Efficient Feature Extraction in Robust Lane Detection of Driving Information

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ABSTRACT - The accuracy of observed lane lines has a significant impact on unmanned vehicle driving decisions. However, improvements in the driving scene make lane recognition algorithms a lot of difficulty during the operation of unmanned vehicle driving. Many modern lane detection models cannot detect unclear and occluded lane lines in many complicated driving scenes, such as busy scenes, low light conditions, and so on. In light of this, we propose a robust lane detection model in complex driving scenes that makes use of vertical spatial features and contextual driving knowledge. The proposed model detects fuzzy and occluded lane lines more robustly due to the more efficient use of contextual information and vertical spatial features through two built blocks: feature merging block and information sharing block. The function merging block will offer more contextual information to the corresponding network, allowing the network to learn more feature specifics to aid in the detection of undefined lane lines. The information sharing block is a novel block that incorporates the benefits of spatial convolution and dilated convolution to improve the method of transferring information between pixels. The incorporation of spatial information improves the network's detection of occluded lane lines. In a number of dynamic driving conditions, experimental findings indicate that our proposed model detects lane lines more robustly and accurately than state-of-the-art models.

Keywords: lane detection; vertical spatial features; contextual information; complex driving scenes

I. INTRODUCTION

We may use convolutional neural networks to process images and help us solve some of the problems faced in the field of unmanned driving, such as lateral control of the vehicle, estimation of driver focus, and understanding of traffic driving scenes, thanks to the advancement of deep learning. Lane recognition [1] is a critical component of how unmanned vehicles comprehend traffic driving scenes. Lane identification may provide more detail about the driving climate, allowing cars to make better driving decisions.

When doing lane identification in dynamic traffic driving scenes, several problems arise. For starters, the appearance of lane lines in various driving situations, such as fencing and stairs, can vary. When confronted with these scenarios, several algorithms fail to correctly predict lanes. Second, as the car drives, the external world of the driver varies.

When the car is in its normal driving routine, it experiences several related phenomena that make lane identification difficult. Finally, the present climate influences lane identification. Vehicles find it impossible to find lanes in many harsh conditions, including low light and blinding light. As a result, lane identification is a difficult challenge in the world of unmanned driving.

Lane detection algorithms are classified into two types: those that use image features that are derived and then fitted [4], and those that use the deep learning approach. Many algorithms in the first group would remove image features such as color and edge features. Following it, certain other algorithms, such as the random

The sample consensus and Hough transform methods are often used to aid in lane identification. However, in order to produce successful outcomes, this type of approach is often based on the selection of particular features in specific scenes, which is difficult to achieve in complicated driving scenarios. Cars that can drive autonomously must meet stringent criteria in terms of understanding driving scenarios, especially lane identification in a variety of scenarios. Deep learning-based lane recognition has significant advantages in this regard. To comprehend the scene, a deep convolutional neural network can be trained to perform semantic segmentation on scene images [10,11].

We suggest a deep convolutional neural network in this paper to detect lane lines in a number of dynamic traffic scenarios. We improve the network's lane recognition precision in dynamic scenes by increasing the amount of spatial information and improving information transfer between pixels. In general, the feature map in the non-bottleneck part of the network can lose contextual information after the convolution process. As a result, we create a function merging block with a skip layer and factorized convolutions

[12] to enable the following network to obtain more contextual information. Spatial convolutions may improve information transfer between neighboring layers in the function diagram, and dilated convolutions can expand the network's receptive area. As a result, we combine their benefits to create an information sharing block that improves the efficient transfer of information between pixels. Despite the lane prediction challenges described previously, our network can still effectively predict unclear or blocked lanes. This thesis is built on our previous work, which was approved for publication in a conference proceeding and includes further performance analysis and experimental presentations.

II. RELATED WORK

Early lane identification work was primarily used to aid the vehicle's driving operation. To satisfy the demands of applications at the moment, lane identification did not necessitate a deep knowledge of traffic scenes and instead allowed the detection of ego lanes. [5] suggested a real-time method for detecting ego-lanes. Collaboration between the RANSAC method and a ridge operator will increase lane detection performance. Many simple-scene algorithms consider using image attributes to detect lanes and achieve good performance. [6] proposed using the Canny edge detection algorithm to track the edges of roads and dividers while simultaneously refining the edges with Huff transform technology Then, in some dynamic scenes, some people started to detect lanes.

[7] proposed a real-time algorithm based on a hyperbola-pair model, and their experimental results indicate that the algorithm performs well when arrow signs and decorative lane markers are present on the route. proposed a three-feature-based automated lane detection algorithm that predicts lane lines very effectively by using the optimal weighted combination of the starting point, direction, and gray-level strength features comprising a lane vector.

[9] proposed a B-snake-based lane detection model that does not include any camera parameters, can represent a wide variety of lane structures, and is resilient to some complex scenes.

III. PROPOSED ARCHITECTURE

In this segment, we go over the proposed network architecture for detecting lanes in great detail. Figure 1 depicts the network architecture. Inspire by the ERFNet, we suggest an end-to-end network that detects lanes using pixel-level prediction. When a driving scene image is fed into the network, it will predict the location of the lane in the image. Our network is made up of an encoder and two decoders, with the two decoders predicting the presence of lanes and the probability map of lanes. As a result, we present the whole network architecture from the perspective of these four network components ((A) Encoder; (B) Chance chart prediction; (C) Current lanes prediction; and (D) Loss function).

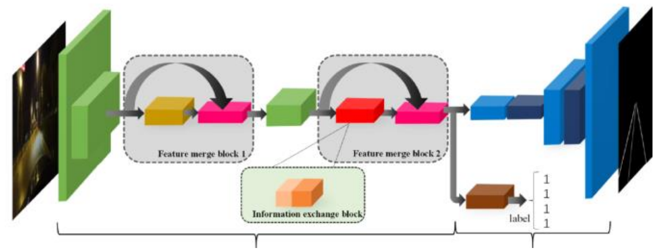

Figure 1. Proposed Architecture

This dataset's frames were captured on the highway throughout the day. Its driving scene is relatively easy, with the goal of detecting several lanes. There are a total of 6408 frames, with 3268 frames for the instruction sets, 358 frames for the verification sets, and 2782 frames for the evaluation sets. Our proposed network model is based on ERFNet, and the information sharing block employs vertical spatial convolution. As seen in Table 1, we selected three comparable models to compare with our network: ERFNet, SCNN, and ERFNet with horizontal and vertical spatial convolution operations (ERFNet + SCNN).

Table 1. Comparison of Results

Network Model	**ERFNet**	**SCNN**	**ERFNet + SCNN**	**Proposed**
F1 (0.3)	81.4	81.9	89.8	82.6
F1 (0.5)	72.8	71.6	71.5	72.9

IV. CONCLUSION

In summary, we suggest a comprehensive lane identification model for complex traffic driving scenes based on the ERFNet. In this paper, we use two designed blocks to improve the use of contextual information and vertical spatial features in our model. More contextual detail, as well as helpful vertical spatial features, will greatly improve the identification of undefined and occluded lanes. After analyzing a series of verification trials, we believe that the suggested model is more stable than others for detecting ambiguous and occluded lanes.

V. REFERENCES

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