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Fuzzy based Hough Transform for Lane Mark Detection

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ABSTRACT

Lane Detection plays an important role in Intelligent Transportation system. Lane detection is an important aspect of autonomous vehicles. It is also a preventive measure for road accidents. Hough Transform technique uses the edge map obtained from segmentation to detect the lane marks. The overall objective of this paper is to improve the lane detection algorithm using adaptive segmentation techniques like Otsu, Fuzzy and K-means. It has been found that the value used to segment the road image containing lanes has been taken statically. To overcome this, a new lane detection method with an adaptive segmentation value has been proposed. This approach has the ability to boost the lane colorization in Far-view, Near-view and curved road images in efficient manner by utilizing the Additive Hough Transform algorithm with optimized segmentation techniques. Various parameters like Accuracy, F-measure, Mean Square Error are used for calculating the effectiveness of this technique. The proposed technique yields accurate results as compared to existing techniques.

KEYWORD

ROI; Hough Transform; Otsu; K-means; FCM; Additive Hough Transform; Lane detection.

1. INTRODUCTION

Roads are one of the finest modes of transportation among all modes of transportation. Due to the negligence of drivers, road crashes are continuously increasing day by day. Localizing lane marks painted in the road image is called Lane detection. The major objective of lane recognition is to detect as well as recognize the lane marks painted on the road and then provide these locations to an intelligent system. In intelligent transportation systems, intelligent vehicles cooperate with smart infrastructure to achieve a safer environment and better traffic conditions.

Advanced driver assistance systems (ADAS) are the systems that are designed to assist the driver in its driving process. Many systems like lane excursion detection and warning, intelligent cruise control, collision avoidance system, blind spot detection are a part of ADAS. Lane departure warning system is a part of ADAS whose objective is to detect the lane marks and to warn the driver in case when the vehicle has tendency to depart from the lane. Many techniques have been made to detect and locate the lane marks. Hough Transform is the most commonly used technique for lane detection but the limitation of Hough Transform is its time complexity to calculate the parameter values. Based on the previous work done in lane detection field, a method is proposed in this paper to detect and localize the lane marks by using Improved Hough Transform based on adaptive segmentation techniques. This technique yields accurate results in lane

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detection of straight or curved roads as well as far-view and near-view road images.

2. LITERATURE SURVEY

Road safety is the major concern of all the lane detection systems. Most of the road accidents happen when the driver departs from the lane. The Hough Transform (HT) developed by Poly Hough in 1962 is the most commonly used technique to detect the lane marks. Many varieties and applications to detect the lane lines can be found in the literatures: Yu et al. have proposed a lane detection technique that uses the Hough Transform with a parabolic model under various road and weather conditions. A multi- resolution strategy has been employed to improve the Hough Transform but the method is computationally tractable and less prone when the noise is present in the image [1].Tseng et al. have proposed a lane detection algorithm that uses Geometry information and Hough transform but the algorithm was time-consuming and also failed when the lane boundaries intersected in a region which is a non-road area [2]. Kim et al. have presented robust lane detection and tracking algorithm based on random sample consensus and particle filtering [3]. An algorithm to detect the painted as well as unpainted roads has been designed by Khalifa that uses Hough Transform for line extraction [4]. Borkar et al. have proposed a lane detection algorithm that is suitable for detecting the lane marks at night. Low resolution Hough Transform has been employed to detect the straight lanes [5]. Wang et al. have used the ideas of region of interest and Random Hough Transform to detect the road edges [6]. Lakshmi et al. have proposed the color segmentation procedure to detect the white and yellow colored lanes on the road [7]. Mariut et al. have proposed a method that detects the lane marks using Hough Transform and has the tendency to determine travelling direction of the vehicle [8]. Ghazali et al. have proposed an algorithm for detecting unexpected lane changes. The algorithm uses H-maxima approach and improved Hough Transform is applied on the near-field of view to detect the straight lines [9]. Phaneendra et al. have proposed an accident avoiding system that uses Hough Transform to detect the left and right marks and determines the position of the vehicle with respect to these marks and gives a warning message whenever the vehicle departs from the lane [10]. Cho et al. have proposed a lane recognition algorithm that uses multiple region of interest. Hough transform with applied accumulator cells has been applied to detect the lane marks in each region of interest [11]. Yi et al. have discussed the existing lane detection techniques and the benefits and limits of existing lane colorization problems. It has been found that most of the existing researchers have used the Hough Transform algorithm for lane detection and also neglected the overheads of existing techniques. The limitation of Hough Transform is its time complexity to solve trigonometric functions to evaluate parameter values. To reduce the limitations of existing researchers, the author has proposed a modified approach for lane detection called as Additive Hough Transform that accelerates the HT process in computationally efficient manner and making it suitable for real-time lane detection. The algorithm randomly selects two points in the image space and solves them using additive property to obtain a point in the parameter space [13]. After surveying the literature, it has been found that most of the existing researchers have used the Traditional Hough transform that is capable for detecting straight lines only and static threshold is used to segment the image to obtain the edge map. In order to reduce the limitations of existing researchers, a new strategy has been proposed in this paper that consists of Improved Hough Transform using adaptive segmentation techniques.

