Survey Paper Based On Lane Detection for Self Driven and Autonomous Vehicles.

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***Abstract*— Lane Detection is a mechanism designed to warn the driver when the vehicle begins to move out of its lane (unless a turn signal is on in that direction) on freeways and arterial roads. These systems are designed to minimize accidents by addressing the main causes of collisions: driver error, distractions and drowsiness. Several approaches have been proposed for lane detection in self-driving and self-driven vehicles. We discuss three of these approaches in this survey paper- Robust Lane Detection Using Multiple Features, Vanishing Point Detection for self-driving car using harmony search algorithm, A Precise Lane Detection Algorithm Based on Top View Image Transformation and Least-Square Approaches**

Keywords*— Lane Detection, Hough transform, Image features,

I. INTRODUCTION

Lan detection is safety system which alerts the driver whenever the car is leaving its lane unless the turn indicator is turned on. This system helps in reducing collisions which happen due to driver error, distractions and drowsiness.

The first method is proposed by Tejus Gupta, Harshit S. Sikchi and Debashish Chakravarty which is Robust Lane Detection using Various features [1]. Here the authors have analysed certain features of a lane and generated an output for the vehicle.

The second method is proposed by Yoon Young Moon et al. which Vanishing Point for Self Driving Car using Harmony Search Algorithm [2]. The authors have proposed a better lane detection via generating a vanishing point using harmony search algorithm which is generally used is the field of acoustics and music, and compared the results with the go-to RANSAC Algorithm

The third method is proposed by Byambaa Dorj et al. which is A Precise Lane Detection Algorithm Based on Top View Image Transformation and Least Squares Approach [3]. Here the researchers have taken into account the top view of lane and generated a lane.

II. LITERATURE SURVEY

A. *Robust Lane Detection using Multiple Features*

Wang et al [4] use CHEVP (Canny-Hough Estimation of Vanishing Points) algorithm for initializing their B-Snake lane model. CHEVP detects edges using Canny edge detection and uses hough lines to fit lines. They compute the intersection of every pair of lines to vote for vanishing point estimate. Then, they assume that the lines voting for the detected vanishing point are road boundaries and use these lines to initialize their lane model parameters.

[5] posed lane detection as an instance segmentation problem with each lane as an instance and proposed a network architecture that can be trained end to- end for this task.

In [6], a spatial CNN architecture was suggested that passes information slice-by-slice within each feature map and is able to exploit the strong shape prior of lane markings.

The proposed algorithm consists for the following steps:

1. Lane Features Extraction:
   Multiples Algorithms are sued to extract different features of the lane. So just in case of the features is not extracted properly the other features compensate for it.
   a. Gradient Based features:
      To extract the gradient based features, the authors have used the lane segment detector method [11]. It helps reduce the errors generated in Hough transform.

      For each line segment Li, the intersection point with every other line segment is considered and used to compute a score for Li.

$$score(L_i) = \sum_{j \subset S(L_i)} length(L_j)$$

$$S(L_i) = \{\, j \mid L_i \text{ and } L_j \text{ intersect at horizon}\}$$

      All lines with a score below the threshold are removed. After this step, only lines corresponding to lane markers and noisy lines that are parallel to road boundary are retained.

Fig. 2: Image with heavy shadows and edges detected by LSD.

b. Intensity Based Features:
Here the authors check for any shadows on the road during lane marker detection and use the second derivative of Gaussian to such that response to bright vertical lines respond in the dark background. The output of this step provides an accurate estimation of the lane markers. Due to noise in the output, the output needs to go for thresholding.

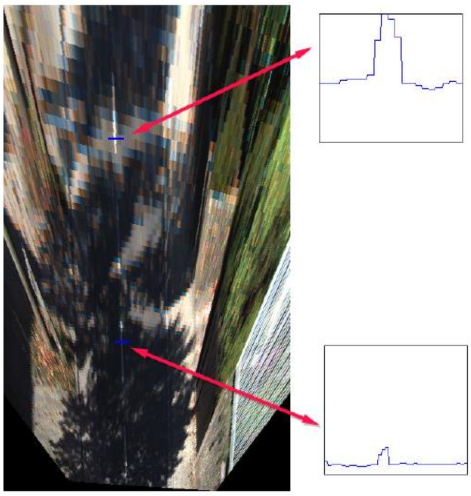


Fig. 4: Top-view image and intensity profile with/without shadow.

