2020-01-0096

Reference test system for machine vision used for ADAS functions

Abhishek Nayak[1], Adam Pike[2], Sivakumar Rathinam[3], Swaminathan Gopalswamy[4]
Department of Mechanical Engineering, Texas A&M University [1,3,4]
Texas A&M Transportation Institute [2]

Abstract

Advanced Driver Assistance Systems (ADAS) like Lane Departure Warning (LDW) and Lane Keep Assist (LKA) have been available for several years now but has experienced low customer acceptance and market penetration. These deficiencies can be traced to the inability of many of the perception systems to consistently recognize lane markings and localize the vehicle with respect to the lane markings in the real-world with poor markings, changing weather conditions and occlusions. Currently, there is no available standard or benchmark to evaluate the quality of either the lane markings or the perception algorithms. This work seeks to establish a reference test system that could be used by transportation agencies to evaluate the quality of their markings to support ADAS functions that rely on pavement markings. The test system can also be used by designers as a benchmark for their proprietary systems. To support this development, an extensive video dataset was collected at different times of day and weather conditions on various roads in Central Texas. The videos were evaluated on different state-of-the art lane detection algorithms and their performance was ranked based on a set of metrics specifically developed for evaluating the effectiveness of the lane estimation system. The test scenarios are comprised of a set of roadways and environmental features, as well as the pavement marking presence and luminance variables. A systems approach is presented by correlating the algorithm performance data to the environmental factors, lane marking types, color, material, and the retroreflectivity of pavement markings.

Introduction

Lane Detection (LD) systems are an integral part of most commercial ADAS products designed to improve safety of automobiles like Lane Departure Warning (LDW), Lane Keep Assist (LKA), Adaptive Cruise Control (ACC), Lane centering, Lane change assist and Autonomous driving modes. LDW and LKA systems alone have the potential to prevent or mitigate 483,000 crashes in the United States every year [1]. This includes 87,000 nonfatal injury crashes and 10,345 fatal crashes every year in the United States. While LDW and LKA technologies are available, there has been low customer acceptance and penetration of these technologies. These deficiencies can be traced to the inability [1,2] of many of the perception systems to consistently recognize lane markings and localize the vehicle with respect to the lane marking in a real-world environment of variable markings, changing weather and other vehicles. These challenges translate to (i) inconsistent detection of lane markings; (ii) misidentification of lane markings; and (iii) the inability of the systems to locate lane markings in some conditions. These challenges can be addressed both by improving the consistency and detectability of the lane markings and by improving the perception algorithms currently employed in the sensors. Currently, there is no available standard or benchmark to evaluate the quality of either the lane markings or the perception algorithms [2].

The key functional feature for a reliable LDW or LKA system is road or lane perception. The main perceptual cues for driving used by both human drivers and autonomous vehicles include road color and texture, road boundaries, and lane markings [2]. Several different modes of sensing have been employed in literature for road and lane understanding, including monocular camera, stereo vision, LIDAR and radar. People have also looked at fusing vehicle dynamics information with global positioning information obtained from global positioning system (GPS) and high definition digital maps with one of the above sensing modalities to develop highly accurate lane detection and positioning systems. However due to extensive background research on image processing techniques and the low-cost of cameras, Vision based lane detection has become the most prominent mode of sensing employed in modern LD systems. The prominence of vision systems in LD can also be attributed to the fact that road markings are primarily developed for human vision [2].

Lane Detection System

Lane Detection system can broadly be divided into 3 functional components: (i) Hardware (ii) Software (iii) Infrastructure. The hardware component corresponds to the equipment used for the sensing modality of the LD system. Although vision-based lane detection systems traditionally suffer from functional limitations due to changing environmental conditions like illumination variation (direct sun on camera, glare, oncoming vehicle lights), shadows, and bad weather (rain, fog, snow, dust), it is still widely adopted sensing mode in modern ADAS systems and is expected to continue dominating in future. Monocular camera and Stereo vision cameras are the main sensors that have been used in vision-based LD systems. The variations in the hardware components include the type of sensor, type of lens (wide angle, fisheye), lens properties (field of view, focal length) and camera specification (Pixel size, megapixels, resolution, frame rate).