3. OVERVIEW OF ALGORITHM

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The proposed algorithm works in two steps – pre-processing and post-processing. Pre-processing is low level image processing that deals with images from the camera and generate useful information for detection parts. It includes ROI selection and gray scale conversion. Initially the road image is captured by the camera and a region of interest is extracted from input image in order to reduce the search area and to save computational time.
Then the gray scale conversion of the image is done to reduce the processing. Post-processing consists of two steps. In first step, image segmentation is done to obtain an edge map which is used as an input by Additive Hough Transform. In second step Additive Hough Transform is applied to detect the lane marks.

3.1 Region of interest

The road image is captured by the camera that is mounted in front of the vehicle. The region of interest is extracted from the original image by cropping the road image. It increases the speed and accuracy of the lane detection algorithm. The maximum region of interest mainly lies in the bottom half of the road image where all the necessary objects such as lane markings, pedestrians and other vehicles are present. On the basis of the dimensions of the image, the region of interest is calculated by reducing each side of the image.

3.2 Gray-scale Conversion

The RGB image is converted into gray- scale format. Gray-scale conversion transforms a 28 bit, 3 channel RGB color image into 8 bit, one channel and gray-scale image. Generally, road surface can be made up of various obstacles such as shadows, tire skids, oil strains, diverse pavement style which changes the color of the road surface and lane markings to form one image region to another. Due to this, the image is converted into gray scale.

3.3 Image Segmentation

Image segmentation is an important step in image analysis and object recognition. It divides an image into meaningful structures. Lane detection algorithm uses edge map of the image to detect the lanes. The proposed algorithm consists of thresholding and clustering based image segmentation techniques that are used to segment the road lane image. The various image segmentation techniques used in this algorithm are Otsu, K-means and Fuzzy segmentation technique. These segmentation techniques divide the road image using an adaptive threshold value which results in better lane detection results.

3.3.1 Otsu Threshold based segmentation

Otsu's segmentation algorithm automatically clusters pixels into two groups: background and foreground. The main idea of Otsu's algorithm is to find threshold that would maximize between-class variance and minimize within-class variance. All pixels are classified into two classes using the threshold. First step is to create a histogram of pixel values. After it, probability of pixel value is estimated. Pseudo code for Otsu's algorithm is given below:

Step 1: Compute Normalized Histogram of the input image and denote the components of the Histogram by

$$p_i = \frac{n_i}{MN} \quad (1)$$

Where MN is pixels of the image and p_i denotes the number of pixels with intensity i.

Step 2: Compute the cumulative sums, $P_1(k)$, for k=0,1,2,………, $L-1$, using eqn. (2).

$$P_1(k) = \sum_{i=0}^{k} p_i \quad (2)$$

Step 3: Compute the cumulative means, $m(k)$, for k=0,1,2,………, $L-1$, using eqn. (3).

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$$m(k) = \sum_{i=0}^{k} ip_i \qquad (3)$$

Step 4: Compute the global intensity mean, m_G using eqn. (4).

$$m_G = \sum_{i=0}^{L-1} ip_i \qquad (4)$$

Step5: Compute the between class variance, $\sigma_B^2(k)$ for k=0, 1, 2, L-1, using eqn. (5).

$$\sigma_B^2(k) = \frac{[m_G P_1(k) - m(k)]^2}{P_1(k)[1-P_1(k)]} \qquad (5)$$

Step 6: obtain the Otsu threshold, k^* as the value of k for which $\sigma_B^2(k)$ is maximum, using eqn. (6).

$$\sigma_B^2(k^*) = \max_{0 \le k \le l-1} \sigma_B^2(k) \qquad (6)$$

The new image is reduced to a binary image where every image is transformed with a dynamic threshold.

