Advanced Lane Finding Project

The goals / steps of this project are the following:

- Compute the camera calibration matrix and distortion coefficients given a set of chessboard images.
- Apply a distortion correction to raw images.
- Use color transforms, gradients, etc., to create a thresholded binary image.
- Apply a perspective transform to rectify binary image ("birds-eye view").
- Detect lane pixels and fit to find the lane boundary.
- Determine the curvature of the lane and vehicle position with respect to center.
- Warp the detected lane boundaries back onto the original image.
- Output visual display of the lane boundaries and numerical estimation of lane curvature and vehicle position.

Rubric Points

Here I will consider the rubric points individually and describe how I addressed each point in my implementation.

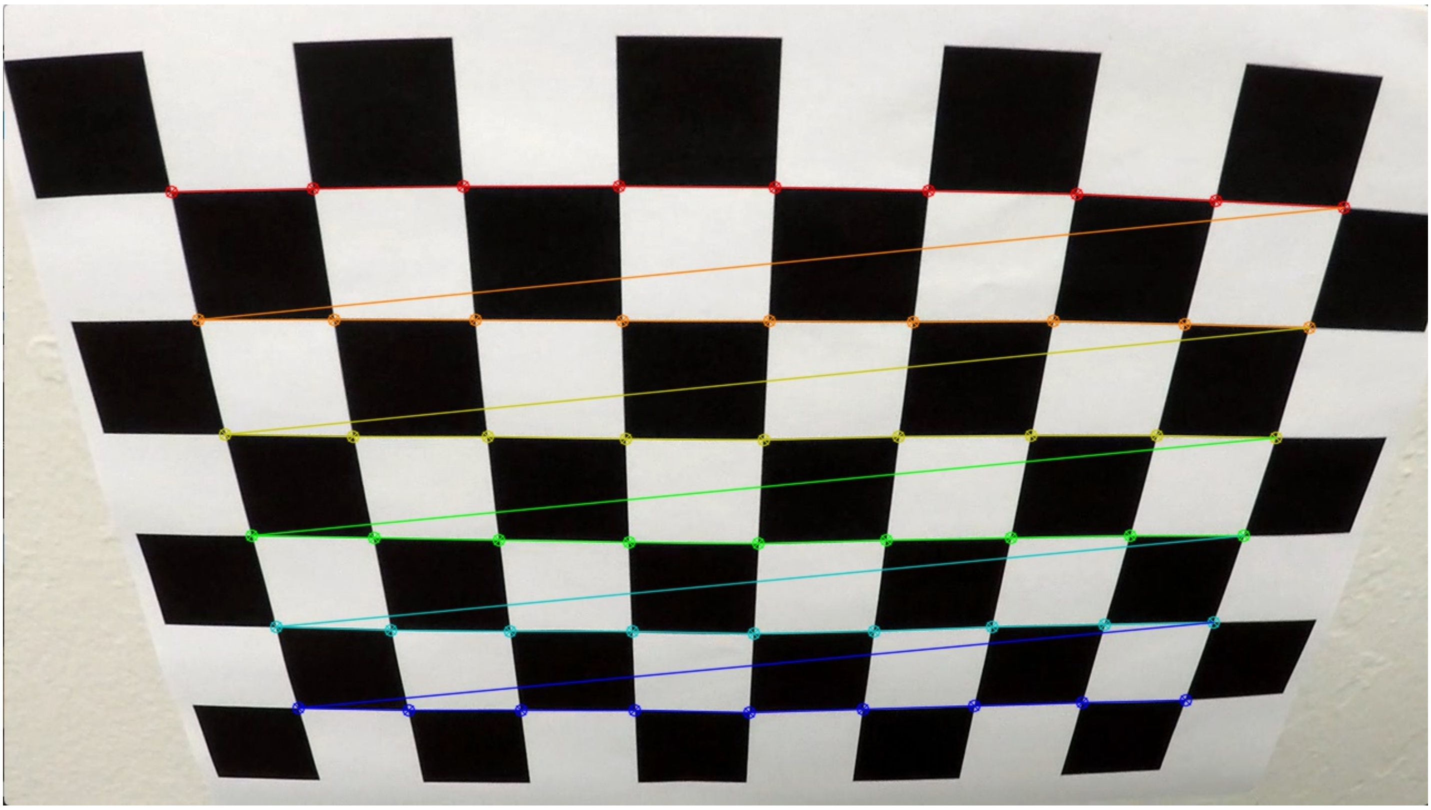
Writeup / README

Camera Calibration

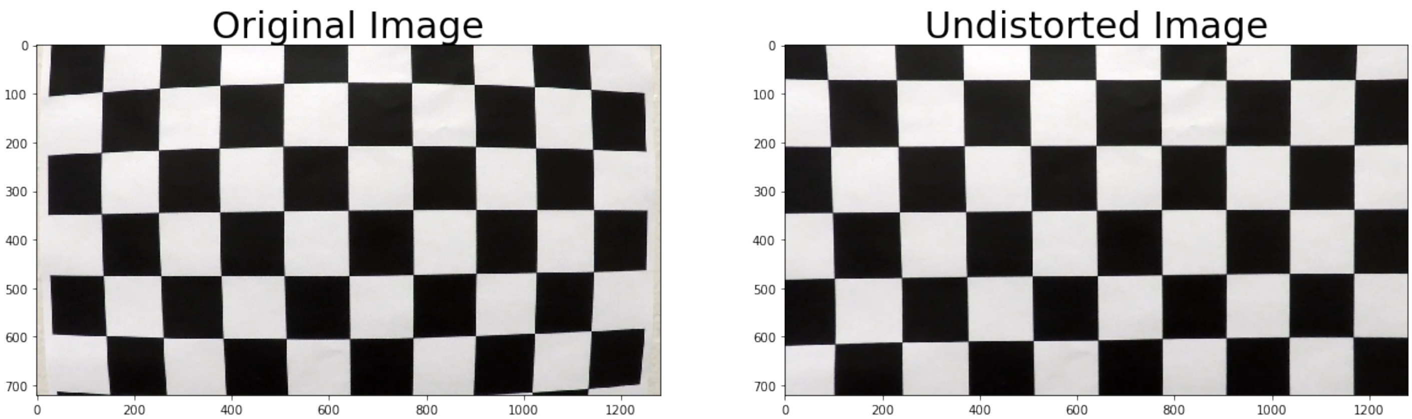
1. Briefly state how you computed the camera matrix and distortion coefficients. Provide an example of a distortion corrected calibration image.

The code for this step is contained in code cells [7] and [8] of the IPython notebook located in "model_v5.ipynb".

