Advanced Lane Finding

Udacity Self Driving Engineer –Term 1 Project 4

Overview

The goals of this project are the following:

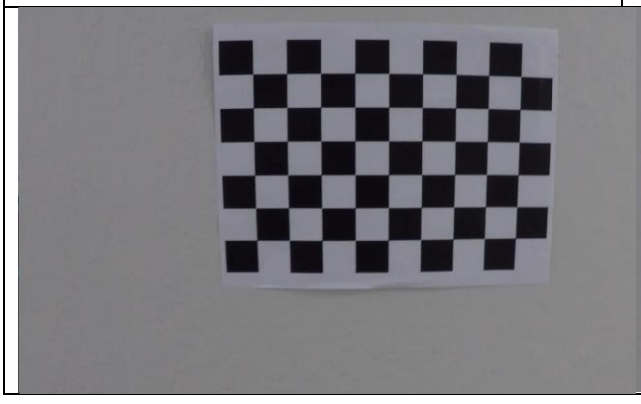
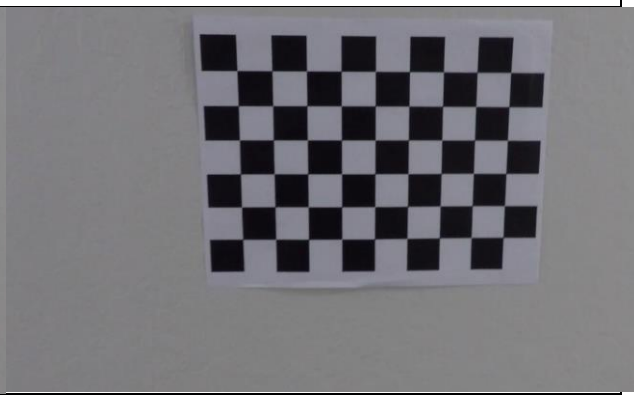
- Compute the camera calibration matrix and distortion coefficients given a set of chessboard images.
- Apply a distortion correction to raw images.
- Use color transforms, gradients, etc., to create a thresholded binary image.
- Apply a perspective transform to rectify binary image ("birds-eye view").
- 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.

The entire project code with relevant comments are implemented in advanced_lane_finding.py file.

Camera Calibration

The code for this step is contained in the function calibrate_camera(). 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.

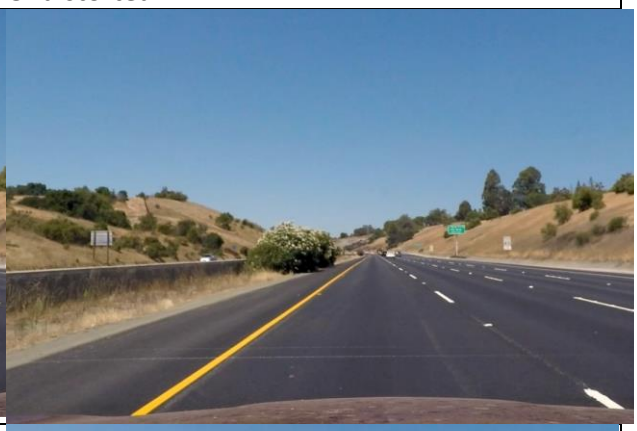
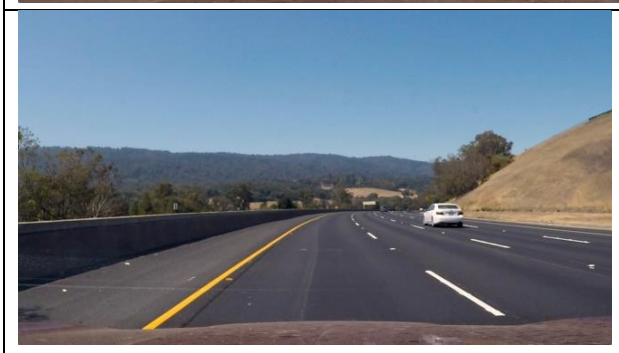
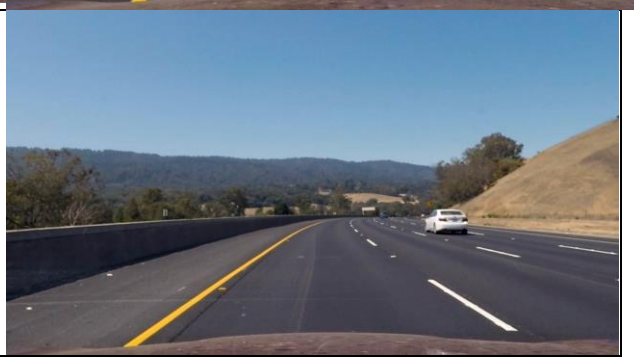
I then used the output objpoints and imgpoints to compute the camera calibration and distortion coefficients using the cv2.calibrateCamera() function. I applied this distortion correction to the test image using the cv2.undistort() function and obtained this results. The distortion coefficients thus found are used for further pipelining for images and video.

