# Robust U-Net-based Road Lane Markings Detection for Autonomous Driving

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***Abstract* – The rapid development of artificial intelligence leads to many studies on autonomous robot and self-driving vehicles, in which, autonomous driving plays one of the most important roles in supporting a robot or a car to be able to observe, move, and avoid obstacles. In this paper, a new method is proposed to detect road lane markings for supporting surveillance and autonomous driving. Images captured from a front-view camera are fed forward into a semantic segmentation network to extract features for detecting road lane markings, the network is constructed based on U-Net architecture, a convolutional neural network developed for biomedical image segmentation, then Hough Transform method is implemented in the system to determine lines in the segmentation network outcomes. In addition, Hough Transform yields plenty of lines from segmented images, thus K-means Clustering algorithm is also investigated to compute and point out the fittest line with each road lane marking. The effectiveness of the system was validated by testing on CARLA simulator, an open-source simulator for research on autonomous driving. Experiments proved that the proposed method can work with favorable results.**

***Keywords – U-Net, lane detection, image segmentation, autonomous driving, CARLA simulator.***

## I. Introduction

Nowadays, the development of computer science and technology along with the power of Graphics Processing Unit (GPU) has brought Artificial Intelligence (AI) to a higher level [1], it helps computers and robots can learn and even have deductions like humans. Robots now can accomplish most of tasks instead of humans, especially in delivery, medical, and military, even with the more effective than humans [1-2]. In near future, machines along with AI will replace people in management, control projects and plans for an organization's activities, or in difficult and dangerous jobs.

Autonomous driving has been an important research field for years [2-3] because of its valuable applications such as helping to save time for driving and the driver can do other works instead, or reduce traffic accident due to doze. With the support of AI, it has become one of the most exciting research topics in automotive technology. In fact, auto manufacturers have brought AI into their manufacturing models and all just in the process of testing [2]. A self-driving car will save much time yet will also be riskier if they are not really smart enough.

Nowadays, research institutes around the world have succeeded in studying advanced driver-assistance systems (ADAS) and many methods are applied such as behavioral cloning, path planning, obstacles avoidance, road lane detection [2], etc. In this paper, we propose a new approach for road lane markings detection based on convolutional neural network.

The process is divided into two parts: In the first part, images collected by using a front-view camera mounted on the car are passed through a U-Net-based segmentation network [4] to extract the features of road lane markings, the outcome of the network is segmented images which have the same size with the input images, 512x512 pixels. In the second part, a series of mathematics methods including Hough Transforms [5-6] and K-means Clustering [7] is applied to produce the straight lines describing the road lane markings in the input image. The final outcome of the system is the lines that are fittest to the road lane markings.

The rest of this paper is organized as follows. In the next part, section II, related work is discussed. Section III introduces CARLA simulator [3], an open-source simulator for autonomous driving studies. Next, section IV firstly describes the process of the system, then the main method including U-Net-based semantic segmentation, Hough Transform method, and K-means Clustering algorithm is presented. After that, the experiments executed on CARLA simulator for validating the effectiveness of the system are discussed in section V. Eventually, section VI concerns the conclusions of the paper.

## II. Related Work

Studies on self-driving vehicles aiding systems have increased significantly in recent years. In particular, road lane markings detection is still an interesting topic that continues to be exploited and developed [8-16], over the years, similar techniques have been studied and tested to detect road lane markings.

An overview of road lane markings detection techniques based on edges, area usage, and continuous tracking, etc. can be found in [5-6][9-14]. However, those methods mostly used computer vision techniques such as pure color filters [9], bird eyes view [10], edge detection [6][10], etc. but those are easily affected by the environmental condition as light, clarity of images, etc. Some notable research papers such as a research used geometric pattern matching and edge detection to detect signs road markers like arrows in [13], however, this method is too slow to be applied on a real car in real time, Histogram of Oriented Gradients (HOG) had been studied to apply to detect road markings in [15], a lane detection method based on improved RANSAC algorithm can be found in [16]. Certainly, studies concerning traffic problems and human life must meet the requirements of safety, especially can operate in real time. Therefore, we propose a new approach to use deep learning and take advantage of the power of GPU to detect road lane markings for supporting autonomous driving.

The issues of autonomous driving research are no longer new problems, but the methods to solve them always need innovation. U-Net is a fully convolutional network that works very well in segmenting biomedical images, it can demonstrate high-precision segmentation results with less training image data [4], therefore, we applied U-Net into road lane markings segmentation and combined it with Hough Transform method and K-means Clustering algorithm to produce more precise detection. This is a new approach that has never been studied and applied before. In addition, CARLA simulator is a powerful open-source simulator for autonomous driving studies, thus we also investigated its robustness and evaluated the model on this simulator.