The figure below shows the final output.

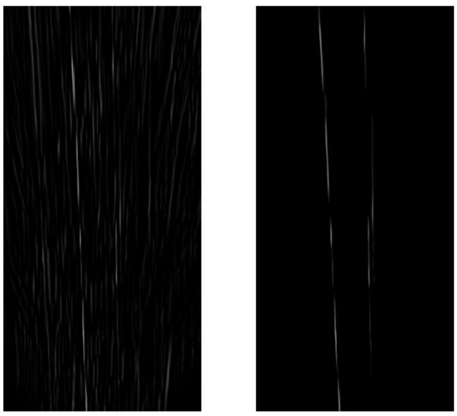


Fig. 5: (Left) Top-view image after convolution, (Right) Image after thresholding.

c. Texture Based Features:
Here the authors identify what is the texture of the road e.g. smooth, dirt road etc. To do so, the authors have used MultiNet model [12]. The MultiNet architecture uses an encoder decode architecture with shared encoder for classification, detection, and semantic segmentation. It achieves state-of- the-art results with 92.2% mean precision in road segmentation on KITTI dataset and takes 43 ms for inference.
The following results are achieved :

Fig. 6: Segmentation results using MultiNet on images from KITTI sequence.

2. Using previous frame's estimate to filter extracted lane features:
Here the authors state that they only use features that are within 2.5 metres of the previous frame estimate. In this way they prevent computation and erroneous detection. They also state that the car runs at a fixed speed of 60 km/h and moves 1.5 metres per second since the algorithm runs at 10 - 15 frames per second.

3. Lane Model Estimation:
The authors have used the RANSAC algorithm to generate a histogram based on the lane estimate generated. Then they have applied filters of specific width to generate lane boundaries.

Also due to presence of non-lane entities in the estimate, the authors have used the RANSAC algorithm such that it selects the inner most points or inliers considering the lane is captured in the centre of the image.

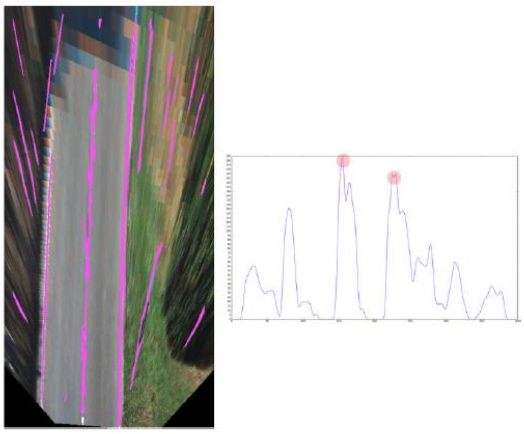


Fig. 7: Features extracted and histogram showing column-wise sum of extracted pixels. The red circles are the lane position estimate.

B. Vanishing Point for Self Driving car using Harmony Search Algorithm

Mainly, the research has focused on how accurately vanishing points could be detected when various noises exist. Among them, the random sample consensus (RANSAC) algorithm, which utilizes straight lines obtained using Hough transform is one of the most popular ones [7,8].

The RANSAC algorithm decides the optimum model parameter by estimating noised data. It randomly selects any partial data from original data, and then identifies good model parameters after iterating the selection process many times [9].

In this study, edges are extracted from the input images, and then candidate vanishing points are estimated using straight line components. Out of many candidate points, the best point is selected as vanishing point using the HS algorithm.

To find the edges from the images, the canary edge detector is used[13] and to detect the straight lines from the detected edges, Hough transform is used [14].

