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Lane Detection Based on Image Processing and Machine Learning

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***Abstract*: Lane detection and object detection are crucial tasks in the field of autonomous driving. In this project, we propose a system that combines both lane and object detection to improve the performance and safety of autonomous vehicles. The project uses Haar-like features and Cascade classifiers to detect objects and lane markings from the video frames. The lane detection algorithm detects lane markings on the road by analyzing the color and edge features of the image. The object detection algorithm uses a pre-trained Cascade classifier to detect objects in the video frames. The system is implemented using Python libraries and Yolo. The results show that the system is able to accurately detect lane markings and objects in the video streams with high accuracy and low latency.**

***Keywords*: lane detection, edge detection, object detection, haar feature, yolo library, cascade classifier, machine learning.**

1. Introduction

The Lane and Object Detection using Haar Features project is a computer vision project that aims to detect and track lanes and objects in real-time using Haar features and machine learning algorithms. The project involves collecting a dataset of images or video frames containing the objects or regions of interest, preprocessing the data, training a Haar cascade classifier, testing the classifier, implementing the lane and object detection algorithm, and evaluating the algorithm's performance.

Lane detection and object detection are important computer vision tasks that have numerous real-world applications. In this project, we will be using the Haar feature-based cascade classifier approach to detect lanes and objects in images. The Haar feature-based cascade classifier is a machine learning-based approach for object detection. This approach uses a set of features to detect objects in an image. These features are simple rectangular features that can be computed very quickly. The cascade classifier uses a series of these features in a hierarchical manner to detect objects. We will use the Haar feature-based cascade classifier to detect the edges of the lanes in an image and to detect objects in an image like cars, people, and animals in real-time video streams.

In our system there are 3 modules:

1) Lane Detection
2) Object Detection
3) Auto Driving Helper System

2. Literature Survey

In paper [1] algorithm proposed is based on Haar feature-based coupled cascade classifiers. The algorithm extracts the Haar features of the lane from the Regions of Interest (ROI) extracted from the input images. A cascade lane classifier is introduced to roughly detect the lane in the ROI. The line segment detector (LSD) method is then used to fit the roughly detected lanes, and geometric checking is applied to optimize the fitting results. The proposed algorithm has been tested on multiple datasets and has shown higher robustness and accuracy compared to current lane detection methods, achieving up to 96.5% accuracy.

In paper [2] algorithm proposed is based on deep learning techniques, specifically the enhanced network Retinexnet and the instance segmentation network Deeplabv3. The algorithm first enhances the original image using the Retinexnet network to improve contrast and clarity. Then, lane line detection and segmentation are carried out using Deeplabv3, while the shape analysis algorithm is introduced to optimize the results. The algorithm has been tested on changeable road environments and at night, achieving a forward detection rate of up to 94.6%, which is 2 percentage points higher than the direct Deeplabv3 network.

In paper [3] proposes an approach to detecting lane boundaries using a camera that captures the view of the road mounted on the front of the vehicle. Image is converted in an set of sub- images, and image features are generated for each of them, which are further used to detect the lanes.

In paper [4] algorithm proposed uses a cascaded convolutional neural network (CNN) structure for end-to-end lane detection. The encoder and decoder structure is used to instance segment the lane boundary, followed by lane classification using a linear classifier. The algorithm is trained on labeled datasets and achieves high accuracy. However, the fixed label limits the scene for lane change, making it difficult to expand the algorithm.

In paper [5] algorithm proposed uses a fast detection

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algorithm based on the combined gradient and color filtering of lane line pixels. The algorithm uses Sobel edge detection operator for detecting edge information and filters white and yellow color features of the lane line in the color space. The algorithm achieves high accuracy and timeliness for the lane detection in the autonomous vehicle camera, making it suitable for real-time applications.

3. Proposed Methodology

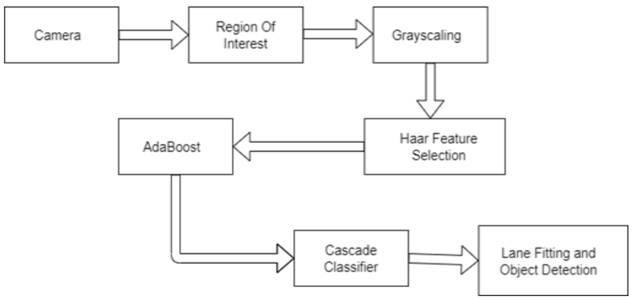

Fig. 1. Architecture diagram

Input: The input to the system will be a video or a sequence of images from a camera mounted on a moving vehicle.