3.3.2 K-means clustering

K-means clustering is another way of classification of given data elements through a certain number of clusters that are fixed prior. The number of clusters is selected randomly. Then the distance between the data element and cluster centre is calculated. The data element is assigned to the cluster centre whose distance from the cluster centre is minimum of all cluster centers. Then new cluster centre is recalculated using eqn. (7).

$$v_i = \left(1/c_i\right) \sum_{j=1}^{c_i} (\mathrm{x_i}) \qquad (7)$$

Where 'c_i' represents the number of data points in i^{th} cluster. This algorithm aims at minimizing an objective function known as squared error function given by:

$$J(V) = \sum_{i=1}^{c} \sum_{j=1}^{c_i} (\|x_{i-}v_j\|)^2 \qquad (8)$$

3.3.3 Fuzzy based segmentation

The fuzzy c-means (FCM) algorithm is a clustering algorithm. It was developed by Dunn and Bezdek. The aim of FCM algorithm is to find an optimal fuzzy c-partition by evolving the fuzzy partition matrix iteratively and computing the cluster centers [12]. In order to achieve this, the algorithm tries to minimize the objective function:

$$J_{FCM} = \sum_{i=1}^{N} \sum_{j=1}^{C} \mu_{ij}^m (\|x_i - v_j\|)^2 \qquad (9)$$

Where m is any real number greater than 1, u_{ij} is the degree of membership of x_i in the cluster j, x_i is the ith data, $v_j$is the center of the cluster. Membership μ_{ij} is given by:

$$\mu_{ij} = \Sigma_{k=1}^{c} \left[\frac{\|x_i - v_j\|}{\|x_i - v_k\|}\right]^{\frac{2}{m-1}} \qquad (10)$$

3.4 Hough Transform

Hough Transform (HT) is an efficient tool for detecting straight lines in an image, even in the presence of noise and missing data. The basic principle of the Hough Transform is that every point in the image has infinite number of lines, which pass through it but with a different angle. The goal of the transform is to identify the lines that pass through the most points in the image. These are the lines that most closely match the features in the image. Hough transform algorithm uses an array, called an accumulator, to detect lines. The dimension of the accumulator is equal to the number of an unknown Hough transform parameters. The ρ parameter represents the distance between the line and the origin, and the parameter θ represents the angle of the vector from the origin to the closest point on the line. A count (initialized at zero) in Hough accumulator at point (ρ, θ) is incremented for each line it considers.

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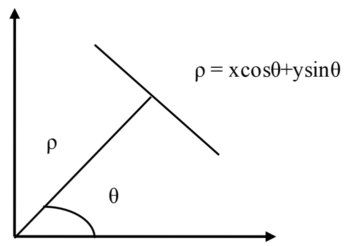

Fig.1 Hough transform for detecting straight lines.

Hough transform is unsuitable for real time applications because high computational time incurred by conventional Hough voting attributed to trigonometric functions and multiplications applied to every edge pixel.

3.5 Additive Hough Transform

From the various implementation of Hough Transform, it is known that the classic Hough algorithm has heavy calculation burden resulted into ineffectiveness to satisfy real-time request. Therefore, we modify it for detecting both straight and curved roads efficiently as well as for calculating more than one edge point. The idea is to select two points and solve them using the equations (11) and (12).

$$\theta_i = \tan^{-1}\big((x_i - x_{i+1}) \big| (y_{i+1} - y_i)\big) \qquad (11)$$

$$\rho = x_i \cos\theta_i + y_i \sin\theta_i \qquad (12)$$

The corresponding accumulator units are set to zero in the parameter space. If the points exist in the parameter space the corresponding accumulators count plus 1. If not, the points are inserted into the parameter space.

4. EXPERIMENTS & RESULTS

We have performed the experiments in MATLAB under Hp computer having Intel(R) Core™ i5 processor, 32 bit windows 7 operating system, 4.00 GB RAM and RADEON Graphics. A database of more than 25 road images has been collected and is divided into three sets on the basis of curved images and images captured by the camera from near and far. This technique has been implemented on a number of images acquired along the roads with different illumination conditions in different situations such as single/double lane marks, supplementary road marks etc.

