Project 2 Simple Lane Detection Perception for Autonomous Robots-ENPM673 Report



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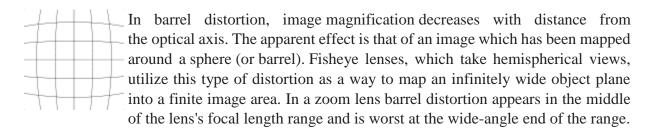
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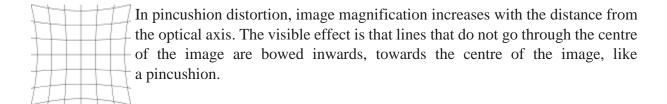
1. Definitions:

1.1 Distortion of an image: In geometric optics, distortion is a deviation from rectilinear projection; a projection in which straight lines in a scene remain straight in an image. It is a form of optical aberration.

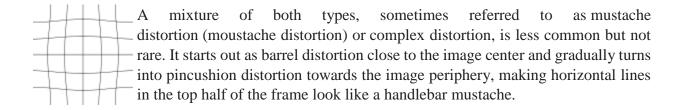
• Barrel Distortion:



• Pincushion Distortion:



Mustache Distortion:



1.2 Image Noise: Image noise is random variation of brightness or color information in images, and is usually an aspect of electronic noise. It can be produced by the sensor and circuitry of a scanner or digital camera.

Types of noise:

- Salt and pepper noise: Contains random occurrences of black and white pixels.
- Impulse noise: Contains random occurrences of white pixels
- Gaussian noise: Variation in intensity drawn form a gaussian normal distribution.

1.3 Edge Detection: Edge detection includes a variety of mathematical methods that aim at identifying points in a digital image at which the image brightness changes sharply or, more formally, has discontinuities. The points at which image brightness changes sharply are typically organized into a set of curved line segments termed edges. The same problem of finding discontinuities in one-dimensional signals is known as step detection and the problem of finding signal discontinuities over time is known as change detection. Edge detection is a fundamental tool in image processing, machine vision and computer vision, particularly in the areas of feature detection and feature extraction.

1.4 Homography Estimation: In the field of computer vision, any two images of the same planar surface in space are related by a homography (assuming a pinhole camera model). This has many practical applications, such as image rectification, image registration, or computation of camera motion—rotation and translation—between two images. Once camera rotation and translation have been extracted from an estimated homography matrix, this information may be used for navigation, or to insert models of 3D objects into an image or video, so that they are rendered with the correct perspective and appear to have been part of the original scene camera motion—rotation and translation—between two images. Once camera rotation and translation have been extracted from an estimated homography matrix, this information may be used for navigation, or to insert models of 3D objects into an image or video, so that they are rendered with the correct perspective and appear to have been part of the original scene.

1.5 Hough Transform: The Hough transform is a feature extraction technique used in image analysis, computer vision, and digital image processing. The purpose of the technique is to find imperfect instances of objects within a certain class of shapes by a voting procedure. This voting procedure is carried out in a parameter space, from which object candidates are obtained as local maxima in a so-called accumulator space that is explicitly constructed by the algorithm for computing the Hough transform.

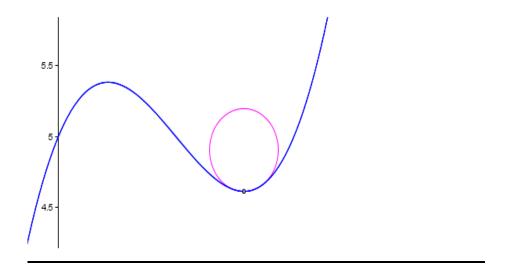
1.6 Histogram: A histogram is an accurate representation of the distribution of numerical data. It is an estimate of the probability distribution of a continuous variable.

1.7 Polynomial Regression: In statistics, polynomial regression is a form of regression analysis in which the relationship between the independent variable x and the dependent variable y is modelled as an nth degree polynomial in x. Polynomial regression fits a nonlinear relationship between the value of x and the corresponding conditional mean of y.

