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Lane Line Detection using Hough Transform and Convolutional neural Networks(CNN)

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Abstract - *Lane line may be a crucial reference for safe driving. so on enhance the accuracy and real- time performance of lane line detection, a lane line detection algorithm supported improved Hough transform and CNN. Firstly, the lifting algorithm of wavelet is used to extract the low-frequency wavelet coefficients of the image, so on reduce the complexity of the image and improve the efficiency of image processing; Then Canny operator is used to detect the sting of the image region of interest, and threshold is automatically selected according to edge information for threshold processing; Finally, three constraints are proposed from two aspects of angle and lane width to reinforce the Hough transform to detect lane lines, and thus the right lane lines are fitted by linear regression method. Experiments show that the proposed algorithm has good correctness and real-time performance for lane line detection.*

***Key Words*: lane line detection, hough transform, convolutional neural networks.**

1. INTRODUCTION

In this, we discover the lane lines on the road by using some software which we are creating now. the power to spot and track lanes is cardinal for developing algorithms for driverless vehicles. In this, we'll determine the due to creating a software pipeline for tracking road lanes using computer vision techniques. we'll approach this task through two different approaches. they're hough transform method and Convolutional Neural Networks (CNN). Lane lines could even be an important reference for safe driving. so on enhance the accuracy and real-time performance of lane line detection, a lane line detection algorithm supported improved Hough transform is proposed during this paper. Firstly, the lifting algorithm of wavelet is employed to extract the low-frequency wavelet coefficients of the image, so on reduce the complexity of the image and improve the efficiency of image processing; Then Canny operator is used to detect the sting of the image region of interest, and therefore the threshold is automatically selected consistent with edge information for threshold processing; Finally, three constraints are proposed from two aspects of angle and lane width to strengthen the Hough transform to detect lane lines, and thus the right lane lines are fitted by a rectilinear regression method. There are a variety of steps in detecting lanes on a road that first involves camera calibration. Cameras use curved lenses to make an image, and light-weight rays often bend slightly an excessive amount of or insufficient at the edges of these lenses. A Convolution Neural Networks (CNN) model is employed to rectify the classification and localization issues for semantic segmentation of lane.

2. RELATED WORK

Most lanes are designed to be relatively straightforward not only on encourage orderliness but also to form it easier for human drivers to steer vehicles with consistent speed. Therefore, our intuitive approach could even be to first detect prominent straight lines within the camera feed through edge detection and have extraction techniques. we'll be using OpenCV, an open-source library of computer vision algorithms, for implementation.

Basic Block Diagram:

The Hough transform could even be a feature extraction technique utilized in image analysis, computer vision, and digital image processing. the aim of the technique is to hunt out imperfect instances of objects within a selected class of shapes by a voting procedure.

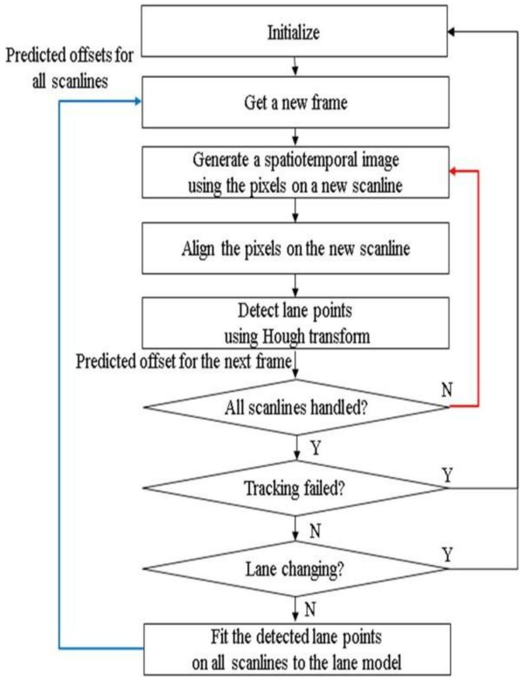


Fig 1. Block diagram

3. PROPOSED METHODOLOGY

3.1.Hough transfom

3.1.1 ApplyingCanny Detector

The Canny Detector is a multi-stage algorithm optimized for fast real-time edge detection. the elemental goal of the algorithm is to detect sharp changes in luminosity (large gradients), as a shift from white to black, and defines them as edges, given a set of thresholds. The Canny algorithm has four main stages:

3.1.2 Noise reduction

As with all edge detection algorithms, noise may be a crucial issue that often leads to false detection. A 5x5 Gaussian filter is applied to convolve (smooth) the image to lower the detector's sensitivity to noise. This is done by using a kernel (in this case, a 5x5 kernel) of normally distributed numbers to run across the entire image, setting each pixel value equal to the weighted average of its neighboring pixels.

$$\mathbf{B} = \frac{1}{159}\begin{bmatrix} 2 & 4 & 5 & 4 & 2 \\ 4 & 9 & 12 & 9 & 4 \\ 5 & 12 & 15 & 12 & 5 \\ 4 & 9 & 12 & 9 & 4 \\ 2 & 4 & 5 & 4 & 2 \end{bmatrix} * \mathbf{A}$$

5x5 Gaussian kernel. The asterisk denotes convolution operation.

3.1.3 Intensity gradient

The smoothened image is then applied with a Sobel, Roberts, or Prewitt kernel (Sobel is employed in OpenCV) along the x-axis and y-axis to detect whether the edges are horizontal, vertical, or diagonal.

$$Edge\_Gradient\ (G) = \sqrt{G_x^2 + G_y^2}$$

$$Angle\ (\theta) = \tan^{-1}\left(\frac{G_y}{G_x}\right)$$

Fig 2: Sobel kernel for calculation of the primary derivative of horizontal and vertical directions

3.1.4 Non-maximum suppression

Non-maximum suppression is applied to "thin" and effectively sharpen the edges. For each pixel, the value is checked if it is a local maximum in the direction of the gradient calculated previously.

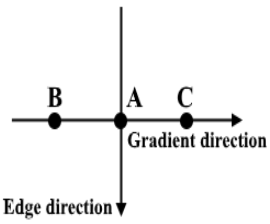


Fig 3. Non-maximum suppression on three-point

A is on the edge with a vertical direction. As gradient is normal to the edge direction, pixel values of B and C are compared with pixel values of A to determine if A is a local maximum. If A is local maximum, non- maximum suppression is tested for the next point. Otherwise, the pixel value of A is set to zero, and A is suppressed.

3.1.5 Hysteresis thresholding

After non-maximum suppression, strong pixels are confirmed to be in the final map of edges. However, weak pixels should be further analyzed to determine whether it constitutes an edge or noise. Applying two pre-defined minVal and maxVal threshold values, we set that any pixel with intensity gradient above maxVal are edges, and any pixel with intensity gradient less than minVal aren't edges and discarded. Pixels with intensity gradient in between minVal and maxVal are only considered edges if they're connected to a pixel with intensity gradient above maxVal.

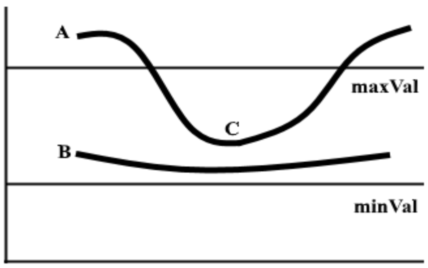


Fig 4. Hysteresis thresholding example on two lines

Edge A is above maxVal so is taken into account a foothold . Edge B is in between maxVal and minVal but isn't connected to any edge above maxVal so is discarded. Edge C is in between maxVal and minVal and is connected to edge A, a foothold above maxVal, so is taken into account a foothold. For our pipeline, our frame is first grayscaled because we only need the luminance channel for detecting edges, and a 5 by 5 Gaussian blur is applied to decrease noise to scale back false edges.

3.1.6 Segmenting line area

We will handcraft a triangular mask to segment the lane area and discard the irrelevant areas within the frame to extend the effectiveness of our later stages. The triangular mask are going to be defined by three coordinates, indicated by the green circles.

