Learning to segment roads for traffic analysis in urban images

Pritesh Lohot (Roll No. 2101111)

Guide: Dr. Debashree Devi

Indian Institute of Information Technology, Guwahati CS300

March 15, 2024



Outline

- Introduction
- Related Work
- Challenges
- Objective
- Tentative Methodology
- Conclusion
- Reference



Introduction



Introduction

- Focus: Road segmentation, crucial for in-vehicle perception and traffic surveillance applications.
- Objective: Develop a robust system for road segmentation in urban scenes.
- Importance: Identification of road regions in images essential for traffic flow analysis and object detection.
- Challenges: Cluttered environments, presence of pedestrians.
- Techniques: Utilization of advanced methods such as superpixel segmentation and feature extraction.
- Goal: Accurate delineation of road areas from complex images captured.

Related Work



Related Work

Detection and classification of highway lanes using vehicle motion trajectories Melo et al. (2006):

- Methodology: The authors utilize vehicle motion trajectories to detect highway lanes. They employ a merge-and-split algorithm with a Kalman filter and RANSAC to estimate the trajectories and categorize highway lanes.
- Drawbacks: Lack of detailed information on datasets used and specific limitations of the methodology.

Related Work (contd.)

Lane detection by orientation and length discrimination Lai and Yung (2000):

- Methodology: The authors propose a lane detection method based on orientation and length discrimination of lane markings and curb structures. They work in a 3D space after camera calibration.
- Drawbacks: Limited discussion on datasets and potential challenges faced in real-world scenarios.

Vehicle classification by road lane detection and model fitting using a surveillance camera Shin et al. (2006):

- Methodology: The authors focus on vehicle classification using road lane detection. They apply a Hough transform over a Sobel edge detector for lane detection and fit a 3D object model over the detected lanes.
- Drawbacks:Lack of information on datasets and potential limitations of the model fitting approach.

Related Work (contd.)

An automatic traffic surveillance system for vehicle tracking and classification Hsieh et al. (2006):

- Methodology: The authors propose an automatic traffic surveillance system for vehicle tracking and classification. They likely utilize methods such as background subtraction and feature extraction for tracking and classification.
- Drawbacks: Limited information on the specific methodologies used and datasets employed for evaluation.

Road boundary detection in challenging scenarios Helala et al. (2012):

- Methodology: This paper proposes a method for road boundary detection, particularly in challenging scenarios. The approach likely involves analyzing image features such as edges and textures to delineate road boundaries.
- Drawbacks: One potential drawback could be the limited effectiveness of edge-based methods in highly cluttered scenes or under poor lighting conditions.

Related Work Summary

These works represent a diverse range of approaches to road segmentation, incorporating various methodologies and addressing different challenges in the field. Each approach has its strengths and weaknesses, and ongoing research aims to further improve the accuracy and robustness of road segmentation algorithms.



Challenges

Challenges



Challenges

Variability in Road Conditions:

- Road segmentation algorithms must cope with diverse road conditions, including varying lighting conditions, road types, and environmental factors such as shadows and occlusions.
- Adapting to these changes is crucial for accurate segmentation.

Complex Backgrounds:

- Urban scenes often contain cluttered backgrounds with numerous objects such as vehicles, pedestrians, and buildings.
- Segmentation algorithms need to effectively distinguish road regions from these background elements to avoid misclassification.

Edge Detection and Adherence:

- Accurate edge detection is essential for identifying road boundaries.
- Ensuring that detected edges adhere closely to the actual contours of the road is challenging, especially in the presence of noise or discontinuities in the image.



Challenges (Cont'd)

Real-time Processing:

- For applications such as traffic surveillance and autonomous driving, road segmentation algorithms must operate in real-time to provide timely information.
- Achieving high processing speeds without sacrificing accuracy is a significant challenge.

