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Real-Time Lane Detection and Tracking for Advanced Driver Assistance Systems

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Abstract: Due to the fast-growing industry of intelligent vehicles the advanced driver assistance system (ADAS) has engrossed a lot of attention of the scholars. One of the biggest hurdles for new autonomous vehicles is to detect curvy lanes, multiple lanes, and lanes with a lot of discontinuity and noise. The purpose of this paper is to analyze the possibilities of image processing techniques for a computer vision application focusing on the problem of lane detection to enable traffic safety and driving comfort. The proposed algorithm is a combination of two sub-algorithms. The first sub-algorithm called Fuzzy Noise Reduction Filter (FNRF); removes the noise and smoothen the sequences of images received by the camera. While the second sub-algorithm aims to detect lane in normal as well as challenging scenarios by applying the concept of Hough Transform (HT) with a capable region of interest. The novelty of the proposed research study is the tracking of the lanes under inclement weather and challenging lightening conditions with improved computational time. The result achieved through our proposed algorithm is satisfactory in video sequences captured on several road types and under very challenging lighting and weather conditions.

Key Words: Advanced Driver Assistance System (ADAS), Hough Transform, Edge Detection, Lane Detection, Fuzzy Noise Reduction Filter (FNRF).

1 Introduction

The need for autonomous vehicles has dramatically increased in the last few years due to growing traffic levels and progressively busier roads across the globe. As a result, an intelligent driver assistance system should be developed for road safety, which either generates an alert in dangerous situations to the driver or takes action in the driving. In the coming decades, such systems will grow more complex to provides full autonomy of the vehicle. In particular, there are two main elements in the development of such autonomous systems, which are lane and obstacle (i.e., objects like vehicles, bicycles, pedestrian, etc.) detection.

In today’s automobiles, machine vision systems play a vital role in providing safety features for advanced driver assistance systems. Hence, enormous academic scholar and engineers have been developed different features using machine vision for the autonomy of intelligent vehicles; these features include but not limited to the Lane Departure Warning (LDW) [2], Adaptive Cruise Control (ACC) [3], Lane Centering (LC) [4], Lane Change Assistance (LCA) [5], Lane Keeping Assistance (LKA) [6], Full autonomous driving for cross country driving [7,8] and so on. But lane detection is the most essential feature of an advanced driver assistant system because it provides essential information that supports driving safety. In this paper, lane detection and tracking algorithm are proposed for machine-vision-based systems.

There are mainly two types of vision-based approaches for lane detection and tracking; namely, feature-based and model-based approach. In this study, we used feature-based strategies for lane detection analyzation. In most of the cases the significant challenges for the lane detection and tracking algorithm are the reduced visibility due to bad weather condition, disconnectivity of lines, lack of clarity of lane markings, shadows, illumination and light reflection, and dense road-based instructions [9]. Numerous scholars have been introduced various feature-based approaches for lane detection and marking [10-14]. Otsuka developed multi-type lane marker recognition (MLR) based on the focus of expansion to detect lane markers [10].

Similarly, an ant colony optimization (ACO) has been developed on canny for edge detection and then further processed by Hough transform to detect by Daigavane [11]. Other feature-based approaches produce the colour information in the images for lane detection and tracking [15–17]. Although the algorithms as mentioned earlier provide very appealing results, there are still noise issues, and these approaches may not perform very well in challenging weather or light condition due to the noise problem. Therefore, various scholars used hybrid approaches which contain a noise reduction filter along with lane detection algorithm.