Software component refers to the algorithms that are employed on the LD system to detect lanes and help navigate the vehicle. Vision-based lane detection systems generally consist of three main subprocesses including image preprocessing, lane detection and lane tracking. According to Xing et.al [3], conventional vision-based lane detection algorithms can be roughly classified into two categories:

feature-based and model-based. Feature-based methods rely on the detection of lane marking features such as colors, textures, and edges. Model-based methods usually assume that lanes can be described with a specific model such as a linear model, a parabolic model, or various kinds of spline models. Since the advent of Machine learning and Deep learning techniques several new algorithms that leverage the power of deep networks, parallel computing, and large data approaches for lane detection have been developed. Many deep learning algorithms have consistently produced significantly better results as compared to the conventional approaches. Bei et al. [16] reported that by using a Convolutional Neural Network (CNN), the lane detection accuracy increased from 80% to 90% compared with traditional image processing methods. Several review papers have been published in literature [2], [3], [4] that give a detailed account of the various works that have been carried out towards development of lane detections algorithms. However, most works conclude that the challenges and limitations for future research extends to the scope of developing better road understanding techniques and methods to increase detection reliability [2]

The infrastructure component corresponds to the lane markings and pavement surfaces that will be used by machine vision systems for sensing lanes. The variations in lane markings could include the color, geometry (continuous/intermittent lanes, width, length), lane marking performance characteristics (luminance, retroreflectivity, color) and other pavement variables (asphalt, concrete). Several independent studies have investigated the effects of various lane marking properties towards an effective machine vision system [5], [6], [7], and [8]. Studies evaluating the effect of wet retroreflective properties of lane markings and their effect on machine vision indicate that considering the lane markings into the detection framework helps in improving performance of LD systems [6], [7], and [8].

The essential requirement for a safe lane detection system is to include accurate and robust lane detection. Most of the modern algorithms that are based on machine learning and deep learning techniques are designed specifically to produce more precise results. However, as noted by Xing et al in [3] the robustness issues are the key aspects that determine if a system can be applied in real life, and the main challenge to future vision-based systems to achieve this is the ability to maintain a stable and reliable lane measurement under heavy traffic and adverse weather conditions. According to [3] the factors that are limiting the progress towards achieving it are the lack of public benchmarks and data sets due to the difficulty of labelling lanes as the ground truth. Hilel et al [2] also makes similar observations stating that the challenge of current research is the inability to compare performance of different methods due to the lack of public annotated benchmarks. Developing a large public video benchmark can reduce evaluation costs. However since [2] was published, several new large public datasets focusing on lane detection were developed. The prominent ones among those are the CULane Dataset [9] (developed by the Multimedia Laboratory at The Chinese University of Hong Kong), TuSimple Benchmark (developed by the San Diego-based tech startup TuSimple) and the lane marking dataset in BDD100K [12] (Developed by the Berkley Artificial Intelligence Research (BAIR) Lab at UC Berkley). CULane consists of more than 55 hours of video data collected by cameras mounted on six different vehicles driven on the roads of Beijing. The dataset is divided into a group of 88880 images for training set, 9675 images for validation set, and 34680 images for test set. The test set is divided into normal and 8 challenging categories including crowded scenes, shadows, night, dazzle light, curved roads, crossroads, arrow and no lanes. TuSimple dataset is made of 1s clips of 20 frames each collected. The dataset consists of data collected in good and medium weather conditions during different times of day and in different traffic conditions.

However, none of these datasets have provisions to evaluate the effects of hardware and lane markings towards comparing the performance of a lane detection systems. As noted by [5] … [8], different types of lane markings do affect the performance of a LD system and thus should be an integral part of evaluation methodology for LD performance. According to [3] another challenging task in lane detection systems is to design an evaluation system that can verify the system performance. Due to the lack of standard evaluation metrics that can comprehensively assess the system performance with respect to both accuracy and robustness, an objective assessment of lane estimation process is still not adequately addressed [17]. Through this work we try to address some of these limitations by considering the infrastructure component i.e. the lane marking characteristics and marking quality into the LD system evaluation framework

College Station Dataset

Identifying the lack of a complete dataset that considers a systems approach for evaluating real world test scenarios, the researchers at Texas A&M University developed a dataset that includes the pavement marking material characteristics for the roads traveled during the lane detection performance evaluation in addition to the pixel-based performance metrics. Video data were collected by driving on roads with varied lane markings in and around Central Texas. These roads included asphalt and concrete road surfaces, multilane and two-lane two-way roadways, and sections with tangents and curves. The pavement markings on these roadways varied from new to several years old to represent a range of marking conditions.

Video Data

The video data were collected by using a 5MP camera mounted on a Lincoln MKZ autonomous driving test vehicle owned by Texas A&M University. The camera setup used was the Blackfly BFS-U3-51S5C-C (Sony IMX250 CMOS - 5MP – USB3.1 camera) camera sensor attached with a Kowa LM8HC Manual Iris C-Mount Lens f=8mm/F1.4 Lens. To maintain homogeneity throughout the dataset the videos were collected at 25 frames per second. To evaluate the lane detection performance during different times of day, video data were collected during 3 different times: (1) Morning (11am CST on a Sunny day with clear sky), (2) Evening (6pm CST on Sunny day with clear sky) and (3) Night (10pm CST with clear sky conditions). Figure 1 shows the variations in lighting conditions during different times of day on the same stretch of road. Figure 4 shows images from different roads that were considered in this dataset.

