Homework 3 - Pedestrian Detection using Histogram of Oriented Gradients

Topics:

- Data Preparation
- Feature extraction: Histogram of Oriented Gradients
- Classification: Support Vector Machine
- Object Detection: Sliding Window + Non Maximum Supression

Sources & Material

- Datasets:
  - https://www.cis.upenn.edu/~jshi/ped_html/
  - http://pascal.inrialpes.fr/data/human/
- Dataset preprocessed: https://github.com/RashadGarayev/PersonDetection
- Paper: Dalal and Triggs, "Histograms of oriented gradients for human detection," CVPR05
  - https://hal.inria.fr/inria-00548512/document/

Further Reading

- https://www.pyimagesearch.com/2015/11/09/pedestrian-detection-opencv/

1. Import Libraries

- OpenCV
- scikit-image
- scikit-learn

In [57]:
```python
import cv2 as cv
import matplotlib.pyplot as plt
from skimage.feature import hog
from skimage import exposure
import os
from sklearn import svm
import numpy as np
from sklearn.metrics import accuracy_score, confusion_matrix, average_precision_score, f1_score, recall_score,

import utils
```

2. Prepare Data

1. Create a dataset by loading all images
   - positive samples that contain pedestrians
   - negative samples that contain background objects
2. Split data into training and test data
   - split positive examples
   - split negative examples

In [58]:
```python
# Read Image files from local file system
positive_files = utils.ls("dataset/positive/")
negative_files = utils.ls("dataset/negative/")

split_pos = int(0.7*len(positive_files))
split_neg = int(0.7*len(negative_files))

train_positive_files, test_positive_files =  positive_files[:split_pos],positive_files[split_pos:]
train_negative_files, test_negative_files =  negative_files[:split_neg],negative_files[split_neg:]

# TODO:
# Read the images and store them in their corresponding lists

train_positive = [cv.imread(train_positive_files[i]) for i in range(len(train_positive_files)) ]
train_negative = [cv.imread(train_negative_files[i]) for i in range(len(train_negative_files)) ]

test_positive = [cv.imread(test_positive_files[i]) for i in range(len(test_positive_files)) ]
test_negative = [cv.imread(test_negative_files[i]) for i in range(len(test_negative_files)) ]
```

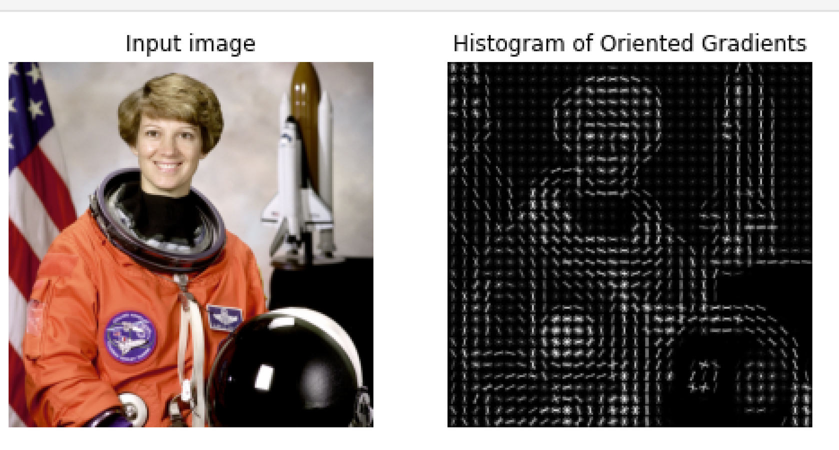
In [59]:
```python
# You can visualize the examples:
utils.showImages(train_positive[:6])
utils.showImages(train_negative[:6])
```

3. Feature Extraction

1. Apply Histogram of Oriented Gradients on all data
2. Create Training Labels

HOG - Example

In [60]:
```python
from skimage import data


img = data.astronaut()


fd, hog_image = hog(img, orientations=8, pixels_per_cell=(16, 16),
                    cells_per_block=(3, 3), visualize=True, multichannel=True)

fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(8, 4), sharex=True, sharey=True)

ax1.axis('off')
ax1.imshow(img, cmap=plt.cm.gray)
ax1.set_title('Input image')

# Rescale histogram for better display
hog_image_rescaled = exposure.rescale_intensity(hog_image, in_range=(0, 10))

ax2.axis('off')
ax2.imshow(hog_image_rescaled, cmap=plt.cm.gray)
ax2.set_title('Histogram of Oriented Gradients')
plt.show()
```



