**Rb-PaStaNet**: A Few-Shot Human-Object Interaction Detection Based on Rules and Part States

Shenying Zhang, Zichen Zhu, Qingquan Bao

*Shanghai Jiao Tong University*

**Abstract**

Existing Human-Object Interaction (HOI) Detection approaches have achieved great progress on non-rare classes while rare HOI classes are still not well-detected. In this paper, we intend to apply human prior knowledge into the existing work. So we add human-labeled rules to PaStaNet and propose Rb-PaStaNet aimed at improving rare HOI classes detection. Our results show a certain improvement of the rare classes, while the non-rare classes and the overall improvement is more considerable.

**Keywords**: Human-Object Interaction, Body Part State, Rule-based Network

**1 Introduction**

When building an intelligent system, understanding human activities from still images plays a critical role. As a sub-task of visual relationship comprehension [10], Human-Object Interaction (HOI) infers types of interactions through retrieving human and object locations. Related to human and object understanding, HOI will boost activity understanding [6], imitation learning [1], etc.

Generally, this high-level cognition task is addressed in one-stage [3], i.e. directly mapping pixels to activity concepts. Closer to our work, Li et al. [8] takes advantages of part-level semantics and builds a human activity knowledge engine to infer interactiveness. However, nearly all state-of-the-art methods encounter few-shot classes’ performance bottleneck due to rare training datasets.

In light of this, we propose a **Rb-PaStaNet** (Rule-based Part State Net) to augment the existing work PaStaNet [8]. With the introduction of human prior knowledge as rules, we believed Rb-PaStaNet would have more information about the physical world besides training data. Specifically, we manually label the weights of each human body part in 162 less-than-ten-shot HOI classes. Two versions are introduced: one consists of weights in Decimal numbers derived from the average of three authors’ labels, the other Boolean numbers derived from the former version. These weights are added to part attentions, which means the importance of certain body parts in an HOI class, to strengthen the learning of few-shot HOI classes.

Finally, our method achieves some insignificant improvement on few-shot HOI classes, e.g. the Decimal version makes 0.13 mAP improvement of the rare classes on HICO-DET [2]. Meanwhile, we gladly found that the Boolean version has improved the non-rare classes and the overall mAP by 0.22 and 0.2. So after we point out the deficiencies of current human-based rules, we propose some viable approaches to enlarge the improvement.

**2 Related Work**

Our work is in the field of Human-Object Interaction (HOI) where image-based, instance-based and body-part-based patterns are mainly used.
Human-object Interaction Most of the daily human activities involve HOI [2, 7]. Thanks to Deep Neural Networks (DNNs), many great improvements have been made in the detection of such events [2, 5, 12]. Chao et al. [2] combined visual features and spatial locations to construct a multi-stream model. Qi et al. [12] proposed Graph Parsing Neural Network (GPNN) incorporating DNN and graphical model to iteratively update states and classify pairs. Gao et al. [5] developed an instance centric attention module to increase the information from the region of interest and improve the HOI classification. Li et al. [9] explored interactiveness knowledge learned from various HOI datasets, implicitly increasing the training data for rare HOI classes. While these works have contributed to the improvement of HOI detection, the progress of the few-shot HOI classes is insufficient [8].

Part States Lu et al. [11] proposed a discrete set of part states through tokenizing the semantic space and bases a sort of basic descriptors on segmentation [4]. Furthermore, Li et al. [8] utilized states of 10 human body natural parts to represent activities and reasons out the activities with part-level semantics. PaStaNet makes great improvements and reaches the state-of-the-art in both full and few-shot tasks. Despite that, the mAP of one-shot set in the PaStaNet is still below 0.3. To improve that, in this paper, we mainly focus on few-shot problems in HOI.

3 Approach

In this section we introduce the construction of (Rb-PaStaNet) in Figure 1 to tackle the few-shot problems. Why current DNN-based models do not perform well in few-shot HOI classes may lie in insufficient information offered by training datasets. Therefore, our method introduces human prior knowledge to reinforce learning in rare HOI classes. Considering PaStaNet [8] using body parts’ action as a medium to infer HOI, adding prior rules into each body parts action weights can be viable. In the following paragraphs, the choice of the dataset, the method to label and the process of rules construction are specified.

