

Project 1: The State Classification Challenge

Introduction:

Object recognition for coarse estimation of the object type has achieved human-like accuracy. However, for robotics, recognizing object type alone is usually not sufficient. When performing a manipulation tasks, a robot would need to know if the desired outcome of the manipulation has been reached or not. This would require fine-grained object state recognition. It is especially important for robotic cooking.

Robotic cooking is very useful especially for seniors and people with severe physical disabilities. Since cooking involves many manipulation tasks that requires physical interaction, such as cutting, it is still very challenging for a robot to perform those tasks in a general kitchen setting [1]. It is well-known that robotic cooking faces tremendous challenges in basic physically-interactive manipulations [2-4] and task-oriented grasping [5-11]. However, the semantic flow of the cooking process has not been fully explored [28].

To perform a cooking task, a robot would need to know not only the cooking process such as a recipe, but also the innate relationship between cooking utensils and food ingredients [12,13]. Once the innate relationship between objects are learned, it could be used to help robots to recognize the right object and carry out the correct manipulation motions [14].

To learn those relationships, instructional cooking videos on YouTube and many cooking sites could be automatically processed to extract the relationships between cooking utensils and food ingredients along with cooking actions [15]. The learned knowledge of cooking is represented by a functional object-oriented network (FOON) [16, 17]. Different from other knowledge representations for service robots [18], FOON connects objects/states and motions.

Object state plays an important role in FOON as it does in cooking. For example, a robot should recognize if an onion is a full onion or a half onion since the robot needs to grasp the onion differently. The robot should also recognize if the onion is a peeled onion or an unpeeled one since the processing steps would be different for the two cases.

An initial state recognition for cooking has been carried out in a small scale [19,29]. In the paper, objects and ingredients in cooking videos were explored and the most frequent objects were analyzed. The paper summarized and examined 11 states from the most frequent cooking objects. A dataset of images containing those objects and their states was created [20].

The state recognition could be tackled using many different convolutional neural networks. In [19], A Resnet [21] based deep model was used and initialized with Imagenet weights and trained on the dataset of 11 classes. VGG nets [22], GoogleNet [23], Inception V3 [24] have also been used.

State recognition is related to captions for images and videos. In [25] Yao et al. use attributes and their interactions with deep networks to provide captions. Other work such as [26], and [27] perform multi-label classification on a single image using RNN- and CNN-based deep architectures. Although these papers provide various labels for an image, they do not consider states of objects as another label for the image.

1) Project Goal:

In this project students will be designing a deep convolutional neural network to classify an image of a cooking object to one of its states. For example given an image of a *“sliced tomato”* or *“sliced bread”*, the network should give as output *“sliced”*.

2) Project Dataset:

The dataset contains 17 cooking objects (chicken/turkey, beef/pork, tomato, onion, bread, pepper, cheese, strawberry, ...) with 11 different states (whole, julienne, sliced, chopped, grated, paste, floured, peeled, juice, mixed, other). The dataset can be downloaded from https://drive.google.com/file/d/1HU0Z3X3OltW8oUIW_Kkgsz_6kA_ma2tX/view. For more information about the dataset we refer the students to <https://arxiv.org/abs/1805.06956/>.

Other food-related datasets:

<http://pic2recipe.csail.mit.edu/>

<http://www.ivl.disco.unimib.it/activities/food-recognition/>

3) Project Description:

Part 1 Data Annotation (20 pts):

The data annotation includes one batch of approximately 180 frames (images). You will be assigned one (or two) objects with a google drive link which contains a directory of frames (images). You have to annotate all frames containing the objects assigned to you. To annotate you need to create a bounding box around the object (e.g. potato) in the frame and also specify the state (e.g. sliced) of that object. You should do this for every frame that contains the assigned object. After annotation you should dump the results into PASCAL VOC format. For annotation you need to create an account in the cvat.ai (previously, cvat.org) website. A video has been uploaded to canvas under this assignment that explains how to create an account in cvat.ai, how to create a task, how to annotate and finally how to dump the results. You need to create a zip file from the dumped annotations files and upload it on canvas. After annotations are done, each student will be given a random set of videos from other students to check for annotation errors. Students could lose points for poor annotation.

The dataset assigned for each student will be found here: https://usfedu-my.sharepoint.com/:f:/g/personal/mdsadman_usf_edu/ErUdFCps81VljgIKveAO6BQBS97ncE22t2M34ROQUSSv9w?e=N0Jfru.

You need to label only those images that are in your folder.

Part 1 submission

- You should submit all labels of the frames (15 pts)
- You will evaluate other student's labels and provide corrections (5 pts)

Part 2 Neural network design and training (50 pts):

The dataset downloaded from this link https://drive.google.com/file/d/1HU0Z3X3OItW8oUIW_KkqsZ_6kA_ma2tX/view will be used for training and validation. You should split the data given to you into train and validation data and use train data for training your model. You should validate your model during and after training with your validation data. You should add convolutional layers, pooling layers and test various deep learning techniques to improve your results as much as possible. Failure to add various layers will result in a deduction of your points. ***The code should be implemented in Python. You can use Tensorflow or PyTorch but no other programming language or platform is acceptable. You are not allowed to use any pretrained model (resnet, vgg etc.). You have to design your own neural network and train it.*** If your program is not easily test-able on the test set, you will loss 10 pts.