I start by preparing "object points", which will be the (x, y, z) coordinates of the chessboard corners in the world. Here I am assuming the chessboard is fixed on the (x, y) plane at z=0, such that the object points are the same for each calibration image. Thus, `objp` is just a replicated array of coordinates, and `objpoints` will be appended with a copy of it every time I successfully detect all chessboard corners in a test image. `imgpoints` will be appended with the (x, y) pixel position of each of the corners in the image plane with each successful chessboard detection.



I then used the output `objpoints` and `imgpoints` to compute the camera calibration and distortion coefficients using the `cv2.calibrateCamera()` function. I applied this distortion correction to the test image using the `cv2.undistort()` function and obtained this result:



Pipeline (single images)

1. Provide an example of a distortion-corrected image.

To demonstrate this step, I will describe how I apply the distortion correction to one of the test images like this one:

2. Describe how (and identify where in your code) you used color transforms, gradients or other methods to create a thresholded binary image. Provide an example of a binary image result.

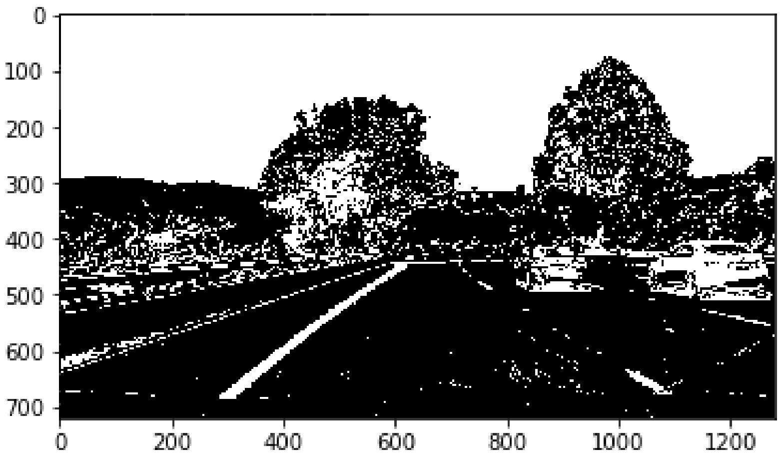
I used a combination of color and gradient thresholds to generate a binary image (thresholding steps at code cell [9]). Here's an example of my output for this step.

