Robust Lane Detection Based On Convolutional Neural Network and Random Sample Consensus

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Abstract. In this paper, we introduce a robust lane detection method based on the combined convolutional neural network (CNN) with random sample consensus (RANSAC) algorithm. At first, we calculate edges in an image using a hat shape kernel and then detect lanes using the CNN combined with the RANSAC. If the road scene is simple, we can easily detect the lane by using the RANSAC algorithm only. But if the road scene is complex and includes roadside trees, fence, or intersection etc., then it is hard to detect lanes robustly because of noisy edges. To alleviate that problem, we use CNN in the lane detection before and after applying the RANSAC algorithm. In training process of CNN, input data consist of edge images in a region of interest (ROI) and target data become the images that have only drawn real white color lane in black background. The CNN structure consists of 8 layers with 3 convolutional layers, 2 subsampling layers and multi-layer perceptron (MLP) including 3 fully-connected layers. Convolutional and subsampling layers are hierarchically arranged and their arrangement represents a deep structure in deep learning. As a result, proposed lane detection algorithm successfully eliminates noise lines and the performance is found to be better than other formal line detection algorithms such as RANSAC and hough transform.

Keywords: lane detection, neural network, deep learning, advanced driver assistance system.

1 Introduction

Road traffic accidents have become one of the most serious problems worldwide today. These accidents are caused by people, vehicle and road infrastructure. Measures to prevent these accidents can be categorized into following 3 types [1]: (1) Changing human behavior; (2) vehicle-related measures; and (3) physical road infrastructure related measures. Changing human behavior can be achieved by law enforcement, information, education and driving instructions while infrastructure measures include construction of new roads. Vehicle related measures include vehicle safety systems such as electronic stability control (ESC), anti-lock braking system (ABS) and advanced driver assistance systems (ADAS). It has been found that ESC and ABS play a crucial role in preventing accidents in crucial situations while ADAS helps to avoid

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accidents by assisting the driver in his/her driving task continuously. Moreover, ADAS can provide more comfortable driving service.

ADAS is a common accessory in passenger and commercial vehicles these days and serves as a good solution for reducing traffic accidents [2, 3]. In general, ADAS technologies consist of adaptive cruise control (ACC), lane departure warning system, collision avoidance system, adaptive light control, automatic parking, etc. For instance, lane departure warning system [4, 5] and lateral control have been developed by detecting the lane markings of a road using forward-facing camera and computer vision techniques. Similarly lane departure system is a safety feature that informs the driver about changing lane situation. In this system and for other such systems, accurate lane detection is necessary and most important factor.

For lane detection, most common method is based on edge detection in the road scene and then application of RANSAC algorithm[6]. However, the results of RANSAC become unreliable with the growing complexity in road scenes, which may include roadside trees, fence, wall or intersection and so on. For such complex scenes, addition of CNN before and after applying the RANSAC can be a good solution. CNN is a kind of deep network and composed of multiple layers of small neuron collections, which looks at small portions of the input image. This algorithm mimics the dorsal stream of human visual system and is used for various object recognition scenarios such as face detection [7, 8], hand written characters [9], traffic signs [10], etc.

Therefore, in this paper, we propose a new robust lane detection method which combines CNN with RANSAC algorithm. When the RANSAC fails to find a load lane, the trained CNN works and provides the candidate of a road lane. The RANSAC is repeatedly applied to the candidates of road lanes that are obtained from the CNN. The proposed method is efficient to find road lanes robustly in complex real roads with noisy environment.

In Section 2, we present details of our proposed method. We present simulation results in Section 3, and followed by conclusion in Section 4.

2 Proposed Method

2.1 Overview of Proposed Method

We use two-step processing for the lane detection from real world driving videos. First step includes blurring and edge detection for removing the environment noises as a preprocessing step. Second step includes the road lane detection based on RANSAC combined with CNN processes for accurate lane detection. The whole process of proposed model is shown in Fig. 1. If road environment changes dynamically due to weather, time and objects on road, the videos contain lots of noises, which decreases lane detection accuracy in real situation. In order to alleviate that problem, we propose a new method which is combination of RANSAC and CNN. If road condition is simple and easy, we can use the RANSAC algorithm only to get lane information. But if road conditions include lots of noise factors, we can use the CNN before and after the RANSAC algorithm to get the lanes robustly.

