Homework4

July 30, 2018

0.0.1 Overview

The goal of this homework assignment is to help you develop a complete face recognition system that embraces the most recent technical advancements. In this module and previous modules, you have learn the following computer vision and machine learning techniques + Histogram of intensities/colors + Histogram of oriented gradients (HOG) + LM filter bank + Local Binary Pattern (LBP) + Bag of words + K-nearest Neighbor (KNN) + Softmax classifier + Feedforward Neural Network + Convolutional Neural Network (CNNs) + Domain specific data augmentation

0.0.2 Problem-1

Problem 1 (Orl dataset+LBP+HOG+SoftMax+FNN)

- The objective of this problem is to develop a program that can identify facial photos.
- The folder "orl_faces" includes facial photos of 40 subjects, each with 10 photos.

Please write a script to extract for each photo a histogram of Local Binary Pattern (LBPs) or a Histogram of Oriented Gradients (HoGs).
For classification purpose, please use SoftMax or Feedforward Neural Network (FNN).
This result in four combinations: + Softmax+LBP + Softmax+HoGs + FNN+LBP + FNN+HoGs

0.0.3 LBPs

- http://www.outex.oulu.fi/publications/pami_02_opm.pdf
- https://www.pyimagesearch.com/2015/12/07/local-binary-patterns-with-python-opencv/

0.1 Step-1

```
In [1]: # Load all the images
        import os
        import glob
        import PIL
        import scipy.misc
        from pathlib import Path
        import numpy as np
        import cv2
        path=os.getcwd()
```

```
folder=path+"\\orl_faces\\"
images=[]
for i in range(1,41):
    val="s"+str(i)
    final_path=folder+val
    temp=[]
    for f in Path(final_path).glob('*.pgm'):
        temp.append(scipy.misc.imread(f))
    images.append(np.asarray(temp))
```

```
C:\Users\sananand\AppData\Local\Continuum\miniconda3\envs\tensorflowpy36\lib\site-packages\ipyk
`imread` is deprecated in SciPy 1.0.0, and will be removed in 1.2.0.
Use ``imageio.imread`` instead.
```

```
In [2]: ## Veerify once the images are extracted
        import cv2
        from PIL import Image
        print(len(images))
        for i in range(0,7):
            print("Image shape of some of the images", images[0][i].shape)
            newimage=np.reshape(images[0][i],(images[0][i].shape[0], images[0][i].shape[1], 1))
            img=Image.fromarray(images[0][i])
            name="test_image"+str(i)+".png"
            img.save(name)
```

```
40
Image shape of some of the images (112, 92)
Image shape of some of the images (112, 92)
Image shape of some of the images (112, 92)
Image shape of some of the images (112, 92)
Image shape of some of the images (112, 92)
Image shape of some of the images (112, 92)
Image shape of some of the images (112, 92)
```

```
In [3]: print(images[0].shape)
```

```
(10, 112, 92)
```

0.2 Step-2

```
In [4]: def train_test_split(Images):
            train=[]
            test=[]
            #print(len(Images[39]))
            for i in range(40):
                temp_train=[Images[i][j] for j in range(6)]
```

```
                temp_test=[Images[i][j] for j in range(6,10)]
                train.append(np.asarray(temp_train))
                test.append(np.asarray(temp_test))
            return np.asarray(train), np.asarray(test)

        X_train, X_test = train_test_split(images)
```

In [5]:
```
print(X_train.shape)
print(X_test.shape)
```

```
(40, 6, 112, 92)
(40, 4, 112, 92)
```

In [6]:
```
# One hot encode the labels as well for the train and test
def labels():
    train_lab, test_lab = [],[]
    for i in range(40): #i is the subject so based on that you will one hot encode
        temp_=[0]*40
        temp_[i]=1
        temp_tr,temp_tst=[],[]
        for j in range(10):
            if j<=5:
                temp_tr.append(temp_)
            else:
                temp_tst.append(temp_)
        train_lab.append(temp_tr)
        test_lab.append(temp_tst)
    return np.asarray(train_lab), np.asarray(test_lab)

y_train, y_test = labels()
```

In [7]:
```
print("Training labels shape: {}, test labels shape: {}".format(y_train.shape, y_test.s
```

```
Training labels shape: (40, 6, 40), test labels shape: (40, 4, 40)
```

In [8]:
```
y_train[39]
```

Out[8]:
```
array([[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1]])
```

0.3 Step-3

- Histogram of LBP for each picture
- Module4/LBP_demo'. We recommend to use 8-bit and uniform LBP histograms.

