VEHICLE DETECTION & TRACKING

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OBJECTIVE

This project requires the developer to develop a pipeline to identify vehicles from car-mounted camera feeds of highway driving given an image training dataset.

GOALS

Project goals were the following:

1. To extract features from a Histogram of Oriented Gradients (HOG) on a labelled training set of images; train a Linear SVM classifier
2. Optionally, to apply a color transform and append binned color features, as well as histograms of color, to the HOG feature vector.
3. To normalize features, randomize a selection for training and testing for steps 1, 2
4. Implement a sliding-window technique and use the trained classifier to search for vehicles in images.
5. To develop a pipeline on a video stream (starting with the test_video.mp4 and later implement on the full project_video.mp4) and create a heat map of recurring detections frame by frame to reject outliers and follow detected vehicles.
6. To estimate a bounding box for vehicles detected.

Note: All of the code developed is in the file p5-final3-mlp.py, and references from here onward will refer to it thus, [1].

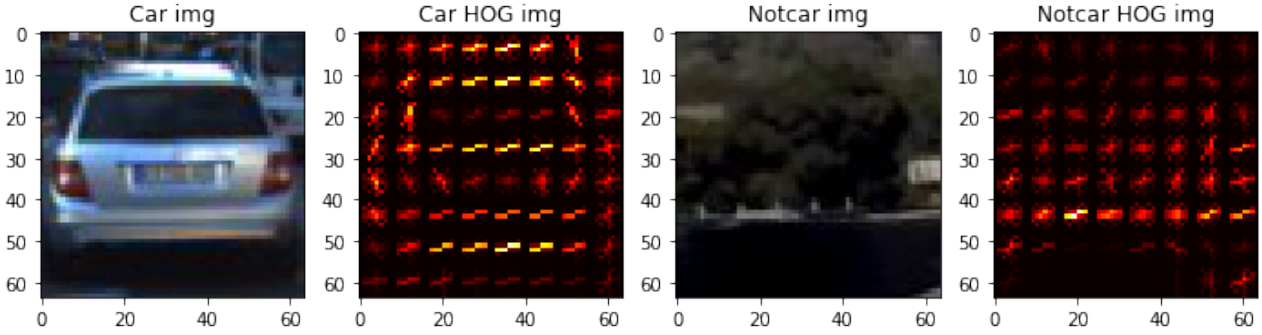
1. HISTOGRAM OF ORIENTED GRADIENTS (HOG): FEATURE EXTRACTION

HOG is useful as a feature descriptor that simplifies a digital image, small or large, by extracting useful information while discarding the rest. It is useful as input to classifiers such as a support vector machine (SVM) or a multi-layer perceptron (MLP). The process yields a one-dimensional array (called a feature vector) with values calculated thus:

1. Calculate the gradient along the X / Y directions to identify edges in image while discarding the remaining information. See Open CV's Sobel() function.
2. Calculate the magnitude and direction of the two gradients

$\text{abs\_sobelx} = \sqrt{(sobelx)^2}$
$\text{abs\_sobely} = \sqrt{(sobely)^2}$
$\text{abs\_sobelxy} = \sqrt{(sobelx)^2 + (sobely)^2}$ — Magnitude
Angle θ = sobely / sobelx — Direction

This yields an image with a magnitude and a direction of that gradient, arranged approximately from 0-180°. Running these operations on the Udacity-provided image dataset (datasets of images of cars and of "not cars") extracts the following information from such images. An example of each type of image is shown next:



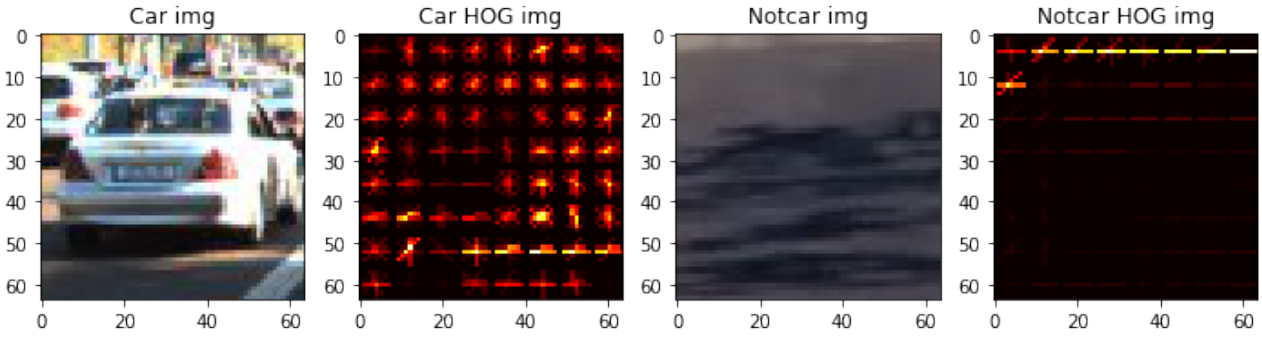
It is worth noting that there is a discernible outline to these features corresponding to the images. These images were extracted using the single_img_features() function in [1], line 220.

```
car_features, car_hog_image = single_img_features(car_image,
      color_space=color_space,spatial_size=spatial_size, hist_bins=hist_bins,
      orient=orient, pix_per_cell=pix_per_cell, cell_per_block=cell_per_block,
      hog_channel=hog_channel, spatial_feat=spatial_feat,hist_feat=hist_feat,
      hog_feat=hog_feat, vis=True)

notcar_features, notcar_hog_image = single_img_features(notcar_image,
      color_space=color_space,spatial_size=spatial_size, hist_bins=hist_bins,
      orient=orient, pix_per_cell=pix_per_cell, cell_per_block=cell_per_block,
      hog_channel=hog_channel, spatial_feat=spatial_feat,hist_feat=hist_feat,
      hog_feat=hog_feat, vis=True)
```

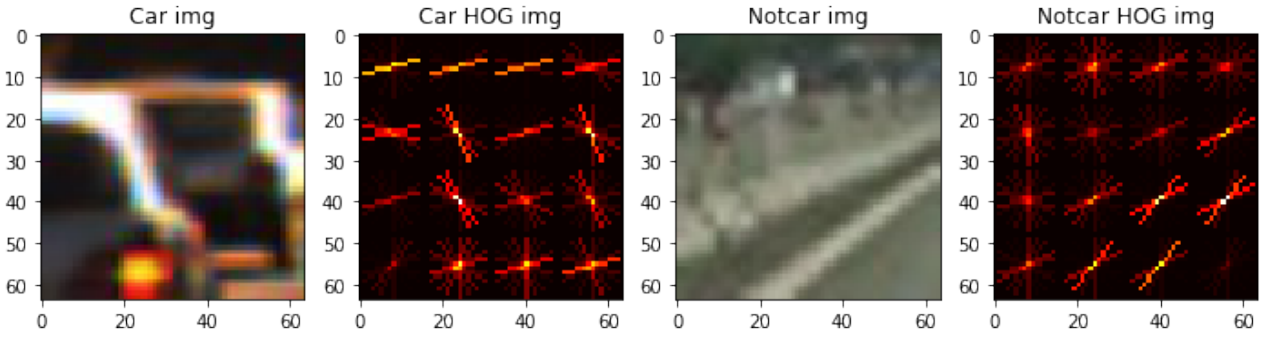
Various parameters (such as the ones shown in the function call above) were used in several combinations to get a better idea of the HOG results.

```
#Set up parameters for the functions to be called
color_space = 'RGB' # Can be RGB, HSV, LUV, HLS, YUV, YCrCb
orient = 9  # HOG orientations
pix_per_cell = 8 # HOG pixels per cell
cell_per_block = 2 # HOG cells per block
hog_channel = “ALL” # Can be 0, 1, 2, or "ALL"
spatial_size = (32, 32) # Spatial binning dimensions
hist_bins = 16    # Number of histogram bins
spatial_feat = True # Spatial features on or off
hist_feat = True # Histogram features on or off
hog_feat = True # HOG features on or off
```

For example, HSV color space (channel S, or 1) with 32 orientations produced the below HOG features.