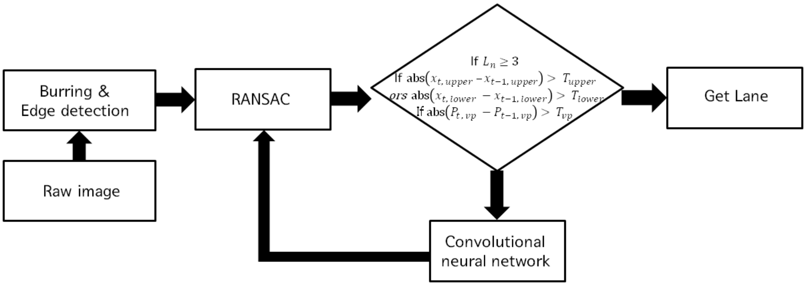

Fig. 1. Structure of proposed model

2.2 Blurred and Edge Detection

The lane is generally a white color in a gray color background road. So, an easy way to detect the lane is to use edge information. However, edge detection itself may not be sufficient way to detect the lanes because of various noises in an image such as shadow, illumination change, etc. Therefore, we use a blurring image, which are obtained by 5x5 Gaussian smoothing function before the edge detection. This blurring step reduces the environment noise, and produces more reliable information in a scene.

Moreover, for robust lane detection, the surround area of the lane needs to be suppressed. So, we use hat-shape kernel[11] to strengthen lane information, while suppressing the surroundings around the lanes in edge detection. Fig. 2.A shows the shape of hat-shape kernel. Thus, edge image calculated using convolution of lane image and this kernel. It's performance is better than other several preprocessing method. Also, result of edge detection in several situation showed in Fig. 2.B

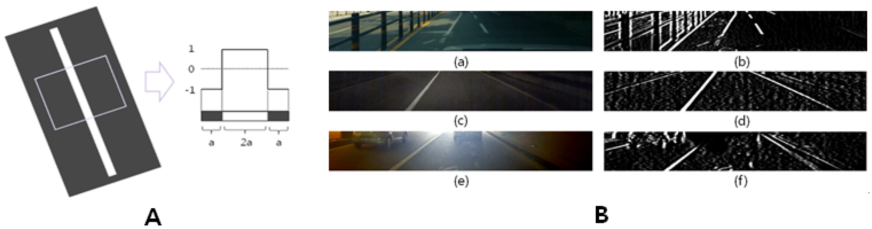

Fig. 2. The kernel of edge detection and examples. **A :** the kernel shape of edge detection. **B**: (a) fence and shadow image (b) fence and shadow image using edge detection (c) night image (d) night image using edge detection (e) changing intensity image in tunnel (f) changing intensity image in tunnel using edge detection.

2.3 Lane Detection Using RANSAC

RANSAC is an estimation technique based on the principle of hypotheses generation and verification [12, 13]. Given a model requiring a minimum of *N* data points to instantiate its free parameters and a set of data points P containing more than N elements, the RANSAC algorithm finds the line that has the highest possibility. We set the ROI to reduce the computation load. Since lanes look like vertical shapes from the car interior, we set the candidates of arrival and departure point on the upper and lower ROI lines. When the road scene is complex, the selected point is not likely to create a lane and accuracy of lane detection may decrease.

2.4 Reinforcement of Lane Detection Using CNN Combined with RANSAC Algorithm

The accuracy of lane detection based on RANSAC is highly dependent on the road conditions. There are three cases to fail the lanes based on the RANSAC algorithm;.(1) detecting more than two lines, (2) the shift of a lane between frames is too big and (3) the shift of the vanishing point determined by the left and right lines is too big. Fig. 3 shows the examples for three cases. In all three cases, we use the CNN before RANSAC algorithm to reinforce the lane information and suppress the surrounding noise information for stable lane detection, and then apply again the LANSAC to the candidate images obtained from CNN.