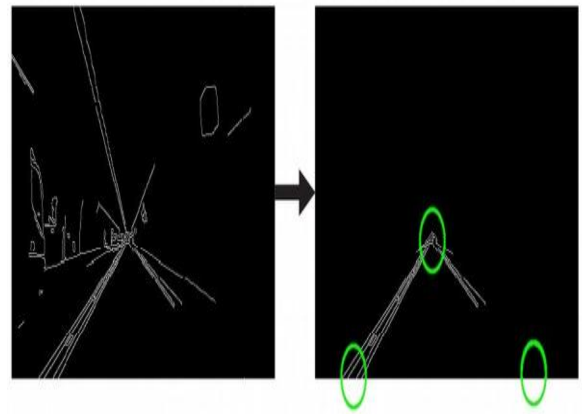
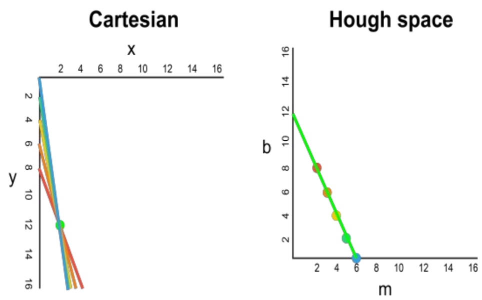


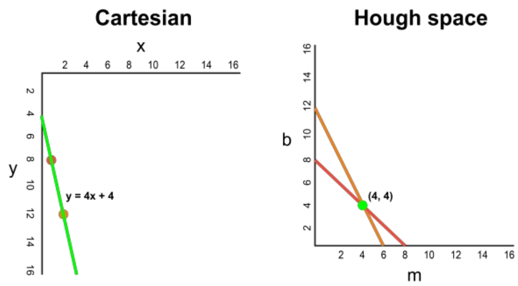
Fig 4. The triangular mask are going to be defined by three coordinates, indicated by the green circles.

3.1.7 Applying Hough transform

In the Cartesian frame of reference , we will represent a line as y = mx + b by plotting y against x. However, we will also represent this line as a single point in Hough space by plotting b against m. for instance , a line with the equation y = 2x + 1 could also be represented as (2, 1) in Hough space. Now, what if rather than a line, we had to plot some extent within the coordinate system. There are many possible lines which will undergo now , each line with different values for parameters m and b. For example, a point at (2, 12) can be gone by y = 2x + 8, y = 3x + 6, y = 4x + 4, y =5x + 2, y = 6x, and so on. These possible lines are often plotted in Hough space as (2, 8), (3, 6), (4, 4), (5, 2), (6, 0). Notice that this produces a line of m against b coordinates in Hough space.



Whenever we see a series of points during a frame of reference and know that these points are connected by some line, we'll find the equation of that line by first plotting each point within the frame of reference to the corresponding line in Hough space, then finding the aim of intersection in Hough space. the aim of intersection in Hough space represents them and b values that pass consistently through all of the points within the series.



Since our frame skilled the Canny Detector could also be interpreted simply as a series of white points representing the edges in our image space, we'll apply the same technique to identify which of those points are connected to an equivalent line, and if they're connected, what its equation is so as that we'll plot this line on our frame.

For the simplicity of explanation, we used Cartesian coordinates to correspond to Hough space. However, there's one mathematical flaw with this approach: When the road is vertical, the gradient is infinity and can't be represented in Hough space. to unravel this problem, we'll use Polar coordinates instead. the method remains an equivalent just that aside from plotting m against b in Hough space, we'll be plotting r against θ.