Figure 1: Images showing roadways under different lighting conditions during different times of day.

To enable lane detection performance evaluation, images extracted from the videos were annotated using the Scalabel Annotation tool. Scalabel was developed by the Berkley Deep Drive group for labelling their BDD100K dataset. Scalabel tool supports various kinds of annotations needed for training computer vision models, especially for driving environment. For each image in the dataset we manually annotate the traffic lanes using 2D polylines as supported in Scalabel. The annotations include 3 feature attributes for the lane markings: (i) Lane categories (Road Curb, White, Yellow, Crosswalk), (ii) Lane Type (Single, Double) (iii) Lane Continuity (Continuous/Solid, Dashed/Skip). An illustration of the lane marking annotations can be seen in Figure 2 and 3.

Lane Material Characteristics Data

Lane marking performance characteristic data were collected around the same time as the video data collection. A mobile retroreflectometer was used to capture the pavement marking retroreflectivity value. The retroreflectivity value is a surrogate measure for how visible the marking will be at night. A higher retroreflectivity value indicates a marking that is more efficient at returning light from the vehicle headlamps back toward the vehicle's driver, making the marking appear bright. Each marking was evaluated for retroreflectivity along the entire length of the test area. The color of the markings was evaluated in the CIE xyY color space using illuminant D65 and a 2-degree standard observer. The x and y values are the color coordinate locations on the CIE 1931 chromaticity diagram. The CIE Y value is the brightness, with 0 representing perfect black and 100 representing perfect white. Color measurements were conducted at multiple locations in each test area at locations that were representative of the test area.

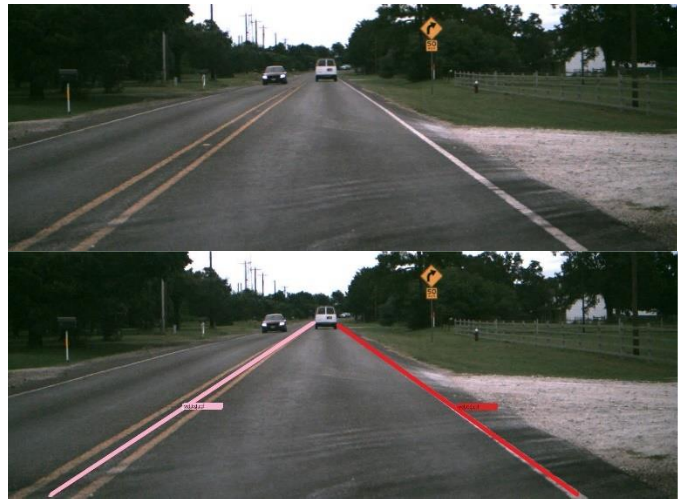

Figure 2: Example of lane marking annotations using Scalabel [12]. Yellow Double Solid line is annotated in Pink White Single Solid line is annotated in Red.

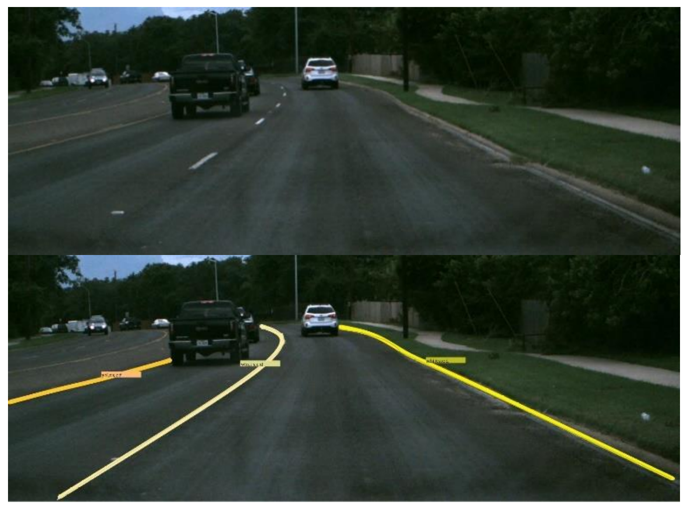

Figure 3: Examples of lane marking annotations using Scalabel [12]. White dashed line is annotated light yellow, Yellow Single Solid line is annotated in orange, and Road Curb is annotated in Yellow