ROI Selection: The next step is to select the region of interest (ROI) from the input image, which will contain the lane and object information. This can be done using various techniques like geometric shape detection, color filtering, or semantic segmentation.

Grayscale Conversion: Once the ROI is selected, the image will be converted to grayscale to reduce the computational complexity of the system.

Haar Feature Selection: Next, Haar features will be selected to detect specific patterns in the grayscale image that correspond to lane and object features. Haar features are similar to edge detection but are more robust and can detect features at different scales and orientations.

AdaBoost Training: The selected Haar features will be used to train an AdaBoost classifier, which is a type of machine learning algorithm that combines multiple weak classifiers into a strong classifier. The AdaBoost classifier will be trained on a set of positive and negative samples, where positive samples contain lane and object features, and negative samples do not.

Cascade Classifier: Once the AdaBoost classifier is trained, a cascade classifier will be created to improve the detection speed of the system. The cascade classifier consists of multiple stages, where each stage contains a set of weak classifiers that progressively filter out false positives.

Lane and Object Detection: Finally, the trained cascade classifier will be used to detect lanes and objects in the ROI. The detected lanes and objects will be marked on the original image or video, and their positions and dimensions will be recorded.

Overall, this methodology combines computer vision techniques with machine learning to detect lanes and objects in a given input image or video. The system can be further improved by fine-tuning the parameters of each step and using more sophisticated models for feature selection and classification

4. Methods/Algorithms

A. ROI (Region of Interest)

In lane detection, the Region of Interest (ROI) refers to the specific area within an image or video frame where the algorithm should search for lanes. Typically, the ROI is defined as a trapezoidal shape that covers the area of the road in front of the vehicle. The selection of the ROI is based on the camera's location and the expected position of the lanes, and the extracted subset of the image or video frame is where the lane detection algorithm is applied.

The use of an ROI in lane detection is crucial for reducing computational cost and increasing the accuracy of the algorithm. By limiting the search to a specific area of the image, the algorithm can focus its attention on the most relevant information, which improves its efficiency and reduces false detections.

Furthermore, the ROI can be adjusted to account for different driving conditions, such as various road layouts, lighting conditions, or weather conditions. This flexibility allows the lane detection algorithm to perform well in a variety of situations and is a critical component of advanced driver assistance systems (ADAS) and autonomous vehicles. The inclusion of an ROI in lane detection algorithms is an essential consideration for researchers and developers working in the field of autonomous driving.


Fig. 2. ROI selection

B. Gray Scaling

Lane detection is an important component of advanced driver assistance systems (ADAS) and autonomous vehicles. In recent years, various techniques have been proposed to improve the accuracy and robustness of lane detection algorithms. One common pre-processing step used in lane detection is gray scaling, which converts a color image into a grayscale image. The grayscale image represents each pixel with a single value that corresponds to its brightness, which ranges from 0 to 255.

Gray scaling simplifies the image and reduces the computational cost of the algorithm by eliminating color information. It allows the algorithm to focus on the brightness values of the pixels, which are directly related to the presence of lane markings. Additionally, gray scaling improves the robustness of the algorithm in different lighting conditions. Color information can vary significantly depending on the lighting conditions, which can affect the accuracy of the lane detection algorithm. Grayscale images, on the other hand, are less affected by changes in lighting conditions and are therefore more reliable.

C. Haar Cascade

Haar Cascade is a machine learning-based object detection technique that can be used in lane detection. In Haar Cascade, a classifier is trained on a set of positive and negative samples to detect a particular object in an image. To use Haar Cascade in lane detection, the classifier is trained on positive samples of lane markings and negative samples of non-lane regions in the image. Once the classifier is trained, it can be used to detect the presence of lane markings in a new image or video frame.

The Haar Cascade classifier can be applied in combination with other lane detection techniques, such as edge detection and Hough transform, to improve the accuracy and robustness of the lane detection algorithm. By incorporating Haar Cascade, the lane detection algorithm can detect lane markings even in challenging lighting conditions or low contrast situations. Moreover, Haar Cascade can be trained on different types of lane markings, such as dashed, solid, or double lines. This flexibility allows the algorithm to detect various types of lane markings, which is critical for its application in different driving scenarios.