4.1 Detection of lane marks using Hough transform and Additive Hough Transform:

Hough Transform and Additive Hough transform techniques have been applied on the different test images. The lane detection results of the following four different test images on applying these techniques are shown in Fig. 2. In Fig.2, column (a) represents the original images captured by the camera, column (b) represents the lane detected images obtained on applying the Traditional Hough Transform technique and column (c) represents the lane detected images on applying AHT Hough Transform technique. From subjective evaluation it is evident that more lines are detected by AHT as compared to HT. Also to evaluate the performance of HT and AHT, the average values of Accuracy, F-measure and MSE are evaluated for three image sets. The average values of these parameters are shown in Tables 1, 2, and 3. From experimental results and performance measures, it is vivid that results of AHT are more accurate as compared to HT.

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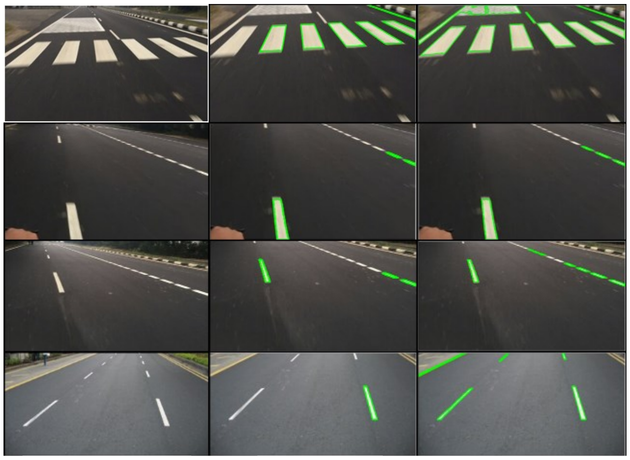

(a) (b) (c)

Fig.2 (a) Input Image; (b) Traditional Hough Transform lane detected image; (c) Additive Hough Transform lane detected image.

Performance Evaluation:

Performance Evaluation table shows the analysis of lane detection techniques using different parameters such as Geometric Accuracy, F-measure and MSE. The average values of parameters of conventional and new techniques have been calculated to analyze the performance. Performance evaluation tables are shown for three sets of images named as sets containing images captured by the camera from Far, Near-view and a set containing curved lane images.

a) Accuracy

Accuracy is the major requirement of the lane detection techniques. Geometric accuracy is the accuracy of a resulted image compared to the original image. In Table 1, 2, 3, Accuracy value obtained by HT and AHT techniques for Far-view, Near-view and Curved lane images is shown. From table values, it is clear that accuracy of AHT is more as compared to HT.

Table 1 Performance evaluations of Accuracy, F-measure and MSE on applying HT and AHT techniques on Far-view images.

IMG.	ACCURACY		F-MEASURE		MSE	
	HT	AHT	HT	AHT	HT	AHT
1	0.3597	0.4259	59.2136	62.8741	0.5562	0.5310
2	0.5246	0.5891	68.3042	71.4368	0.4871	0.3935
3	0.8523	0.9173	89.4269	93.7638	0.0924	0.0779
4	0.8621	0.8906	88.5713	92.1536	0.0648	0.0601
5	0.7953	0.8261	84.1367	87.3642	0.1726	0.1587
6	0.8796	0.9083	86.7432	91.7680	0.0982	0.0900
7	0.8478	0.8957	88.2149	94.5796	0.0824	0.0781
8	0.8876	0.9310	87.1567	90.2926	0.2493	0.2105
9	0.7820	0.8196	89.2674	93.2478	0.0416	0.0397
10	0.8936	0.9279	82.3648	87.4965	0.0587	0.0429
11	0.8706	0.9201	88.2146	92.7543	0.0816	0.0631
12	0.9150	0.9486	84.2397	90.7462	0.0220	0.2114
Avg.	**0.7892**	**0.8334**	**52.9878**	**87.3731**	**0.1672**	**0.1630**

b) F-measure

F-measure parameter is used to compute the average of information retrieval precision and recall matrices.

Table 2 Performance evaluations of Accuracy, F-measure and MSE on applying HT and AHT techniques on Near-view images.