Distorted	Undistorted
	

Pipeline for images

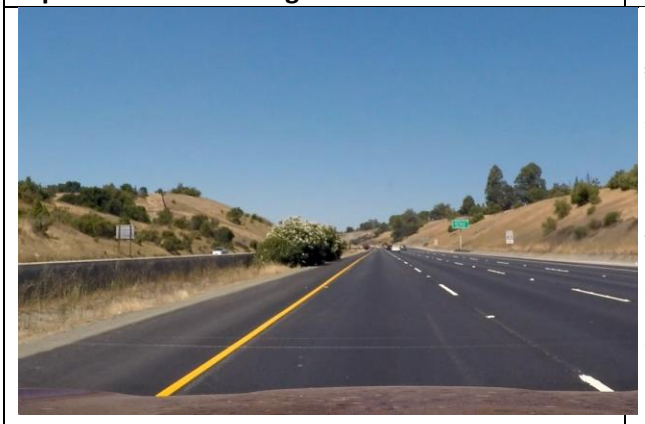
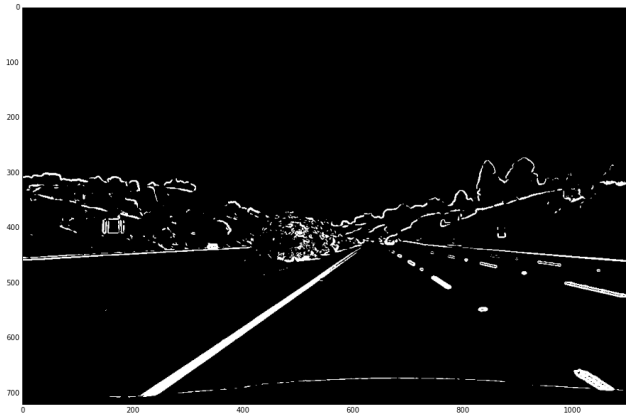
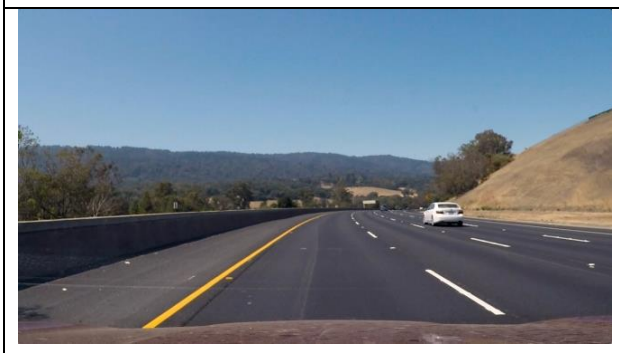
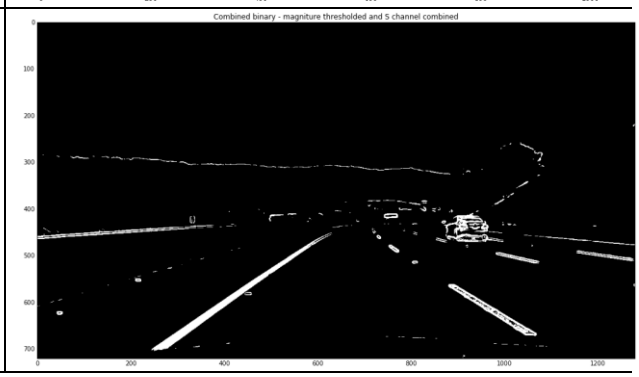
The image pipe line is detailed in steps below:

Step1: Each image is undistorted using cv2.undistort() using the camera calibration matrix found from the initial camera calibration step.