To get lane detection precision, various image pre-processing practices are used by several scientists. These techniques include; histogram equalization [24], Canny edge detector [25], polyline extraction [26], clustering [27], smoothing, and the spitting of an image [28] and the application of a Gaussian low-pass filter to remove noise [29] and so on. For noise reduction in the sequence of images, several fuzzy filters have already been developed [18-23]. Nachtegael has been introduced a fuzzy filter for noise reduction to deal with the complex Gaussian noise in the image [19]. Likewise, Schulte developed a novel fuzzy-based wavelet shrinkage image denoising algorithm for the removal of additive Gaussian noise from digital greyscale photos [20]. Kwan carried out a comparative study of four fuzzy filters with standard median and moving average filters for different kinds of noises and concluded

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that fuzzy filters produce excellent results over standard filters [22]. Mostly these filters are developed reduction of impulse noise, and therefore these fuzzy techniques do not provide impressive results for additive noise. Another major shortcoming of these methods is that they are designed for grayscale images. To fill the gap, it is possible to extend these filters to colour images and further sequences of images (real-time video captured by a camera) by applying them to each colour element independently. Consequently, this paper presents a simple fuzzy based algorithm for filtering the colour sequence of images received by the car-mounted camera. To get an intact (e.g., edges, colour component distances, etc.) lane detection for advanced driver assistance a fuzzy noise reduction filter (FNRF) algorithm used to remove the noise in the sequence of the image.

Lower computational time and complexity are always being a requirement for a robust algorithm that to be implemented in a real-time lane detection and tracking purposes of an autonomous vehicle. Similarly, in this paper, robust, fast and straightforward lane detection and tracking algorithms are proposed that consists of two sub-algorithms; i.e., fuzzy noise reduction filter and Hough transform algorithms.

2 Proposed Algorithms

The main components of the proposed algorithm are fuzzy noise reduction filter, a region of interest, segmentation, and Hough transform as shown in Figure 1 and 2. Image pre-processing using the fuzzy noise reduction filter (FNRF) is designed. In the very first stage, a video sequence is fed and scaled down into a low resolution to 255x255 pixels. In the next step, the input coloured lane image sequence is fed into the fuzzy noise reduction filter.

Similarly, a grayscale image sequence is achieved after filtering the input coloured lane image sequence. The Grayscale values are normalized to the range [0, 1] where ones (1) represent the edges (white pixels) whereas zeroes (0) mean non-edges (black pixels). Lastly, the Hough transform technique is used to detect and track the lane after the complete pre-processing of the image sequence. The FNRF is used to remove the noise and improve the contrast level of the input image sequence, particularly the ROI.

2.1 Fuzzy Noise Reduction Filter

The objective of this filter is to average the pixel values by using the neighborhood pixel. At the same time, the edges of the image sequence and color component distances are kept intact in order not to destroy the vital structure of the images sequences. The main concern of the proposed filter is to distinguish between the variations occurred in the image sequences structure such as edges due to the noise. The uniqueness, which gives to this filter over other standard filters, is the use of membership functions to calculate the weights.

The noisy input color image-sequence can be denoted as $M(x,y,z)$ where $z=1,2,3$ for a specific pixel position of red, green, and blue component respectively. Therefore, for pixel position three elements are used to define the color. Furthermore, for each pixel position (x,y) of the color image we describe the following pairs:

Pair 1: The pair of red and green denoted as $RG(x,y)$ = $(M(x,y,1),M(x,y,2))$

Pair 2: The pair of red and blue indicated as $RB(x,y)$ = $(M(x,y,1),M(x,y,3))$

Pair 3: The pair of green and blue meant as $GB(x,y)$ = $(M(x,y,2),M(x,y,3))$

To filter the current image pixel at the position (x,y), we use the window of size $(2N+1)\times(2N+1)$ centered at (x,y). Similarly, individual weights are assigned to each pixel in the window with parameters of $p,q\in\{-N,...,N\}$ such as; $W(x+p,y+q,1)$ for red, $W(x+p,y+q,2)$ for green, and $W(x+p,y+q,3)$ for the blue component at the position $(x+p,y+q)$. These weights are assigned according to the following fuzzy rules.

First Fuzzy Rule: This fuzzy rule defines the weights $W(x+p,y+q,1)$ *for the red component of the neighbor* $M(x+p,y+q,1)$*, such as;*

IF the distance between the pair $RG(x,y)$ and $RG(x+p,y+q)$ is small

AND the distance between the pair $RB(x,y)$ and $RB(x+p,y+q)$ is small

THEN the weight $W(x+p,y+q,1)$ is larger.