The combination of color transforms, gradients and thresholds that worked best in my case was:

Method	Parameters
Gradient X	sobel_kernel=5, thresh=(20, 255)
Gradient Y	sobel_kernel=5, thresh=(20, 255)
Combined Gradient Magnititude	sobel*kernel=5, mag*thresh=(60, 255)
Gradient Direction Threshold	sobel_kernel=5, thresh=(1.4, Pi/2)
HLS Colour Space Thresholding	Channel='S', thresh=(90, 255))

These were combined into a binary image using the logical operation below:

combined[((gradx == 1) & (grady == 1)) | ((mag*binary == 1) & (dir*binary == 1)) | (hls_binary==1)] = 1



3. Describe how (and identify where in your code) you performed a perspective transform and provide an example of a transformed image.

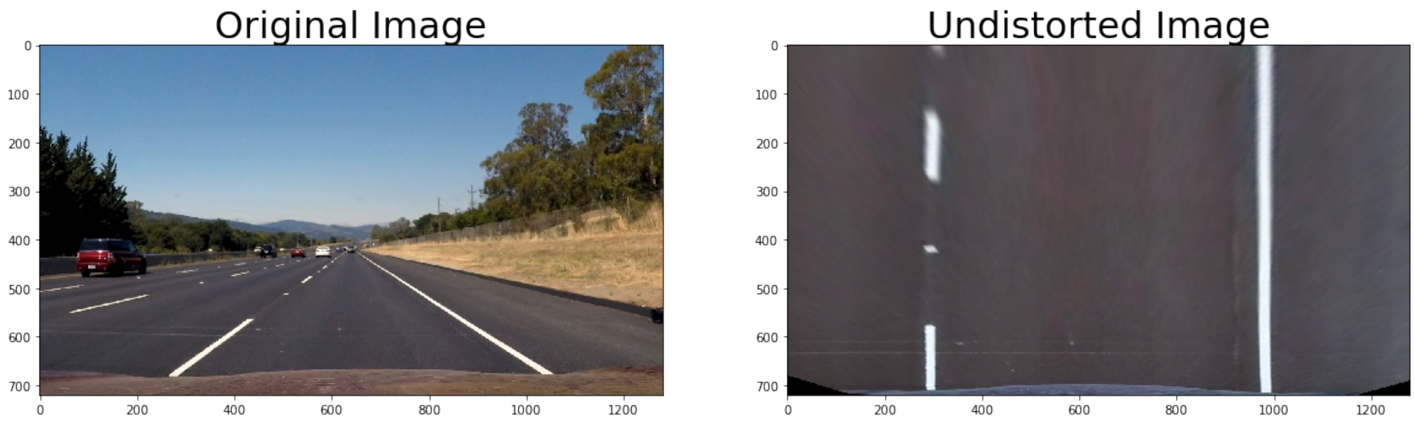
The code for my perspective transform includes a function called `reproject()` , which appears in code cell [8] in the file `model_v5.ipynb` . The `reproject()` function takes as inputs an image (`img`), as well as source (`src`) and destination (`dst`) points. I chose the hardcode the source and destination points in the following manner:

```
    src = np.float32([(200, 720), (580, 480), (720, 480), (1050, 700)])
    dst = np.float32([(280, 720), (400, 190), (920, 190), (960, 720)])
```

This resulted in the following source and destination points:

Source	Destination
200, 720	280, 720
580, 480	400, 190
720, 480	920, 190
1050, 700	960, 720

