and obtain stable recognition performance. However, if diverse texts are used uniformly, texts with low recognition performance may have a negative impact. In addition, the recognition of the beginning and end of state changes relies on human thresholding. It is desirable to have a system that automatically obtains high-performance state recognition with as little human intervention as possible.

Therefore, we propose a method to automatically obtain a high-performance state recognizer by adjusting the weighting of various texts, as shown in Fig. 2. We obtain data on the state changes only once, fit the continuous similarity changes to a sigmoid function, compute an evaluation function, and adjust the weighting of each text based on black-box optimization. By obtaining similarity changes with larger state changes and smaller variance, accurate and robust continuous state recognition can be achieved. Here, no annotation of the data is required. Moreover, there is no need to prepare a model or program for each state recognition, as only the text set and weighting need to be changed for each state recognition, which facilitates the management of source codes and computational resources.

Here, we discuss the reason for using the sigmoid function for fitting. As shown in Fig. 3, there are basically four possible state changes: (i), (ii), (iii), and (iv) (note that the vertical axis of the graph,  $a_w^t$ , is the weighted similarity of Eq. 1 described subsequently). They are (i) the case where the state change continues at all times, (ii) the case where there is no change at the beginning but a continuous change happens thereafter, (iii) the case where a state change occurs from the beginning but the change eventually converges, and (iv) the case where (ii) and (iii) are combined. The sigmoid function can represent all of these cases by changing the slope of its shape or by shifting it to the left or right, and is suitable for representing continuous state changes. It is also useful in that the value range falls within (0, 1), which allows automatic threshold design such that the state change is considered to have ended when, for example, the value reaches the 80% change point (0.8).

In the following, we describe the optimization procedure. First, the data D of the state change to be recognized is obtained once. This D consists of a time series of images



Fig. 4. Changes in the sigmoid function when changing the parameters  $\alpha$  and  $\beta$ . By increasing  $\alpha$ , the sigmoid function becomes steeper, which means that the state change can be detected more easily. By increasing  $\beta$ , the state change is less likely to be misidentified early in the process.

 $V_t$   $(1 \le t \le T)$ , where T denotes the number of images). We also prepare a set of texts  $Q_i$   $(1 \le i \le N)$  that describe the state change to be recognized. Here, let  $Q_i^1$  (e.g. "boiled water" and "melted butter") be the set of texts that indicate the change has occurred, and  $Q_i^{-1}$  (e.g. "unboiled water" and "unmelted butter") be the set of texts that indicate the change has not occurred.

Next, for each weight  $w_i$   $(1 \le i \le N, 0 \le w_i \le 1)$  of each text, we set an evaluation function E to be maximized based on black-box optimization. Here,  $w_i$  represents the importance of each text and how to weigh recognition results computed from each text. First, given a weight w, the similarity  $a_w^t$  between the current image  $V_t$  and the text set Q is calculated as follows,

$$a_w^t := \sum_i^N p_i w_i \boldsymbol{v}_t^T \boldsymbol{q}_i / \sum_i^N w_i \tag{1}$$

where  $p_i$  is a variable that returns 1 for  $Q_i^1$  and -1 for  $Q_i^{-1}$ . It can be said that the similarity  $v_t^T q_i$  for each text is weighted by  $p_i w_i$ . The continuous change of this value is fitted to a sigmoid function. The sigmoid considered in this study has the following form,

$$f(t) := \frac{1}{1 + e^{-\alpha(t-\beta)}}$$
(2)

where  $\alpha$  and  $\beta$  are adjustable parameters that determine the shape of the sigmoid. As shown in Fig. 4, the larger the  $\alpha$  is, the larger the slope of the sigmoid function becomes, and the more clearly the similarity changes.  $\beta$  is a parameter that shifts the center of the sigmoid function along the *t*-axis, and the larger it is, the less likely the state change is misidentified early in the process, since the change in f(t) occurs at the end of process. Since 0 < f(t) < 1 for this sigmoid function, the scale of  $a_w^t$  must be changed. In this study, we compute  $\hat{a}_w^t$  where  $a_w^t$  is scaled as follows,

$$\hat{a}_w^t := \frac{a_w^t - a_w^{min}}{a_w^{max} - a_w^{min}} \tag{3}$$

where  $a_w^{\{min,max\}}$  denotes the minimum and maximum values in the moving average of  $a_w^t$   $(1 \le t \le T)$  over 3 seconds. This makes  $0 \le \hat{a}_w^t \le 1$ , which facilitates fitting to f(t). During inference, it is important to note that the entire time series data D is not available from the beginning, and so Eq. 3 is performed using the computed  $a_w^{\{min,max\}}$  during the optimization process. Assuming that the default parameter of  $(\alpha, \beta)$  is (0.1, T/2), we obtain  $(\alpha, \beta)$  by fitting using the nonlinear least-squares method. Note that the constraints  $\alpha \ge 0$  and  $\beta \ge 0$  are imposed in the fitting. From these, we define the evaluation function E to be maximized as follows,

$$E(\boldsymbol{w}) := \alpha \beta / \sigma \tag{4}$$

where  $\sigma$  is the root mean squared error of the fitting. In other words, the evaluation function is designed to minimize the fitting error while making the amount of change as large as possible and ensuring that a large change in f(t) occurs at the end of the state change as possible.