In [11]:
```
"""
===============================================
Local Binary Pattern for texture classification
===============================================

In this example, we will see how to classify textures based on LBP (Local
Binary Pattern). LBP looks at points surrounding a central point and tests
whether the surrounding points are greater than or less than the central point
(i.e. gives a binary result).

Before trying out LBP on an image, it helps to look at a schematic of LBPs.
The below code is just used to plot the schematic.
"""
from __future__ import print_function
import numpy as np
import matplotlib.pyplot as plt


METHOD = 'uniform'
plt.rcParams['font.size'] = 9


def plot_circle(ax, center, radius, color):
    circle = plt.Circle(center, radius, facecolor=color, edgecolor='0.5')
    ax.add_patch(circle)


def plot_lbp_model(ax, binary_values):
    """Draw the schematic for a local binary pattern."""
    # Geometry spec
    theta = np.deg2rad(45)
    R = 1
    r = 0.15
    w = 1.5
    gray = '0.5'

    # Draw the central pixel.
    plot_circle(ax, (0, 0), radius=r, color=gray)
    # Draw the surrounding pixels.
    for i, facecolor in enumerate(binary_values):
        x = R * np.cos(i * theta)
        y = R * np.sin(i * theta)
        plot_circle(ax, (x, y), radius=r, color=str(facecolor))
```

```
    # Draw the pixel grid.
    for x in np.linspace(-w, w, 4):
        ax.axvline(x, color=gray)
        ax.axhline(x, color=gray)

    # Tweak the layout.
    ax.axis('image')
    ax.axis('off')
    size = w + 0.2
    ax.set_xlim(-size, size)
    ax.set_ylim(-size, size)


fig, axes = plt.subplots(ncols=5, figsize=(7, 2))

titles = ['flat', 'flat', 'edge', 'corner', 'non-uniform']

binary_patterns = [np.zeros(8),
                   np.ones(8),
                   np.hstack([np.ones(4), np.zeros(4)]),
                   np.hstack([np.zeros(3), np.ones(5)]),
                   [1, 0, 0, 1, 1, 1, 0, 0]]

for ax, values, name in zip(axes, binary_patterns, titles):
    plot_lbp_model(ax, values)
    ax.set_title(name)

######################################################################
# The figure above shows example results with black (or white) representing
# pixels that are less (or more) intense than the central pixel. When
# surrounding pixels are all black or all white, then that image region is
# flat (i.e. featureless). Groups of continuous black or white pixels are
# considered "uniform" patterns that can be interpreted as corners or edges.
# If pixels switch back-and-forth between black and white pixels, the pattern
# is considered "non-uniform".
#
# When using LBP to detect texture, you measure a collection of LBPs over an
# image patch and look at the distribution of these LBPs. Lets apply LBP to a
# brick texture.

from skimage.transform import rotate
from skimage.feature import local_binary_pattern
from skimage import data
from skimage.color import label2rgb

# settings for LBP
radius = 3
n_points = 8 * radius
```

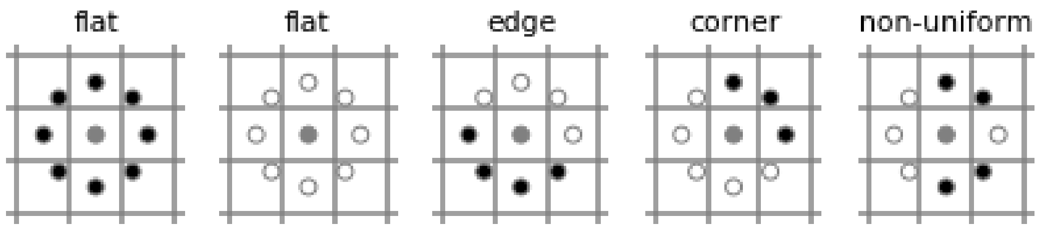
```python
def overlay_labels(image, lbp, labels):
    mask = np.logical_or.reduce([lbp == each for each in labels])
    return label2rgb(mask, image=image, bg_label=0, alpha=0.5)


def highlight_bars(bars, indexes):
    for i in indexes:
        bars[i].set_facecolor('r')


image = data.load('brick.png')
lbp = local_binary_pattern(image, n_points, radius, METHOD)

print("Check the dimensions of the image\n")
print(image.shape)
print("Check the dimensions of the LBP\n")
print(lbp.shape)


def hist(ax, lbp):
    n_bins = int(lbp.max() + 1)
    return ax.hist(lbp.ravel(), normed=True, bins=n_bins, range=(0, n_bins),
                   facecolor='0.5')


# plot histograms of LBP of textures
fig, (ax_img, ax_hist) = plt.subplots(nrows=2, ncols=3, figsize=(9, 6))
plt.gray()

titles = ('edge', 'flat', 'corner')
w = width = radius - 1
edge_labels = range(n_points // 2 - w, n_points // 2 + w + 1)
flat_labels = list(range(0, w + 1)) + list(range(n_points - w, n_points + 2))
i_14 = n_points // 4            # 1/4th of the histogram
i_34 = 3 * (n_points // 4)      # 3/4th of the histogram
corner_labels = (list(range(i_14 - w, i_14 + w + 1)) +
                 list(range(i_34 - w, i_34 + w + 1)))

label_sets = (edge_labels, flat_labels, corner_labels)

for ax, labels in zip(ax_img, label_sets):
    ax.imshow(overlay_labels(image, lbp, labels))

for ax, labels, name in zip(ax_hist, label_sets, titles):
    counts, _, bars = hist(ax, lbp)
    highlight_bars(bars, labels)
```