## III. CARLA SIMULATOR

CARLA is an open-source simulator developed to support self-driving research and development [3]. CARLA provides simulation-based digital resources such as buildings, vehicles, roads, etc. and can be used freely. The vehicle's sensor system includes LiDARs, cameras which users can specify the number and the position mounted on the car, the different environmental conditions, the weather can be changed to adapt to the actual conditions. The data displayed on the main screen illustrates useful information for research and evaluation [3]. Fig. 1 depicts some images of CARLA simulator.

Fig. 1. Scenes which were captured from CARLA Simulator.

CARLA supports studies in developing, illustrating and analyzing the detailed performance of autonomous driving systems. CARLA is carried out for issues to evaluate three autonomous driving approaches. First of all, a subsystem for visual perception, planning, and control, this is the most popular architecture for almost autonomous driving systems. The second approach is based on an end-to-end deep learning network such as behavioral cloning. The final approach is based on reinforcement learning, another branch of autonomous driving research and a type of machine learning technique [3].

## IV. METHOD

This section firstly discusses the process of the system, then each step of the process will be presented. There are three main steps corresponding to subsections *B*, *C* and *D* to process an image in order to find out the road lane markings with the lines which depict them.

### A. System Process

The process of the system is divided into 3 steps: After an image is captured by using a front-view camera mounted on the car, (S1) the image is passed forward into a U-Net-architecture-based convolutional neural network to extract features of road lane markings, (S2) Hough Transforms is applied to find lines and parameters of these lines which describe the detected road lane markings in the previous step, (S3) K-means Clustering finally is used to compute the lines which are the best description for the actual road lane markings. These 3 steps are illustrated in Fig. 2.

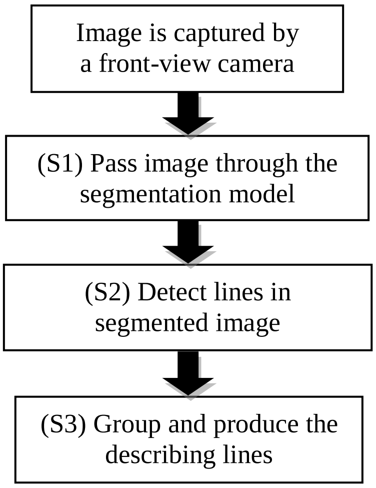



Fig. 2. The System Process.

### B. U-Net-based Semantic Segmentation

U-Net is a fully convolutional network published in MICCAI 2015 [4] and achieved more than 4000 citations at the end of 2018. U-Net was developed for biomedical image segmentation, its architecture was modified to yield more precise segmentation results yet fewer training images. Besides, the processing speed is also very fast because the input size of the model is just 512x512 pixels and the segmentation of an image with that size may take only a few milliseconds on a recent GPU. The network architecture looks like U-shape which is depicted in Fig. 3.

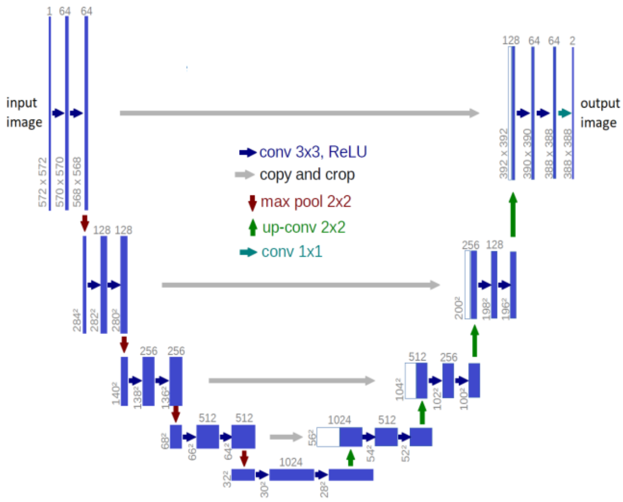



Fig. 3. U-Net Architecture.

The network architecture composes of a contracting path and an expansive path [4]. The contracting path is a convolutional neural network (CNN) that consists of repeated convolution layers, similar to general CNN, each of them is followed by rectified linear units (ReLU) and max-pooling operation. The expansive path is a sequence of up-convolution layers which combines spatial information and features, and concatenations of high-resolution features from the contracting path. The two main things that make U-Net different from other convolutional neural network architectures are: U-Net is symmetric; and U-Net applies concatenation operator instead of a sum in the skip connections between the down-sampling path and the up-sampling path [4].