The flowchart for the Harmony Search algorithm is as follows:

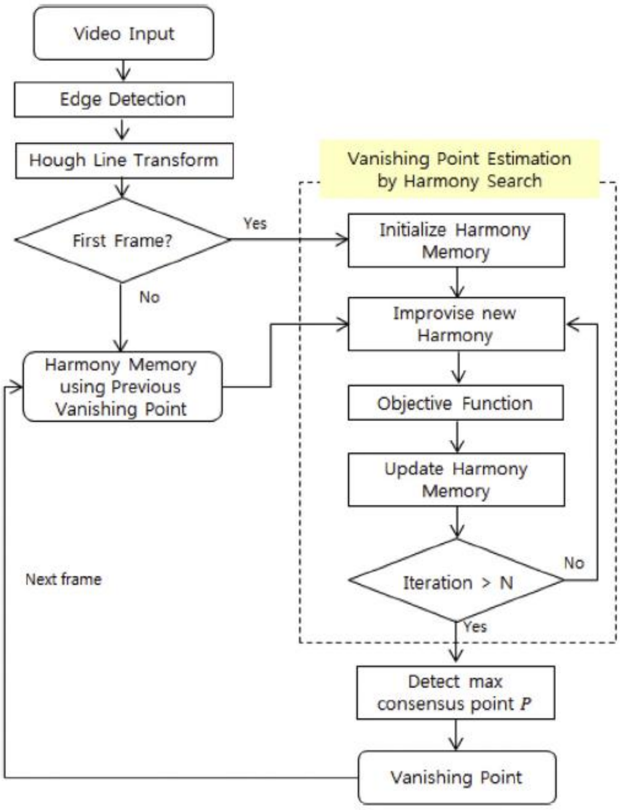


Fig. 4. Flow chart of harmony search-based vanishing point detection.

The algorithm goes as follows:

1. The algorithm parameters are set and random solution vectors are filled in the Harmony Memory(HM) during Harmony Memory Search.(HMS).
2. A New Harmony(NH) is generated using the HMCR and PAR parameters
3. The objective function values of NH are compared to the worst solution of the existing HM and the better one is stored in the HM.
4. Return to Step 2 if the condition for calculation termination is not satisfied.
5. A point is selected that receives the most agreements from the straight lines. This point is the Vanishing Point.
6. Go to Step 1 for detecting the vanishing point of the next frame. Instead of using random HM, the next frame uses current HM as initial HM.

The results are obtained as follows:

Table 1
Comparison of performance between RANSAC and HS methods.

Method	Try Number	Road (a)	Road (b)	Road (c)	Road (d)
RANSAC	Image	Fig. 9-(a)	Fig. 9-(b)	Fig. 9-(c)	Fig. 9-(d)
	Try 1	0.12	3.04	8.75	15.01
	Try 2	0.15	3.18	8.26	15.22
	Try 3	0.13	3.05	8.44	14.71
	Try 4	0.14	3.11	8.19	14.83
	Try 5	0.17	3.08	8.77	14.98
	Average	**0.14**	**3.09**	**8.78**	**14.95**
HS	Image	Fig. 10-(a)	Fig. 10-(b)	Fig. 10-(c)	Fig. 10-(d)
	Try 1	0.08	0.09	0.09	0.10
	Try 2	0.09	0.07	0.08	0.09
	Try 3	0.07	0.08	0.10	0.09
	Try 4	0.08	0.09	0.09	0.08
	Try 5	0.09	0.09	0.10	0.09
	Average	**0.086**	**0.084**	**0.092**	**0.090**

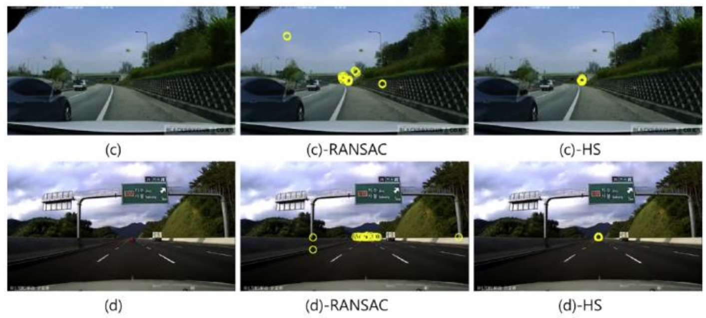


Fig. 11. Additional examples of vanishing point detection.