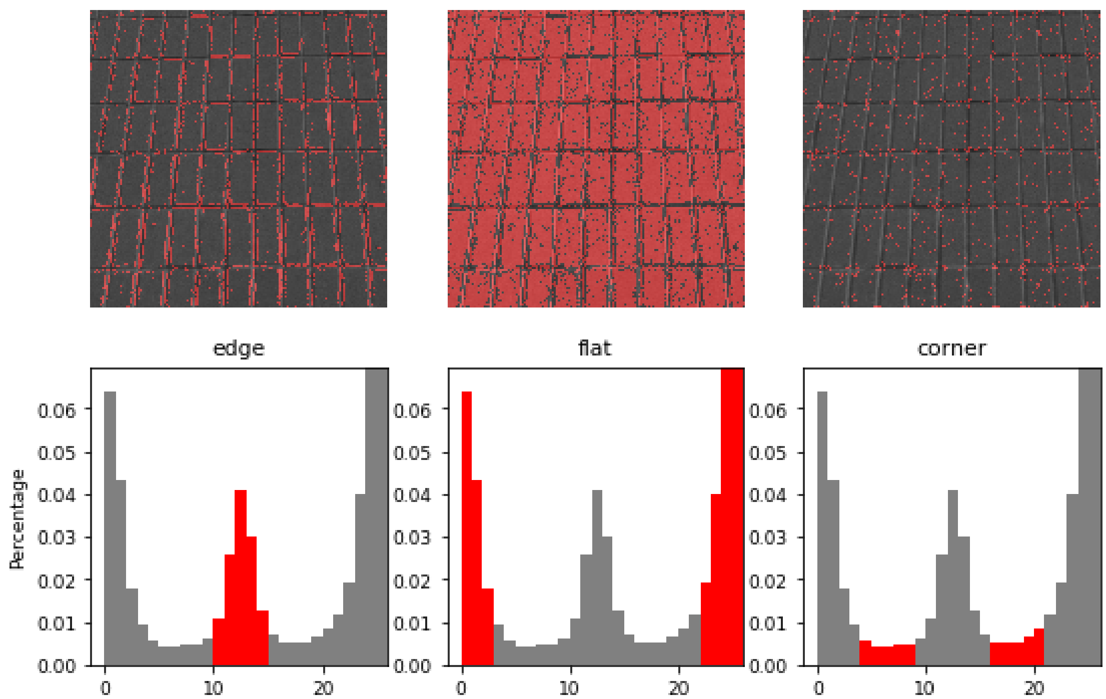
```
    ax.set_ylim(ymax=np.max(counts[:-1]))
    ax.set_xlim(xmax=n_points + 2)
    ax.set_title(name)

ax_hist[0].set_ylabel('Percentage')
for ax in ax_img:
    ax.axis('off')


######################################################################
# The above plot highlights flat, edge-like, and corner-like regions of the
# image.
#
# The histogram of the LBP result is a good measure to classify textures.
# Here, we test the histogram distributions against each other using the
# Kullback-Leibler-Divergence.

# settings for LBP
radius = 2
n_points = 8 * radius


def kullback_leibler_divergence(p, q):
    p = np.asarray(p)
    q = np.asarray(q)
    filt = np.logical_and(p != 0, q != 0)
    return np.sum(p[filt] * np.log2(p[filt] / q[filt]))


def match(refs, img):
    best_score = 10
    best_name = None
    lbp = local_binary_pattern(img, n_points, radius, METHOD)
    n_bins = int(lbp.max() + 1)
    hist, _ = np.histogram(lbp, normed=True, bins=n_bins, range=(0, n_bins))
    for name, ref in refs.items():
        ref_hist, _ = np.histogram(ref, normed=True, bins=n_bins,
                                   range=(0, n_bins))
        score = kullback_leibler_divergence(hist, ref_hist)
        if score < best_score:
            best_score = score
            best_name = name
    return best_name


brick = data.load('brick.png')
grass = data.load('grass.png')
wall = data.load('rough-wall.png')
```