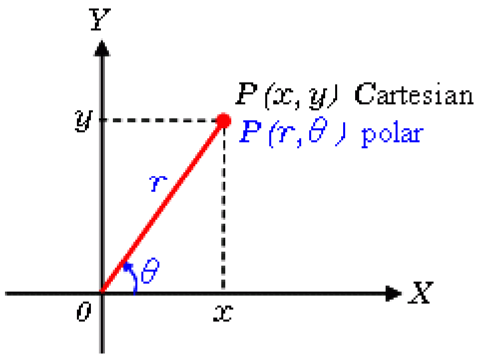
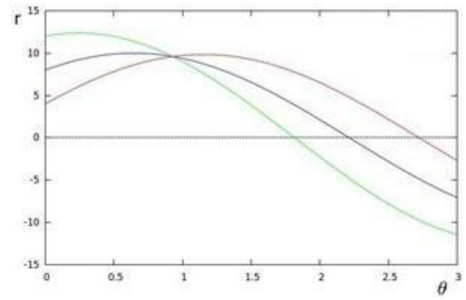


Fig 5. graph with Cartesian and polar

For example, for the points on the frame of reference with x = 8 and y = 6, x = 4 and y = 9, x =

12 and y = 3, we'll plot the corresponding

Hough space.



We see that the lines in Hough space intersect at θ = 0.925 and r = 9.6. Since a line within the frame of reference is given by r = xcosθ + ysinθ, we'll induce that one line crossing through of these points is defined as 9.6 = xcos0.925 + ysin0.925.

Generally, the more curves intersecting in Hough space means the road represented by that intersection corresponds to more points. For our implementation, we'll define a minimum threshold number of intersections in Hough space to detect a line. Therefore, Hough transform basically keeps track of the Hough space intersections of every point within the frame. If the quantity of intersections exceeds an outlined threshold, we identify a line with the corresponding θ and r parameters.

We apply Hough Transform to spot two straight lines which may be our left and right lane boundaries. The lane is visualized as two light green, linearly fitted polynomials which may be overlayed on our input frame.

3.2 Convolution Neural Networks (CNN)

It is the deep neural networks, most commonly applied to analyzing visual imagery. they have applications in image and video recognition, recommender systems, image classification, medical image analysis, language processing, and financial statistic . CNNs are great for extracting semantics from raw pixels but perform poorly on capturing the spatial relationships (e.g. rotational and translational relationships) of pixels during a frame. These spatial relationships, however, are important for the task of lane detection, where there are strong shape priors but weak appearance coherences.

For example, it's hard to figure out traffic poles solely by extracting semantic features as they lack distinct and coherent appearance cues and are often occluded.

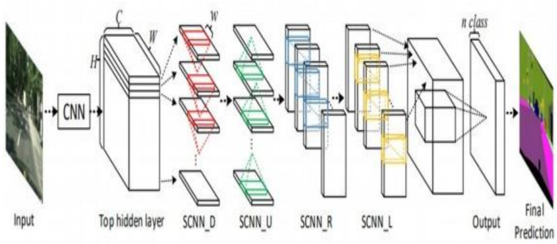


Fig 6. CNN

3.2.1 Traditional CNN

In a traditional layer-by-layer CNN, each convolution layer receives input from its preceding layer, applies convolutions and nonlinear activation, and sends the output to the succeeding layer. SCNN takes this a step further by treating individual feature map rows and columns because the "layers", applying an equivalent process sequentially (where sequentially means a slice passes information to the succeeding slice only after it's received information from the preceding slices), allowing message passing of pixel information between neurons within the same layer, effectively increasing emphasis on spatial information.

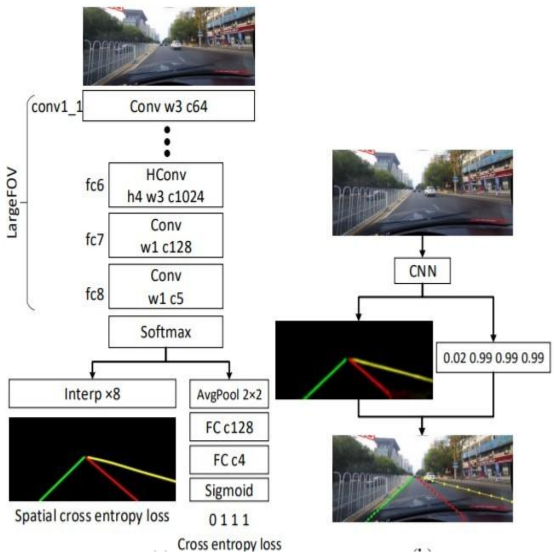


Fig 7. model of CNN

To determine whether if a lane marking is detected, the Intersection-over- Union (IoU) between the ground truth (correct labels) and prediction is calculated, where IoUs above a set threshold are evaluated as true positives (TP) to calculate precision and recall.