Robust Feature Extraction:

- Extracting meaningful features from the input images is critical for accurate segmentation.
- Variations in road appearance, texture, and motion patterns pose challenges for feature extraction algorithms.

Training Data Availability:

- Developing machine learning-based segmentation methods requires access to annotated training data.
- Obtaining diverse and representative datasets for training can be challenging, especially for specialized applications or unique environments.

Generalization to Different Scenarios:

- Road segmentation algorithms should generalize well to different scenarios, including varying road types, environmental conditions, and camera viewpoints.
- Ensuring robust performance across diverse settings is a key challenge.

Objective



Objective

- Develop a fast and accurate method for segmenting roads in urban traffic surveillance videos.
- Support tasks like traffic flow analysis and violation detection.
- Utilize superpixel detection, feature extraction, and machine learning.
- Aim for real-time performance.
- Address challenging scenarios such as intersections and varying lighting conditions.

Tentative Methodology

Tentative Methodology

Background Modeling and Edge Detection:

- We employ a robust median filtering technique for background modeling, effectively separating foreground objects from the background.
- Through the application of a Canny edge detector, we identify and accumulate stable edges, forming the basis of our edge-based background model.
- The equation for the process is given by:

$$BG_k = \begin{cases} BG_{(k-1)} + 1, & \text{if } FG_k > 0, \text{if } FG_k < 0 \\ BG_{(k-1)} - 1, & \text{if } FG_k < 0 \end{cases}$$

 \bullet Where BG and FG denote background and foreground, $FG_k={\rm Frame}_k-1$ and k=1,2,...N frames. $BG_{(k-1)}$

Superpixel Detection via Edge Density Estimation:

- Leveraging edge density estimation, we achieve superior edge adherence and continuity, essential for accurate road segmentation.
- Our methodology employs spatial filtering and thinning morphological operations to refine detected edges, ensuring high-quality superpixel detection

$$ED = \frac{1}{N} \sum_{i=1}^{N} p_i$$

Where the edge density ED is a simple arithmetic median calculated in the neighborhood N of the pixels pi.

17 / 27

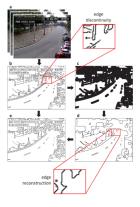


Figure:

Superpixel detection. In (a),image provided after background subtraction after n frames;(b) shows the result of the accumulated Canny detector (with an edge discontinuity example) over the subtracted back- ground;(c) shows the result of the spatial filter;(d) illustrates the result of a thinning morphological operation (without edge discontinuities); finally,(e) shows the results of the OR bit-wise operation between Canny detector and the resulting image of the morphological operation.

Feature Extraction for Road Segmentation:

- Multiple road priors are extracted, including horizon line estimation, texture homogeneity, gray amount, and motion, to comprehensively characterize road regions.
- These features are computed efficiently, utilizing edge density and background modeling, ensuring adaptability to diverse urban environments.

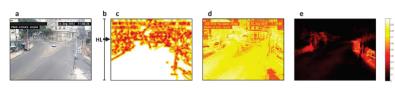


Fig. 4. Heat map illustrating the contributions of each road priors (the closer to one, the hotter, as in the legend on the most right). In (a), the original image: (b) horizon line: (c) texture homogeneity. (d) gray amount; (e) motion.

Feature Extraction Using Convolutional Neural Networks (CNNs):

- CNNs can automatically learn relevant features from input images, including textures, edges, shapes, and colors, which are essential for distinguishing road regions from the background.
- Training a CNN on a large dataset of annotated road images enables the network to learn features indicative of road areas.
- After training, the CNN can serve as a feature extractor by passing input images through the network.
- Features can be extracted from one of the intermediate layers of the CNN.
- The extracted features can then be utilized as input to an Support Vector Machine(SVM) classifier for further processing, such as segmentation..

Classification Using Support Vector Machine (SVM):

- Training an SVM classifier with extracted features enables precise classification of superpixels as road or non-road regions.
- Our approach considers various SVM kernels to optimize classification performance, ensuring robust road segmentation results.