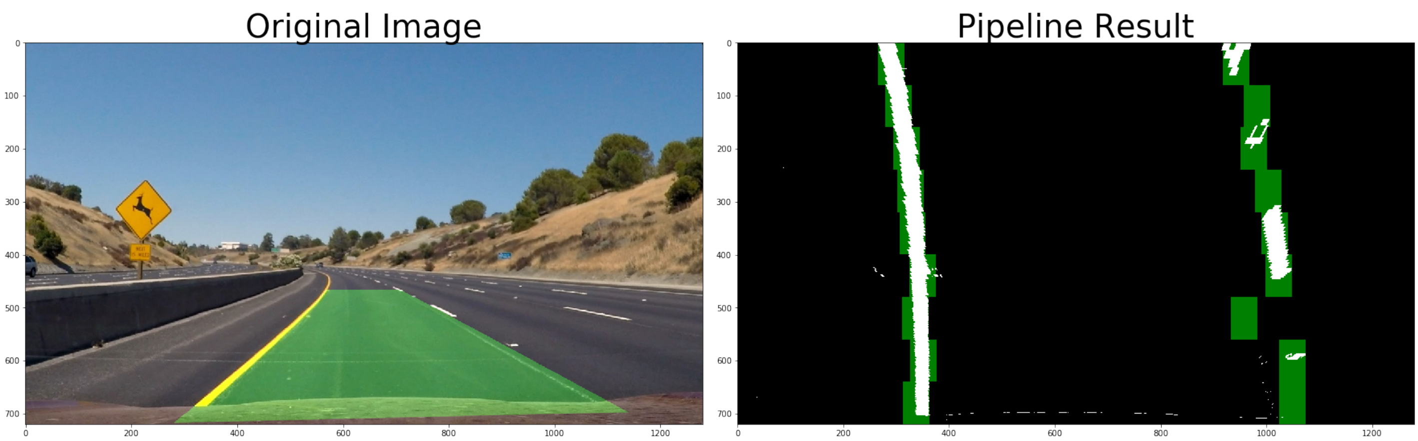
I verified that my perspective transform was working as expected by drawing the `src` and `dst` points onto a test image and its warped counterpart to verify that the lines appear parallel in the warped image.



4. Describe how (and identify where in your code) you identified lane-line pixels and fit their positions with a polynomial?

The code to identify lane pixels is in code cell [12]. Here I use a convolution to slide across the image to identify "hot" pixels. As the window slides across the image from left to right and any overlapping values are summed together, creating the convolved signal. The peak of the convolved signal is where there was the highest overlap of pixels and the most likely position for the lane marker. The output of this can be seen in the image labelled "Pipeline Result" below.

I then took these 18 convolved windows (9 each side) and used them to mark the "hot" pixels in the image where I gathered their (x,y) coordinates. I then took these points and fit a 2nd order polynomial to them using function `measureCurve()` in code cell [13]. The result of this can be seen in the figure below with the blue and red curves fitted.



Road Image with 2nd order polynomial

5. Describe how (and identify where in your code) you calculated the radius of curvature of the lane and the position of the vehicle with respect to center.

I did this in code cell [13] by using the derivation of the radius of a second order function. This result was in pixels so I multiplied through by the number of meters per pixel in the X and Y directions to convert the radius into the real world units of meters.

6. Provide an example image of your result plotted back down onto the road such that the lane area is identified clearly.

I implemented this step in code cell [16] in the function `carpetPlotter()`. It really does look like a green carpet. Here is an example of my result on a test image:

Pipeline (video)

1. Provide a link to your final video output. Your pipeline should perform reasonably well on the entire project video (wobbly lines are ok but no catastrophic failures that would cause the car to drive off the road!).

Here's a link to my video result

Discussion

1. Briefly discuss any problems / issues you faced in your implementation of this project. Where will your pipeline likely fail? What could you do to make it more robust?

I found that combining a combination of color transforms, gradient and thresholds worked best to detect the lane lines. I found when I only used the gradient and thresholding the lane lines often ended up hollow when using a kernel size of 5. I believe this is to do with the lane line being too flat in colour at this kernel size. When adding in the thresholding on the S channel of the HLS colour space I found these lane lines fill in.

My pipeline works well in sunny well lit videos. However, when large shadows appear, like in the challenge video, it has issues detecting the lane lines. This could be improved by using the H Channel of the HLS colour space which is less sensitive to shadows.