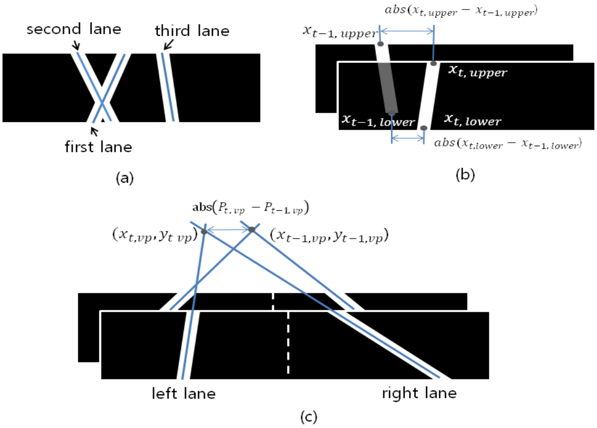

Fig. 3. Example of three cases (a) the number of lanes is three (b) position of the lane, where $x_{t,\ upper}$, $x_{t-1,\ upper}$ and $x_{t,\ lower}$, $x_{t-1,\ lower}$ in the x-axis direction are represented upper and lower points of lane in t and t-1 frame and T_{upper} *and* T_{lower} are threshold values at upper and lower positions of lane, respectively. (c) vanishing point of lane, where $P_{t,\ vp}$ is the vanishing point at $(x_{t,vp}, y_{t,vp})$ in t frame and $P_{t-1,\ vp}$ is the vanishing point at $(x_{t-1,vp}, y_{t-1,vp})$ in t-1 frame. T_{vp} is threshold value of vanishing point.

On the other hand, the CNN is a kind of deep network which imitates the dorsal stream in human brain[14]. The dorsal stream is known as a brain area for object detection and recognition. Therefore, CNN is generally used for object detection and recognition and includes convolutional layer (simple cell) and subsampling layer (complex cell). The simple cell treats local receptive field information. In the CNN, convolutional layer works same as the simple cell. In the convolutional layer, kernels are shifted over the valid region of the input image. The subsampling layer mimics the complex cell's functions and store max-pooling or average information from convolutional layer using down sampling. After multiple convolutional and subsampling layers, a fully connected multilayer perceptron (MLP) is used to complete the CNN. In the MLP, the error back propagation is used for weight control. The output of MLP is the final image of the CNN. In this paper, we considered 2 subsampling layers, 3 convolutional layers and an MLP including 3 fully connected layers in the CNN. Fig. 4 shows its structure.

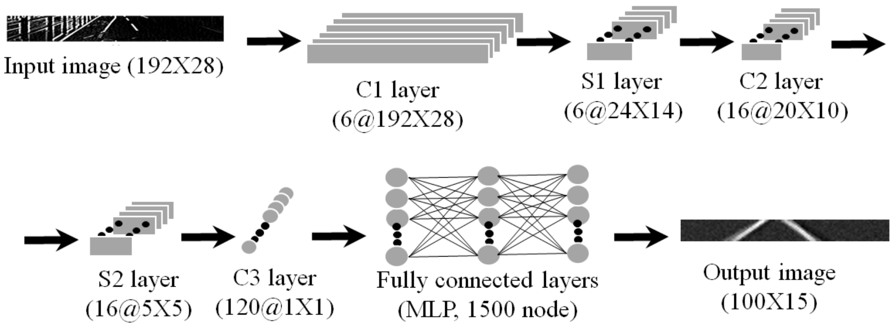

Fig. 4. Structure of CNN

Due to the difference of input image's width and height (as shown in Fig. 4), we use 8x2 kernel and 4x2 kernel for subsampling. At the final step, we use an MLP network with one hidden layer. The size of output image is 100x15. For training the CNN, we need target information of the lane. So, we manually prepare the target lane data which include lane information only.

In a test mode, when the above three cases in subsection 2.4 happen, the CNN works to find the candidate of lanes, and the output of CNN produces the 100x15 output image. Then, we apply again the RANSAC to the output images from the CNN. Finally, we can get robust lane information even when the RANSAC itself fails to lanes.

3 Experimental Results

The result of lane detection using RANSAC algorithm is shown in Fig. 5. The results highly depend on the degree of complexity of input road scenes. If there are lots of noises such as fence, wall, reflecting light in front window, lane detection based on RANSAC is very poor as shown in Fig. 5 (b).