Second Fuzzy Rule: This fuzzy rule defines the weight $W(x+p,y+q,2)$ *for the green component of the neighbor* $M(x+p,y+q,2)$*, such as;*

IF the distance between the pair $RG(x,y)$ and $RG(x+p,y+q)$ is small

AND the distance between the pair $GB(x,y)$ and $GB(x+p,y+q)$ is small

THEN the weight $W(x+p,y+q,2)$ is large.

Third Fuzzy Rule: This fuzzy rule defines the weight $W(x+p,y+q,3)$ *for the blue component of the neighbor* $M(x+p,y+q,3)$*, such as;*

IF the distance between the pair $RB(x,y)$ and $RB(x+p,y+q)$ is small

AND the distance between the pair $GB(x,y)$ and $GB(x+p,y+q)$ is small

THEN the weight $M(x+p,y+q,3)$ is large.

Fourth Fuzzy Rule: This fuzzy rule defines the weight $W(x+p,y+q,1)$ *for the green component of the neighbor* $M(x+p,y+q,1)$*, such as;*

IF the distance between the pair $GR(x,y)$ and $GR(x+p,y+q)$ is large

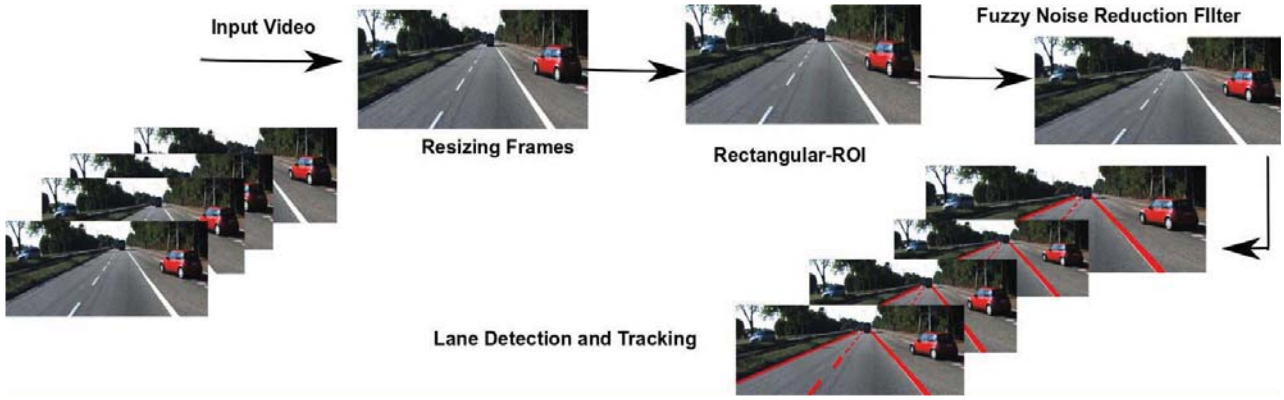

Fig. 1 Pipeline of the proposed approach: detection with the tracking function fuzzy noise reduction filter

AND the distance between the pair $BG(x,y)$ and $BG(x+p,y+q)$ is large

THEN the weight $M(x+p,y+q,1)$ is small.

Fifth Fuzzy Rule: This fuzzy rule defines the weight $W(x+p,y+q,2)$ for *the red component of the neighbor* $M(x+p,y+q,2)$*, such as;*

IF the distance between the pair $GR(x,y)$ and $GR(x+p,y+q)$ is large

AND the distance between the pair $BR(x,y)$ and $BR(x+p,y+q)$ is large

THEN the weight $M(x+p,y+q,2)$ is small

Sixth Fuzzy Rule: This fuzzy rule defines the weight $W(x+p,y+q,3)$ *for the blue component of the neighbor* $M(x+p,y+q,3)$*, such as;*

IF the distance between the pair $BG(x,y)$ and $BG(x+p,y+q)$ is large

AND the distance between the pair $BR(x,y)$ and $BR(x+p,y+q)$ is large

THEN the weight $M(x+p,y+q,3)$ is small

The two linguistic variables, i.e., *small* and *large* are assumed to define the weights for the red, green and blue components of the color image. As fuzzy rules usually represented by a membership function. Therefore, triangular membership functions are chosen for the first three rules while Gaussian membership is considered for the last three fuzzy rules. If the distance between the two couples is small, the weight will be significant and vice-versa. These fuzzy rules are used for reducing the noise among the color component differences. The calculation of the local variations in the red, green and blue environment separately give the local estimation of the central pixel.