Evaluation

The lane detection performance was evaluated using lane detection algorithms powered by 3 different neural networks. (i) Spatial CNN (SCNN) [9] (ii) LaneNet [10] (iii) ENet [11]. Spatial CNN was developed to address these prevalent issues of lane detection including processing speeds and complexity, and to more efficiently learn the spatial relationship of lane markings of structured objects like lane markings in driving scenarios. SCNN generalizes the traditional deep layer-by-layer convolutions to slice-by-slice convolutions within feature maps, and enables message passing between pixels across rows and columns in each layer. Thus, SCNN type algorithms are particularly suitable for long continuous shape structures or large objects, with strong spatial relationship but minimal appearance features, such as poles, walls and traffic lanes etc. SCNN with its optimized implementation won the 1st place on the TuSimple Benchmark Lane Detection Challenge achieving an accuracy score of 96.53%. For evaluating the performance of SCNN algorithm on the College Station dataset the annotations in BDD100K format need to be converted to annotations to suit SCNN format. SCNN supports detection of three lanes corresponding to 4 lane marking in an image. For SCNN, all the different categories of lane markings as represented in BDD100K are reduced to a single class and collectively considered as lanes. A text file containing the X-Y pixel coordinates of every lane marking in the image is generated for each image. The ground truth information from the annotation files are used to evaluate the lane detection performance.

Neven et al [13] developed an end-to-end algorithm that approaches lane detection as an instance segmentation problem. LaneNet is used as the backbone CNN which combines the benefits of binary lane segmentation by forming an instance of each lane that can be trained end-to-end. Additionally, a network referred to as H-Net is trained, that estimates the parameters for an "ideal" perspective transformation customized for each input image in contrast to the typical "bird's eye view" transformation, thus ensuring a robust lane fitting model. LaneNet supports a maximum of 5 lane markings in lanes, where 4 lane markings correspond to the current lane and left/right lanes. The extra lane is in place for cases during lane changes to reduce confusion in identifying the current lane. Annotations for LaneNet-lane detection are listed in a .json file. Each json line in the annotation file contains polyline data of the lane markings constructed using pixel data organized by the same distance gap ('h_sample' in each label data) from the recording car/bottom of the image frame. Annotation in SCNN are converted to LaneNet label data format using a custom script and the algorithm performance is evaluated.

ENet short for Efficient neural Network, is a deep neural network architecture specifically created for tasks like semantic segmentation which require to have low latency in its execution that can operate in real-time on low-power mobile devices. ENet-label [15] is a light-weight lane detection model based on ENet and adopts self-attention distillation [14]. It has 20x fewer parameters and runs 10x faster compared to SCNN. ENet-label achieves a F1-measure of 72.0 on CULane testing set (better than SCNN which achieves 71.6). It also achieves 96.64% accuracy in TuSimple testing set (better than SCNN which achieves 96.53%) and 36.56% accuracy in BDD100K testing set (better than SCNN which achieves 35.79%). We choose to evaluate this algorithm because of its claims of higher performance and lower latency. The annotation format required for ENer-label are same as SCNN, hence the annotation files generated to serve as ground truth to evaluate SCNN was used.

The lane detection algorithm performance is measured in terms of the conventional pixel-accuracy based performance metrics accuracy metrics such as True Positives (TP), False Positive (FP), False Negative (FN), F-Measure etc. Both SCNN and ENet-label follow the same performance evaluation method. In order to evaluate if a lane marking is successfully detected, the lane markings are detected as lines with width equal to 30 pixels. The intersection-over-union (IoU) metric is calculated between the ground truth annotation and the lane prediction from the algorithm. The lane predictions where IoUs are larger than certain threshold (in our evaluation we consider 0.5) are viewed as true positives (TP). Based on the predictions the F-Measure is calculated as

$$F - measure = \frac{(1+\beta^2)(P*R)}{\beta^2(P+R)} \qquad (1)$$

Where,

$Precison\ (P) = \frac{TP}{(TP+FP)} = \frac{True\ Positives}{Total\ detections\ marked\ Positive}$,
$Recall\ (R) = \frac{TP}{(TP+FN)} = \frac{True\ Positive}{Total\ positives\ in\ Ground\ truth}$, and β is set to 1, which gives the harmonic mean (F1-measure). Performance of the algorithms is related to Precision (P), Recall (R), and F1 scores on a linear scale. Higher scores represent better LD performance of the algorithms.