Distorted	Undistorted
	
	

Step2: Undistorted image is converted to edge detected thresholded image by using magnitudes of the sobel with kernel size of 9 and thresholds set to 75 and 255. In addition, S component of the HLS converted image with thresholds of 175 and 255. These are combined to form a combined binary image. The methods and threshold values are derived after experimentation with different methods of sobel operation and thresholds. The chosen values are shown to provide satisfactory results. These steps are

implemented in the function edge_detect() and mag_thresh(). Functions abs_sobel_thresh() and dir_threshold() are developed to get absolute and directional value of the sobel operated image values. These functions are used for experimentation and are not used in the final pipeline.

Input undistorted image	Binary combined image
	
	

Step 3: In this step, the binary image is perspective transformed to provide a bird's eye view. The bird's eye image is subjected to lane detection. The detected lane pixels are curve fitted using 2nd order polynomial.

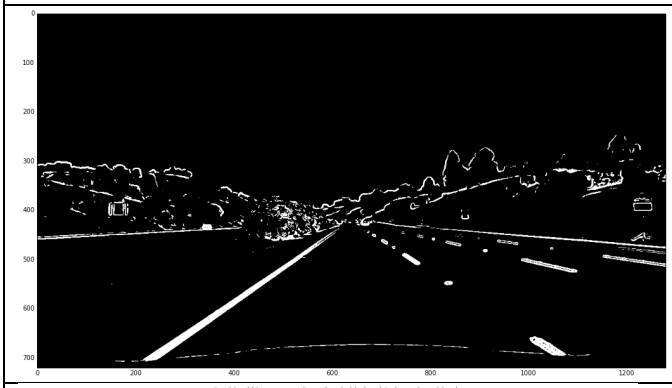
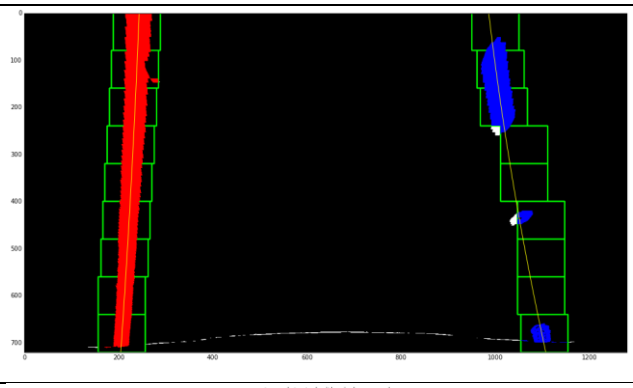
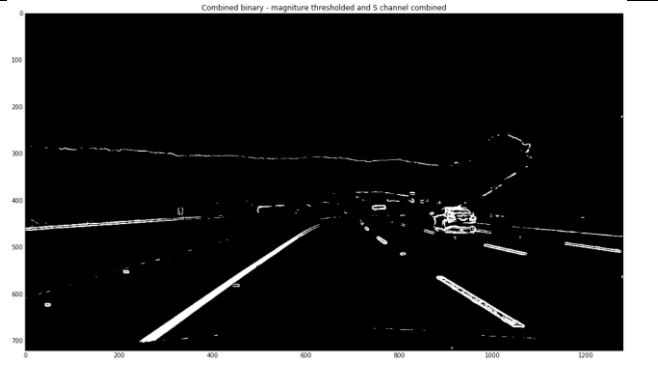
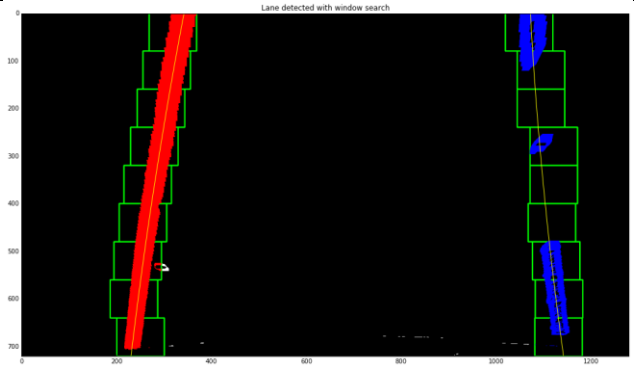
The code for my perspective transform is includes a function called perspective_transformation (). The function takes source (src) and destination (dst) points. I chose the hardcoded the source and destination points in the following manner:

src = np.array([[490, 482],[810, 482],[1250, 720],[40, 720]], dtype=np.int32)

