Panoptic Vehicle Segmentation for Real-Time Obstacle Detection and Road Safety

Maryam Mohamed Mohamed Mahmoud Abd-ElRahman 2400062
Salma Ehab Mohamed Kamal Hassan 2400055

October 25, 2024

1 Introduction

The growing complexity of urban environments poses considerable challenges for autonomous vehicles, particularly in accurately perceiving and interpreting the surrounding environment. To address this, we propose leveraging advanced deep learning architectures to develop a model that enhances real-time obstacle detection through panoptic segmentation. This approach combines semantic segmentation, which identifies pixel-level class labels, with instance segmentation which differentiates between individual objects within those classes. This combined approach enhances the vehicle's ability to understand its surroundings, identify obstacles, and make safer navigation decisions in real time.

2 Research Problem and Objectives

Despite the advancements of existing panoptic segmentation architectures such as SOGNet and Detectron2, both models are not optimized for real-time performance, as they both face challenges with:

- Computational Efficiency: High memory and processing power are required, making real-time deployment extremely difficult.
- Inference Speed: In dynamic environments where decisions such as detecting fast-moving vehicles or obstacles in real-time need to be made, latency can be problematic and hinder the performance of autonmous vehicles.

In response to these challenges, the objective is to create a hybrid panoptic segmentation model that combines both SOGNet and Detectron2. This model will be optimized for faster inference and reduced memory usage while perserving segmentation accuracy. Ultimately, this approach aims to facilitate safer navigation for autonomous vehicles in real-time scenarios.

3 Literature Review

This research is grounded in the advancements made by existing panoptic segmentation models, particularly SOGNet and Detectron2, which will serve as the foundation for our project.

- SOGNet: employs a graph-based approach to manage overlaps in panoptic segmentation, excelling at differentiating overlapping objects and efficiently managing both semantic and instance segmentation. [2]
- Detectron2: Is recognized for its modular architecture and high performance in instance segmentation tasks achieving remarkable accuracy and adaptability across various object detection scenarios. [1]

4 Methodology

- Model Architecture Development: We will develop a hybrid segmentation model by integrating both SOGNet and Detectron2, while streamlining the architecture to reduce computation overhead. This architecture will be optimized using techniques such as model pruning, quantization, and architectural simplifications to reduce memory usage and improve real-time processing speeds.
- One-Shot Learning: We will incorporate one-shot learning to effectively address the challenges associated with real-time obstacle detection and classification. This approach will enable our model to recognize and segment objects on-the-fly, ensuring timely decision-making.

5 Data Collection and Pre-processing

We will collect diverse image and video datasets representing various driving scenarios. The pre-processing phase will involve data augmentation to create a more robust training set, alongside annotation of vehicles, pedestrians, and obstacles. This step ensures that the model is exposed to a wide range of situations, improving its performance in real-world applications.

6 Experimental Design

The experimental design will evaluate the proposed hyper-panoptic segmentation model by utilizing metrics such as Mean Intersection over Union, precision, recall, F1 score, frames per second, and memory usage. Additionally, the model's performance will be bench-marked against existing architectures, including SOGNet and Detectron2, using diverse datasets to ensure robust assessment across various conditions.

7 Expected Results and Analysis

The expected results from the proposed panoptic segmentation model include enhanced segmentation accuracy, real-time processing capabilities, and reduced memory usage compared to existing models. we anticipate that the model will effectively segment and classify vehicles, pedestrians, and obstacles in diverse urban environments while demonstrating improved adaptability through one-shot learning, To analyze the outcomes, we will employ metrics such as MIoU, F1 score, precision, recall, and comparing our model's performance against baseline architectures to assess improvements.

8 Timeline

The timeline of our project is structured as follows:

- Literature Review and Model Selection (Weeks 1-2)
- Data Collection and pre-processing (Weeks 3-4)
- Model Development and Architecture Design (Week 5)
- Training and Fine-Tuning (Weeks 6-7)
- Evaluation and Experimental Analysis (Week 8)
- Final Adjustments and Documentation (Week 9)

9 Potential Contributions

This project will contribute to autonomous vehicle navigation by improving real-time segmentation accuracy for vehicles and obstacles, enhancing decision-making in complex environments.The use of one-shot learning will also enable quick adaptation to new object classes, potentially promoting safer autonomous driving technologies.

References

[1] Bowen Cheng, Maxwell D Collins, Yukun Zhu, Ting Liu, Thomas S Huang, Hartwig Adam, and Liang-Chieh Chen. Panoptic-deeplab: A simple, strong, and fast baseline for bottom-up panoptic segmentation. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 12475–12485, 2020.

[2] Yibo Yang, Hongyang Li, Xia Li, Qijie Zhao, Jianlong Wu, and Zhouchen Lin. Sognet: Scene overlap graph network for panoptic segmentation. In *Proceedings of the AAAI conference on artificial intelligence*, volume 34, pages 12637–12644, 2020.