Dataset Description:

- Dataset consisted of 17 videos capturing various urban road scenarios under challenging conditions.
- Total of 4,536 frames collected, encompassing factors like side cars, shadows, lighting changes, and non-structured roads.
- 6,691 superpixels detected in the images, with 2,230 frames used for training and 4,461 frames for testing the SVM classifier.
- Performance metrics such as accuracy, precision, and recall are evaluated to gauge the effectiveness of our approach in real-world scenarios.

By integrating cutting-edge techniques in background modeling, edge detection, feature extraction, and classification, our methodology offers a sophisticated yet efficient solution for road segmentation. With its potential applications in traffic analysis, driver assistance systems, and surveillance, our approach represents a significant advancement in computer vision research.

Dataset Used:

The datasets commonly used for road segmentation tasks are:

- KITTI Vision Benchmark Suite: High-quality images from moving vehicles equipped with cameras and LiDAR sensors, providing labeled instances of road areas.
- Cityscapes Dataset: Large dataset featuring urban street scenes with detailed annotations for road segmentation and semantic segmentation, offering diverse environmental conditions.
- CamVid Dataset: Video sequences from urban and highway settings with pixel-level annotations, presenting challenges like occlusions, dynamic objects, and lighting changes.
- Aerial Semantic Segmentation Drone Dataset (ASU-Drone): Images captured by drones showing various types of roads and terrains, providing ground truth annotations for road areas.
- Mapillary Vistas Dataset: Street-level images collected worldwide with pixel-level annotations, offering diverse geographic regions and environmental conditions for segmentation algorithms.

Conclusion



Conclusion

Presented a fast and efficient method for road segmentation, which plays a crucial role in various computer vision applications, including in-vehicle perception and traffic surveillance. This method utilizes superpixel-based segmentation and incorporates multiple road features to achieve accurate segmentation results. Demonstrated the effectiveness of this approach through experiments conducted on a dataset comprising challenging urban road scenes. Key contributions of this method include:

- Utilization of superpixel-based segmentation for efficient image processing.
- Integration of multiple road features including horizon line estimation, texture homogeneity, gray amount, and motion to enhance segmentation accuracy.
- Development of simple yet effective strategies for feature extraction, ensuring computational efficiency and robustness in different scenarios.



Conclusion

- Experimental results have shown that this method achieves high accuracy, precision, and recall rates, making it suitable for real-life applications where precision and speed are crucial factors. The proposed method outperforms existing state-of-the-art approaches in terms of segmentation accuracy and computational efficiency.
- As future work, it aim to further refine the motion estimation component of our method, particularly addressing noise caused by non-vehicle objects in the scene.
- Overall, this method offers a promising solution for road segmentation tasks, providing valuable support for various computer vision applications such as in-vehicle assistance systems and traffic surveillance.

Reference



Reference

- Helala, M., Pu, K., and Qureshi, F. (2012). Road boundary detection in challenging scenarios. In IEEE International Conference on Advanced Video and Signal-Based Surveillance.
- Hsieh, J., Yu, S., Chen, Y., and Hu, W. (2006). An automatic traffic surveillance system for vehicle tracking and classification. *IEEE Transactions on Intelligent Transportation Systems*, pages 175–187.
- Lai, A. and Yung, N. (2000). Lane detection by orientation and length discrimination. IEEE Transactions on System, Man, Cybernetics - Part B, pages 539–548.
- Melo, J., Naftel, A., Bernardino, A., and Santos-Victor, J. (2006). Detection and classification of highway lanes using vehicle motion trajectories. *IEEE Transactions on Intelligent Transportation* System, pages 188–200.
- Shin, W., Song, D., and Lee, C. (2006). Vehicle classification by road lane detection and model fitting using a surveillance camera. *Journal of Information Processing Systems*, 2:52–57.