3.1 Compute HOG for each Image

In [61]:
```python
def feature_extraction(img, ppc = 8, cpb = 2):
    """
    img: A coloured image
    ppc: Pixels per cell
    cpb: Cells per block

    return: HOG feature vector
    The
    """
    # TODO: compute HOG feature vector
    # - try different parameters
    # - the output should be a one-dimensional array
    fd, hog_image = hog( img, orientations=8, pixels_per_cell=(ppc, ppc), cells_per_block=(cpb, cpb), visualize
    return fd


# Training Samples
train_positive_hog = np.array([feature_extraction(img) for img in train_positive])
train_negative_hog = np.array([feature_extraction(img) for img in train_negative])

# Testing Samples
test_positive_hog = np.array([feature_extraction(img) for img in test_positive])
test_negative_hog = np.array([feature_extraction(img) for img in test_negative])
```

3.2 Labels

In [62]:
```python
# Combine positive and negative samples into data matrices
X = np.concatenate((train_positive_hog,train_negative_hog))
X_test = np.concatenate((test_positive_hog,test_negative_hog))

# Create array of corresponding labels
Y = np.zeros(len(X))
Y[:len(train_positive_hog)] = 0
Y[len(train_positive_hog):] = 1

Y_test = np.zeros(len(X_test))
Y_test[:len(test_positive_hog)] = 0
Y_test[len(test_positive_hog):] = 1
```

4. Classifier

1. Initialize Model
2. Train Model
3. Evaluate Model

4.1 & 4.2

In [63]:
```python
svc = svm.LinearSVC(C=0.6,max_iter=10000)
svc.fit(X,Y)
```

Out[63]:
```
LinearSVC(C=0.6, max_iter=10000)
```

4.3 Evaluate Model

In [64]:
```python
Y_pred = svc.predict(X_test)
```

Confusion Matrix

$$C = \begin{pmatrix} \text{True Negatives} & \text{False Positives} \\ \text{False Negatives} & \text{True Positives} \end{pmatrix}$$

In [65]:
```python
confusion_matrix(Y_test,Y_pred)
```

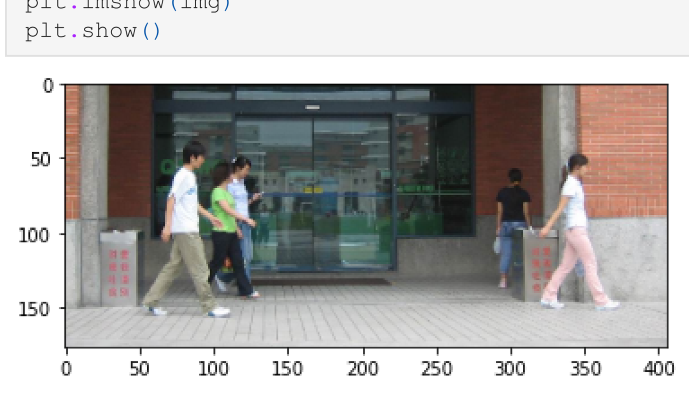
Out[65]:
```
array([[ 651,   74],
       [  60, 1176]], dtype=int64)
```

In [66]:
```python
print("AP:", average_precision_score(Y_test,Y_pred))
print("Accuracy:", accuracy_score(Y_test,Y_pred))
print("Recall:", recall_score(Y_test,Y_pred))
print("Precision:", precision_score(Y_test,Y_pred))
print("F1:", f1_score(Y_test,Y_pred))
```

```
AP: 0.925726731457598
Accuracy: 0.9316675165731769
Recall: 0.9514563106796117
Precision: 0.9408
F1: 0.9460981496379728
```

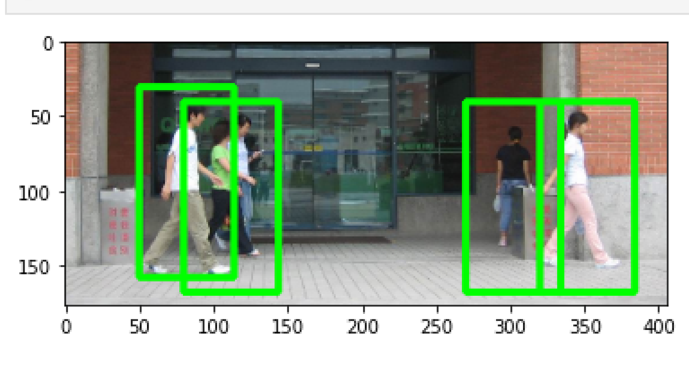
5. How to use the classifier on real images