2.2 Region of Interest

In the computational complexity, and lane detection and tracking the selection of a region of interest (ROI) plays an important role. The rectangular ROI is selected from the input image sequence and preserve left and right road lanes for further use of lane detection, as shown in Figure 3. A vanishing point (VP) is used in the rectangular ROI to remove the background part of the image (unwanted region of the image) which includes the region above the vanishing point (VP). The rectangular ROI helps to reduce the computational load of the designed lane detection and tracking algorithm. The lane detection algorithm is applied in the selected region of interest (ROI) for the estimation of the lane boundary in each frame.

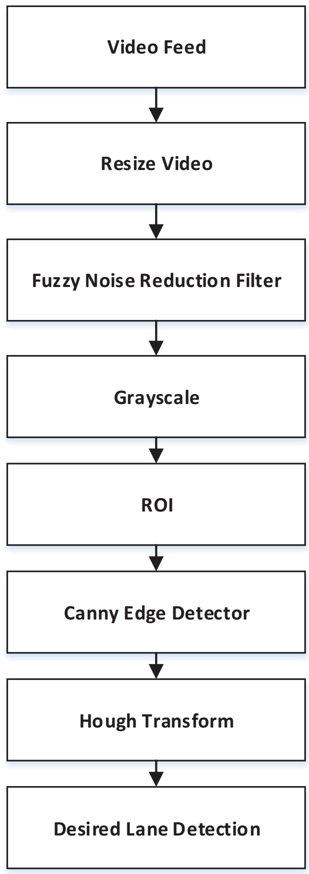

Fig. 2. Flowchart of the proposed algorithm

2.3 ROI Segmentation

The rectangular ROI is divided into two sub-regions, i.e., right and left as shown in Figure 3 (b). To get better performance in the next phase, we need to get a binary image with detected edges out of this phase. The binary image is valued 1 and 0 where ones (1) represent the edges (white pixels) whereas zeroes (0) mean non-edges (black pixels). Using the grayscale image and vanishing point (VP) saves time and give better performance because we

Fig.3. (a) Input source image

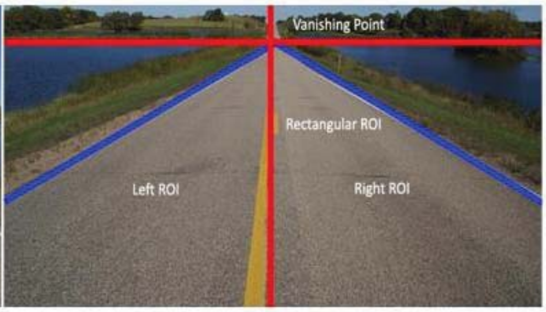

Fig.3. (b) Rectangular Region of interest

altogether remove the top half of the image above the VP as it is out of ROI. The lane detection is then carried out with the help of Hough transform (HT) in each subregion separately. Independently processing the segmented sub-regions reduces the computational load of the lane detection algorithm. Accordingly, the ROI segmentation process precisely enables better lane detection with a minimum time per frame.

2.4 Canny Edge Detector

The edges in the image can be defined by a sharp contrast between the road surface and painted lines. To determine the location of lane boundaries, an edge detector can be used. Using Canny edge detector algorithms, the edges are extracted from the initial grayscale images. A threshold value is defined, and the edges shorter than a threshold value are removed, and the surviving edges are clustered to form line segments. The output image with detected edges and a small amount of noise is shown in Figure 4.