Finally, we perform black-box optimization. In this study, we apply a genetic algorithm using the library DEAP [16] as the algorithm. The gene sequence represented by  $w_i$  is optimized based on the maximization of E. The function cxBlend is used for crossover with a probability of 50%, and mutGaussian is used for mutation with a probability of 20% with mean 0 and variance 0.1. Individuals are selected by the function selTournament, where the tournament size is set to 5, the number of individuals is set to 300, and the number of generations is set to 300. The choice of optimization method is flexible, and we have tried several methods such as Treestructured Parzen Estimator (TPE) and Covariance Matrix Adaptation Evolution Strategy (CMAES), but we did not observe significant differences in the results. Therefore, we used a common genetic algorithm with minimum computational cost.

## **III. EXPERIMENTS**

In this study, we perform four experiments: recognition of water boiling, butter melting, egg cooking (fried egg), and onion stir-frying. Each experiment with the prepared text set Q are shown in Fig. 5. First, we prepare a dataset  $D_{opt}$  for optimization and a dataset  $D_{eval}$  for evaluation. The state changes of water, butter, and egg are obtained at 10 Hz when the mobile robot PR2 looks at the stove that is heated to a certain degree. For onion stir-frying, the image of the onion is acquired every time PR2 stirs the pan with a spatula, because the onion would get burned if not stirred constantly. Although all experiments are conducted at the same heat intensity, the length T of each data is slightly different. For each experiment, the time when the state change ends is annotated as  $t_{data}$ . Next, we prepare at most a set of 50 texts Q describing the state change for each experiment. We prepare a large number of Q by changing the article, state expression, and expression form. We use five kinds of articles: "a", "the", "this", "that", and no article. For state expressions, antonyms such as "boiled"/"unboiled" and "melted"/"not melted" are used (synonyms are also used). The expression form is slightly changed, such as "boiled water" and "water that is boiled" are used.

In this study, we conduct experiments using two models, CLIP and ImageBind. For each model, we evaluate both  $D_{opt}$  and  $D_{eval}$  datasets in three settings, **OPT**, **ONE**, and **ALL**.

**OPT** is the result of applying the black-box optimization proposed in this study. ONE is the result when only the best Q that maximizes E is used among the prepared Q. Using only one best Q means that a state in which only one of the N scalar values in w is 1 and the rest are 0 is created, and the  $\boldsymbol{w}$  with the highest E is selected. ALL is the result when all the prepared Q are used equally without optimization. This means that  $w_i = 1$   $(1 \le i \le N)$ . Regarding  $D_{opt}$ , we plot the transition of  $\hat{a}_w^t$  and its moving average over 3 seconds for OPT, ONE, and ALL, respectively. Note that the moving averages are not plotted for the onion stir-frying experiment, since the number of images is small. Regarding  $D_{eval}$ , we plot  $\hat{a}_{w}^{t}$ , which is transformed by each Eq. 3 obtained from **OPT**, **ONE**, and **ALL** in  $D_{opt}$ , and its moving average. For each plot,  $t_{detected}$  is the time when the moving average first exceeds the set threshold  $C_{thre}$  ( $C_{thre} = 0.8$  in this study). As  $t_{diff} = |t_{detected} - t_{data}|$ ,  $t_{diff}$  should be as small as possible. For each experiment, the evaluation value E when fitting the change in  $\hat{a}_w^t$  into the sigmoid function f(t) is described. Note that while E is appropriate regarding  $D_{opt}$ , it is for reference only regarding  $D_{eval}$ , since  $\hat{a}_w^t$  may not fall between [0, 1] depending on the experiment.

Finally, as a cooking experiment utilizing the proposed method, the PR2 robot boils water, blanches broccoli, and stir-fries it with melted butter.