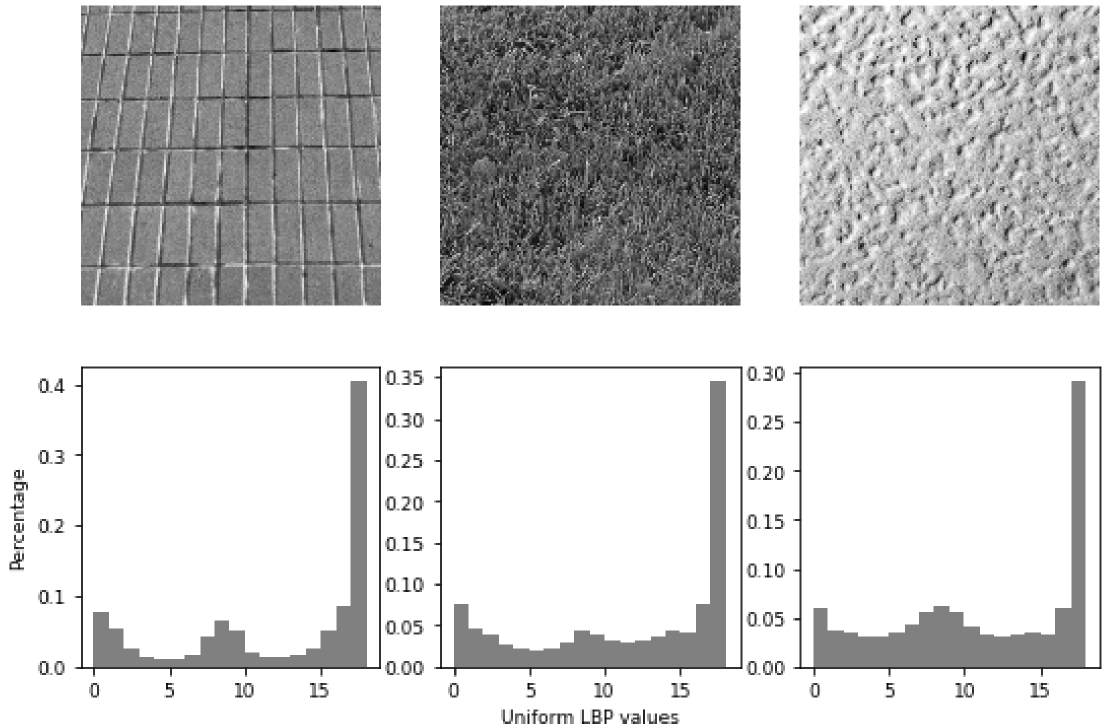
```
refs = {
    'brick': local_binary_pattern(brick, n_points, radius, METHOD),
    'grass': local_binary_pattern(grass, n_points, radius, METHOD),
    'wall': local_binary_pattern(wall, n_points, radius, METHOD)
}

# classify rotated textures
print('Rotated images matched against references using LBP:')
print('original: brick, rotated: 30deg, match result: ',
      match(refs, rotate(brick, angle=30, resize=False)))
print('original: brick, rotated: 70deg, match result: ',
      match(refs, rotate(brick, angle=70, resize=False)))
print('original: grass, rotated: 145deg, match result: ',
      match(refs, rotate(grass, angle=145, resize=False)))

# plot histograms of LBP of textures
fig, ((ax1, ax2, ax3), (ax4, ax5, ax6)) = plt.subplots(nrows=2, ncols=3,
                                                       figsize=(9, 6))
plt.gray()

ax1.imshow(brick)
ax1.axis('off')
hist(ax4, refs['brick'])
ax4.set_ylabel('Percentage')

ax2.imshow(grass)
ax2.axis('off')
hist(ax5, refs['grass'])
ax5.set_xlabel('Uniform LBP values')

ax3.imshow(wall)
ax3.axis('off')
hist(ax6, refs['wall'])

plt.show()
```

```
Check the dimensions of the image

(512, 512)
Check the dimensions of the LBP

(512, 512)


C:\Users\sananand\AppData\Local\Continuum\miniconda3\envs\tensorflowpy36\lib\site-packages\matp
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```

```
Rotated images matched against references using LBP:
original: brick, rotated: 30deg, match result:  brick
original: brick, rotated: 70deg, match result:  brick
original: grass, rotated: 145deg, match result:  grass
```








```
In [12]: # getting the LBP for each image for each subject for all the training and test sets
         print(X_train.shape)
         print(X_test.shape)
```

```
(40, 6, 112, 92)
(40, 4, 112, 92)
```

```
In [13]: def get_lbp(X_train, X_test):
             #do something
             # settings for LBP
             radius = 2
             n_points = 8 * radius
             METHOD = 'uniform'
             subjects, num_images_train, img_ht, img_wid = X_train.shape
             num_images_test=X_test.shape[1]
             X_train_new,X_test_new=[],[]