The use of Haar Cascade in lane detection is an effective way to improve the accuracy and robustness of the algorithm. The incorporation of Haar Cascade along with other lane detection techniques can lead to better detection of lane markings, making it an essential consideration for researchers and developers working in the field of autonomous driving.

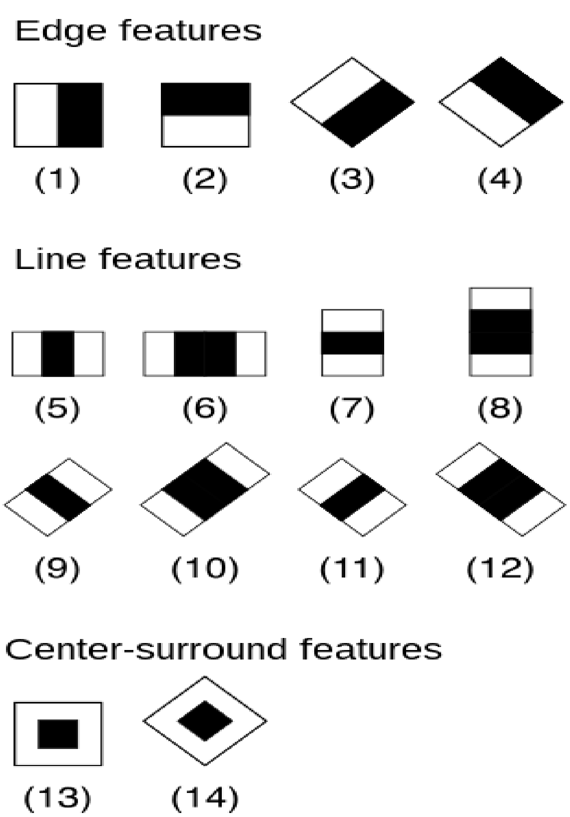

Fig. 3. Haar feature

D. Yolo library

YOLO (You Only Look Once) is a popular deep learning library used for object detection tasks. It is a real-time object detection system that uses a single neural network to predict bounding boxes and class probabilities directly from full images in a single forward pass. YOLO works by dividing the input image into a grid of cells and predicting bounding boxes and class probabilities for each cell. Each bounding box is associated with a confidence score, indicating the probability that the box contains an object, and a class probability vector, indicating the probability of the object belonging to each class.

To use YOLO for object detection, you would typically start by downloading a pre-trained YOLO model and using it to detect objects in images or video frames. You can also fine-tune the model on a custom dataset to improve its accuracy on specific classes of objects. There are several open-source implementations of YOLO available, including Darknet, a C-based neural network framework, and various Python wrappers such as PyTorch-YOLO and TensorFlow-YOLO.

5. Experimental Results

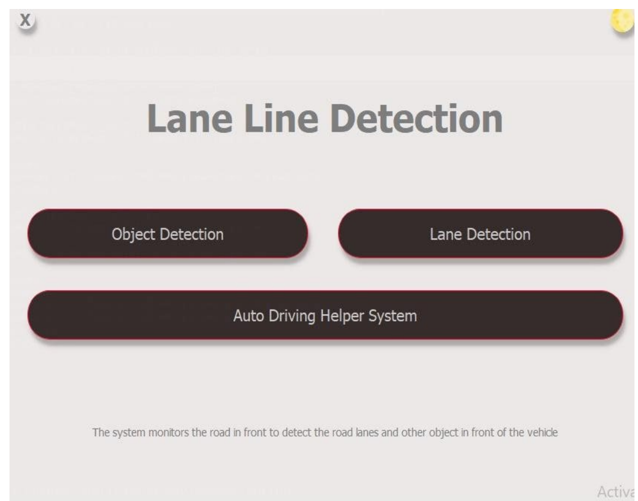

Fig. 4. Lane line detection

Fig. 5.

6. Conclusion

Our approach is based on Haar features, which are efficient at capturing the most relevant information in the image. We trained our system using a combination of positive and negative examples, which allowed us to obtain accurate results in real-time. The lane detection algorithm will be based on Haar feature to detect lanes in extreme weather conditions. Machine Learning algorithm will be used to classify large scale images.

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