Another example: LUV color space (channel L, or 0) with 16 pixels per cell and 9 orientations produced the below HOG features.

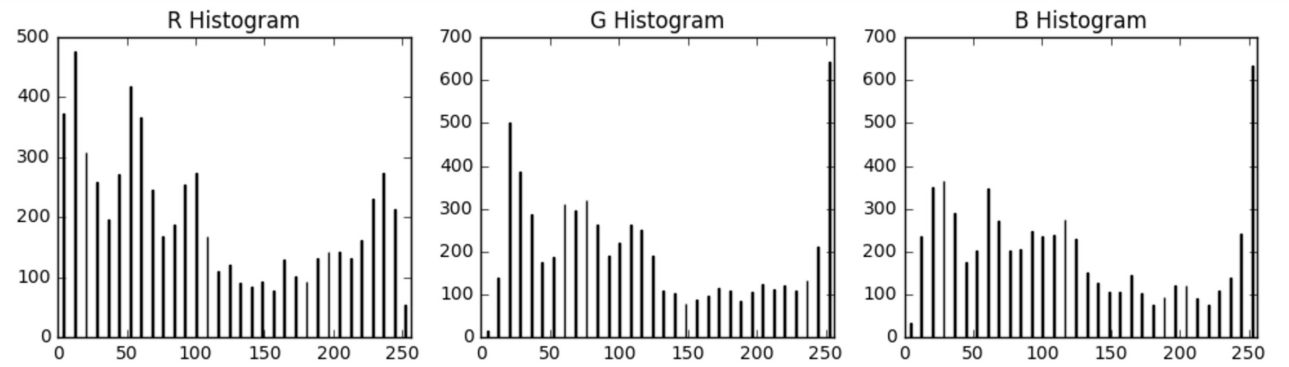


After many manual combinations of the parameters, the final set was fixed as follows: `{RGB color space, ALL channels, 9 orientations, 8 pixels per cell, 2 cells per block}.`

Extraction of HOG features form the feature vectors to be used for classifier training.

2. COLOR HISTOGRAMS AND SPATIAL BINNING AS FEATURE DESCRIPTORS

Histograms of colors (the constituent channels, for e.g., Red, Green and Blue in RGB) can also act as features. As they affect performance of the classifier, they have been included in the pipeline.



The spatial binning feature, which is upsizing or downsizing an image from the original image in the dataset, each of which is 64 x 64 pixels (RGB), did not yield a consistently good result during program execution, and hence was dropped. For example, setting the binning size to (32,32) would downsize by a factor of ½ to 32 x 32 pixels.

So, color histograms only are included as features in this pipeline along with HOG. Example images above are shown from the Udacity course material.

A PROPER APPROACH

A more "scientific" approach was adopted to ferret out the best set of parameters. Time constraints, however, ruled against finishing that line of inquiry. One could however, use a routine like the one below to arrive at an optimal set of parameter values.

```
def generate_feature sets():
        #Setup for best parameter set search to feed the SVM training
        color_space_range = ['RGB', 'HSV', 'LUV', 'HLS', 'YUV', 'YCrCb']  # 6 color spaces
        orient_space = list(range(6,10)) # range is 6,7,8,9
        pix_per_cell_range = list(range(6,9)) # range is 6,7,8
        hog_channel_range = ['0', '1', '2', 'ALL']
        hist_bin_range = [16, 32]

        #Establish the total # of combinations to sift through
        iter_count=len(color_space_range)*len(orient_space)*len(pix_per_cell_range)*len(hog_channel_range)*len(his
        t_bin_range)
        featureset_list = [dict() for x in range(iter_count)] #Define a list or an array of dictionaries to store
        the feature set run to gen car_features etc.

        import pickle
        import time

        iter_count = 0 #Reset counter to count again
        for color_space in color_space_range:
            t1 = time.time()
            print ('Generating featureset ', iter_count, 'at:', t1)
            for orient in orient_space:
                for pix_per_cell in pix_per_cell_range:
                    for hog_channel in hog_channel_range:
                        for hist_bins in hist_bin_range:
                            print ('Color_Space:', color_space,' Orientation:', orient,' Pix /cell:',
                                  pix_per_cell,' HOG Chnl #:', hog_channel, ' # of Hist Bins:', hist_bins)
                            featureset_list[iter_count] = [{'Color Space': color_space,'Orientation':
                                  orient,'Pix_per_cell': pix_per_cell,'HOG_Channel #': hog_channel,
                                  'Num_of_Hist_Bins': hist_bins}]
                            car_features = extract_features(cars, color_space=color_space,
                                  spatial_size=spatial_size, hist_bins=hist_bins,
                                  orient=orient, pix_per_cell=pix_per_cell, cell_per_block=cell_per_block,
                                  hog_channel=hog_channel, spatial_feat=spatial_feat, hist_feat=hist_feat,
                                  hog_feat=hog_feat)

                            notcar_features = extract_features(notcars, color_space=color_space,
                                  spatial_size=spatial_size, hist_bins=hist_bins,
                                  orient=orient, pix_per_cell=pix_per_cell, cell_per_block=cell_per_block,
                                  hog_channel=hog_channel, spatial_feat=spatial_feat,
                                  hist_feat=hist_feat, hog_feat=hog_feat)
                            fn = 'car_noncar_features'+str(iter_count)+'.p'

                            with open(fn, 'wb') as picklefileh:
                                pickle.dump((featureset_list[iter_count], car_features, notcar_features),
                                  picklefileh, protocol=pickle.HIGHEST_PROTOCOL)
                            print ('Finished in ', time.time()-t1, 'sec.')
                            iter_count+=1

        print (featureset_list[0], '\n',featureset_list[101] )
        print ('Total # of iterations for feature preparation: ', iter_count)
```

The above developed functional code (not part of [1]) generated 576 feature sets all stored into pickled dictionaries (~50 GB), awaiting a plan to continue this investigation in short order! (Datasets can be shared, if needed on Google Drive).

The plan was to either do my own GridSearchCV type of function or randomly sample across the featuresets. Then, the best set would be the one that offered the highest validation accuracy during training of the (SVM) classifer with its own GridSearchCV().

As mentioned above, further investigation was stopped pending availability of more powerful hardware and time!

3A. SUPPORT VECTOR MACHINE (SVM) CLASSIFIER TRAINING

A support vector machine can be used to perform linear and nonlinear classification of complex but small to medium sized datasets; used here to classify car images from noncar images (also see section 3B).

This classifier too comes with its bag of parameters, whose best combination for a given dataset, fortunately, can be found by employing the very useful function GridSearchCV () found in the sklearn library.