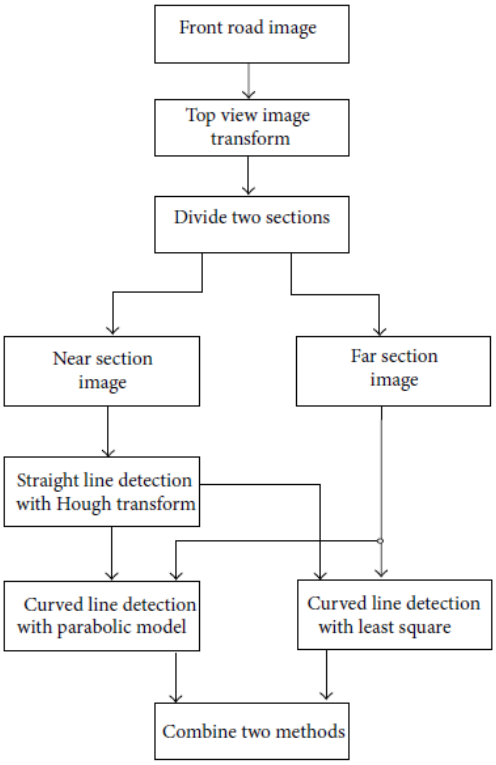
The authors conclude by saying that their further study will consist of using Convolutional Neural Networks. Also they prove that their proposed algorithm is better than the RANSAC algorithm.

This is seen from the results where the covariance of the RANSAC algorithm was in the range 0.14 -14.95 whereas for the HS algorithm the range was 0.084 - 0.092.

C. A Precise Lane Detection Algorithm Based on Top View Image Transformation and Least Squares Approach

[3] states that most of the algorithms proposed for lane detection utilise the image in front of the car which helps in near range but makes it difficult to detect curved lanes.

In hostile road conditions, a recognition and detection capability of road signs, road lanes, and traffic lights is very important and plays a critical role for the ADAS systems [10].
Flowchart for the proposed algorithm:



1. Top View Image Transformation:
   Top view image transformation is a very effective method as an advanced image processing. An object's shape on the road is infracted in the top view transformed image where a lane and a sign of the road are almost the same as the real lane and sign. Therefore, the usage of the top view image transformation becomes very effective for the lane detection, leading to providing an advanced safe lane-keeping and control capabilities.

   After generating the top view image, it is divided in two parts. A near view image and a far view image. In the near view section, a straight line model is used to find a linear lane with a Hough transformation, while for the far view section a parabolic model approach is adopted for a curved lane detection in the top view image and its parameters are estimated by utilizing a least-square approach.

2. Straight Line Detection with Hough Transform:
   Here the line with the max length is chosen form the set of lines generated using the Hough transform so that the maximum data can be extracted from the line. The final output is given below: -

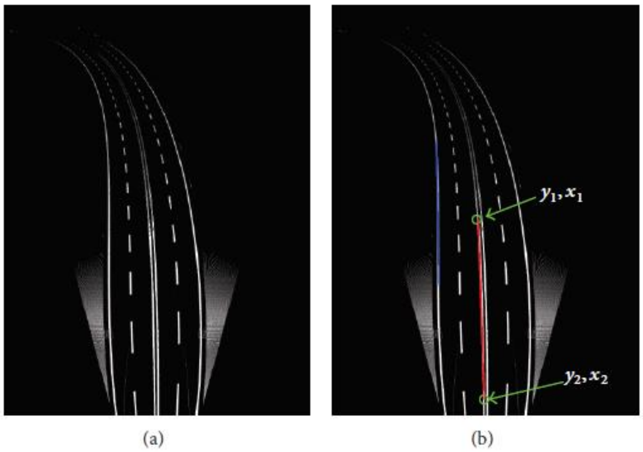


Figure 7: (a) Binary image of top view. (b) Hough transform results.

