Homework 5 Writeup

Instructions

- Describe any interesting decisions you made to write your algorithm.
- Show and discuss the results of your algorithm.
- Feel free to include code snippets, images, and equations.
- There is no page limit.

Feature extraction

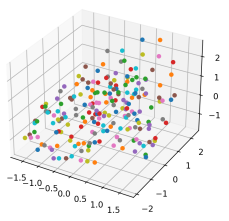
```
import cv2
import numpy as np


def feature_extraction(img, feature):
    """
    This function computes defined feature (HoG, SIFT) descriptors of the 

    :param img: a height x width x channels matrix,
    :param feature: name of image feature representation.

    :return: a N x feature_size matrix.
    """

    if feature == 'HoG':
        # HoG parameters
        win_size = (32, 32)
        block_size = (32, 32)
        block_stride = (16, 16)
        cell_size = (16, 16)
        nbins = 9
        deriv_aperture = 1
        win_sigma = 4
        histogram_norm_type = 0
        l2_hys_threshold = 2.0000000000000001e-01
        gamma_correction = 0
        nlevels = 64

        # Your code here. You should also change the return value.

        hog_descriptor = cv2.HOGDescriptor(win_size, block_size,
        block_stride, cell_size, nbins, deriv_aperture, win_sigma,
        histogram_norm_type, l2_hys_threshold, gamma_correction, nlevels)
        feature = np.array(hog_descriptor.compute(img))

         return np.reshape(feature, ((int)(feature.shape[0]/36), 36))

    elif feature == 'SIFT':

        # Your code here. You should also change the return value.

        sift = cv2.SIFT_create()
        keypoints, descriptor = sift.detectAndCompute(img, None)

    return np.array(descriptor)
```

I found features of images using hog and sift. For HOG, Accuracy (mean of diagonal of confusion matrix) is 0.498 For SIFT, Accuracy (mean of diagonal of confusion matrix) is 0.380 SIFT should result better accuracy, so my implementation is not perfect.

Principle component analysis (PCA) for vocabulary

```
import numpy as np

def get_features_from_pca(feat_num, feature):

    vocab = np.load(f'vocab_{feature}.npy')

    vocab_normalized = (vocab - vocab.mean(axis=0)) / vocab.std(axis=0)
    cov_vocab = vocab_normalized.T @ vocab_normalized
    _, eig_vec = np.linalg.eig(cov_vocab)

    return vocab_normalized @ (eig_vec[:, :feat_num] @ eig_vec[:, :feat_num
```

I normalized the feature vectors of vocabularies, and performed PCA by finding eigen vectors. Image result below for HOG descriptor



Bag of words representation of scenes

```
from matplotlib.pyplot import axis
import cv2
import numpy as np
from numpy import linalg

from distance import pdist
from feature_extraction import feature_extraction


def get_bags_of_words(image_paths, feature):
    vocab = np.load(f'vocab_{feature}.npy')

    vocab_size = vocab.shape[0]

    all_hists = []

    for path in image_paths:
        img = cv2.imread(path)[:, :, ::-1]

    features = feature_extraction(img, feature)
    hist, _ = np.histogram(np.argmin(pdist(features, vocab), axis=1), bins
    hist = (hist - hist.mean()) / hist.std()
    all_hists.append(hist)

    return np.array(all_hists)

def get_spatial_pyramid_feats(image_paths, max_level, feature):

    vocab = np.load(f'vocab_{feature}.npy')

    vocab_size = vocab.shape[0]

    all_hists = []
    for path in image_paths:
        img = cv2.imread(path)[:, :, ::-1]
        img_hist = []
        w, h, _ = img.shape
        for i in range(max_level+1):
            for j in range(4**i):
                pyramid_img = img[w*(j//2**i)//2**i:w*(j//2**i+1)//2**i, h
                features = feature_extraction(pyramid_img, feature)
                if features.shape == ():
                    hist = np.zeros(200)
                else:
                    hist, _ = np.histogram(np.argmin(pdist(features, vocab
                    hist = (hist - hist.mean()) / hist.std()
            img_hist.append(hist)
            img_hist = np.concatenate(img_hist, 0)
            all_hists.append(img_hist)

    return np.array(all_hists)
```

From the given words, find closest vocabulary and put it in the histogram. To find closest vocabulary, I computed distance between given word and vocabularies. For spatial pyramid representation, I splitted images for pyramid and extracted features from those image pieces, where bag of words compute it by extracting features of whole image. I used double loop to split image.

Accuracy (mean of diagonal of confusion matrix) is 0.498 for HOG descriptor with bag of words method. Accuracy (mean of diagonal of confusion matrix) is 0.615 for HOG descriptor with spacial pyramid representation. Spacial pyramid representation should result in better accuracy, so my result corresponds with theory.

SVM

```
from matplotlib.pyplot import axis
import numpy as np
from sklearn import svm


def svm_classify(train_image_feats, train_labels, test_image_feats, kernel_
    categories = np.unique(train_labels)

    score = []
    for label in categories:
        model = svm.LinearSVC(C=1, max_iter=100000)
        model.fit(train_image_feats, train_labels==label)
        score.append(model.decision_function(test_image_feats))
    score = np.array(score)
    classified_label = np.argmax(np.array(score), axis=0)

    return np.array([categories[i] for i in classified_label])
```

For all the labels, I computed SVM and its score to compare and get the best one, as shwon in ”argmax” For kernel trick, which I did not implemented, it projects data into higher-dimensional space defined by polynomials and Gaussian basis functions to fit for nonlinear relationships with a linear classifier. As a result, if implemented correctly, using RBF will increase accuracy.