The parameters that can be tuned are:
Value of C, gamma and choice of kernel, whether RBF or Linear.

```
'''GRID SEARCH OPTION WAS DONE ONCE  (This code is not part of [1])

parameters = {'kernel':('linear', 'rbf'), 'C':[0.1, 1, 10], 'gamma':[0.01, 0.1, 1]}
svr = svm.LinearSVC()
t=time.time()
grid_search = GridSearchCV(svr, parameters)
t2 = time.time()
print(round(t2-t, 2), 'Seconds to GridSearch SVC...')
grid_search.fit(X_train, y_train)
t3 = time.time()
print(round(t3-t2, 2), 'Seconds to GridSearch SVC...')
print ('\nBEST PARAMS', grid_search.best_params_)
'''

BEST PARAMETERS: {Kernel: Linear, C=0.1, Gamma: 0.01}   (Took 557 secs.)
```

GridSearchCV (), so employed to find the best parameter combination for the image datasets, yielded C=0.1 with a Linear kernel.

Next, the features data was split 80%/20% for training and testing, and normalized and shuffled.

The SVM classifier was trained using the above parameters. The code is as shown below.

```
# Using a linear SVC  (Code starts at line 640 in [1])
svc = LinearSVC(C=0.1)

# Check the training time for the SVC
t=time.time()
svc.fit(X_train, y_train)
t2 = time.time()

print(round(t2-t, 2), 'Seconds to train SVC...')

# Check the score of the SVC
print('Test Accuracy of SVC = ', round(svc.score(X_test, y_test), 4))
```

With the previously noted feature parameter combination (RGB, ALL channels etc.), the classifier was tried on different subsets of data. Based on the future classifier performance of the SVM, the test dataset that was finalized was the one with approx. 1200 images, with an accuracy of ~97%. See screenshots below.

Some standard experimental runs are documented here:

```
Number of car images:      8466
Number of non-car images:  8968
Using: 9 orientations 8 pixels per cell and 2 cells per block
Feature vector length: 8412
74.0 Seconds to train SVC...
Test Accuracy of SVC =  0.9977
```

Due to some reported (unconfirmed by the student and beyond the scope of this project) aberration in "intercept_scaling" in LinearSVC(), the standard SVC() function was tried to train the model (the training time, 74 sec, is a lot more than SVC()'s training time, shown below).

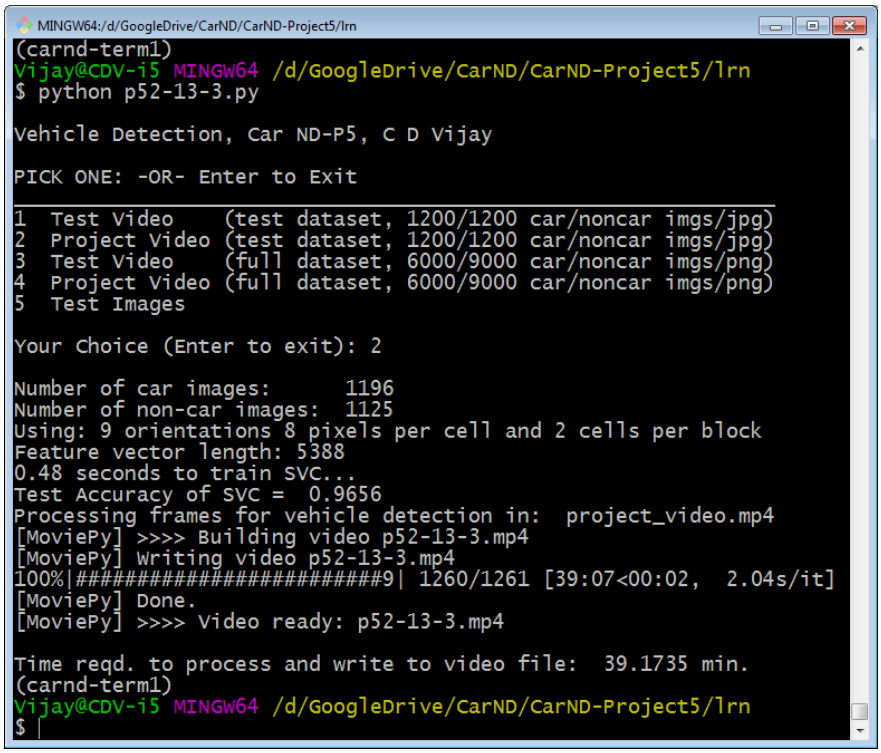
```
Number of car images:      8466
Number of non-car images:  8968
Using: 9 orientations 8 pixels per cell and 2 cells per block
Feature vector length: 8412
22.31 Seconds to train SVC...
Test Accuracy of SVC =  0.9977
```

Due to nary a difference between the two in classifier accuracy, the latter one was chosen earlier due to its faster classification time.

With some other changes as noted below (using SVC()):

```
Number of car images:      8466
Number of non-car images:  8968
Using: 6 orientations 8 pixels per cell and 2 cells per block
Feature vector length: 6696
11.03 Seconds to train SVC...
Test Accuracy of SVC =  0.9987
```

Example Run



3B. MULTI-LAYERED PERCEPTRON CLASSIFIER TRAINING

This is a classifier from the sklearn.neural_network library that implements a multi-layer perceptron (MLP) algorithm which trains using Backpropagation.

From Scikit's online documentation: "MLP trains on two arrays: array X of size (n_samples, n_features), which holds the training samples represented as floating point feature vectors; and array y of size (n_samples,), which holds the target values (class labels) for the training samples."

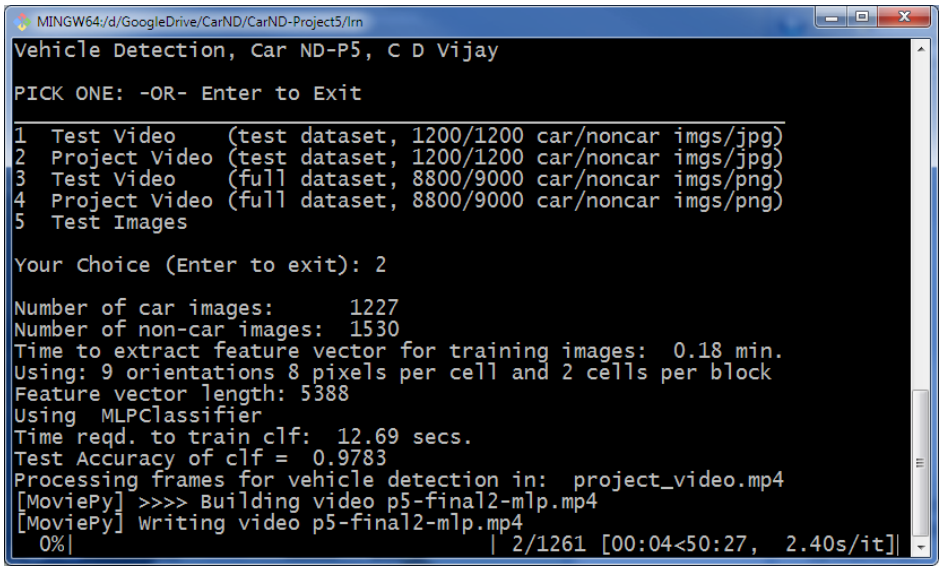
While an SVM is known generally to outperform (in terms of prediction speed and accuracy), an MLP classifier has its own advantages.

The validation accuracy of this classifier still ranges between 95-98% as was for SVM. The hyperparameter (Alpha, an L2 regularization parameter that controls overfitting) after some experimentation was set to 0.01.