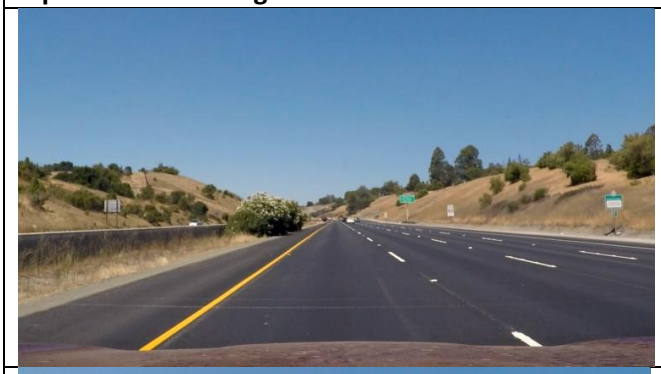
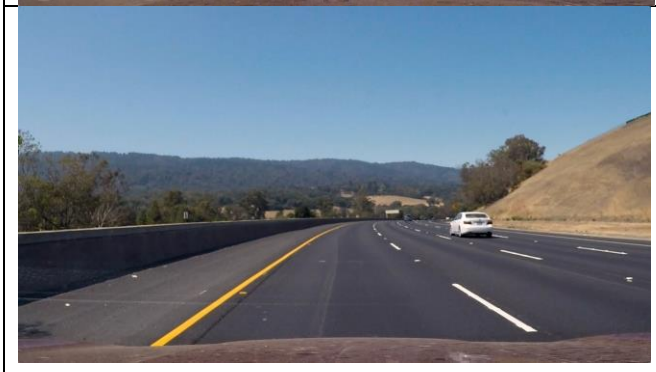
dst = np.array([[0, 0], [1280, 0],[1250, 720],[40, 720]], dtype=np.int32)

These values are chosen based on observation and visualization.

The resulting transformation matrix is used to convert combined binary image into perspective transformed image. The resulting binary warped image is provided to detect_lanes() routine to detect the lanes using histogram and window search method. The same routine calculates the polynomial fitting the lane lines, curvature of the lanes and the vehicle offset from center and returns these values. I have based these measurements on US regulation which is - the lane is about 30 meters long and 3.7 meters wide for converting pixel measurements to measurements in meters.

Input combined binary image	Perspective transformed lane detected image with fitted curves shown.
	
	

Step 4: In this final step, the lane lines are drawn on the undistorted image for visualization. In addition, the radius of curvature (which is the average of radius of curvature of left lane and right lane) is written and the vehicle offset from the lane center. This is implemented in draw_lanes_on_road() function.

Input distorted image	Final image after the pipelined steps
	
	

Pipeline for Video:

All the above steps for image pipeline are called from process_video_frame() function. This function accepts image are as its input and returns the final visualization as output. For video frame processing, below additional implementations are made:

- Line class – this class is implemented to store and process lane lines detected. To minimize the jitter, the co-efficient of the line fit are averaged over 3 frames. The Line class also stored and provide the radius of curvature and vehicle offset from center distance.
- Optimized lane detect- This is implemented in function opt_detect_lanes(). This function uses the information from the previous lane detections to perform a quick lane detect. In case if not enough lane pixels are detected (tested and empirically set to 7200), complete lane detect algorithm with histogram and window search is run.
- The program prints the number of times complete histogram and window search based lane detect is called and number of times optimized quick lane detect is called.

Results Conclusions and further work

The output for the project_video.mp4 (https://youtu.be/QiPN4YgjoWE) is shown below which shows minimized jitter with good lane detection under various road conditions.

The project build run output shows the number of times histogram and window search used (20) and th e number of times quick lane detect is used (1241).

```
[MoviePy] >>>> Building video p4_project_video.mp4
[MoviePy] Writing video p4_project_video.mp4
100%|████████████████████████████████████████████████████████████████████████████████| 1
260/1261 [05:00<00:00,  3.19it/s]
[MoviePy] Done.
[MoviePy] >>>> Video ready: p4_project_video.mp4

Number of times histogram and window search is used: 20
Number of times quick lanes detect is used : 1241
```

The pipeline did not perform well on the challenge video. To improve performance on the challenge videos, the pipeline need to be tuned for better lane detection and prediction. Some of important improvements include – improving the edge/lane detection, improving the lane prediction based on previous lane detections. Overall, this project provided a deeper understanding into the lane detection challenges and thanks to Udacity for putting this up as part of the course.