Although U-net was invented for the application of biomedical image segmentation, now it has been applied to a wider range of applications, for example, supporting self-driving vehicles, image-segmentation-based object detection, etc. Fig. 4 depicts input images and labeled images for training the U-Net segmentation model, Fig. 4-a shows an input image and Fig. 4-b is its labeled image, similarly, Fig. 4-d shows a labeled image corresponding to the input image depicted in Fig. 4-c.

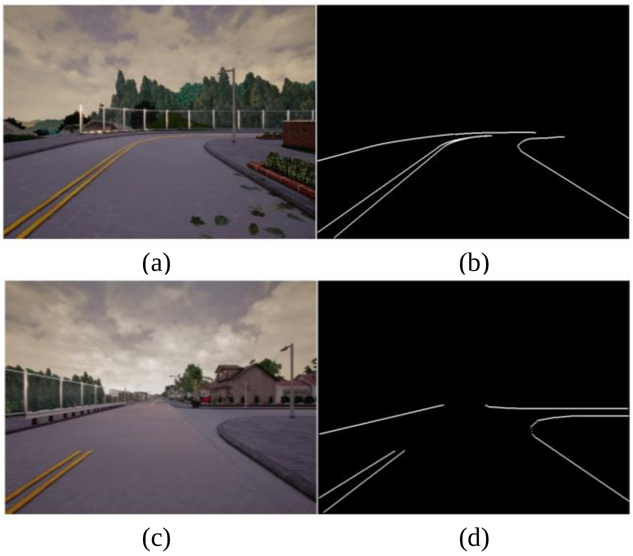



Fig. 4. Input Images and Labeled Images for Training the Segmentation Model.

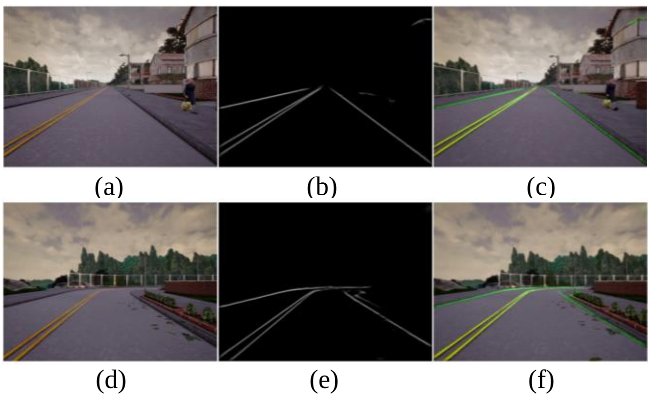



Fig. 5. Examples of Segmentation Result.

The segmentation model was trained in over 20 hours with the dataset of approximately 4000 images for both the training image data captured from CARLA simulator and labeled image data (2000 images for each). In the training process, the data was also augmented by flipping images, adding salt-and-pepper noise, blurring with 3x3, 5x5, and 7x7 filters.

Fig. 5 demonstrates some examples of the segmentation result; in which, Fig. 5-(a, d) shows images which were captured by using a front-view camera in CARLA simulator, Fig. 5-(b, e) are the segmented images that were yielded by the segmentation network, Fig. 5-(c, f) are the mergers of the captured images and the segmented images to show up the detection results.

### C. Search of Straight Lines

Segmented images yielded in the previous step include thick curves which describe detected road lane markings, but the parameters describe those curves were not known. Thus, for the sake of simplicity, a process of finding straight lines that depict the straight parts of the detected curves was carried out. Furthermore, Hough Transform is the most popular technique for detecting straight lines [5-6] or even other shapes, hence, the technique was deployed for the straight lines searching part in the system.

Particularly, Hough Transforms describes a straight line as in (1), in which, $\rho$ is the distance from the straight line to the origin of the coordinates, and $\theta$ is the angle between the horizontal axis and the perpendicular line from the origin to the straight line. Fig. 6 illustrates those parameters in the coordinate system *Oxy*.

$$(d): \rho = x.\cos\theta + y.\sin\theta \qquad (1)$$

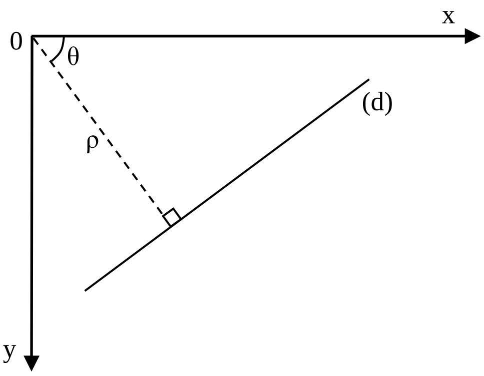



Fig. 6. Hough Transforms.