Each has its own **merits and demerits**, however: SVM training (if employed in real-time) has to solve a "Lagrangian dual problem" – a problem that involves transformation and incorporation of constraints, if any, which can lead to a large number of variables, and hence slow. Prediction however, is much faster – the task involves determining which side of the decision boundary a given point lies on. MLP training, on the other hand, can be faster (in which the network keeps making constant adjustments to the weights by going back and forth through the layers while trying to minimize the difference between the predicted and the expected outputs. MLP prediction can take longer (depending on model size) as it requires multiplication of an input vector by two 2D weight matrices. Only, serious experimentation can yield the better candidate in real-time applications.

In this model however, an MLP-based classifier yields slightly better execution results and hence, employed here.

Example Run



4. DETECTION (SLIDING WINDOW TECHNIQUE) & PREDICTION BY SVM CLASSIFIER

The technique is to divide the "to-be-searched" image into fine or coarse windows as the detections show. The bigger image (shown next) is divided into say (m x m) chunks starting from a given point, which has been chosen to be (0,400 in pixels), about the vertical midpoint so that the extraneous information (skyline, trees in the foreground etc.) can be filtered out.

The above process yields a specific number of windows in our view zone (from 0,400) downwards. Now, the tasks are to:

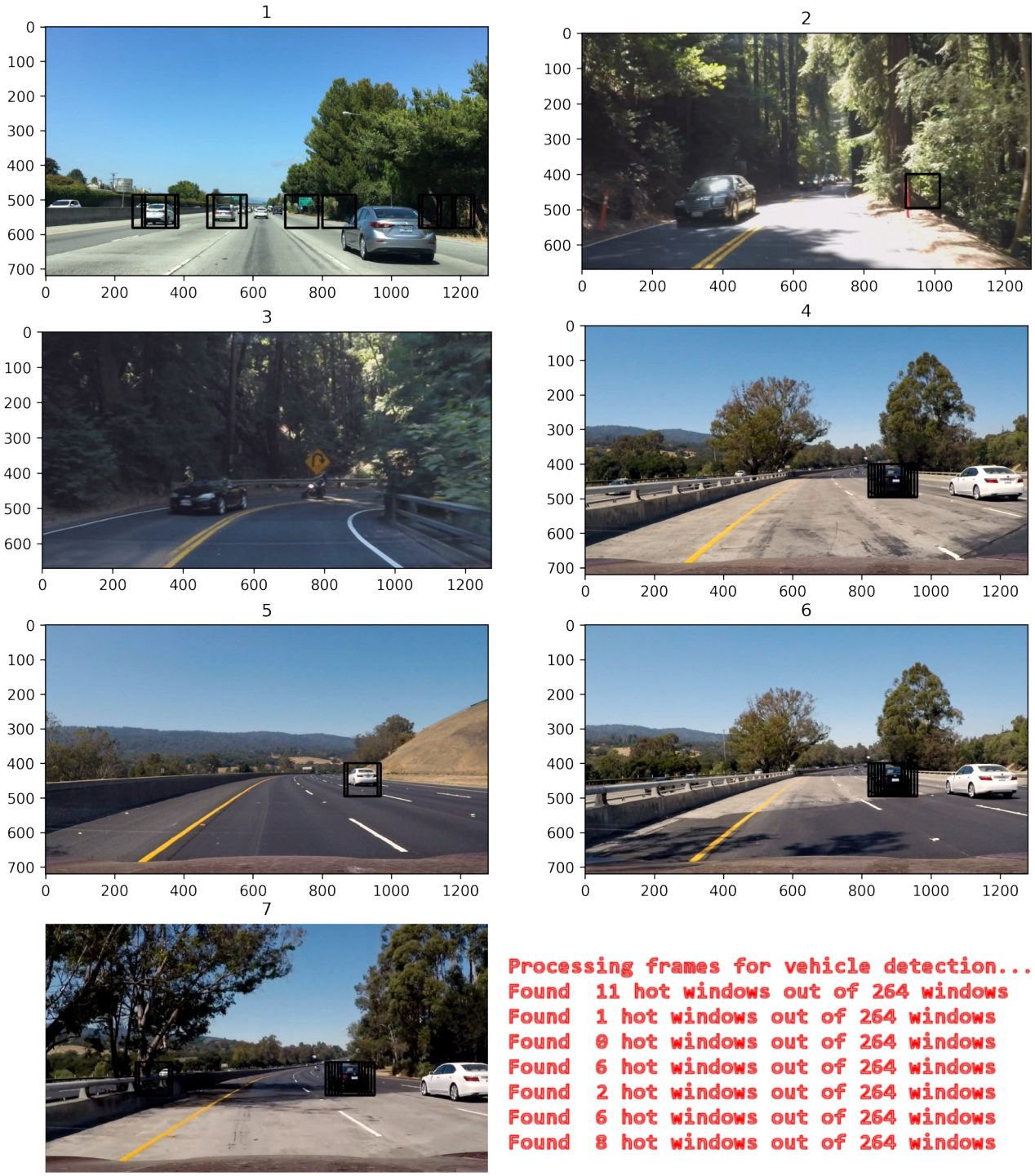
1. Scale this window down to the original dataset image size (in this case, m x m down to 64x64 pix).
2. Extract the feature vector for this smaller (or sub)image (HOG, color histogram and spatial as selected), and have the trained classifier prove its mettle on it (that is, predict).
3. If a car is detected, then add this window to a running list of "hot" windows. The windows so detected are now considered to have car objects in them (or not, ergo, called a false positive).

This algorithm too brings its bag of parameters. So, after much tweaking, two parameter sets were chosen (based on the test images). Figures are shown later in this section. Functions slide_windows() and search_windows() are used to extract feature vectors as described above, for testing on test images.

```
Functions in Code:
      slide_windows (), [1], line 163
      search_windows(), [1], line 274
```

EXPERIMENTS

{ Subwindow size: 96 x 96 pix, (X/Y overlap) = (0.9/0.1) } setting yielded this: 34 ‘hot’ windows, see next image.




```
Processing frames for vehicle detection...
Found  11 hot windows out of 264 windows
Found  1 hot windows out of 264 windows
Found  0 hot windows out of 264 windows
Found  6 hot windows out of 264 windows
Found  2 hot windows out of 264 windows
Found  6 hot windows out of 264 windows
Found  8 hot windows out of 264 windows
```

```
{ Subwindow size: 50 x 50 pix, (X/Y overlap) = (0.9/0.1) } setting yielded this:
91 hot windows
```

Note that this subimage size (50x50 pix) runs counterintuitive to the recommended integer multiple of the original (trained) image size (64 x 64), and produced more windows than the earlier setting including detecting a car in the image from P4's challenge video (see image 3).

Automated parameter optimization is recommended here as the next investigation step. As there was no clear outcome, both settings were run independently and the window