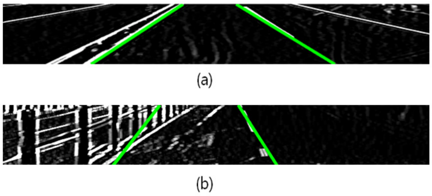

Fig. 5. Results of lane detection using RANSAC algorithm (a) well detected lane in simple image (b) wrong detected lane in complex image

To improve the accuracy of lane detection in complex road scenes, we use the RANSAC combined with CNN. The results are shown in Fig. 6. Since the CNN gives the candidate region for the lanes, and resultantly noise reduced results can be obtained as shown in Fig. 6 (b). We apply again the RANSAC to the candidate of CNN. Finally, we can get final detected actual lanes. Notice that the proposed method is robust to the road environment in lane detection as shown in Fig. 6 (c).

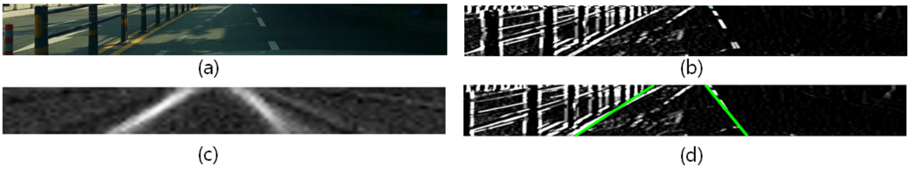

Fig. 6. Simulation results, (a) original image (b) Edge image (c) output image of CNN and (d) result of RANSAC combined with CNN

We tested our proposed RANSAC combined with CNN algorithm on complex video clips containing three different conditions. The conditions include detecting more than three lines (case 1), changing of lane position is too big (case 2) and the distance of vanishing points of left and right lanes is too big (case 3). We consider corrected detection, missed detection and false detection to evaluate the performance of these clips in Table 1. Corrected detection means that more than half region of the detected lane overlaps with a target lane. Missed detection means that less than half region of detected lane overlaps with a target lane, and false detection means that detected lane never overlaps with a target lane.

Table 1. Performance evaluation in three different conditions

Clips	Corrected detection	Missed detection	False detection
Case 1	94.7.0%	5.1%	0%
Case 2	93.9%	4.9%	1.2%
Case 3	93.2%	4.5 %	2.3%

Fig. 7 shows some experimental results of road lane detection in several complex road scenes. The experimental results show that the proposed method is appropriately performed in complex situations.

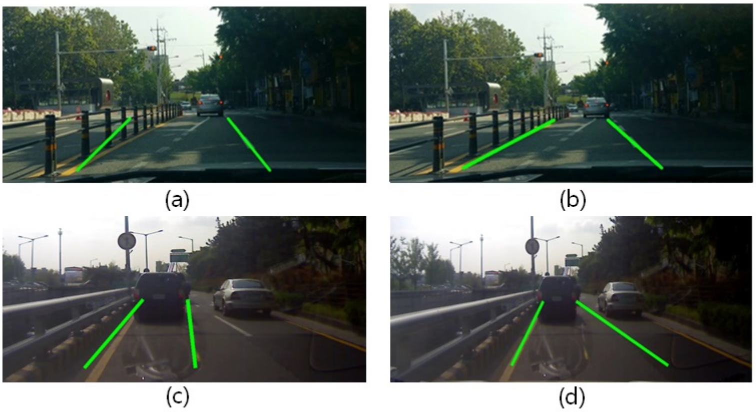

Fig. 7. Results of lane detection in different road environment conditions (a) fence and shadow image using RANSAC only (b) fence and shadow image using RANSAC and CNN (c) fence and reflecting light in front window image using RANSAC only (d) fence and reflecting light in front window image using RANSAC and CNN.

4 Conclusions

In this paper, we proposed a new method combined RANSAC with CNN for lane detection in complex scenes. As a preprocessing, we use blurring and edge detection using Gaussian smoothing and hat-type kernel. To detect the lane, we apply the RANSAC algorithm only for simple road scenes, and combined CNN with RANSAC algorithm is used for complex road scenes. The complexity of road condition is determined by the results of RANSAC algorithm. We simulated several real road environment conditions and tested the accuracy of our proposed method. Our results confirm that the proposed method has robust lane detection performance in spite of complex road conditions. In our future work, we would like to test the proposed method with larger dataset, and try to optimize it on an embedded platform.

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