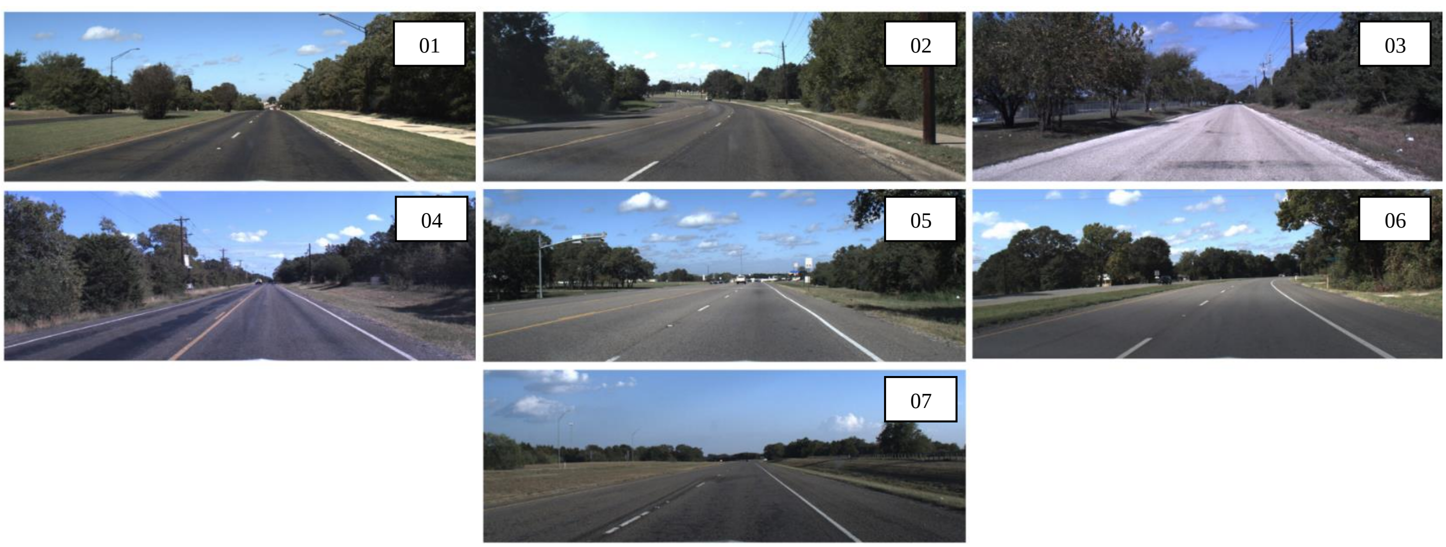

Figure 4: Images of different roads in the College Station dataset collected during morning time lighting

Table 1: Performance of different algorithms on different roads in College station dataset. Comparison performed with IoU threshold = 0.5

Road	**Road Conditions**	**Driving Direction**	**Time of day**	**Image Count**	**SCNN [9]**			**LaneNet [13]**			**ENet-label [15]**		
					Precision (P)	**Recall (R)**	**Fmeasure (F1)**	**Precision (P)**	**Recall (R)**	**Fmeasure (F1)**	**Precision (P)**	**Recall (R)**	**Fmeasure (F1)**
01. S. College Ave	2-Lane Road Medium lane markings Medium Contrast	Towards North-West	Morning	84	0.6	0.547	0.572	0.587	0.603	0.595	0.734	0.650	0.689
			Evening	25	0.306	0.339	0.322	0.424	0.485	0.452	0.435	0.357	0.392
			Night	94	0.494	0.391	0.437	0.325	0.468	0.384	0.506	0.382	0.435
02. W Villa Maria	2-Lane road Medium Lane Markings Medium Contrast	Towards South-West	Morning	225	0.445	0.444	0.445	0.318	0.357	0.336	0.551	0.377	0.448
			Evening	76	0.246	0.358	0.292	0.224	0.325	0.265	0.321	0.386	0.351
			Night	166	0.470	0.407	0.437	0.412	0.384	0.397	0.462	0.450	0.456
03. Jones Road	1-Lane road, Yellow Centre Line / No lane Markings	Towards North-West	Morning	116	0.100	0.491	0.167	0.102	0.152	0.122	0.089	0.403	0.146
			Evening	58	0.081	0.474	0.128	0.076	0.228	0.114	0.107	0.632	0.183
			Night	97	0.107	0.684	0.186	0.085	0.156	0.110	0.098	0.449	0.161
04. Leonard Road	1-Lane road Good lane markings High contrast	Towards North-East	Morning	116	0.799	0.794	0.796	0.751	0.698	0.723	0.619	0.651	0.635
			Evening	71	0.811	0.771	0.791	0.824	0.726	0.772	0.791	0.749	0.769
			Night	192	0.786	0.765	0.775	0.691	0.712	0.701	0.659	0.721	0.688
05. Harvey Mitchell Pway	2-Lane road Good Lane markings Medium Contrast	Towards North-West	Morning	87	0.729	0.866	0.791	0.735	0.811	0.771	0.755	0.931	0.834
			Evening	48	0.547	0.761	0.637	0.673	0.587	0.627	0.589	0.787	0.674
			Night	95	0.494	0.391	0.437	0.356	0.483	0.410	0.506	0.381	0.435
06. TX – 21	2-Lane Highway Good lane markings High Contrast	Towards South-West	Morning	130	0.676	0.792	0.729	0.659	0.735	0.695	0.682	0.759	0.718
			Evening	106	0.577	0.687	0.627	0.563	0.628	0.594	0.528	0.683	0.595
			Night	242	0.470	0.407	0.437	0.441	0.412	0.426	0.462	0.450	0.456
07. Hway 47	2-Lane Highway Good lane markings High contrast	Towards South-East	Morning	35	0.712	0.743	0.727	0.699	0.724	0.711	0.701	0.744	0.722
			Evening	15	0.611	0.628	0.619	0.712	0.602	0.652	0.536	0.628	0.579
			Night	28	0.103	0.450	0.167	0.105	0.126	0.114	0.098	0.449	0.162

Table 2: Lane marking characteristics data based on ASTM standards.