### D. Clustering Process

After using Hough Transform technique to find the lines in the image, the output will be a group of lines describing the road lane markings, afterward, the task would be computing the lines which are the best description for the road lane markings, hence, a clustering process can be applied. K-Means Clustering and DBSCAN are two potential candidates for this problem, however, the one that was chosen was K-Means Clustering because of its performance which outperforms DBSCAN [17].

K-means Clustering uses iterative refinement to produce the final result. The input of the algorithm is cluster number K and dataset. Dataset is a set of features depicted by point data. The algorithm starts with initial estimates for the centroids of K clusters, which can be randomly generated or randomly selected from the dataset, then the centroids are updated continuously until they no longer change [7].

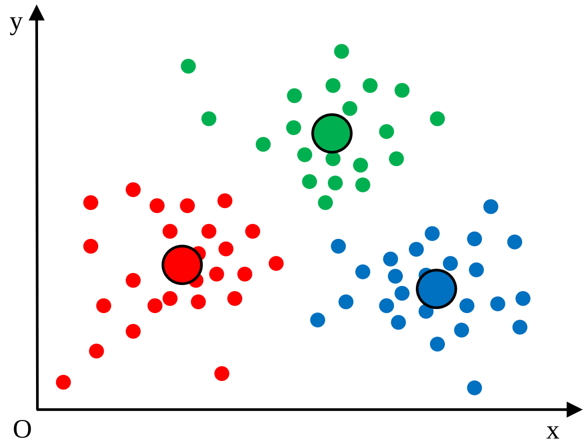


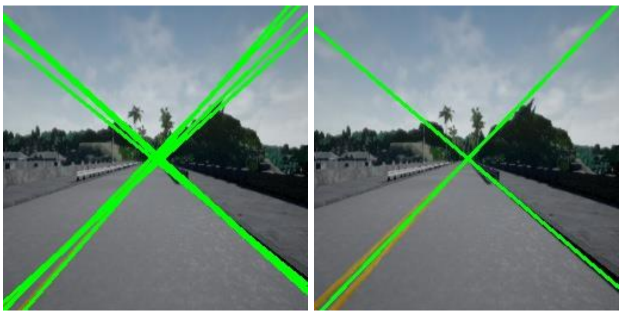

Fig. 7. K-means Clustering Algorithm.

Fig. 7 illustrates K-means Clustering algorithm with the dataset consisting of all the small dots. The assumption is that the number of clusters is 3 corresponding to 3 colors red, green, and blue, the three bigger dots are the centroids of the clusters that K-means Clustering would produce.

Clustering algorithms mathematically employ an iterative approach to group the data into a pre-determined number of clusters by minimizing a cost function as in (2), where $c_j$ is the centroid of $j$th cluster and is the centroid nearest to data object $x_i$, $n$ is the number of elements in data set, $q$ is an integer which determines the distance function ($q$ = 2 for Euclidean distance) [7].

$$E = \sum_{i=1}^{n} \left\| x_i - c_j \right\|^q \tag{2}$$

The current dataset is a set of points in the coordinate system, each point is defined with coordinates ($\rho$, $\theta$), so the points describing the same road lane marking will have values ($\rho$, $\theta$) close together or in other words in the coordinate system these points will lie close together to form a defined cluster of points. This research focuses on identifying the two road lane markings corresponding to the road lane on which the vehicle is located. Depending on the route, the number of clusters K can be chosen accordingly. This research investigates the case of vehicles running on only one lane, so the number of clusters must be 2 (K = 2). Fig. 8 shows an example of applying K-means Clustering algorithm to compute the final road line markings, in which, Fig. 8-a is an output of the lines-searching process then K-means Clustering computes and points out the fittest lines shown in Fig. 8-b.