Part 2 Submission:

- Training code (30 pts)
- Testing script of the train model. It should include loading a dataset and provide accuracy. (10 pts)
- Training and validation results as figures (10)

Part 3 Improvement and comparison (30 pts)

To improve your neural network's performance, you should perform at least the follow techniques:

- data augmentation (6 pts)
- different drop rates (4 pts)
- batch normalization (5 pts)
- use Inception module (5 pts)
- use residual connections (5 pts)

The remain 5 pts is based on your model's classification accuracy on unpublished test data.

Your submission should include

- Source code for training the best model
- Your best trained model and a architecture drawing of the model
- Test script load your best trained model so that we can test it on the test data
- Figures showing the performance differences using the required techniques

References:

- [1] Sun, Yu. "AI Meets Physical World--Exploring Robot Cooking." *arXiv preprint arXiv:1804.07974* (2018).
- [2] Sun, Yu, and Joe Falco. "Robotic Grasping and Manipulation: First Robotic Grasping and Manipulation Challenge, RGMCMC 2016, Held in Conjunction with IROS 2016, Daejeon." (2018).
- [3] Huang, Y. and Sun, Y. (2017). Learning to Pour, IROS, pp 7005-7010
- [4] Huang, Y. and Sun, Y. (2018) A Dataset of Daily Interactive Manipulation, International Journal of Robotics Research (Accepted)
- [5] Huang, Yongqiang, and Yu Sun. "A Dataset of Daily Interactive Manipulation." *arXiv preprint arXiv:1807.00858*(2018).
- [6] Sun, Y., Yun Lin, and Yongqiang Huang (2016) Robotic Grasping for Instrument Manipulations, URAI, 1-3 (Invited)
- [7] Lin, Y. and Sun, Y., 2016. Task-oriented grasp planning based on disturbance distribution. In Robotics Research (ISRR). Springer International Publishing, pp. 577-592.
- [8] Lin, Y. and Sun, Y., (2015) Grasp Planning to Maximize Task Coverage, Intl. Journal of Robotics Research, 34(9): 1195-1210.
- [9] Lin, Y., and Sun, Y. (2015) Robot Grasp Planning Based on Demonstrated Grasp Strategies, Intl. Journal of Robotics Research, 34(1): 26-42.
- [10] Lin, Y. and Sun, Y. (2015) Task-Based Grasp Quality Measures for Grasp Synthesis, IROS, 485-490.
- [11] Lin, Y., Sun, Y. (2014) Grasp Planning Based on Grasp Strategy Extraction from Demonstration, IROS, pp. 4458-4463.
- [12] Sun, Yu, and Yun Lin. "Modeling paired objects and their interaction." *New Development in Robot Vision*. Springer, Berlin, Heidelberg, 2015. 73-87.
- [13] Ren, Shaogang, and Yu Sun. "Human-object-object-interaction affordance." *Robot Vision (WORV), 2013 IEEE Workshop on*. IEEE, 2013.
- [14] Sun, Yu, Shaogang Ren, and Yun Lin. "Object-object interaction affordance learning." *Robotics and Autonomous Systems* 62.4 (2014): 487-496.
- [15] Babaeian, J.A., Paulius, D. and Sun, Y. (2019) Long Activity Video Understanding using Functional Object-Oriented Network, IEEE Transactions on Multimedia, 21(7): 1813-1824.
- [16] Paulius, David, et al. "Functional object-oriented network for manipulation learning." *Intelligent Robots and Systems (IROS), 2016 IEEE/RSJ International Conference on*. IEEE, 2016.
- [17] Paulius, David, Ahmad B. Jelodari, and Yu Sun. "Functional Object-Oriented Network: Construction & Expansion." *2018 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2018.
- [18] Paulius, David, and Yu Sun. "A Survey of Knowledge Representation and Retrieval for Learning in Service Robotics." *arXiv preprint arXiv:1807.02192* (2018).

- [19] Jelodar, Ahmad Babaeian, Ms Sirajus Salekin, and Yu Sun. "Identifying Object States in Cooking-Related Images." *arXiv preprint arXiv:1805.06956* (2018).
- [20] http://rpal.cse.usf.edu/datasets_cooking_state_recognition.html
- [21] C. Szegedy, S. Ioffe, V. Vanhoucke, and A. A. Alemi, "Inception-v4, inception-resnet and the impact of residual connections on learning." In AAAI, vol. 4, 2017, p. 12.
- [22] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *arXiv preprint arXiv:1409.1556*, 2014.
- [23] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, A. Rabinovich et al., "Going deeper with convolutions." *Cvpr*, 2015.
- [24] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Rethinking the inception architecture for computer vision," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2016, pp. 2818–2826.
- [25] T. Yao, Y. Pan, Y. Li, Z. Qiu, and T. Mei. Boosting image captioning with attributes. In *2017 IEEE International Conference on Computer Vision (ICCV)*, volume 00, pages 4904–4912, Oct. 2018.
- [26] S. Venugopalan, L. A. Hendricks, M. Rohrbach, R. Mooney, T. Darrell, and K. Saenko. Captioning images with diverse objects. In *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 1170–1178, July 2017.
- [27] J. Wang, Y. Yang, J. Mao, Z. Huang, C. Huang, and W. Xu. Cnn-rnn: A unified framework for multi-label image classification. In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 2285–2294, June 2016
- [28] Paulius, David, and Yu Sun. "A survey of knowledge representation in service robotics." *Robotics and Autonomous Systems* 118 (2019): 13-30.
- [29] Jelodar, Ahmad Babaeian, and Yu Sun. "Joint Object and State Recognition Using Language Knowledge." *2019 IEEE International Conference on Image Processing (ICIP)*. IEEE, 2019.