3. Curved Line Detection based on Parabolic Model:
   The current and the following section are a combined process.

   The far view image and the parameters from the previous straight line model are used to match the boundaries of the generated curved line to the linear line.

   However, the generated curved line is not perfectly aligned to the original curved line due to the parameters used in the parabolic model have some biases and errors. To compensate the misalignment in the far view image, a measure is described in the following section.

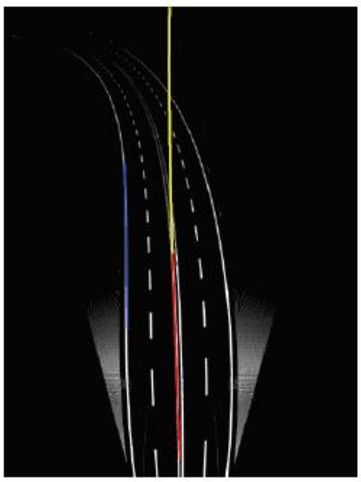


Figure 11: Result of curve lane detection based on parabolic model.

4. Curved Line Detection based on Least Square Model.
   In this section, the output from the previous section is refined such that the curved line is aligned to the original white line. But the boundaries of the linear line are not aligned.

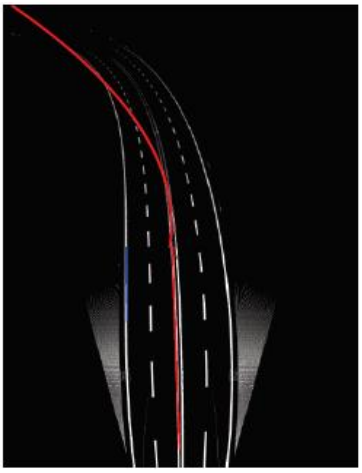
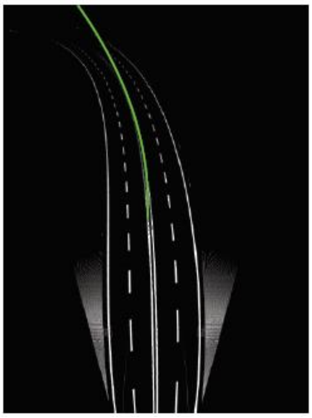
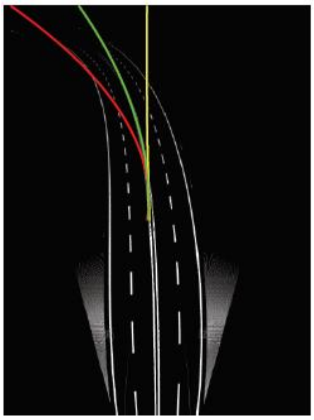


FIGURE 12: Result of curve lane detection based on least-square method.

So the approach of least square methods is used in which the parameters generated in the parabolic model and the least square model are averaged to obtain a precise output. The output is as follows:





III. COMPARATIVE ANALSYIS

A. *Key Features*

1) ROBUST LANE DETECTION WITH MULTIPLE FEATURES:
   - Lane detection using gradient, intensity and texture based features.
   - The algorithm is proved to be better than the vanishing point algorithm.

2) Vanishing Point for Self Driving car using Harmony Search Algorithm:
   - The Harmony Search algorithm is proposed to return better results for the vanishing point which improves the efficiency of Lane Detection.
   - The Outputs of both algorithms are compared side by side (RANSAC & HS).

3) A Precise Lane Detection Algorithm Based on Top View Image Transformation and Least Squares Approach:
   - To generate the lane, a top view of the image is captured.
   - The image is divided in 2 parts. Both parts are processed separately and joined together to obtain the final lane.

B. *Pros*

1) ROBUST LANE DETECTION WITH MULTIPLE FEATURES:
   - Helps to detect the lane even when the road has shadows or the lane marker detected is of less intensity.
   - Also the proposed algorithm works for curved roads.