In [67]:
```python
img = cv.imread("Images/FudanPed00036.png")[:,:,::-1]
scale = 0.4
img = cv.resize(img, (int(scale*img.shape[1]),int(scale*img.shape[0])))
plt.imshow(img)
plt.show()
```



In [68]:
```python
height, width = 128, 64
import utils
def detect(img, svc, step = 10, height = 128, width = 64):
    """
    img: any image
    svc: Support Vector Classifier
    step: Step size of window operation

    return:
        result: a matrix with the predicted labels result[i,j] != 0 means that at the given window a pedestrian
        bounding_boxes [N, 4]: A matrix of bounding boxes corresponding to found pedestrians.
        bounding_boxes[i,0:2] describe the upper left corner and bounding_boxes[i,2:4] describe the bottom righ
    """
    # Iterate over image and apply classifier
    result = np.zeros(img.shape[:2])-1
    for i in range(0,img.shape[0]-height, step):
        for j in range(0,img.shape[1]-width, step):
            result[i,j] = svc.predict(feature_extraction(img[i:i+height,j:j+width]).reshape(1, -1))[0]

    y,x = np.nonzero(result==0)
    bounding_boxes = np.stack([x,y,x+width,y+height],1)
    return result, bounding_boxes

result, bounding_boxes = detect(img, svc)
```

In [69]:
```python
bounding_boxes_filtered = utils.non_max_suppression_fast(bounding_boxes, 0.5)

res = img.copy()
for i in range(len(bounding_boxes_filtered)):
    x_1, y_1 = bounding_boxes_filtered[i,0],bounding_boxes_filtered[i,1]
    x_2, y_2 = bounding_boxes_filtered[i,2],bounding_boxes_filtered[i,3]

    res = cv.rectangle(res.astype(np.float32),(x_1, y_1),(x_2, y_2),(0,255,0),3).astype(np.uint8)

plt.imshow(res)
plt.show()
```



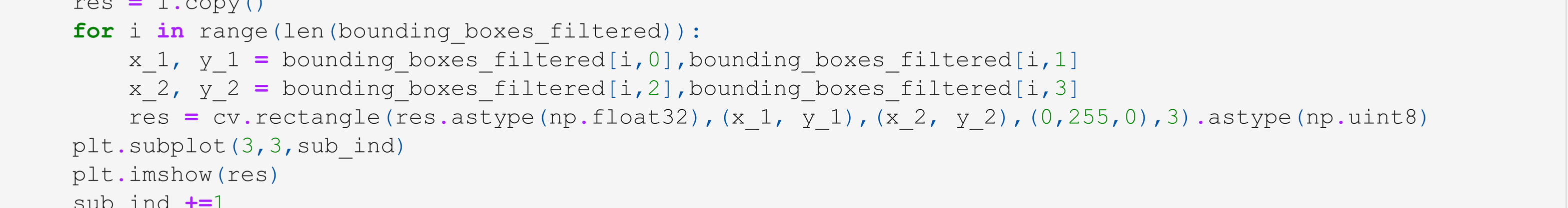
6 Deploy Model on Multiple Scales

The model only detects pedestrians in a specific resolution (64x128). Extend the application of the model to any resolution.

TODO

- Scale the images
- Detect people
- apply nonmaxima supression over multiple scales

In [70]:
```python
scales = [cv.GaussianBlur( img,(101,101),s ) for s in range(1,10)]
utils.showImages(scales)
```



In [71]:
```python
sub_ind = 1
plt.figure(figsize=(10,6))
for I in scales:
    result, bounding_boxes = detect(I, svc)
    bounding_boxes_filtered = utils.non_max_suppression_fast(bounding_boxes, 0.5)
    res = I.copy()
    for i in range(len(bounding_boxes_filtered)):
        x_1, y_1 = bounding_boxes_filtered[i,0],bounding_boxes_filtered[i,1]
        x_2, y_2 = bounding_boxes_filtered[i,2],bounding_boxes_filtered[i,3]
        res = cv.rectangle(res.astype(np.float32),(x_1, y_1),(x_2, y_2),(0,255,0),3).astype(np.uint8)
    plt.subplot(3,3,sub_ind)
    plt.imshow(res)
    sub_ind +=1
```