(a) (b)

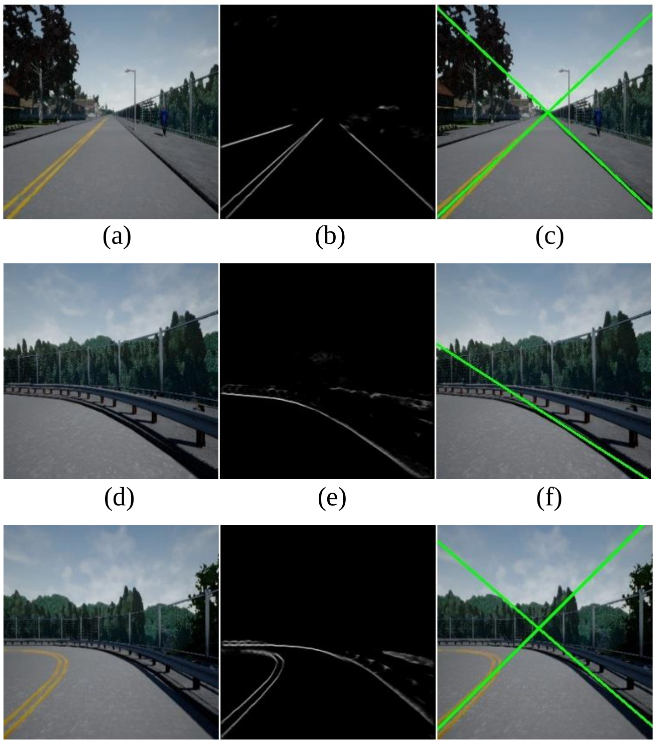
Fig. 8. Before and After Applying K-means Clustering.

In the case of the detected road lane markings are curved, Hough Line method might find much more lines than the case of the road lane markings are straight and the $\theta$ parameters of these lines might be different. Then K-means Clustering algorithm will compute to find the mean of these $\theta$ parameters, therefore, the final lines which depict those curve road lane markings are tangent lines to the curves at the points that are the average of $\theta$ parameters.

## V. System Validation

This section shows the experiment results of testing the system in CARLA simulator with the GeForce GTX 1080 Ti Graphics Cards. The experiment proved that the system can obtain the processing speed of over 100 FPS. In addition, to reduce the processing time, the images before being fed into the segmentation model are resized from 800x600 pixels to 512x512 pixels. Training images were captured in different conditions, moreover, to augment the dataset, original images were flipped, blurred with 3x3, 5x5, 7x7 filters, and added noises, thus, the number of the images in the dataset were increased approximately of 10 times.

Fig. 9-(a, b, c) depicts some examples of the experiment, Fig. 9-a is a captured image, Fig. 9-b is an outcome of the segmentation model, apply Hough Transform and K-means Clustering then the lines are drawn on the original image in Fig. 9-c; similarly with Fig. 9-(d, e, f); Fig. 9-(g, h, i) illustrates a case of detected road lane marking is curved.



(a) (b) (c)

(d) (e) (f)

(g) (h) (i)

Fig. 9. Experimental Results in CARLA Simulator.

## VI. Conclusions

In this paper, a robust road lane markings detection system based on the U-Net convolutional neural network is proposed. After many efforts to improve the method, the system has demonstrated favorable detected results. Once road lane markings are detected, the lines parameters that depict the road lane can be used to support the surveillance system or even the main controller in autonomous vehicles. The experiments were executed on CARLA simulator with the performance is over 100 FPS when running on the GeForce GTX 1080 Ti Graphics Cards. During the research, there was still a problem that we had to face that the system worked well in the case of the road is straight but still did not give very good results in the curve ones.

An improvement of the system to be capable of detecting curve road lane markings with greater accuracy will be proposed in the future.

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## REFERENCES

[1] Kafiev Irshat, Romanov Petr, and Romanova Irina, “The Selecting of Artificial Intelligence Technology for Control of Mobile Robots,” in *2018 International Multi-Conference on Industrial Engineering and Modern Technologies (FarEastCon)*, Vladivostok, Russia, Oct. 3-4, 2018, pp. 1-4.

[2] Jesse Levinson, Jake Askeland, Jan Becker, Jennifer Dolson, David Held, Soeren Kammel, J. Zico Kolter, Dirk Langer, Oliver Pink, Vaughan Pratt, Michael Sokolsky, Ganymed Stanek, David Stavens, Alex Teichman, Moritz Werling, and Sebastian Thrun, “Towards Fully Autonomous Driving: Systems and Algorithms,” in *2011 IEEE Intelligent Vehicles Symposium (IV)*, Baden-Baden, Germany, June 5-9, 2011, pp. 163-168.