Road	Lane Marking on the Left					Lane Marking on the Right				
	Color				Continuous R_L (mcd/m^2/lx)	Color				Continuous R_L (mcd/m^2/lx)
	Lane Type	x	y	Cap Y		Lane Type	x	y	Cap Y	
01. S. College Ave	White Skip	0.334	0.35	24.758	190.34	White Edge	0.3375	0.3530	28.7339	200
	White Skip	0.3361	0.3522	34.7373	212	No Lane Marking				
02. W Villa Maria	White Skip	0.333	0.3502	35.8026	114.33	No Lane Marking				
	Yellow Centre	0.4237	0.3958	25.2798	73.33	White Edge	0.3316	0.3493	44.87	149
03. Jones Road	Yellow Centre	0.4057	0.3894	24.124	88	No Lane Marking				
04. Leonard Road	Yellow Centre	0.4111	0.3900	24.3590	107.67	White Edge	0.3406	0.3559	34.6	171
05. Harvey Mitchell Pway	White Skip	0.3303	0.3469	36.4182	56.67	White Edge	0.3329	0.3495	33.324	88
06. TX – 21	White Skip	0.3375	0.3534	38.09	254.33	White Edge	0.3356	0.3518	33.67	259.34
07. Hway 47	White Skip	0.3406	0.3570	37.61	191	White Edge	0.3344	0.3519	46.21	199

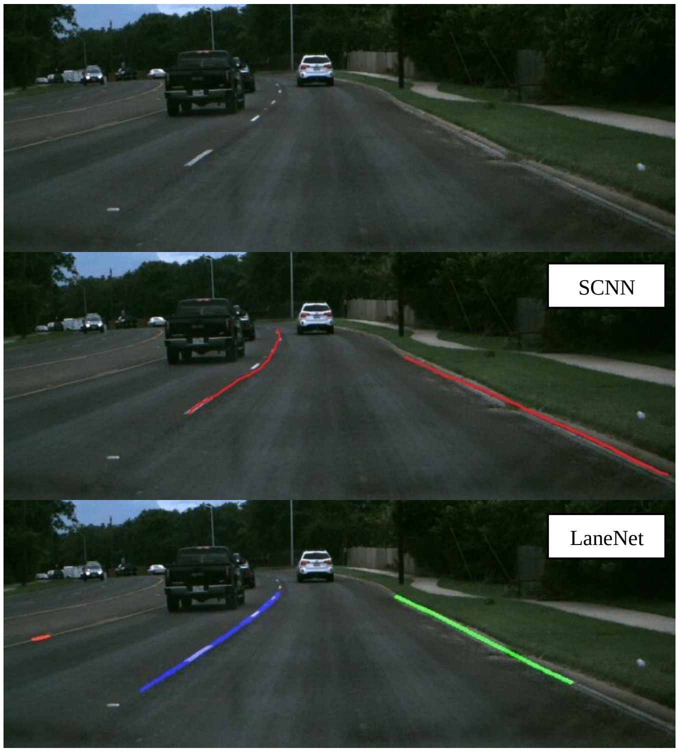

Figure 5: Image of lanes on W Villa Maria road and the lane detection outputs from SCNN and Lanenet lane detection algorithms. The different colors of lanes detected in LaneNet represents the order in which they are detected (Blue first, Green Second and Red third)