Data We conduct model training based on the PaStaNet database, with more than 200k training examples. The existing network divides object-action into 600 classes (including the no-interaction ones). A total of 162 classes only appear in the training set less than ten times. Our experiments are targeted at optimizing existing networks in terms of these rare classes.

Label As for the rare classes, three authors perform manual annotations respectively based on the body parts’ involvement in the corresponding object-action according to our prior knowledge. In our annotation, label 1 indicates a strong correlation; 0.5 indicates a certain degree of correlation; 0 indicates irrelevance. As for common classes, all parts are labelled 1. Then we average three annotations as one type of label. The average value is distributed between 0 and 1. Besides, to find a better rule, we map the resulting Decimal label to the Boolean label (True if the decimal label is no less than 0.5, or False otherwise). The two groups of labels and the All-True control group (original label) were trained separately. Table 1 shows an example of labelled weights in an HOI “feed a cat” and all weights are displayed in Figure 2 where the upper one represents the Boolean version and the lower one represents the Decimal version.
**Implementation** In PaStaNet \[8\], all features will be initially input to a Part Relevance Predictor telling a body part’s importance in an action. Formally, a certain attention is

\[
a_i = \mathcal{P}_{pa}(f_p^{(i)}, f_o)
\]

where \(\mathcal{P}_{pa}()\) is the part attention predictor and \(f_p^{(i)}, f_o\) indicate features of a part and an interacted object respectively. In Rb-PaStaNet, we introduce rules:

\[
a_i^{rb} = a_i \cdot a_{rules}
\]

where \(a_i^{rb}\) represents attentions added with rules and \(a_{rules}\) indicates weights we have labeled in the last paragraph. Then we compute scores and cross-entropy loss like PaStaNet with \(a_i^{rb}\) instead of \(a_i\).

| Body Parts | Method          | RFoot | RThigh | LThigh | LFoot | Hip    | Head   | RHand | RArm | LArm | LHand | Average |
|------------|-----------------|-------|--------|--------|-------|--------|--------|-------|------|------|-------|---------|
|            | Original        | 1     | 1      | 1      | 1     | 1      | 1      | 1     | 1    | 1    | 1     | 1       |
|            | Decimal         | 0     | 0.33   | 0.33   | 0     | 0.33   | 0.5    | 1     | 0.83 | 0.83 | 1     | 0.52    |
|            | Bool            | 0     | 0      | 0      | 0     | 0      | 1      | 1     | 1    | 1    | 1     | 0.5     |

Table 1: The weights of "feed a cat"

![Figure 2: the Boolean and Decimal label matrix](image)

### 4 Experiment

**Settings** We adopt one HOI datasets HICO-DET \[2\] with 600 HOI categories on 80 objects categories and 117 verbs. We first use best pre-trained Activity2Vec with instance-level Pasta labels \[8\] and then fine-tune Rb-PaStaNet on HICO-DET. All testing data are separated from pre-training and fine-tuning. We follow the metrics of \[2\] for results and PaSta detection. The fine-tuning takes 2M iterations and the learning rate is 1e-3 with 1:4 of positive and negative samples. A late fusion strategy is adopted.

| Method           | Full(def) | Rare(def) | Non-rare(def) | Full(ko) | Rare(ko) | Non-rare(ko) |
|------------------|-----------|-----------|---------------|----------|----------|--------------|
| PaStaNet         | 21.92     | 20.44     | 22.37         | 23.86    | 22.31    | 24.33        |
| Rb-PaStaNet(Boolean)| 22.12     | 20.54     | 22.59         | 24.04    | 22.43    | 24.52        |
| Rb-PaStaNet(Decimal)| 21.94    | 20.57     | 22.35         | 23.86    | 22.46    | 24.28        |

Table 2: Results on HICO-DET. We follow the evaluation metrics in \[2\]: def means Default setting where the full test set is detected, while ko means Known Object setting where the target object category is given.