IMG.	ACCURACY		F-MEASURE		MSE	
	HT	AHT	HT	AHT	HT	AHT
1	0.1478	0.1834	9.2197	11.0130	0.9754	0.9527
2	0.6520	0.6982	79.2036	82.9742	0.3152	0.2942
3	0.8472	0.8860	88.3796	92.7481	0.1287	0.0963
4	0.6752	0.7089	79.1053	82.7952	0.3168	0.2840
5	0.8950	0.9581	92.1406	95.1009	0.0298	0.0176
6	0.7835	0.8509	86.4113	89.9745	0.3249	0.2067
7	0.8291	0.8862	90.2014	92.4978	0.1921	0.1132
8	0.8973	0.9359	92.3674	95.7201	0.0845	0.0798
9	0.7924	0.8660	89.4783	90.3478	0.2871	0.1392
10	0.7861	0.8446	88.3607	90.8119	0.4129	0.2510
11	0.5532	0.5982	71.2413	74.2940	0.4073	0.3823
12	0.5607	0.6391	75.4971	78.3495	0.3574	0.3341
Avg.	**0.7016**	**0.7546**	**78.4671**	**81.3855**	**0.3193**	**0.2625**

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A larger F-measure value indicates high classification or clustering quality. In Table 1, 2, 3, F-measure value obtained by HT and AHT techniques for Far-view, Near-view and Curved lane images is shown. From table values, it is clear that F-measure of AHT is more for all image sets as compared to HT.

c) Mean Square Error

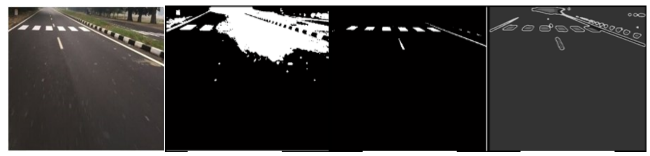
Mean Square Error is a risk function corresponding to expected value of squared error loss or quadrate loss. It is a measure of image quality index. The large value of MSE means the image is a poor quality image. In Table 1, 2, 3, the MSE taken by HT and AHT techniques on Far-view, near-view and curved images is shown. From table values, it is clear that AHT has least value of MSE for all image sets as compared to HT.

Table 3 Performance evaluations of Accuracy, F-measure and MSE on applying HT and AHT techniques on Curved lane images.

IMG.	ACCURACY		F-MEASURE		MSE	
	HT	AHT	HT	AHT	HT	AHT
1	0.1587	0.1979	9.1276	12.7569	0.9590	0.9406
2	0.8852	0.9167	90.0378	94.3715	0.1084	0.0981
3	0.8219	0.8892	91.0078	93.6473	0.1162	0.0982
4	0.1086	0.1379	19.6347	24.8413	0.9634	0.8796
5	0.8331	0.8856	89.1439	92.9309	4.1009	2.9645
Avg.	**0.5615**	**0.6054**	**59.7903**	**63.7095**	**1.2495**	**0.9962**

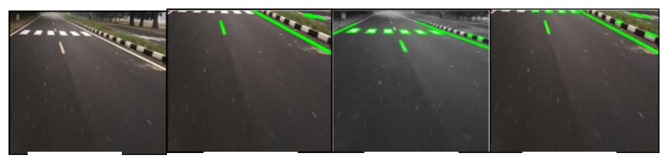
4.2 Improved Hough Transform using segmentation techniques:

Additive Hough Transform (AHT) technique uses an edge map obtained by image gradient processing method as an input for lane detection. The threshold value used to segment the image is taken statically. Therefore adaptive threshold value is required to improve the results further. The Additive Hough Transform technique is applied with three adaptive segmentation techniques based on Otsu Algorithm, Fuzzy Segmentation algorithm and K-means clustering algorithm. These techniques are applied on three data sets of images that contain images captured by the camera from far view, near view and curved images. The segmentation results obtained by Otsu, Fuzzy and K-means are shown in Fig.3. From visual perspective, it is clear that the segmentation results of Fuzzy are more accurate than others.



(a) (b) (c) (d)

Fig.3 (a) Input Image (b) Otsu Segmented Image (c) Fuzzy Segmented Image (d) K-means Segmented Image (e) Improved Lane Detected Image.



(a) (b) (c) (d)

Fig.4 (a) Input Image (b) Otsu based AHT lane detected Image (c) Fuzzy based AHT lane detected Image (d) K-means based AHT lane detected Image.