             #Train images for LBP
             for i in range(subjects):
                 temp=[]
                 for j in range(num_images_train):
                     img=X_train[i][j]
                     lbp=local_binary_pattern(img, n_points, radius, METHOD)
```

```
                temp.append(lbp)
            X_train_new.append(np.asarray(temp))

        #Test images for LBP
        for i in range(subjects):
            temp=[]
            for j in range(num_images_test):
                img=X_test[i][j]
                lbp=local_binary_pattern(img, n_points, radius, METHOD)
                temp.append(lbp)
            X_test_new.append(np.asarray(temp))
        return np.asarray(X_train_new), np.asarray(X_test_new)
```

In [14]:
```
X_train_transf, X_test_transf = get_lbp(X_train, X_test)
```

In [15]:
```
print("New Training set with feauture {}, New Test set with feature {}".format(X_trai
```

```
New Training set with feauture (40, 6, 112, 92), New Test set with feature (40, 4, 112, 92)
```

In [16]:
```
## Verify once the images are extracted
from matplotlib import pyplot as plt
def img_show(image_mat):
    print("Image shape of some of the images", image_mat.shape)
    img=Image.fromarray(image_mat)
    name="test_image_x"+".png"
    img.save(name)
    imgpath=os.getcwd()+"\\"+name
    im=cv2.imread(imgpath, 0)
    plt.imshow(im, cmap = 'gray', interpolation = 'bicubic')
    plt.xticks([]), plt.yticks([])  # to hide tick values on X and Y axis
    plt.show()
    return img

#plot some random images
subs=[np.random.randint(1,10) for id in range(10)]
for s in subs:
    img_show(X_train[s][5])
```

```
Image shape of some of the images (112, 92)
```

```
Image shape of some of the images (112, 92)
```

```
Image shape of some of the images (112, 92)
```

Image shape of some of the images (112, 92)

Image shape of some of the images (112, 92)

```
Image shape of some of the images (112, 92)
```

```
Image shape of some of the images (112, 92)
```

```
Image shape of some of the images (112, 92)
```

```
Image shape of some of the images (112, 92)
```

```
Image shape of some of the images (112, 92)
```

0.3.1 Verify the LBPs of the Face Images

```
In [17]: # Let's Plot some of the LBPs
         # plot histograms of LBP of textures
```

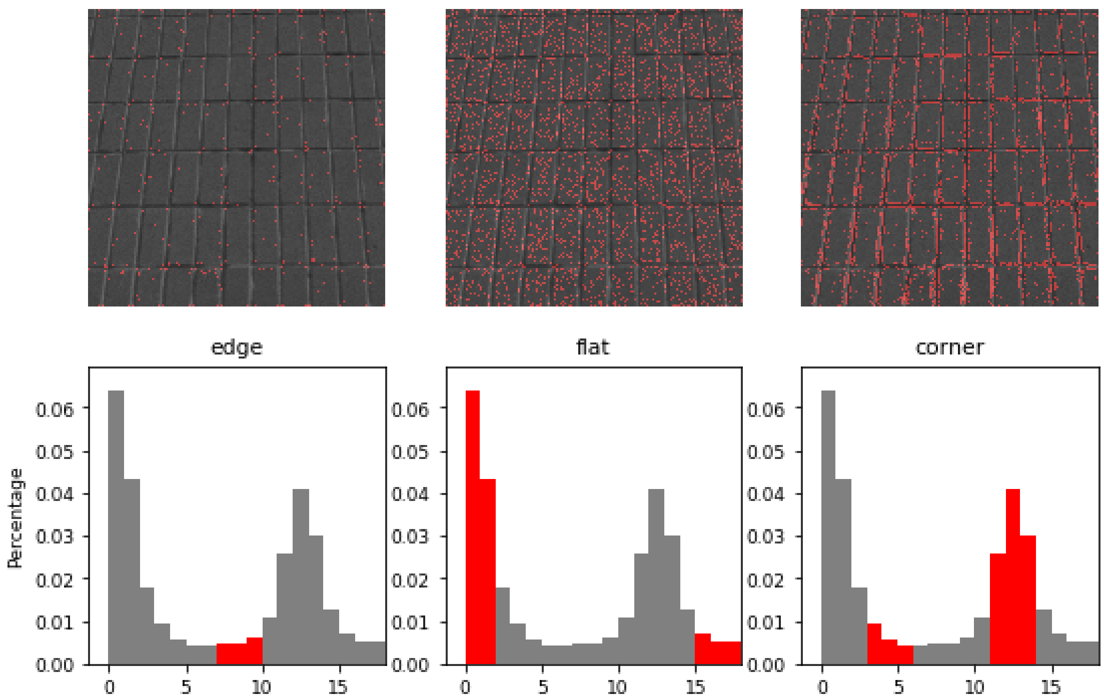
```python
fig, (ax_img, ax_hist) = plt.subplots(nrows=2, ncols=3, figsize=(9, 6))
plt.gray()