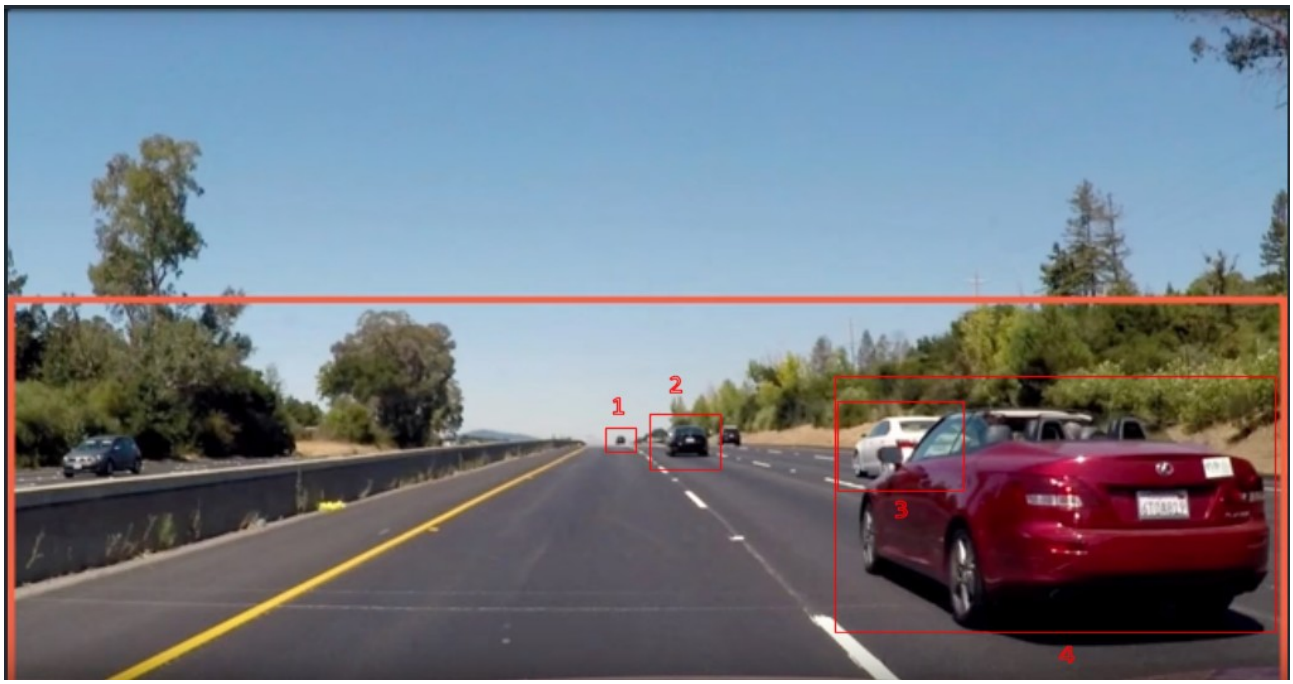
lists concatenated thus —
`windows  = windows1 + windows 2; which produced the following:`


```
Processing frames for vehicle detection...
Found  30 hot windows out of 1804 windows
Found  13 hot windows out of 1799 windows
Found   4 hot windows out of 1799 windows
Found  31 hot windows out of 1804 windows
Found   2 hot windows out of 1804 windows
Found  20 hot windows out of 1804 windows
Found  30 hot windows out of 1804 windows
```

This produced 130 hot windows in total including several false positives; but the outcome is acceptable from looking at the quality of detections (and the low number of FPs).

SEARCH WINDOW SCALING

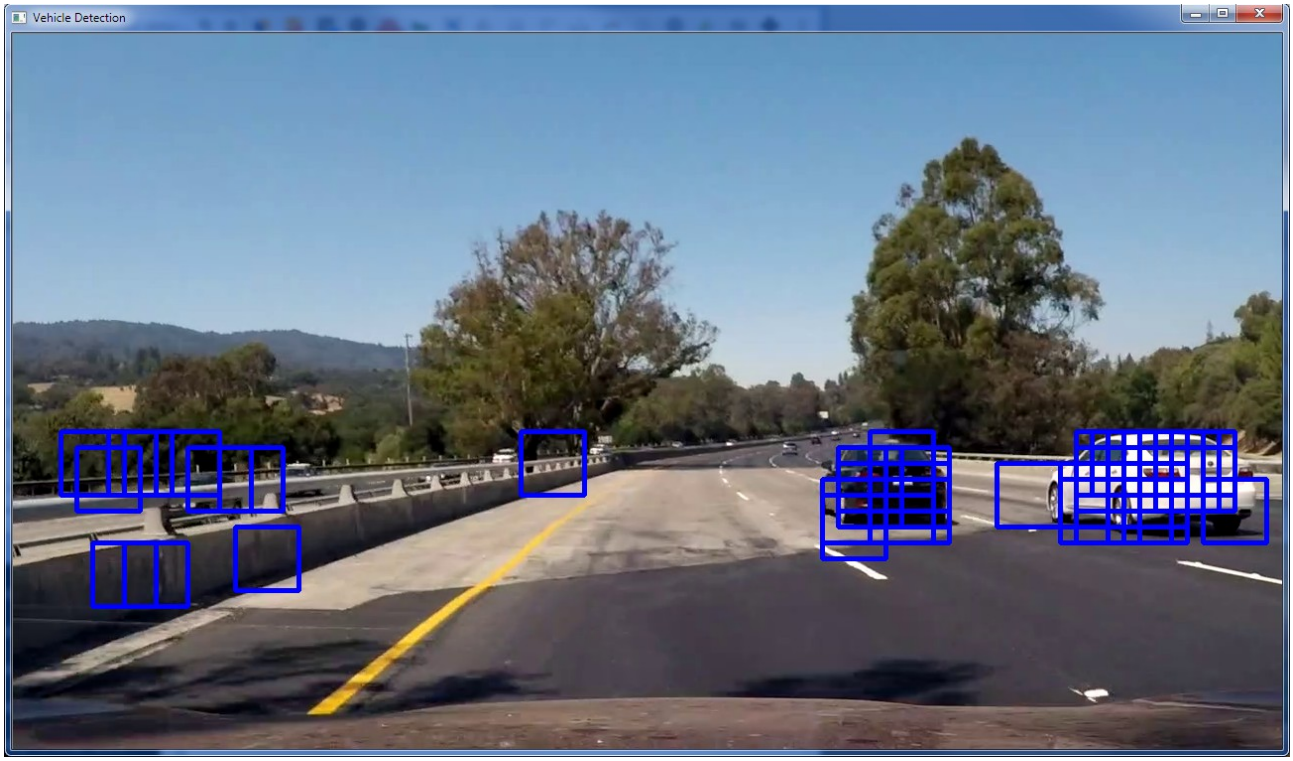
Using different scales to size the search windows up or down (as required) to be able to detect cars far away and the ones close to the camera can be a useful task.



The algorithm shown below was employed to obtain as many detections as possible.