### A. Water Boiling Experiment

The results of the water boiling experiment are shown in Fig. 6. Here, "raw" is the raw value, "average" is the moving average, "sigmoid" is the result of fitting f(t) to  $\hat{a}_{w}^{t}$ , "detected" is the function that becomes 1 after  $t_{detected}$ , and the red arrow indicates  $t_{data}$ . As for CLIP, the change in similarity of ALL fluctuates and does not change proportionally with the boiling state. Thus, the fitting is not successful, the evaluation value E is zero, and  $t_{diff}$  is large. On the other hand, the change in similarity of **ONE** gradually increases with time, thus E is larger and  $t_{diff}$  is smaller than that of ALL. However, because of the gradual change in the similarity, the state is determined to be boiling earlier than in actuality. In contrast, for **OPT**, the abrupt change in similarity occurs almost simultaneously with boiling, thus E is the largest and  $t_{diff}$  is quite small (about 1 second). The variance of the similarity changes is also small and stable recognition results are obtained. As for ImageBind, reasonable performance is obtained even for ALL and ONE, and  $t_{diff}$  is relatively small. The change in similarity of **OPT** is more stable than that of **ALL** and **ONE**, indicating higher performance. Note that the top 5 text prompts and their weights are water that is not boiling in the pot (0.12), water that is boiled in pot (0.12), water that is not boiling in the pot (0.12), water that is not boiling in this pot (0.12), and *boiling water in that pot* (0.11) (the weight is normalized to be  $\Sigma w_i = 1$ ).

### B. Butter Melting Experiment

The results of the butter melting experiment are shown in Fig. 7. As for CLIP, the change in similarity of ALL





Fig. 6. Results of the water boiling experiment. For the two models CLIP and ImageBind, the results of OPT, ONE, and ALL are shown regarding  $D_{opt}$  and  $D_{eval}$ . In the graphs, "raw" expresses the raw value of similarity, "average" expresses the moving average of the raw value over 3 seconds, "sigmoid" expresses the sigmoid function fitted to "average", and "detected" expresses the function that becomes 1 after t<sub>detected</sub>. The red arrow shows  $t_{data}$ , the annotated time of state change.

fluctuates as with Section III-A, and does not change proportionally with the degree of melting. Thus, E is small and  $t_{diff}$  is large. The performance of **ONE** is better than that of ALL, but the change in similarity still fluctuates. Compared to ONE, OPT shows a stable change in the similarity, but the state change is detected earlier, especially for  $D_{opt}$ . As for ImageBind, state changes are recognized with high accuracy for all settings, thus E is large and  $t_{diff}$  is small. ALL has a larger variance of similarity changes compared to ONE and **OPT**, resulting in *E* being approximately halved. Note that the top 5 text prompts and their weights are butter that is not melted in that frying pan (0.24), butter that is not melted in frying pan (0.24), not melted butter in a frying pan (0.19),

not melted butter in that frying pan (0.18), and melted butter in frying pan (0.08).

### C. Egg Cooking Experiment

The results of the egg cooking experiment are shown in Fig. 8. As for CLIP, the change in similarity of ALL fluctuates as with Section III-A and Section III-B, and thus E is small and  $t_{diff}$  is large. For  $D_{opt}$ , the performance of **ONE** and **OPT** is reasonable and  $t_{diff}$  is small. On the other hand, the results for  $D_{eval}$  are significantly different from those for  $D_{opt}$ , and the accuracy is low. As for ImageBind, there is no large difference between  $D_{opt}$  and  $D_{eval}$  as with CLIP, but in most cases, the similarity increases significantly



Fig. 7. Results of the butter melting experiment. For the two models CLIP and ImageBind, the results of **OPT**, **ONE**, and **ALL** are shown regarding  $D_{opt}$  and  $D_{eval}$ . In the graphs, "raw" expresses the raw value of similarity, "average" expresses the moving average of the raw value over 3 seconds, "sigmoid" expresses the sigmoid function fitted to "average", and "detected" expresses the function that becomes 1 after  $t_{detected}$ . The red arrow shows  $t_{data}$ .



Fig. 8. Results of the egg cooking experiment. For the two models CLIP and ImageBind, the results of **OPT**, **ONE**, and **ALL** are shown regarding  $D_{opt}$  and  $D_{eval}$ . In the graphs, "raw" expresses the raw value of similarity, "average" expresses the moving average of the raw value over 3 seconds, "sigmoid" expresses the sigmoid function fitted to "average", and "detected" expresses the function that becomes 1 after  $t_{detected}$ . The red arrow shows  $t_{data}$ .

in the early phase of the state change and then remains constant. Therefore, the state change cannot be detected properly, thus  $t_{diff}$  is large. Note that the top 5 text prompts and their weights are raw egg in that frying pan (0.07),



Fig. 9. Results of the onion stir-frying experiment. For the two models CLIP and ImageBind, the results of **OPT**, **ONE**, and **ALL** are shown regarding  $D_{opt}$  and  $D_{eval}$ . In the graphs, "raw" expresses the raw value of similarity, "sigmoid" expresses the sigmoid function fitted to "raw", and "detected" expresses the function that becomes 1 after  $t_{detected}$ . The red arrow shows  $t_{data}$ .

cooked egg in a frying pan (0.07), cooked egg in the frying pan (0.07), cooked egg in this frying pan (0.07), and egg that is fried in frying pan (0.06).

the broccoli. Finally, ⑦ the robot stir-fries the boiled broccoli in the frying pan and then turns off the heat. A series of cooking behaviors using the proposed method was realized.