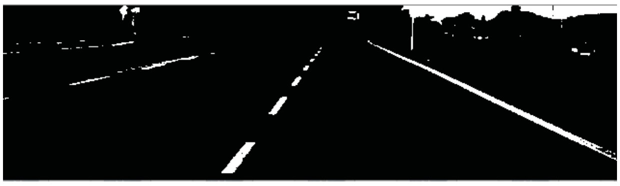

Fig. 4. Detection of the lane edges in ROI

In Figure 4 we can see that the Canny edge detector CED provided the most accurate results with little noise. Moreover, it delivered the output images with the lowest amount of white pixels which will generate better performance.

2.5 Detection of Lane Using Hough Transform

The Hough transform algorithm is used to detect the features of a particular shape within a grayscale image sequence. The significant advantage of the Hough transform algorithm is that, it is unaffected by noise in an image and uneven illumination. The Hough transform algorithm is applied to each sub-region to set of lane pixels to detect the lanes. The algorithm extracts the candidate features that are used to estimate the lane-related parameters. The accumulator cell is generated by Hough transform which can be represented as $C(\rho,\theta)$ [1]. The ρ can be expressed as follows;

$$\rho = x\cos\theta + y\sin\theta ,$$

Where ρ is the distance between the fitted line and origin while θ is the angle of the vector from the origin to this closest point, and x y is the coordinate value of a pixel. The range of θ is kept between 0° and 90°. The value associated with accumulator cell array is determined by θ, and the resulting ρ are added by 1, whenever $\rho = x\cos\theta + y\sin\theta$ is computed for θ. A local maximum in each accumulator array is searched to extract these points of intersection, map them back to Cartesian space and overlay this image on the original image to get the detected lane boundaries.

3 Experimental Results

The presented lane detection and tracking algorithm are implemented using C++ and OpenCV library with visual studio and Window 10. The purpose of this study is to operate the proposed algorithm in real time in vehicles. To evaluate the performance of the proposed algorithm, self-made dataset and Kitti dataset was used which includes different video clips captured in different countries; and light, weather conditions, and lane marking.

The proposed algorithm has been tested on image -sequences (video) captured in a variety of conditions; such as weather and light. In the proposed algorithm, the fuzzy noise reduction filter is used as the primary tracking function as well as to remove the noise and smoothen the edges by taking the neighborhood pixel into account. To achieve best results, first, we use FNRF for input image sequence and then find ROI to eliminate the background above the vanishing point. Furthermore, the segmentation techniques are used to get more precise edges of image sequences for further process. In Figure 5 (a) the Canny edge detector (CED) is used to detect the edges, while Hough transform is used to find the lane boundaries without using the tracking function the fuzzy noise reduction filter. In this part, the self-made dataset was used where we can only get a better result in gray form. But we can get a better result in color form of a real-time capturing video of the road by using FNFR with Hough Transform. Therefore, the results presented in Figure 5 (b) show the robust performance by using the tracking function fuzzy noise reduction filter and Hough transform. To measure the effectiveness of FNFR a more challenging dataset were used for these results. The FNFR algorithm totally removes the noise and smoothen the edges of the color sequences of images received from a camera mounted in the car and allow us to detect the lane precisely even in color form of real-time video. Since we can claim that the fuzzy noise reduction filter (FNFR) gives rigorous robustness and add novelty to the proposed algorithm. Also, the presented algorithm possess simplicity and less computational time. However, the planned algorithm cannot detect roads when the roads are fully covered by snow, or there are no lane markings at