1.8 Curve Fitting: Curve fitting is the process of constructing a curve, or mathematical function, that has the best fit to a series of data points, possibly subject to constraints. Curve fitting can involve either interpolation, where an exact fit to the data is required, or smoothing, in which a "smooth" function is constructed that approximately fits the data.

1.9 Image Warp: Image warping is the process of digitally manipulating an image such that any shapes portrayed in the image have been significantly distorted. Warping may be used for correcting image distortion as well as for creative purposes. The same techniques are equally applicable to video.

1.10 Radius of curvature:



The radius of curvature of the curve at a particular point is defined as the radius of the approximating circle. This radius changes as we move along the curve.

The formula for radius of curvature is:

$$ext{Radius of curvature} = rac{\left[1+\left(rac{dy}{dx}
ight)^2
ight]^{3/2}}{\left|rac{d^2y}{dx^2}
ight|}$$

2. PROCEDURE:

- The first step is to **undistort the image**. Generally, camera lenses distort incoming light to focus on the camera sensor. Though its useful to capture images, it may distort the light significantly which may result in inaccurate measurements. So, we have undistorted the image using undistort function.
- Then we have used the **Gaussian blur** to denoise the image. It is also known as Gaussian smoothing. Mathematically, applying a Gaussian blur to an image is the same as convolving the image with a Gaussian function. Since the Fourier transform of a Gaussian is another Gaussian, applying a Gaussian blur has the effect of reducing the image's high-frequency components; a Gaussian blur is thus a low pass filter.
- After applying the Gaussian blur, we extract the **Hue**, **Saturation and Lightness (HSL)** values which would be used later in the code for isolating candidate lane pixels.
- After this step, we used the **perspective warp**. This is done by using the cv2.getPerspectiveTransform () function to get the **transformation matrix**. After that, we used the cv2.warpPerspective () function to warp the image. By taking an approximate of 4 points which form a trapezoid in the frame that can be mapped to a square on transformation.
- Then, use the **Sobel edge detector** to detect edges and get the gradient along the x direction.
- Using the HSL color space, we set a threshold for the lightness and saturation channels and binarize the image using this threshold.
- A histogram is obtained by adding the pixel values in the y direction of the binary image i.e it gives maximum value for the column with the maximum number of white pixels. This helps identify where the contrast is maximum to fit the two curves for the lane.

- After getting the histogram, we used sliding window algorithm to identify the pixels to
 fit the curve. By creating windows throughout the binary image and keeping only the
 windows with non-zero pixel values, we get the windows stacked according to the curve
 of the lane.
- Once the required windows are obtained, we use the polyfit() function and apply polynomial regression to plot the curve that fit the lane pixels.
- This is applied to the warped image and then the inverse perspective transform is used
 to transform it back to the original image and the lanes are overlaid on the original color
 frame.

3. RESULTS:



Fig1. Lane Detection



Fig 2. Lane detection in varied illumination setting

In our initial attempts to try various color spaces, we used HSV for color segmentation. However, we did not get satisfactory results when the illumination changes as shown in the below picture. Using Hough line transform did not seem ideal as our intention was to fit a curve to the lanes.



Fig 3. HSV segemntation results in varied illumination

Therefore we settled on using HSL color space for the segmentation.

Using the above stated formulas for radius of curvature we were able to calculate the left and right curvatures and based on the difference in curvatures, we tried to implement the turn prediction.



Fig 4. Left Turn Prediction



Fig 5. Right Turn Prediction

3. LIMITATIONS AND SCOPE FOR IMPROVEMENT

- Pipeline for implementation can be optimized further by splitting it into constituent methods that robustly handles adverse scenarios.
- Roust turn prediction using better curvature estimation techniques.
- Better curve fitting for lanes with sharp turns as the histogram calculated for that will be more spread out causing problems in lane detection.
- Making the lane prediction algorithm immune to the effect of shadows or the high gradient change on the shadow line such as the scenario in the challenge video.

4. REFERENCES:

- 1. https://www.cs.ubc.ca/grads/resources/thesis/May09/Dubrofsky_Elan.pdf
- 2. https://www.uio.no/studier/emner/matnat/its/UNIK4690/v16/forelesninger/le https://www.uio.no/studier/emner/
- 3. <u>Lane Detection Techniques- A Review</u>