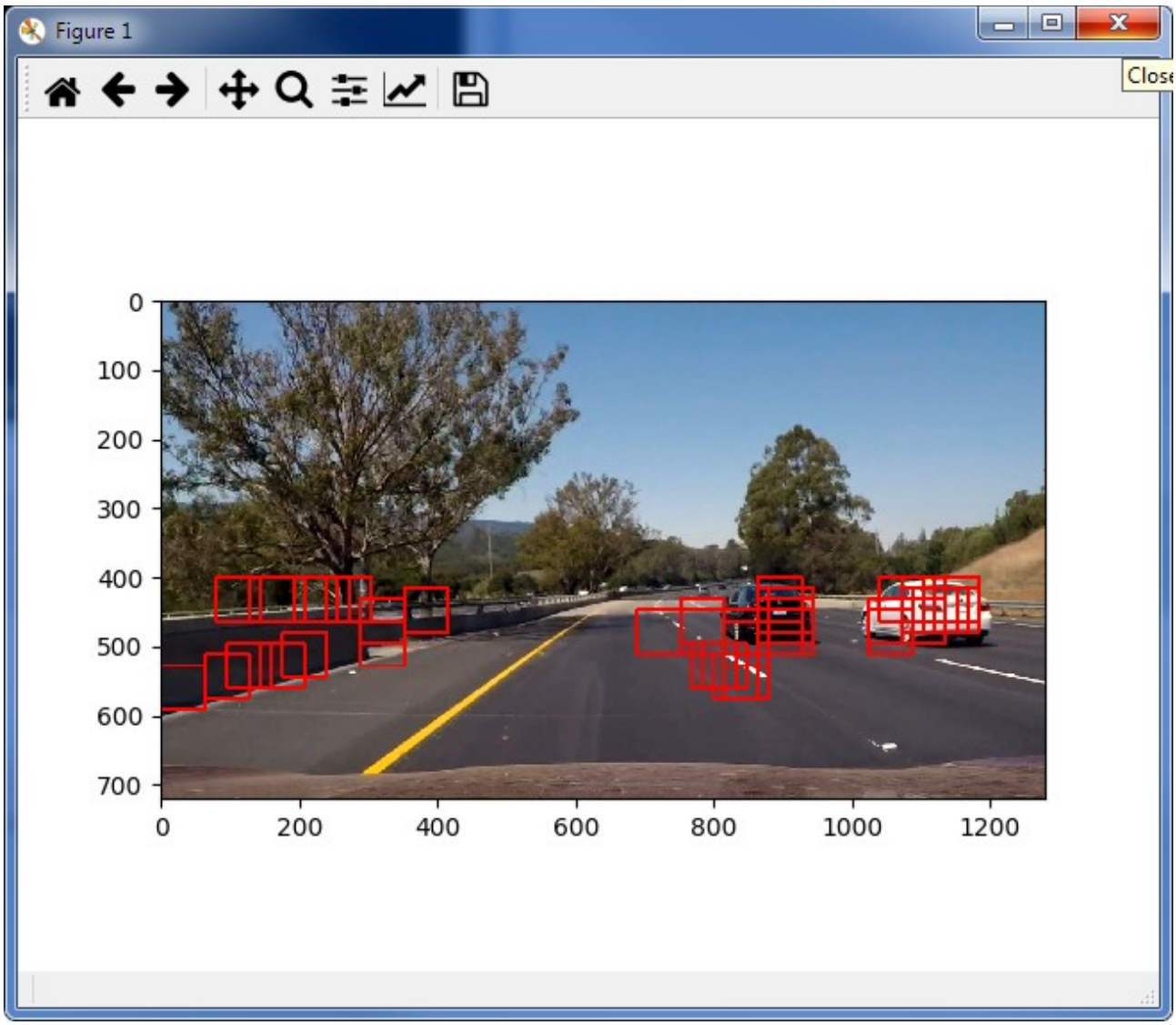
The scales chosen were: {1.0, 1.5, 2.0, 2.5, 3.0]

```
#Below Not used, ystart and ystop set to (400,660)
ystart_stop = ([[y1, y2], [y3, y4], [y5, y6], [y7, y8])

for ystart, ystop in ystart_stop:
      for scale in linspace (1, scale_max, 0.25):
            find cars (img, scale)
            #Detect false positives
            #Draw video / display image
```


Vehicle Detection


Vehicle Detection

Based on these experiments with scaling, a similar scaling did not perform as well when applied to detecting cars in video frames. So, for the video processing, a scale of 1 is used.



As the images above show, this detection technique detects cars well but produces far too many false positives (FPs). The next section details two techniques employed to try removing them.

5. ELIMINATING FALSE POSITIVES (FP)

HEATMAP

One technique to eliminate false positives is by making a heatmap – a method in which each "hot" window (i.e., a window in which a car is detected) is marked (given added heat) in every frame. Over the course of several windows, the cars if truly present in a frame will get multiple detections thus making that zone "hot". False positives tend to be isolated cases (with low heat) whereas real car detections tend to cluster around the same area (with high heat) as processing progresses over the frames.

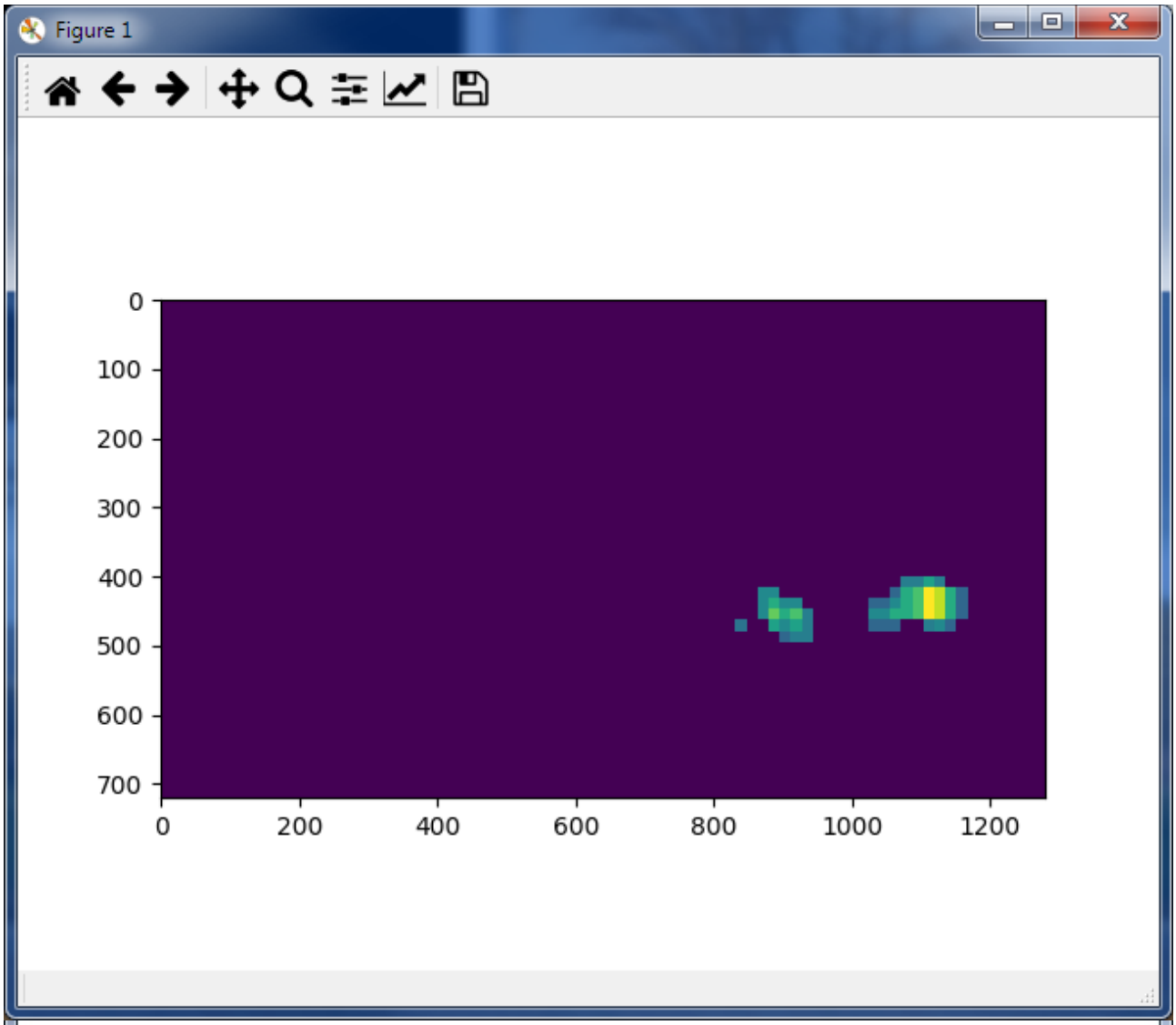
Heatmaps are tracked over many frames (12) (collections.deque(maxlen=12), line 503, [1]) and the heat value averaged before a threshold is applied. Then, a threshold (a limit) is used to filter out low "heat" values (false positives) while retaining "hot" zones, in essence, removing false positives. The numpy.clip() function is used to simplify the heatmap.