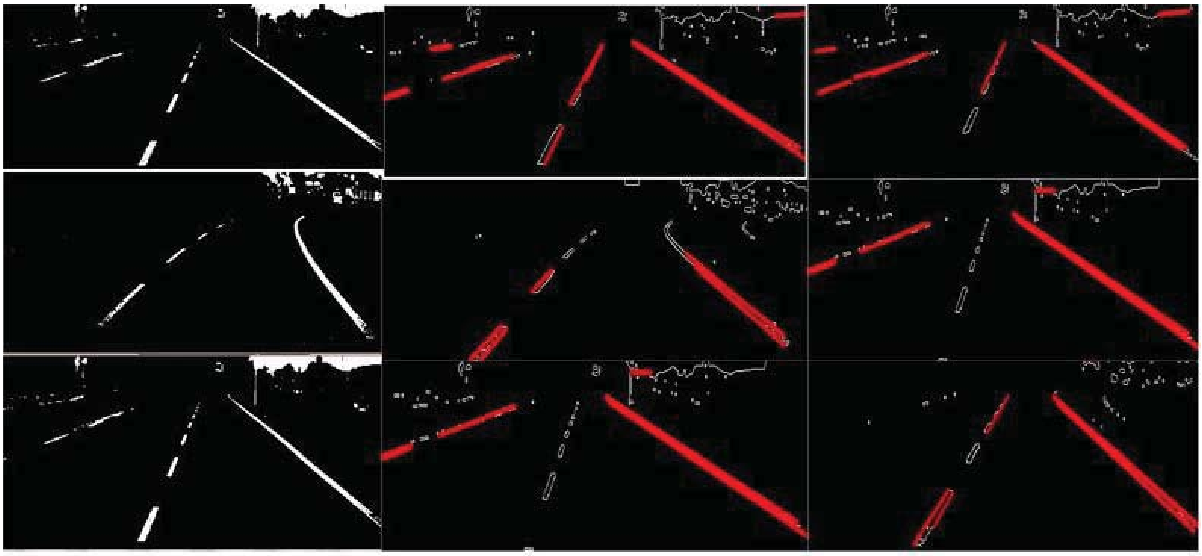

Figure 5. (a) Proposed algorithm without FNFR

Figure 5. (b) Proposed algorithm with FNFR

Fig. 5. Lane detection and tracking results under various road condition without FNFR and with FNFR

all. Table 1 shows the outstanding performance of the offered approach in terms of rectangular ROI and tracking function FNFR, in lane detection and tracking application for intelligent vehicles. The first column of Table 1 represents the road types; that is, multiple urban mark, urban mark, bright, shadow and dark road.

Similarly, the second column describes the detection rates of rectangular ROI in different road conditions. The third column shows the detection rate of Hough transform (HT) without tracking function FNFR while the fourth column shows the detection rates of Hough transform (HT) with monitoring function FNFR. The FNFR generates promising results, reduces the noise component and increases the detection rates with an average of 13.30%.

Table 1. The detection rate in rectangular ROI and in the HT without FNFR and with FNFR

Road Type	Rectangular ROI [%]	HT without FNFR Fcn [%]	HT with FNFR Function [%]
Urban multiple marked	82.5	84.5	98.44
Urban mark	81.3	86.3	97.8
Clear road	83.2	87.6	99.2
Shadow road	52.4	61.7	94.3
Dark road	41.3	53.4	92.1

4 Conclusion

In this study, computer vision techniques were used for lane detection and tracking purpose of autonomous driving assistance systems (ADAS). We proposed an effective and robust algorithm for the detection and tracking of the lane. The proposed algorithm is straightforward which is mainly based on fuzzy noise reduction filter (FNRF) and Hough Transform (HT). Firstly, FNRF is used to increase the contrast level of the ROI, which can improve the lane detection rate. Secondly, the segmentation of the region of interest is carried out to detect lane boundaries in each region of ROI. This way we can reduce the computational time of the proposed algorithm for lane detection. Finally, the Hough transform techniques are used to detect the boundaries of the lane. In short, the proposed algorithm computational time is less, and the performance is very high and robust compared to other classical techniques. Also, the designed algorithm is successful and verified with real videos and images under diverse lighting conditions.

5 Future Work

The authors aim to extend this study to include object detection on the road with lane detection and tracking. It will give more autonomy to the ADAS of intelligent vehicle. Moreover, we can add the feature of the alert system to the algorithm; Like, if the object (Car, Bike, Pedestrian) detected in the camera so that the car speed should be controlled accordingly.

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