### D. Onion Stir-frying Experiment

The results of the onion stir-frying experiment are shown in Fig. 9. Unlike the previous experiments, the number of images is small, so there is no "average" and only "raw" is shown. As for CLIP, the changes in similarity of **ALL** and **OPT** are stable as the state changes, indicating that the recognition is highly accurate. On the other hand, for **ONE**, the change in similarity is not as clear as for **ALL** and **OPT**, and  $t_{diff}$  is larger. As for ImageBind, the recognition performance is not so high for **ALL** and **ONE**, since the change in similarity fluctuates. On the other hand, **OPT** recognizes the state change with high accuracy as with CLIP. Note that the top 5 text prompts and their weights are *cooked onion in this frying pan* (0.36), *raw onion in that frying pan* (0.19), grilled onion in this frying pan (0.11), cooked onion in frying pan (0.1), and fresh onion in frying pan (0.08).

### E. Cooking Experiment

The experimental result is shown in Fig. 10. We place a pot with water and a frying pan with butter on the stove. (1) The robot PR2 turns on the heat for the pot, and (2) when boiling is detected using the proposed method (ImageBind with **OPT**), (3) adds the broccoli in a sieve to the pot. After boiling for 3 minutes, (4) the robot takes the broccoli out, turns on the heat for the frying pan, and (5) when the proposed method detects that the butter has melted, (6) adds

# IV. DISCUSSION

The obtained experimental results are summarized, and their properties and limitations are discussed. In the experiments, we handled state changes related to water boiling, butter melting, egg cooking, and onion stir-frying, each of which has different properties, and a variety of results were obtained. The state change of water boiling is similar to (ii) in Fig. 3, and is easy to be recognized because the change of state occurs at once towards the end of the process. The state change of butter melting is close to (iv) and that of onion stir-frying is close to (i), and both of them can be recognized with high performance for the same reason as above. On the other hand, the state change of egg cooking is close to (iii), and the performance is limited because a large state change occurs at the beginning and the subsequent state changes are difficult to be recognized. More specifically, the color of the egg white first turns from transparent to white at once, and subsequently there is only a slight color change in egg yolk. CLIP and ImageBind, which were used in this study, were not able to overcome this problem, but we expect that the performance will be improved if VLM capable of detecting more precise changes is developed in the future. As an overall trend, we found that **OPT** with black-box optimization has higher recognition performance than ALL and ONE. Although the performance of ONE is somewhat higher than that of ALL, it may be reversed depending on the



Fig. 10. Results of the cooking experiment. The PR2 robot boils water, blanches broccoli, and stir-fries it with melted butter.

state to be recognized. Finally, when comparing CLIP and ImageBind, ImageBind shows relatively more stable changes in similarity. For CLIP, the results of  $D_{opt}$  and  $D_{eval}$  are sometimes significantly different from each other, while there are less of these cases for ImageBind. On the other hand, there are cases where CLIP performs better than ImageBind, so it is difficult to say which model is better. We believe that the simultaneous use of multiple models in the future will improve the performance of continuous state recognition by taking advantage of the characteristics of each model.

We discuss the prospects of future research. First, in this study, continuous state recognition is based only on the correspondence between images and texts, and there are still many unused modalities. In particular, video, audio, and heatmaps are indispensable information for cooking, and higher performance can be expected by integrating them into the proposed method. Also, in this study, the text set Q is manually created. A more practical system can be constructed by obtaining this text set automatically. We can use large-scale language models [17] to obtain multiple synonyms and antonyms of the state to be recognized. In addition, we would like to consider various other methods in the future, such as changing the viewing area for robots to focus on, using multiple models described above at the same time, and taking into account incomplete images [18].

### V. CONCLUSION

In this study, we proposed a continuous state recognition method for cooking robots based on the spoken language through pre-trained large-scale vision-language models. A set of texts related to the state to be recognized is prepared, and the similarity between the current image and texts is calculated in the temporal direction. In order to make the changes in similarity easier to use for state recognition, we adjusted the weighting of each text based on black-box optimization by fitting it to a sigmoid function and calculating its evaluation value. The sigmoid function is suitable for continuous state recognition because it can handle various patterns of state changes. The recognition performance with optimization is much better than that without optimization, and we succeeded in recognizing the states of water boiling, butter melting, and onion stir-frying. On the other hand, the recognition of egg cooking was difficult due to the fact that a large change in the image occurs in the early stage of the recognition, and the subsequent smaller changes are difficult to be recognized. We used CLIP and ImageBind as large-scale vision-language models, and while ImageBind produces more stable recognition results over all, each model has different strengths and weaknesses, and we may consider using both models in combination in the future.

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