4. EXPERIMENTAL RESULTS AND CONCLUSION

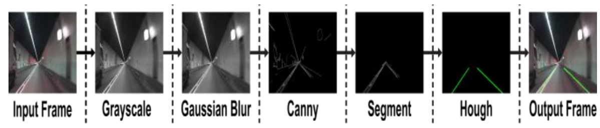


Fig 8. Total pipeline software

Firstly we need to take the input of road image. By doing some image processing we get the Gaussian blur image. That image should be done by segmentation process.

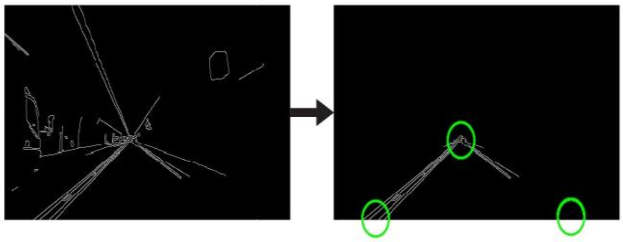


Fig 9. The triangular mask will be defined by three coordinates, indicated by the green circles.

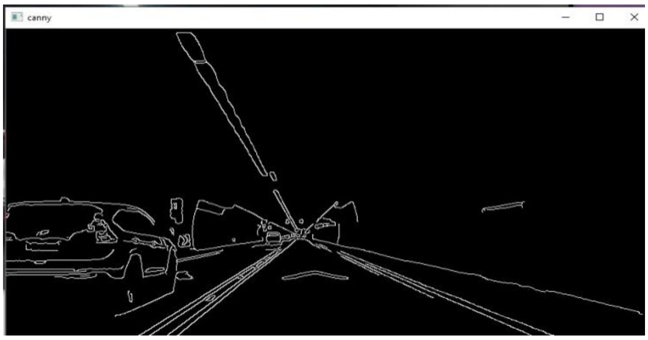


Fig 10. Canny image

Canny edge detector detected the wide range of edges in the input image and with edges, the image looks like the fig10

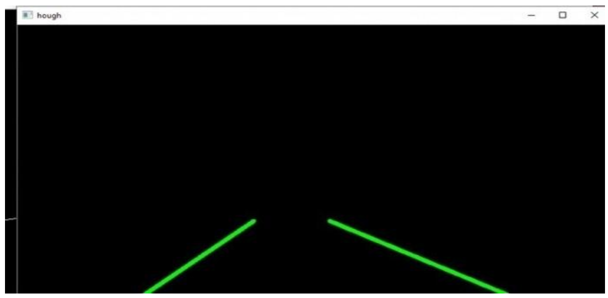


Fig 11. Hough transform image

This is extracted by the image analysis, computer vision, and digital image processing. It finds the imperfect instances of objects within a certain class of shapes.

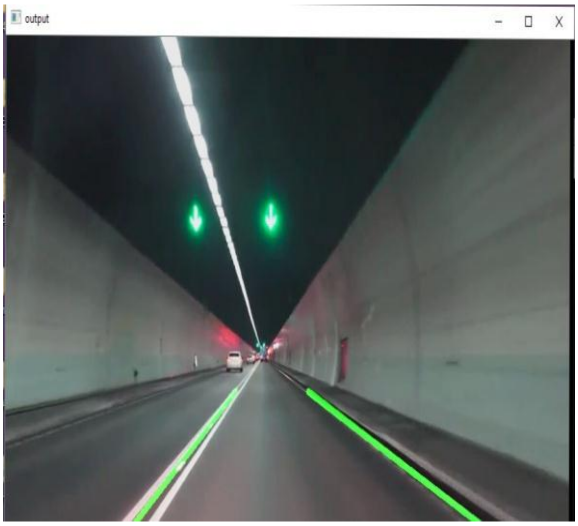


Fig 12. Final output

The final output shows the concept of Hough transform and Convolutional neural network.

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