titles = ('edge', 'flat', 'corner')
w = width = radius - 1
edge_labels = range(n_points // 2 - w, n_points // 2 + w + 1)
flat_labels = list(range(0, w + 1)) + list(range(n_points - w, n_points + 2))
i_14 = n_points // 4            # 1/4th of the histogram
i_34 = 3 * (n_points // 4)      # 3/4th of the histogram
corner_labels = (list(range(i_14 - w, i_14 + w + 1)) +
                 list(range(i_34 - w, i_34 + w + 1)))

label_sets = (edge_labels, flat_labels, corner_labels)

for ax, labels in zip(ax_img, label_sets):
    ax.imshow(overlay_labels(image, lbp, labels))

for ax, labels, name in zip(ax_hist, label_sets, titles):
    counts, _, bars = hist(ax, lbp)
    highlight_bars(bars, labels)
    ax.set_ylim(ymax=np.max(counts[:-1]))
    ax.set_xlim(xmax=n_points + 2)
    ax.set_title(name)

ax_hist[0].set_ylabel('Percentage')
for ax in ax_img:
    ax.axis('off')


######################################################################
# The above plot highlights flat, edge-like, and corner-like regions of the
# image.
#
# The histogram of the LBP result is a good measure to classify textures.
# Here, we test the histogram distributions against each other using the
# Kullback-Leibler-Divergence.

# settings for LBP
radius = 2
n_points = 8 * radius


def kullback_leibler_divergence(p, q):
    p = np.asarray(p)
    q = np.asarray(q)
    filt = np.logical_and(p != 0, q != 0)
    return np.sum(p[filt] * np.log2(p[filt] / q[filt]))
```

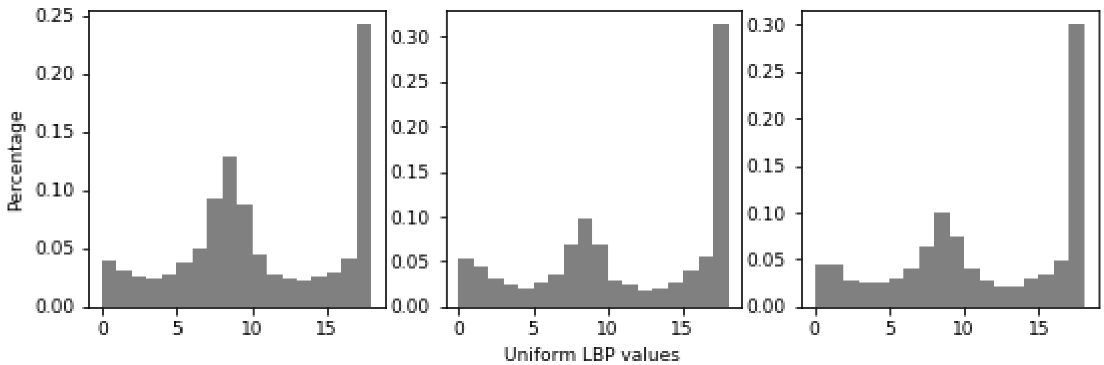
```python
def match(refs, img):
    best_score = 10
    best_name = None
    lbp = local_binary_pattern(img, n_points, radius, METHOD)
    n_bins = int(lbp.max() + 1)
    hist, _ = np.histogram(lbp, normed=True, bins=n_bins, range=(0, n_bins))
    for name, ref in refs.items():
        ref_hist, _ = np.histogram(ref, normed=True, bins=n_bins,
                                   range=(0, n_bins))
        score = kullback_leibler_divergence(hist, ref_hist)
        if score < best_score:
            best_score = score
            best_name = name
    return best_name

randsubs=[np.random.randint(0,40) for id in range(3)]
for i,s in enumerate(randsubs[0:3]):
    if i==0:
        img1=X_train[s][5]
    if i==1:
        img2=X_train[s][5]
    if i==2:
        img3=X_train[s][5]

refs = {
    'img1': local_binary_pattern(img1, n_points, radius, METHOD),
    'img2': local_binary_pattern(img2, n_points, radius, METHOD),
    'img3': local_binary_pattern(img3, n_points, radius, METHOD)
}

# classify rotated textures
print('Rotated images matched against references using LBP:')
print('original: img1, rotated: 30deg, match result: ',
      match(refs, rotate(img1, angle=30, resize=False)))
print('original: img2, rotated: 70deg, match result: ',
      match(refs, rotate(img2, angle=70, resize=False)))
print('original: img3, rotated: 145deg, match result: ',
      match(refs, rotate(img3, angle=145, resize=False)))