2) Vanishing Point for Self Driving car using Harmony Search Algorithm:
   - Shows that the HS algorithm works better and requires smaller sample size than a RANSAC Algorithm
   - The algorithm returns almost the same result for a no. of trials (10,000)

3) A Precise Lane Detection Algorithm Based on Top View Image Transformation and Least Squares Approach:
   - This method helps to detect lanes for longer range
   - The top view of the road also helps in detection of curved roads

C. *Cons*

1) ROBUST LANE DETECTION WITH MULTIPLE FEATURES:
   - The algorithm doesn't work for scenarios where there are diversions or potholes on the road.
   - Since the lane width is not variable the algorithm might not work in situations where the lane width varies.

2) Vanishing Point for Self Driving car using Harmony Search Algorithm:
   - The algorithm is not applicable for curved roads
   - The algorithm is not tested for bad weather
   - Doesn't work for non-highway roads

3) A Precise Lane Detection Algorithm Based on Top View Image Transformation and Least Squares Approach:
   - The algorithm is not tested in real life scenario
   - The algorithm is applicable only for single lane roads
   - Highways and intersections are not tested

D. *Key Assumptions*

1) ROBUST LANE DETECTION WITH MULTIPLE FEATURES:
   - Flat Road
   - Lane markers parallel to the ground
   - The car has a maximum speed of 60 km/hr and the algorithm runs at 10-15 frames per second, so the car moves at most 1.5 meters between consecutive frames.
   - Lane features which are less than 2.5 meters are used and beyond that limit are discarded.

2) Vanishing Point for Self Driving car using Harmony Search Algorithm:
   - Flat roads
   - Straight roads
   - Highways
   - Three variables are required as a dataset for the algorithm HMS, HMCR, PAR

3) A Precise Lane Detection Algorithm Based on Top View Image Transformation and Least Squares Approach:
   - Flat roads
   - The parameters used for used in parabolic model have some bias and errors
   - To compensate for the misalignment of the lane boundary an effective estimation technique is used

E. *Quantitaive Results*

1) ROBUST LANE DETECTION WITH MULTIPLE FEATURES:
   - The detection percentage range between 83% to 94% for the dataset entered by the researchers and the mean deviation ranged between 30cm to 60 cm

2) Vanishing Point for Self Driving car using Harmony Search Algorithm:
   - The HS Algorithm has a covariance range of 0.084 to 0.094 which is better than the RANSAC Algorithm which has a covariance range of 0.14-14.92.

3) A Precise Lane Detection Algorithm Based on Top View Image Transformation and Least Squares Approach:
   - It is shown that a curved line shape of the white lines after the top view image transformation almost perfectly matches the real road's white lines.
   - The effectiveness of the proposed integrated lane detection method can be applied to not only the self-driving car systems but also the advanced driver assistant systems in smart car system

F. *Analysis*

1) ROBUST LANE DETECTION WITH MULTIPLE FEATURES:
   - One of the issue with the algorithm is that it is not able to detect the lane for longer distances,
     since the frames captured only under 2.5 meters is used for generating the new frame.

2) Vanishing Point for Self Driving car using Harmony Search Algorithm:

- This proposed algorithm is a step forward in the right direction but just an improvement in go-to algorithm.
- One of the limitations is that the vanishing point is generated at the center of the image generated. Considering intersections, traffic jams, the point would be difficult to generate since some amount of distance is required between 2 cars for generating the vanishing point

3) A Precise Lane Detection Algorithm Based on Top View Image Transformation and Least Squares Approach:

- One of the design limitations is that the top view image has to be broken down into two parts and after generating the far lane and the near lane both have to be concatenated for the final detected lane.
- Also since the parabolic step in the algorithm returns biased values, a whole new algorithm of least squares is required to for compensating the errors.