In Fig. 4, the lane detection results of AHT by using Otsu, Fuzzy and K-means segmentation are shown.

Table 4 Performance evaluation of Accuracy on applying segmentation based AHT techniques on Far-view images.

Accuracy Evaluation			
IMG.	IMPROVED AHT		
	OTSU	FUZZY	K-MEANS
1	0.8965	0.9881	0.4986
2	0.6310	0.9790	0.9789
3	0.9496	0.9843	0.9484
4	0.9559	0.9804	0.9437
5	0.8557	0.9700	0.9590
6	0.9538	0.9968	0.9633
7	0.9485	0.9966	0.9258
8	0.9638	0.9780	0.9590
9	0.8584	0.9983	0.8408

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10	0.9675	0.9768	0.9753
11	0.9637	0.9773	0.9609
12	0.9808	0.9832	0.9811
Avg.	**0.9104**	**0.9841**	**0.9112**

From the experimental results, it is vivid that Fuzzy based AHT gives more accurate lane results as compared to the other techniques. In Table 4, 5, 6, accuracy values obtained by segmentation based AHT techniques on far-view, near- view and curved lane images are shown. From the table values, it is vivid that Fuzzy based AHT has more accuracy as compared to Otsu and K-means based AHT for all image sets.

Table 5 Performance evaluation of Accuracy on applying segmentation based AHT techniques on Near-view images.

Accuracy Evaluation			
IMG.	IMPROVED AHT		
	OTSU	FUZZY	K-MEANS
1	0.2198	0.9980	0.3850
2	0.9401	0.9664	0.7409
3	0.9535	0.9789	0.9409
4	0.9179	0.9841	0.7535
5	0.9945	0.9999	0.9911
6	0.9164	0.9816	0.8968
7	0.9335	0.9855	0.9497
8	0.9860	0.9947	0.9902
9	0.9028	0.9890	0.9464
10	0.9082	0.9984	0.8944
11	0.6975	0.9847	0.6409
12	0.8171	0.9738	0.6835
Avg.	**0.8489**	**0.9863**	**0.8177**

In Table 7, 8, 9, F-measure values obtained by segmentation based AHT techniques on far-view, near- view and curved lane images are shown.

Table 6 Performance evaluation of Accuracy on applying conventional and segmentation techniques on Curved lane images.

Accuracy Evaluation			
IMG.	IMPROVED AHT		
	OTSU	FUZZY	K-MEANS
1	0.2198	0.9980	0.3850
2	0.9535	0.9789	0.9409
3	0.9496	0.9843	0.9484
4	0.1633	0.8718	0.6371
5	0.9409	0.9777	0.9453
Avg.	**0.6454**	**0.9621**	**0.7713**

Table 7 Performance evaluation of F-measure on applying segmentation based AHT techniques on Far-view images.

F-measure Evaluation			
IMG.	IMPROVED AHT		
	OTSU	FUZZY	K-MEANS
1	93.8230	99.4013	66.0001
2	76.7785	98.9357	98.9356
3	97.4138	99.1657	97.3522
4	97.6471	98.9448	97.0804
5	91.8641	98.4624	97.9056
6	96.9549	99.5355	98.1854
7	98.1074	99.8326	98.1174
8	97.2963	99.8169	96.1486
9	98.1455	98.8407	97.9074
10	92.3676	99.9006	91.6310
11	96.6253	98.4313	97.5536
12	96.9746	98.4284	98.3244
Avg.	**94.4998**	**99.1413**	**94.5951**

Table 8 Performance evaluation of F-measure on applying segmentation based AHT techniques on Near-view images.

F-measure Evaluation			
IMG.	IMPROVED AHT		
	OTSU	FUZZY	K-MEANS
1	12.2197	97.9879	25.6197
2	96.0104	97.6440	84.9242
3	97.6178	98.9057	96.7979
4	94.5478	98.8982	85.1516
5	99.7254	99.9972	99.5536
6	94.4997	98.7349	92.6138
7	95.9187	99.0822	96.8828
8	98.8863	99.7182	99.2468
9	94.4821	99.3457	96.7402
10	95.1784	99.9116	94.3362
11	81.9304	98.8995	77.8151
12	87.5205	98.0860	80.9472
Avg.	**87.3781**	**98.9342**	**85.8857**

From table values, it is clear that Fuzzy based Improved AHT technique has higher F-measure values for far-view, near-view and curved images. In Table 10, 11, 12, MSE values obtained by segmentation based AHT techniques on far-view, near- view and curved lane images are shown. From table values, it is clear that Fuzzy based AHT has least value of MSE as compared to Otsu and K-means based AHT.