# plot histograms of LBP of textures
fig, ((ax1, ax2, ax3), (ax4, ax5, ax6)) = plt.subplots(nrows=2, ncols=3,
                                                       figsize=(9, 6))
plt.gray()

ax1.imshow(img1)
ax1.axis('off')
hist(ax4, refs['img1'])
```

```
ax4.set_ylabel('Percentage')

ax2.imshow(img2)
ax2.axis('off')
hist(ax5, refs['img2'])
ax5.set_xlabel('Uniform LBP values')

ax3.imshow(img3)
ax3.axis('off')
hist(ax6, refs['img3'])

plt.show()
```

```
C:\Users\sananand\AppData\Local\Continuum\miniconda3\envs\tensorflowpy36\lib\site-packages\matp
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```

```
Rotated images matched against references using LBP:
original: brick, rotated: 30deg, match result:  img1
original: brick, rotated: 70deg, match result:  img2
original: grass, rotated: 145deg, match result:  img1
```





0.3.2 Step 4: Learn softmax classifiers

- Refer to 'Module2/main_softmax_cifar10.py' and related scripts.
- These scripts use the tensorflow to implement the softmax classifier.
- Similar to Homework Assignment 2

0.3.3 Some steps for preprocessing before applying softmax using TF

- change the Training set into the dimensions [240, 10304] , as 112x92
- change the Testing set into the dimensions [160, 10304]
- Change the One hot encoded labels to dimentions [240, 40] and [160, 40] respectively

```
In [27]: ## Using the Softmax Classifier with Tensorflow
         import tensorflow as tf
         print("TensorFlow version " + tf.__version__)
         tf.set_random_seed(0)
```

```
TensorFlow version 1.2.1
```

```
In [35]: # Reshaping the Training set and test set to use with TF
         reshaped_train_set = np.reshape(X_train_transf, (240, X_train_transf.shape[2], X_trai
         reshaped_train_set = reshaped_train_set.reshape(-1, 10304)
         reshaped_test_set = np.reshape(X_test_transf, (160, X_test_transf.shape[2], X_test_tra
```

```
reshaped_test_set = reshaped_test_set.reshape(-1, 10304)
print("Reshaped Train set shape {}, Reshaped Test set shape {}".format(reshaped_train_
```

```
Reshaped Train set shape (240, 10304), Reshaped Test set shape (160, 10304)
```

In [38]:
```
# Reshaping the Labels
reshaped_train_labels  = np.reshape(y_train, (240, y_train.shape[-1]))
reshaped_test_labels   = np.reshape(y_test, (160, y_test.shape[-1]))
print("Reshaped Train labels shape {}, Reshaped Test labels shape {}".format(reshaped_
```

```
Reshaped Train labels shape (240, 40), Reshaped Test labels shape (160, 40)
```

In [42]:
```
reshaped_train_labels[0:12]
```

Out[42]:
```
array([[1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
         0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
        [1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
         0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
        [1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
         0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
        [1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
         0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
        [1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
         0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
        [1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
         0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
        [0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
         0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
        [0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
         0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
        [0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
         0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
        [0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
         0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
        [0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
         0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
        [0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
         0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]])
```

In [59]:
```
# Normalize the feature data before training
maximum_tr=max(reshaped_train_set[0])
reshaped_train_set_norm = reshaped_train_set/(1.0*maximum_tr)
maximum_test=max(reshaped_test_set[0])
reshaped_test_set_norm = reshaped_test_set/(1.0*maximum_test)
```

In [61]:
```
reshaped_train_set_norm[9][0:30]
```

Out[61]: array([0.29411765, 0.05882353, 1.   , 1.   , 1.   ,
       1.   , 1.   , 0.17647059, 0.   , 0.52941176,
       1.   , 0.41176471, 0.05882353, 1.   , 0.52941176,
       0.   , 0.52941176, 0.05882353, 1.   , 0.52941176,
       1.   , 1.   , 1.   , 1.   , 1.   ,
       1.   , 0.52941176, 1.   , 1.   , 0.17647059])

In [62]:
```
reshaped_test_set_norm[5][0:30]
```

Out[62]: array([1.   , 1.   , 1.   , 0.47058824, 0.   ,
       0.17647059, 1.   , 0.47058824, 1.   , 0.52941176,
       0.   , 0.05882353, 0.52941176, 0.52941176, 0.05882353,
       0.   , 0.47058824, 0.52941176, 0.52941176, 1.   ,
       1.   , 0.17647059, 1.   , 1.   , 1.   ,
       0.29411765, 0.47058824, 0.52941176, 0.52941176, 0.52941176])