**Results** As Table 2 shows, Boolean and Decimal versions of Rb-PaStaNet achieve 0.1 and 0.13 mAP improvements on rare HOI classes. Although the human labels are not very precise concerning they are based on few people’s intuition and comprehension, the result has proved that by applying human prior knowledge the mAP can be improved. Meanwhile, the result shows that the Boolean version has improved the non-rare classes and the overall mAP by 0.22 and 0.2. After analysing the scores of each classes, we find out that the rules are also influencing those non-rare classes(just think those classes share the same label-[1,1,1,1,1,1,1,1,1,1,1,1,1,1,1]). So we have proposed a few possible approaches that may increase the competitiveness of Rb-PaStaNet:
5 Conclusion

In this article, based on the existing PaStaNet, we propose Rb-PaStaNet instead. Our goal is to improve on rare classes by adjusting the training weights of different parts. The experiment result has proved our method is feasible, but it also leaves much room for improvement. The probable reason is that our rule itself is not accurate enough because it is generated by three authors. In the future, we hope to get a more accurate and detailed version with the help of volunteers. We believe a better rule can make more improvement.

Acknowledgments

We would like to express our very great appreciation to Cewu Lu and Yong-Lu Li for their constructive suggestions and guidance throughout this research work. We would also like to extend our thanks to Liang Xu for his assistance in terms of codes. Their patience and carefulness have been very much appreciated.

References

[1] Brenna D. Argall, Sonia Chernova, Manuela Veloso, and Brett Browning. A survey of robot learning from demonstration. Robot. Auton. Syst., 57(5):469–483, May 2009.
[2] Y. Chao, Y. Liu, X. Liu, H. Zeng, and J. Deng. Learning to detect human-object interactions. In 2018 IEEE Winter Conference on Applications of Computer Vision (WACV), pages 381–389, 2018.
[3] Vincent Delaitre, Josef Sivic, and Ivan Laptev. Learning person-object interactions for action recognition in still images. In J. Shawe-Taylor, R. S. Zemel, P. L. Bartlett, F. Pereira, and K. Q. Weinberger, editors, Advances in Neural Information Processing Systems 24, pages 1503–1511. Curran Associates, Inc., 2011.
[4] Hao-Shu Fang, Jianhua Sun, Runzhong Wang, Minghao Gou, Yong-Lu Li, and Cewu Lu. Instaboost: Boosting instance segmentation via probability map guided copy-pasting, 2019.
[5] Chen Gao, Yuliang Zou, and Jia-Bin Huang. ican: Instance-centric attention network for human-object interaction detection. CoRR, abs/1808.10437, 2018.
[6] F. C. Heilbron, V. Escorcia, B. Ghanem, and J. C. Niebles. Activitynet: A large-scale video benchmark for human activity understanding. In 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 961–970, 2015.
[7] Yong-Lu Li, Xinpeng Liu, Han Lu, Shiyi Wang, Junqi Liu, Jiefeng Li, and Cewu Lu. Detailed 2d-3d joint representation for human-object interaction. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 10166–10175, 2020.
[8] Yong-Lu Li, Liang Xu, Xinpeng Liu, Xijie Huang, Yue Xu, Shiyi Wang, Hao-Shu Fang, Ze Ma, Mingyang Chen, and Cewu Lu. Pastanet: Toward human activity knowledge engine. In CVPR, 2020.
[9] Yong-Lu Li, Siyuan Zhou, Xijie Huang, Liang Xu, Ze Ma, Hao-Shu Fang, Yanfeng Wang, and Cewu Lu. Transferable interactivity knowledge for human-object interaction detection. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 3585–3594, 2019.
[10] Cewu Lu, Ranjay Krishna, Michael S. Bernstein, and Fei-Fei Li. Visual relationship detection with language priors. CoRR, abs/1608.00187, 2016.
[11] Cewu Lu, Hao Su, Yonglu Li, Yongyi Lu, Li Yi, Chi-Keung Tang, and Leonidas J Guibas. Beyond holistic object recognition: Enriching image understanding with part states. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 6955–6963, 2018.
[12] Siyuan Qi, Wenguan Wang, Baoxiong Jia, Jianbing Shen, and Song-Chun Zhu. Learning human-object interactions by graph parsing neural networks. In Computer Vision – ECCV 2018, pages 407–423, Cham, 2018. Springer International Publishing.