



SEMANTIC-EMBEDDED KNOWLEDGE ACQUISITION AND REASONING FOR IMAGE SEGMENTATION

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Ideas



 Previous work focus on improving visual features for segmentation

Our methods use correlation between objects

- Introduce a knowledge reasoning module (KRM) for external knowledge aggregation
- Use GNN to aggregate the knowledge feature
- Enhance the visual feature with external knowledge feature for final segmentation



Main contribution



- A novel knowledge reasoning module is proposed to introduce the external knowledge feature. GCN is introduced to aggregate the external knowledge to enhance the features for segmentation task.
- The proposed module can be flexibly integrated with other semantic segmentation framework.
- The effectiveness of the proposed method is proved by the evaluation on the public dataset FoodSeg103 and Cityscapes



Our methods -architecture

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 Our method is designed on the basic encoder decoder framework and can be flexibly applied to all networks based thereon



Methods: Knowledge reasoning module

Node representation

 comes from word embedding(by Glove or CLIP) of the object name or visual embedding of convolution transformation weights

• Edge representation

• The edge between two nodes represent the relationship of two objects in the image



N x N adjacent matrix: Number of Co-occurrence

SETR plug-in: proposed knowledge reasoning module





Methods: Knowledge feature transformation

Detailed transformation Foodseg103 dataset :

Feature to be enhanced [8,104,W=768,H=768]



EXPERIMENTS



 Our experiment results outperform the baseline methods on the food dataset FoodSeg103 and Cityscapes, and demonstrate the effectiveness of our proposed method

Method	mIoU	Model size
FPN [3](ResNet50)	27.3	218M
FPN-KRM(CLIP+GCN)	28.3	227M
CCNet [4](ResNet50)	35.1	381M
CCNet-KRM(CLIP+GCN)	36.4	399M
SETR [6](Vit-16/B)	44.6	776M
SETR-KRM(CLIP+GCN)	45.7	805M

Method	mIoU	Model size
FPN [3](ResNet50)	74.5	218M
FPN-KRM(CLIP+GCN)	76.4	227M
CCNet [4](ResNet50)	79.3	381M
CCNet-KRM(CLIP+GCN)	80.5	399M
SETR [6](Vit-16/B)	78.1	776M
SETR-KRM(CLIP+GCN)	79. 7	805M

Table 1. Segmentation evaluation results of MIou on Food-Seg103 dataset

Table 2. Segmentation evaluation results of MIou on C-ityscapes(test), training schedule with 80k



Ablation study



 Experimental results shows that a combination of CLIP based module and visual knowledge module can achieve the best mIoU performance

Method	mIoU
SETR[6](Vit-16/B)	44.6
SETR-KRM(GCN+CLIP)	45.7
SETR-KRM(GCN+CLIP+GLOVE)	45.3
SETR-KRM(GCN+CLIP+VISUAL)	45.8
SETR-KRM(GCN+CLIP+GLOVE+VISUAL)	45.2

Table 4. Results of different modules on FoodSeg103



Visualization

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- Some visualization examples are demonstrated. SETR is used as the baseline method in the third column, the fourth column is proposed method
- From the visualization observations, the SETRknowledge reasoning module (KRM) achieves better performance and more detailed results



Fig. 4. Visualization of testing samples in FoodSeg103: SETR with knowledge achieves better performance.



Conclusion



- In this paper, a semantic segmentation framework that incorporates the KRM for image segmentation task is introduced
- GCN is used to aggregate the external knowledge feature
- Experiments show that our proposed method outperforms the baseline methods on the FoodSeg103 and Cityscapes datasets
- We hope our proposed method can contribute to the community in semantic segmentation tasks





Thank you for your watching