Table 9 Performance evaluation of F-measure on applying segmentation based AHT techniques on Curved lane images.

F-measure Evaluation			
IMG.	IMPROVED AHT		
	OTSU	FUZZY	K-MEANS
1	15.2197	97.9009	25.6197
2	97.9009	98.2197	96.6132
3	97.4138	99.1657	97.3522
4	27.7523	90.7637	77.6383
5	96.9569	98.8013	97.1735
Avg.	**67.0487**	**96.9702**	**78.8793**

Table 10 Performance evaluation of MSE on applying segmentation based AHT techniques on Far-view images.

MSE Evaluation			
IMG.	IMPROVED AHT		
	OTSU	FUZZY	K-MEANS
1	0.0943	0.0119	0.5014
2	0.3690	0.0210	0.0212
3	0.0504	0.0157	0.0156
4	0.0441	0.0196	0.0563
5	0.1443	0.0300	0.0410
6	0.0867	0.0032	0.0367
7	0.0515	0.0034	0.0742
8	0.1416	0.0017	0.2010
9	0.0325	0.0232	0.0247
10	0.0367	0.0227	0.0391
11	0.0565	0.0310	0.0322
12	0.0192	0.0168	0.0189
Avg.	**0.0939**	**0.0166**	**0.0885**

Table 11 Performance evaluation of MSE on applying segmentation based AHT techniques on Curved images.

MSE Evaluation			
IMG.	IMPROVED AHT		
	OTSU	FUZZY	K-MEANS
1	0.9493	0.0020	0.8963
2	0.0465	0.0211	0.0591
3	0.0504	0.0157	0.0516
4	0.8367	0.1282	0.3629
5	1.4766	0.0223	0.0547
Avg.	**0.6719**	**0.0378**	**0.2849**

Table 12 Performance evaluation of MSE on applying segmentation based AHT techniques on Near-view images.

MSE Evaluation			
IMG.	IMPROVED AHT		
	OTSU	FUZZY	K-MEANS
1	0.9493	0.0020	0.8963
2	0.0599	0.0336	0.2591
3	0.0465	0.0211	0.0591
4	0.0821	0.0159	0.2465
5	0.0055	0.0010	0.0089
6	0.0836	0.0184	0.1024
7	0.0665	0.0145	0.0503
8	0.0629	0.0053	0.0421
9	0.0972	0.0110	0.0602
10	0.0918	0.0016	0.1056
11	0.3025	0.0153	0.3591
12	0.1829	0.0262	0.3165
Avg.	**0.1692**	**0.0138**	**0.2088**

From the experiments and performance measures, it is clear that Fuzzy based Hough Transform yields better lane detection results for three types of image sets than Otsu and K-means based AHT and is capable to detect lanes from far-view and near view of image as well as to detect straight or curved road lanes.

4.2 Fuzzy based Hough Transform:

Fuzzy based Hough Transform technique is implemented on the three sets of road images containing lane marks. The enhanced lane detection results are obtained by Fuzzy based

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HT as compared to AHT technique. Fig. 5 shows the enhanced lane detection results of original image obtained by using AHT and Fuzzy based HT techniques. Performance evaluation Tables 13, 14, 15 are showing the comparison and complete analysis of AHT and Fuzzy based HT techniques. In Table 13, for the Far-view images, the average values of Accuracy, F-measure and MSE obtained by AHT and Fuzzy based Hough Transform techniques are shown. From the table values, it is clear that the results of Fuzzy based Hough transform technique are more accurate as compare to AHT technique.

(a) (b) (c)

Fig.5 (a) Input Image (b) AHT lane detected Image (c) Fuzzy based Improved HT lane detected Image.

Table 13 Performance evaluations of Accuracy, F-measure and MSE on applying AHT and Fuzzy based HT techniques on Far-view images.