In [85]:
```
import time
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix

beginTime = time.time()

# Parameter definitions
batch_size = 10
learning_rate = 0.0003
max_steps = 1000

# Define input placeholders for images and labels
images_placeholder = tf.placeholder(tf.float32, shape=[None, 10304])
labels_placeholder = tf.placeholder(tf.float32, shape=[None, 40])

# Define variables (these are the variables we want to optimize)
weights = tf.Variable(tf.zeros([10304, 40]))
biases = tf.Variable(tf.zeros([40]))

# define classifier's output, linear classification
#logits = tf.matmul(images_placeholder, weights) + biases
logits = tf.nn.softmax(tf.matmul(tf.reshape(images_placeholder, [-1, 10304]), weights

# Define the loss function, softmax loss
#loss = tf.reduce_mean(tf.nn.sparse_softmax_cross_entropy_with_logits(logits=logits,l
loss = -tf.reduce_sum(labels_placeholder*tf.log(logits))

# Define the training operation: gradient descent
train_step = tf.train.GradientDescentOptimizer(learning_rate).minimize(loss)

# Operation comparing prediction with true label
#correct_prediction = tf.equal(tf.argmax(logits, 1), labels_placeholder)
```

```
        correct_prediction = tf.equal(tf.argmax(logits,1), tf.argmax(labels_placeholder,1))

        # Operation calculating the accuracy of our predictions
        accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))
        confusion_matrix = tf.confusion_matrix(tf.argmax(labels_placeholder,1), tf.argmax(logi
        #print(labels_placeholder.shape, logits.shape)

        with tf.Session() as sess:
            # Initialize variables
            sess.run(tf.global_variables_initializer())

            # Repeat max_steps times
            for i in range(max_steps):
                # Generate input data batch
                indices = np.random.choice(reshaped_train_set_norm.shape[0], batch_size)
                images_batch = reshaped_train_set_norm[indices]
                labels_batch = reshaped_train_labels[indices]

                # Periodically print out the model's current accuracy
                if i % 100 == 0:
                    train_accuracy = sess.run(accuracy, feed_dict={images_placeholder: images_
                    print('Step {:5d}: training accuracy {:g}'.format(i, train_accuracy))

                # Perform a single training step
                sess.run(train_step, feed_dict={images_placeholder: images_batch,labels_placel
            # After finishing the training, evaluate on the test set
            test_accuracy, conf_mat = sess.run([accuracy, confusion_matrix], feed_dict={images
            print('Test accuracy {:g}'.format(test_accuracy))
            print('Confusion Matrix',conf_mat)
        endTime = time.time()
        print('Total time: {:5.2f}s'.format(endTime - beginTime))
```

```
Step     0: training accuracy 0
Step   100: training accuracy 0.5
Step   200: training accuracy 1
Step   300: training accuracy 1
Step   400: training accuracy 1
Step   500: training accuracy 1
Step   600: training accuracy 1
Step   700: training accuracy 1
Step   800: training accuracy 1
Step   900: training accuracy 1
Test accuracy 0.55625
Confusion Matrix [[1 0 0 ... 0 0 0]
 [0 4 0 ... 0 0 0]
 [0 0 1 ... 0 0 0]
 ...
 [0 0 0 ... 2 0 0]
```

```
 [0 0 0 ... 0 1 0]
 [1 0 0 ... 0 0 1]]
Total time:  5.43s
```

```
In [94]: # Making sense of the confusion matrix
         for idx,c in enumerate(conf_mat[:]):
             if idx!=np.argmax(c, 0):
                 print("Wrong Prediction for class : {}".format(idx))
```

```
Wrong Prediction for class : 0
Wrong Prediction for class : 2
Wrong Prediction for class : 13
Wrong Prediction for class : 15
Wrong Prediction for class : 16
Wrong Prediction for class : 26
Wrong Prediction for class : 30
Wrong Prediction for class : 32
Wrong Prediction for class : 34
Wrong Prediction for class : 35
Wrong Prediction for class : 38
Wrong Prediction for class : 39
```

0.3.4 Results for LBP and use of Softmax classifiers

- One of the Output runs are pretty good as you see below, caught one of the good runs !!

  ```
  (?, 40) (?, 40)
  Step     0: training accuracy 0
  Step   100: training accuracy 0.4
  Step   200: training accuracy 0.9
  Step   300: training accuracy 1
  Step   400: training accuracy 1
  Step   500: training accuracy 1
  Step   600: training accuracy 1
  Step   700: training accuracy 1
  Step   800: training accuracy 1
  Step   900: training accuracy 1
  Test accuracy 0.5375
  Total time:  6.60s
  ```

- Training accuracy reaches 100%
- Test accuracy reaches almost 50%
- Dataset is extremely small so not much data to work with, data-augmentation will help a lot here, will try that later