Employing the very useful label() function ("connected component modeling") from scipy.ndimage.measurements, multiple contiguous contours in the heatmap are labeled or bound. **These are the final detected car positions.**

Finally, a composite image comprised of these bound boxes superimposed on the original image is created to show the areas where cars were detected.

A separate function, find_cars () ([1], line 345) is the heart of the pipeline. The action of this

pipeline is shown via images next.



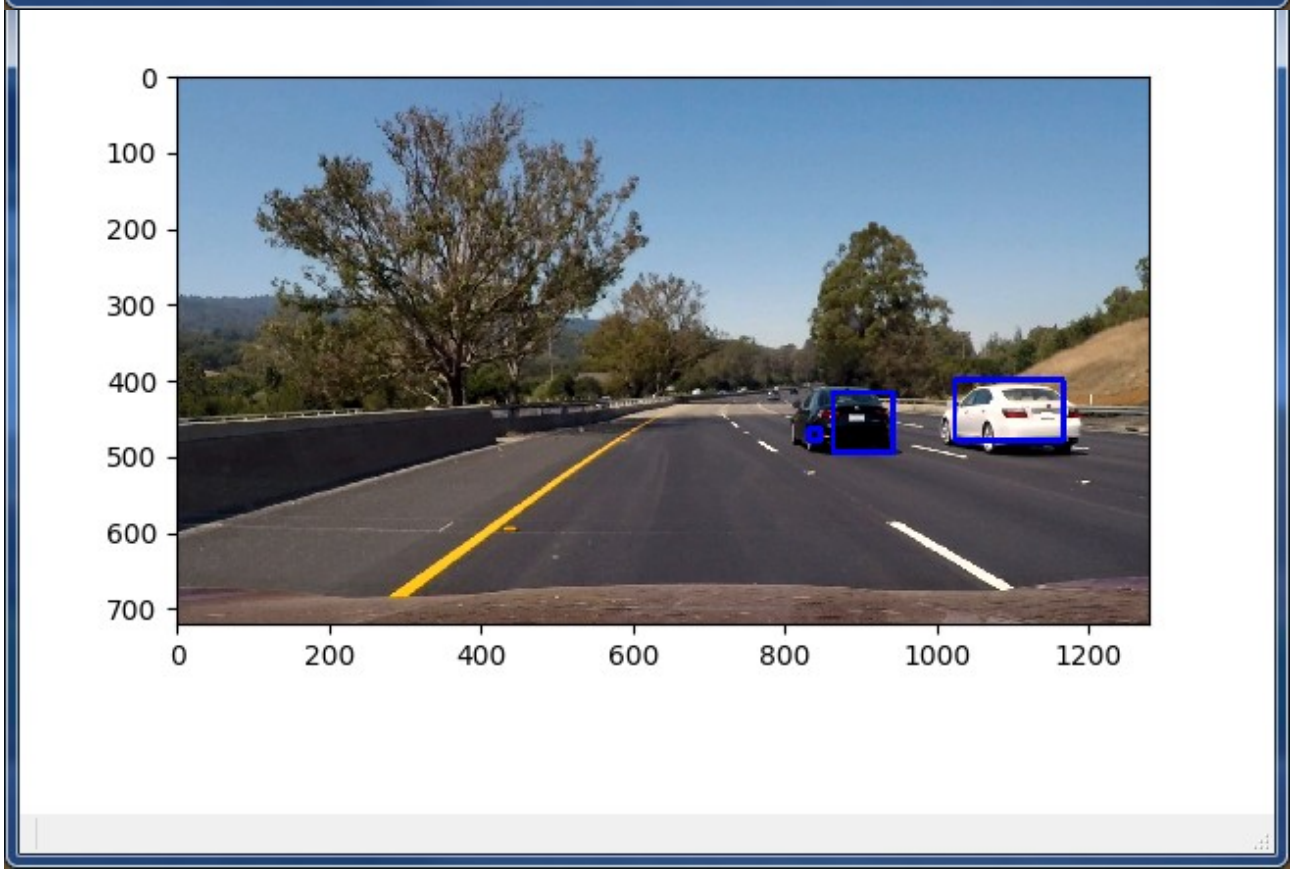



Figure 1
0
100
200
300
400
500
600
700
0
200
400
600
800
1000
1200

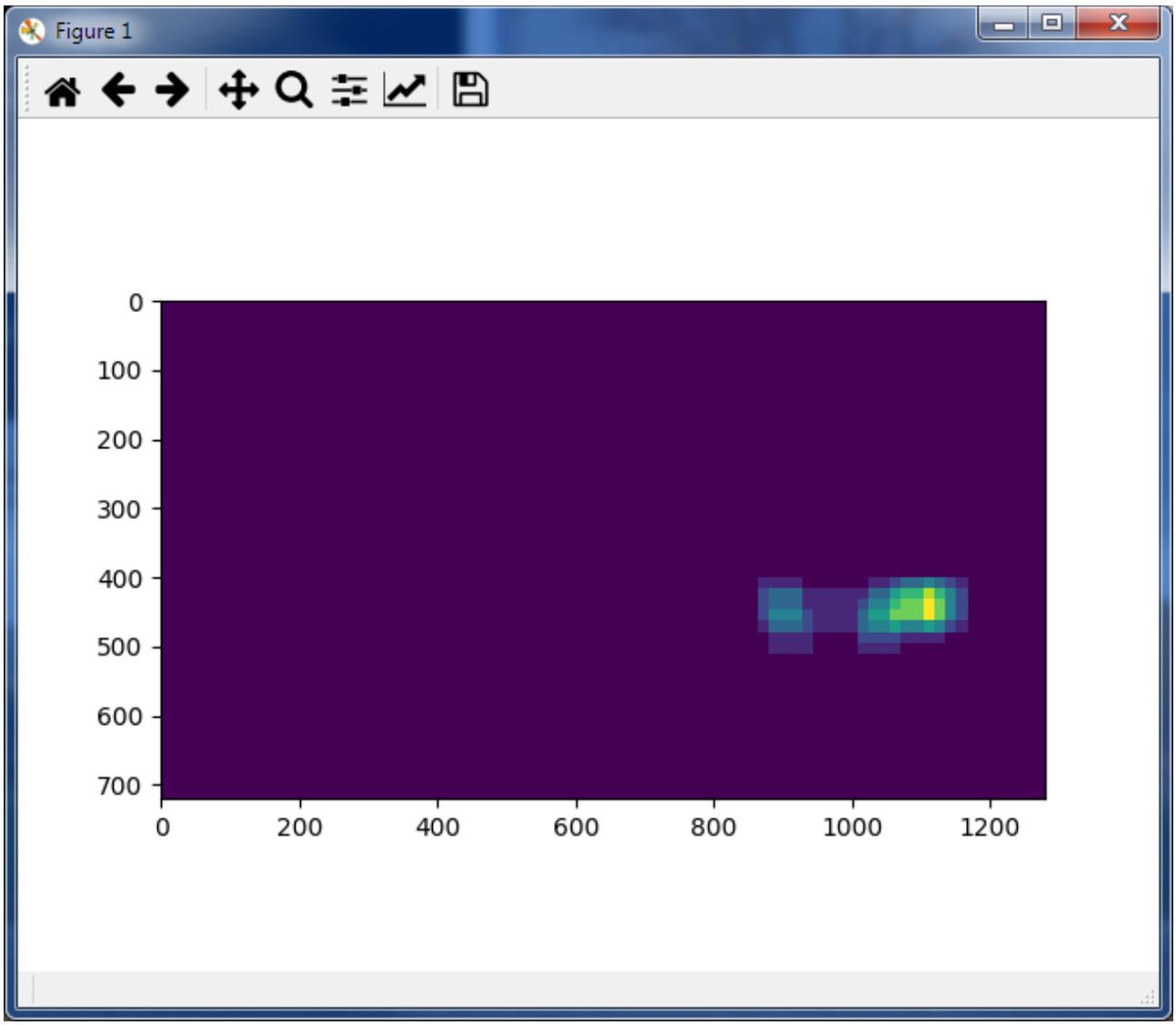


Figure 1
0
100
200
300
400
500
600
700
0
200
400
600
800
1000
1200

NEGATIVE MINING

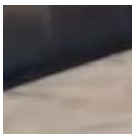
Another technique for non-generalized use involves adding training data from the untrained dataset. This involved obtaining noncar images from the project video from a few frames. Approximately, 800 images were added this way to remove FP s during the detection phase.