[3] Alexey Dosovitskiy, German Ros, Felipe Codevilla, Antonio Lopez, and Vladlen Koltun, “CARLA: An Open Urban Driving Simulator,” in *1st Conference on Robot Learning (CoRL 2017)*, Mountain View, United States, Nov. 13-15, 2017.

[4] Olaf Ronneberger, Philipp Fischer, and Thomas Brox, “U-Net: Convolutional Networks for Biomedical Image Segmentation,” in *18th International Conference on Medical Image Computing and Computer Assisted Interventions (MICCAI 2015)*, Munich, Germany, Oct. 5-9, 2015.

[5] Jia He, Hui Rong, Jinfeng Gong, and Wei Huang, “A Lane Detection Method for Lane Departure Warning System,” in *2010 International Conference on Optoelectronics and Image Processing (ICOIP 2010)*, Haikou, China, Nov. 11-12, 2010, pp. 28-31.

[6] Chan Yee Low, Hairi Zamzuri, and Saiful Amri Mazlan, “Simple robust road lane detection algorithm,” in *2014 5th International Conference on Intelligent and Advanced Systems (ICIAS 2014)*, Kuala Lumpur, Malaysia, June 3-5, 2014, pp. 1-4.

[7] Amir Ahmad, and Lipika Dey, "A k-mean clustering algorithm for mixed numeric and categorical data," *Data & Knowledge Engineering*, vol. 63, issue 2, pp. 503-527, November 2007.

[8] Davy Neven, Bert De Brabandere, Stamatios Georgoulis, Marc Proesmans, and Luc Van Gool, “Towards End-to-End Lane Detection: an Instance Segmentation Approach,” in *2018 IEEE Intelligent Vehicles Symposium (IV)*, Changshu, China, June 26-30, 2018, pp. 286-291.

[9] L.A.N. Yapa and A. S. Atukorale, “Lane detection using hybrid colour segmentation and perpendicular traversal linear search algorithm,” in *2017 Seventeenth International Conference on Advances in ICT for Emerging Regions (ICTer)*, Colombo, Sri Lanka, Sept. 6-9, 2017, pp. 1-5.

[10] Van-Quang Nguyen, Changjun Seo, Heungseob Kim, and Kwangsuck Boo, “A Study on Detection Method of Vehicle Based on Lane Detection for a Driver Assistance System Using a Camera on Highway,” in *11th Asian Control Conference (ASCC 2017)*, Gold Coast Convention Centre, Australia, Dec. 17-20, 2017, pp. 424-429.

[11] Pradnya N. Bhujbal and Sandipann P. Narote, “Lane departure warning system based on Hough transform and Euclidean distance,” in *Third International Conference on Image Information Processing (ICIIP 2015)*, Waknaghat, India, Dec. 21-24, 2015, pp. 370-373.

[12] Mirko Meuter, Stefan Muller-Schneiders, Adalbert Mika, Stephanie Hold, Christian Nunn, and Anton Kummert, “A novel approach to lane detection and tracking,” in *2009 12th International IEEE Conference on Intelligent Transportation Systems*, St. Louis, MO, USA, pp. 1-6.

[13] Ioana Maria Chira, Ancuta Chibulcutean, and Radu Gabriel Danescu, “Real-time detection of road markings for driving assistance applications,” in *The 2010 International Conference on Computer Engineering & Systems (ICCES 2010)*, Cairo, Egypt, Nov. 30-Dec. 2, 2010, pp. 158-163.

[14] Yue Dong, Jintao Xiong, Liangchao Li, and Jianyu Yang, “Robust lane detection and tracking for lane departure warning,” in *2012 International Conference on Computational Problem-Solving (ICCP 2012)*, Leshan, China, Oct. 19-21, 2012, pp. 461-464.

[15] Tao Wu, and Ananth Ranganathan, “A practical system for road marking detection and recognition,” in 2012 IEEE Intelligent Vehicles Symposium, June 3-7, 2012, Alcala de Henares, Spain, pp. 25-30.

[16] Jie Guo, Zhihua Wei, and Duoqian Miao, “Lane Detection Method Based on Improved RANSAC Algorithm,” in *2015 IEEE Twelfth International Symposium on Autonomous Decentralized Systems*, Taichung, Taiwan, March 25-27, 2015, pp. 258-288.

[17] Sanjay Chakraborty, N.K.Nagwani, and Lopamudra Dey, “Performance Comparison of Incremental K-means and Incremental DBSCAN Algorithms,” *International Journal of Computer Applications*, vol. 27, no. 11, pp. 14-18, August 2011.