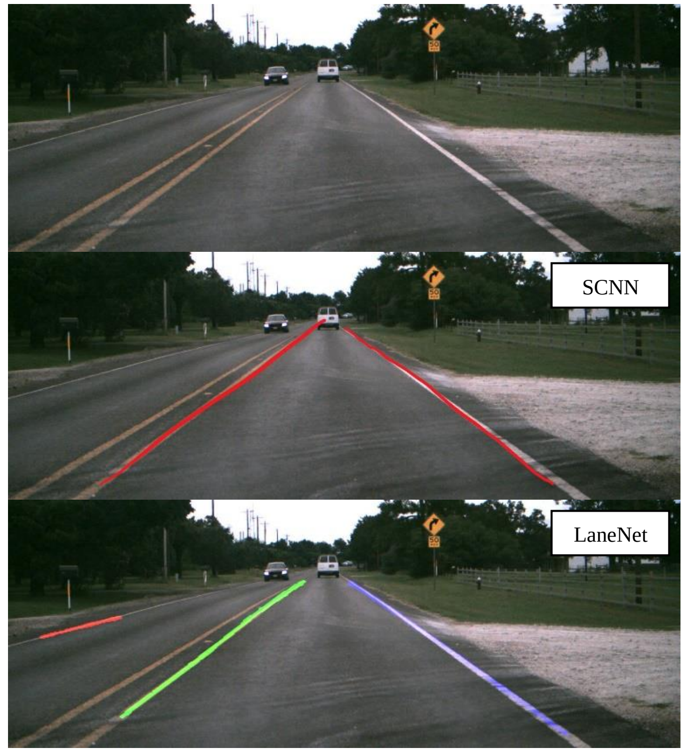

Figure 6: Image of lanes on Leonard road and the lane detection outputs from SCNN and Lanenet lane detection algorithms. The different colors of lanes detected in LaneNet represents the order in which they are detected (Blue first, Green Second and Red third)

Results and Discussion

The performance of each lane detection algorithm was evaluated on the College Station dataset and the Precision, Recall and F1 scores were tabulated. The evaluation was carried out without explicitly training the algorithms on the College Station dataset. The reasoning behind choosing to do so is to evaluate the performance of a LD algorithm when it encounters a completely new test scenario and check how the lane detections could co-relate to the lane marking characteristics. Table 1 lists the performance of each algorithm on different test scenarios of the College Station dataset. Table 2 lists the lane marking performance characteristic data collected along the same roads. The lane detection outputs from different algorithms are illustrated in Figure 5 and 6.

ENet-Label performed best on the College Station dataset among the three LD algorithms evaluated. The LD algorithms had the lowest performance on 03. Jones road, mainly due to the absence of pavement markings for most part of the road. Lane markings on 04. Leonard road had the best overall performance in terms of detectability. This can be attributed to several factors including high contrast between roadway and the pavement markings, and viewing conditions which include observation direction and time of day.

LD algorithms performed better detections overall during morning times as compared to other times of day. Since the sun was more overhead at 11am the glare inducing light sources are absent and the luminance of the roadway surface is relatively constant resulting in improved LD performance.

Under these conditions the LD performance appears to correspond directly to the CapY and retroreflectivity values of lane markings as seen by the data in Table 1 and 2. Roads with higher CapY and R_L values of pavement markings produced better LD performance scores.

Overall LD performance is significantly lower on roads (01, 02, 03, 05, 06) during evening times than other times of day when driving westwards. This can be attributed to the direct sun glare on the camera sensor and the low angle solar illumination of the road. In these cases, since the source of light i.e. the sun is over the horizon emitting light towards the camera at a low angle, the specular reflections on the roads are high. These specular reflections tend to reduce the contrast between pavement marking and road, affecting the ability of LD algorithms to detect pavement markings. However, we observe the exact opposite trend on roads where the data was collected when driving east wards (04 Leonard Road) during evening times. Since the source of light is illuminating the road along the field-of-view (FOV) of the camera, these lighting conditions results in high illumination of the road improving the detectability of the lane markings which results in better LD performance during evening times.

During night times since the source of light (vehicle headlights) illuminates the road along the FOV of the camera, the light source contributes to the luminance of the pavement markings by making the roadway appear darker in pixel intensity. Thus, the perceived levels of contrast are expected to be much higher on roads with higher retroreflectivity and CapY which aid towards better lane detections. Similarly, roads (01, 02 and 04) with pavement markings having higher retroreflectivity (R_L) values showed better performance during nighttime detection as compared to roads with lower retroreflectivity values (03 and 05). The retroreflectivity values and CapY appeared to have a positive effect on LD performance during nighttime conditions. However, roads 06 and 07 exhibited unanticipated behavior. Even though they had the highest retroreflectivity values among all the roads, their nighttime detections were found to be poor, which points towards the fact that additional parameters also need to be considered to predict road detectability behavior. Parameters like road surface roughness, road surface cracks, ghost marking can also affect the performance of LD algorithms whose effects we plan to explore in future work.

Future Work

In this work we have evaluated the different state-of-the-art LD algorithms and their performance under different test scenarios and observed the correlation of the algorithm performance with Lane material characteristic data. The lane detection performance was evaluated using conventional accuracy metrics such as Precision, Recall and F1 scores and the performance was correlated to the Lane material characteristics. However, as Satzoda et al. explains in [17], there are several aspects of a lane estimation algorithm evaluation which needs evaluation in order constitute a robust LD system. A set of performance metrics were proposed in [17] that can be used to benchmark lane estimation algorithms. A future scope of this work is to incorporate some of those metrics for LD performance evaluation and develop metrics that consider the quality of lane markings and lane marking characteristics to quantify LD system performance. Using the different performance metrics, we propose to develop a lane detection system goodness metric that can be used to rank LD systems. Using these metric based evaluation methods, a reference Lane Detection (LD) test system is proposed to be developed to benchmark and rank new perception algorithms, sensors, and lane markings that constitute a reference LD system.