IMG.	ACCURACY		F-MEASURE		MSE	
	AHT	Fuzzy based HT	AHT	Fuzzy based HT	AHT	Fuzzy based HT
1	0.4259	0.9881	62.8741	99.4013	0.5310	0.0119
2	0.5891	0.9790	71.4368	98.9357	0.3935	0.0210
3	0.9173	0.9843	93.7638	99.1657	0.0779	0.0157
4	0.8906	0.9804	92.1536	98.9448	0.0601	0.0196
5	0.8261	0.9700	87.3642	98.4624	0.1587	0.0300
6	0.9083	0.9968	91.7680	99.5355	0.0900	0.0032
7	0.8957	0.9966	94.5796	99.8326	0.0781	0.0034
8	0.9310	0.9780	90.2926	99.8169	0.2105	0.0017
9	0.8196	0.9983	93.2478	98.8407	0.0397	0.0232
10	0.9279	0.9768	87.4965	99.9006	0.0429	0.0227
11	0.9201	0.9773	92.7543	98.4313	0.0631	0.0310
12	0.9486	0.9832	90.7462	98.4284	0.2114	0.0168
Avg.	**0.8334**	**0.9841**	**87.3731**	**99.1413**	**0.1630**	**0.0166**

Table 14 Performance evaluations of Accuracy, F-measure and MSE on applying AHT and Fuzzy based HT techniques on Near-view images.

IMG.	ACCURACY		F-MEASURE		MSE	
	AHT	Fuzzy based HT	AHT	Fuzzy based HT	AHT	Fuzzy based HT
1	0.1834	0.9980	11.0130	97.9879	0.9527	0.0020
2	0.6982	0.9664	82.9742	97.6440	0.2942	0.0336
3	0.8860	0.9789	92.7481	98.9057	0.0963	0.0211
4	0.7089	0.9841	82.7952	98.8982	0.2840	0.0159
5	0.9581	0.9999	95.1009	99.9972	0.0176	0.0010
6	0.8509	0.9816	89.9745	98.7349	0.2067	0.0184
7	0.8862	0.9855	92.4978	99.0822	0.1132	0.0145
8	0.9359	0.9947	95.7201	99.7182	0.0798	0.0053
9	0.8660	0.9890	90.3478	99.3457	0.1392	0.0110
10	0.8446	0.9984	90.8119	99.9116	0.2510	0.0016
11	0.5982	0.9847	74.2940	98.8995	0.3823	0.0153
12	0.6391	0.9738	78.3495	98.0860	0.3341	0.0262
Avg.	**0.7546**	**0.9863**	**81.3855**	**98.9342**	**0.2625**	**0.0138**

Table 15 Performance evaluations of Accuracy, F-measure and MSE on applying AHT and Fuzzy based HT techniques on Curved lane images.

IMG.	ACCURACY		F-MEASURE		MSE	
	AHT	Fuzzy based HT	AHT	Fuzzy based HT	AHT	Fuzzy based HT

1	0.1979	0.9980	12.7569	97.9009	0.9406	0.0020
2	0.9167	0.9789	94.3715	98.2197	0.0981	0.0211
3	0.8892	0.9843	93.6473	99.1657	0.0982	0.0157
4	0.1379	0.8718	24.8413	90.7637	0.8796	0.1282
5	0.8856	0.9777	92.9309	98.8013	2.9645	0.0223
Avg.	**0.6054**	**0.9621**	**63.7095**	**96.9702**	**0.9962**	**0.0378**

From subjective analysis and performance measures, it is observed that Fuzzy based HT technique gives more accurate lane detection results than AHT technique.

5. CONCLUSION

The lane detection technique is an essence of Intelligent Transportation Systems. It has been found that the value used to segment the image in lane detection algorithm is taken as static. To overcome this limitation, we have introduced a modified Hough approach that uses different adaptive segmentation techniques like Otsu, Fuzzy and K-means clustering to enhance the segmentation results which in turn results in better lane detection. The proposed technique is implemented on a database of more than 25 road images that is further divided into three image sets based on images captured by the camera from Far-view, near-view and curved. From quality measures, it has been analyzed that the value obtained by Fuzzy based HT technique is more efficient than HT and AHT techniques. Fuzzy based Hough Transform technique yields more accurate results for Far-view, Near-view and Curved images than other techniques. Therefore, the proposed technique is capable to detect straight as well as curved lanes. In the future, we will further enhance the results of this technique using filters in order to remove the noise from the road image.

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