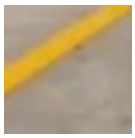
The following script (not part of [1]) was developed to take multiple image frames (project_video.mp4) and divide each one as required into 64 x 64 pixel images, and manually curate them to separate car from noncar images. These cropped noncar images only were later added to the original images datasets.

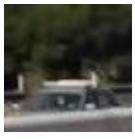
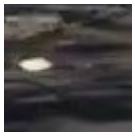
Script to clip/save subimages of a set size (e.g., 64 x 64 pixels) from images

```
import cv2
import glob
import numpy as np
import matplotlib.image as mpimg
import matplotlib.pyplot as plt

ystart = 400
ymax   = 656

croph = 64
cropw = 64

i = 0

filepath = 'image*.jpeg'
images = glob.glob(filepath)
for filename in images:
    image = mpimg.imread (filename)
    xmax = image.shape[1]
    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)

    for y in range (ystart, ymax, croph):
        for x in range (0, xmax, cropw):
            i += 1
            roi = image [y:y+croph, x:x+cropw]
            fn = 'roi'+str(i)+'.jpeg'
            cv2.imwrite(fn, roi)
            print (y, y+croph, x, x+cropw, 'generating', fn)
```

A few samples are shown next:



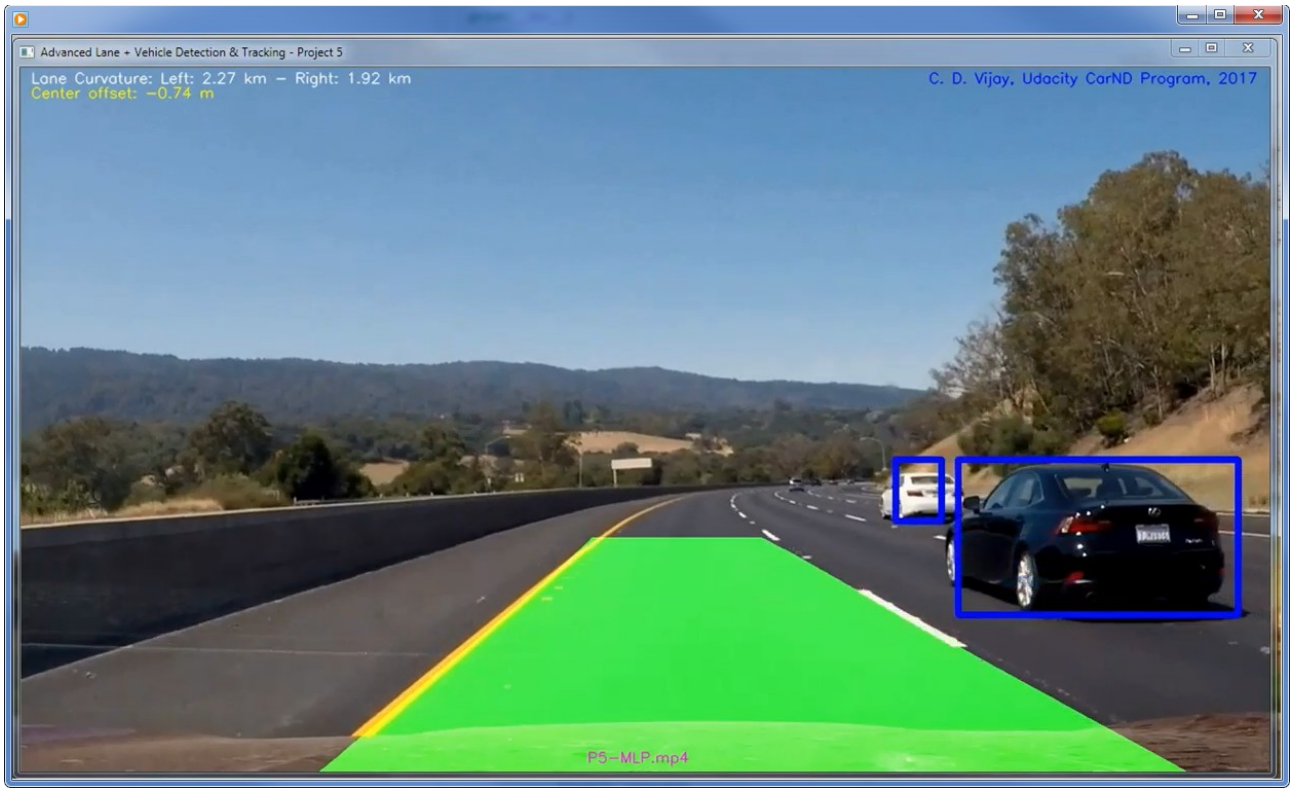



6. PIPELINE

The final output video is generated using the fine moviepy.editor module from Zulko. The ProcessImage() function ([1], line 506) runs the pipeline on every frame in project_video.mp4 file.

This output video was further run through the Advanced Lane Detection code (project 4) to produce a video in which the lanes are marked along with the cars. This composite video is available at the link shown on next page.



Link to: [Youtube (code running on project_video.mp4)]

7. DISCUSSION

Several things are noteworthy here.

1. This algorithm is more proof-of-concept than an industry-grade one. Of course, any code can be optimized but the concept does not seem to lend itself to real-time operation, unless more powerful hardware becomes affordable and prevalent for real-time use (Drive PX2 from Nvidia?). The fact that one needs to use moviepy.editor to generate a composite video after processing stands testimony to the fact that this technique could be sped up.

2. With a lot more data (SVM may not be the classifier of choice then), detections will become more accurate. Even though an MLP classifier was chosen for its better detection quality, it may not be the classifier of choice in a real-world application.

3. Due to the programmatic nature of the code, again as in P4, the possibility of using deep learning for this task (like Nvidia, AutoX) is intriguing.

4. My code here is far from perfect. More work, when time permits, is required in the area of solidifying false positives elimination, experimenting with different classifiers and code optimization.

5. Due to the vast array of regular parameters (color space, orientations, features [HOG, spatial, color histograms]), some degree of optimization work must be performed to gain classification confidence and improve speed, as detailed in a procedure on page 5 of this report.

6. Just looking at this code in action is great, I wonder how much more exciting a real-world application will be! I will soon have more advanced versions of this project!

REFERENCES

[1]. Source code file, p5-final3-mlp.py, submitted with this project

[2]. Udacity CarND Term 1, Course material

[3]. Aurélion Géron, Hands-on Machine Learning with Scikit-Learn & Tensorflow, O'Reilly: Mar 2017.