References

1. Pape, Doug, and Filmon Habtemichael. “Infrastructure Initiatives to Apply Connected-and Automated-Vehicle Technology to Roadway Departures,” No. FHWA-HRT-18-035. United States. Federal Highway Administration. Office of Safety Research and Development, 2018.
2. Hillel, Aharon Bar, Ronen Lerner, Dan Levi, and Guy Raz. "Recent progress in road and lane detection: a survey." Machine vision and applications 25, no. 3 (2014): 727-745.
3. Xing, Yang, Chen Lv, Long Chen, Huaji Wang, Hong Wang, Dongpu Cao, Efstathios Velenis, and Fei-Yue Wang. "Advances in vision-based lane detection: algorithms, integration, assessment, and perspectives on ACP-based parallel vision." IEEE/CAA Journal of Automatica Sinica 5, no. 3 (2018): 645-661.
4. Narote, Sandipann P., Pradnya N. Bhujbal, Abbhilasha S. Narote, and Dhiraj M. Dhane. "A review of recent advances in lane detection and departure warning system." Pattern Recognition 73 (2018): 216-234.
5. Davies, Chris. Effects of Pavement Marking Characteristics on Machine Vision Technology. No. 17-03724. 2017.
6. Carlson, Paul J., Jeffrey David Miles, Michael P. Pratt, and Adam M. Pike. Evaluation of wet-weather pavement markings: First year report. No. FHWA/TX-06/0-5008-1. 2005.
7. Pike, Adam M., Jordan Whitney, Thomas Hedblom, and Susannah Clear. “How Might Wet Retroreflective Pavement Markings Enable More Robust Machine Vision?” Transportation Research Record, (June 2019). doi:10.1177/0361198119847620.
8. Pike, Adam, Susannah Clear, Timothy Barrette, Thomas Hedblom, and Jordan Whitney. Effects of the Wet Retroreflectivity and Luminance of Pavement Markings on Lane Departure Warning in Nighttime Continuous Rain with and without Glare Sources. No. 2019-01-1014. SAE Technical Paper, 2019.
9. Pan, X., Shi, J., Luo, P., Wang, X. and Tang, X., 2018, April. Spatial as deep: Spatial cnn for traffic scene understanding. In Thirty-Second AAAI Conference on Artificial Intelligence.
10. Wang, Ze, Weiqiang Ren, and Qiang Qiu. "LaneNet: Real-Time Lane Detection Networks for Autonomous Driving." arXiv preprint arXiv:1807.01726 (2018).
11. Paszke, A., Chaurasia, A., Kim, S. and Culurciello, E., 2016. Enet: A deep neural network architecture for real-time semantic segmentation. arXiv preprint arXiv:1606.02147.
12. Yu, F., Xian, W., Chen, Y., Liu, F., Liao, M., Madhavan, V. and Darrell, T., 2018. Bdd100k: A diverse driving video database with scalable annotation tooling. arXiv preprint arXiv:1805.04687.
13. Neven, D., De Brabandere, B., Georgoulis, S., Proesmans, M. and Van Gool, L., 2018, June. Towards end-to-end lane detection: an instance segmentation approach. In 2018 IEEE Intelligent Vehicles Symposium (IV) (pp. 286-291). IEEE.
14. Hou, Y., Ma, Z., Liu, C. and Loy, C.C., 2019. Learning lightweight lane detection cnns by self-attention distillation. arXiv preprint arXiv:1908.00821.
15. Yuenan Hou. Agnostic lane detection, 2019
16. He, Bei, Rui Ai, Yang Yan, and Xianpeng Lang. "Lane marking detection based on convolution neural network from point clouds." In 2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC), pp. 2475-2480. IEEE, 2016.
17. Satzoda, Ravi Kumar, and Mohan M. Trivedi. "On performance evaluation metrics for lane estimation." In 2014 22nd International Conference on Pattern Recognition, pp. 2625-2630. IEEE, 2014.

Contact Information

Contact details for the main author should be included here. Details may include mailing address, email address, and/or telephone number (whichever is deemed appropriate).

Acknowledgments

Support for this research was provided in part by a grant from the U.S. Department of Transportation, University Transportation Centers Program to the Safety through Disruption University Transportation Center (451453-19C36).

Disclaimer

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated in the interest of information exchange. The report is funded, partially or entirely, by a grant from the U.S. Department of Transportation's University Transportation Centers Program. However, the U.S. Government assumes no liability for the contents or use thereof.

Definitions/Abbreviations

ADAS	Advanced Driver Assistance Systems
LD	Lane Detection
LDW	Lane Departure Warning
LKA	Lane Keep Assist
FOV	Field-of-View