Name of the Scheme	Key Features	Pros	Cons	Key Assumptions	Quantitative results	Analysis
Robust Lane Detection	Lane detection using gradient, intensity and texture based features using ego lane detection. The algorithm is proved to be better than the vanishing point algorithm[3]	• Helps to detect the lane even when the road has shadows or the lane marker detected is of less intensity. • Also the proposed algorithm works for curved roads.[5]	• The algorithm doesn't work for scenarios where there are diversions or potholes on the road. • Since the lane width is not variable the algorithm might not work in situations where the lane width varies.	• Flat Road • Lane markers parallel to the ground • The car has a maximum speed of 60 km/hr and the algorithm runs at 10-15 frames per second, so the car moves at most 1.5 meters between consecutive frames. • Lane features which are less than 2.5 meters are used and beyond that limit are discarded.	The detection percentage range between 83% to 94% for the dataset entered by the researchers and the mean deviation ranged between 30cm to 60 cm	• One of the issue with the algorithm is that it is not able to detect the lane for longer distances, since the frames captured only under 2.5 meters is used for generating the new frame.
Vanishing Point Algorithm using Harmony Search(HS)	The vanishing point generated for self-driving car is compared with the RANSAC Algorithm	• Shows that the HS algorithm [20] works better and requires smaller sample size than a RANSAC Algorithm • The algorithm returns almost the same result for a no. of trials (10,000)	• The algorithm is not applicable for curved roads • The algorithm is not tested for bad weather • Doesn't work for non-highway roads	• Flat roads • Straight roads • Highways • Three variables are required as a dataset for the algorithm HMS, HMCR, PAR	• The HS Algorithm has a covariance range of 0.084 to 0.094	• This proposed algorithm is a step forward in the right direction but just an improvement in go-to algorithm. [1] • Considering intersections, traffic jams, the point would be difficult to generate since a some amount of distance is required between 2 cars for generating the vanishing point
Lane Detection based on Top View Transformation	This method focuses on better lane detection than straight line and front view image lane detection methods.[4]	• This method helps to detect lanes for longer range • The top view of the road also helps in detection of curved roads	• The algorithm is not tested in real life scenario • The algorithm is applicable only for single lane roads • Highways and intersections are not tested	• Flat roads • The parameters used for used in parabolic model have some bias and errors • To compensate for the misalignment of the lane boundary an effective estimation technique is used	• It is shown that a curved line shape of the white lines after the top view image transformation almost perfectly matches the real road's white lines. The effectiveness of the proposed integrated lane detection method can be applied to not only the self-driving car systems but also the advanced driver assistant systems in smart car system	• One of the design limitations is that the top view image has to be broken down into two parts and after generating the far lane and the near lane both have to be concatenated for the final detected lane. • Also since the parabolic step in the algorithm returns biased values, a whole new algorithm of least squares is required to for compensating the errors.[9]

IV. Issues and Future Work

These 3 papers have proposed some excellent techniques for lane detection. However, there are some issues that need to be addressed which can enhance these techniques.

1. Research Gaps:

    - The lane detection algorithm does not work for turns. So for example if a car has to take a U-Turn, the detection will not work.
    - Also the algorithm might detect lane when two lanes are merging, e.g. On a highway
    - There is no reference to testing the algorithm in night time
    - The lane detection becomes only active at high speeds (60 km/h)

2. Proposed Solutions:

    - The proposed algorithms can be improved by using a Lidar camera and CNN based lane segmentation.
    - The algorithms have to be implemented in real life scenarios.
    - Using computational photography, the lanes have to be detected at night time.
    - Also an algorithm has to be proposed so that the lane detection doesn't stop at 90 degree turns and merging lanes etc.

3. Benefits of the Proposed Solutions:

- Due to the ability to detect the lanes at night, the algorithms will help the driver and self-driving car to maintain lane driving.
- Due to continuous testing in real life scenarios, the results will help to tweak the methods accordingly to improve the results
- As the merging lanes will be detected accurately, the automobile will be able to maintain its lane rather than joining the main road in a harmful way.
- Since the lane detection will be available for low speeds, it will help the driver to not meander between the lane and teach the driver to judge the lane width at low speeds

V. Conclusion

In this survey paper, we looked at three different methods for Lane Detection for Self –Driving and Self-Driven vehicles. Each method takes a different perspective towards lane detection and returns positive results. Although some of the problems are not solved using these methods, future work will help these methods to more effective and efficient hence leading to better and safer Lane Detection Systems.

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