EE 569: Homework #4

Issued: 3/9/2022 Due: 3/27/2022, 11:59PM

General Instructions:

1. Read *Homework Guidelines* and *MATLAB Function Guidelines* for the information about homework programming, write-up, and submission.
2. If you make any assumptions about a problem, please clearly state them in your report.
3. Do not copy sentences directly from any reference or online source. Written reports and source codes are subject to verification for any plagiarism. You need to understand the USC policy on academic integrity and penalties for cheating and plagiarism. These rules will be strictly enforced.

Problem 1: Texture Analysis (35%)

In this problem, you will implement texture analysis and segmentation algorithms based on the 5x5 Laws Filters constructed by the tensor product of the five 1D kernels in Table 1.

Table 1: 1D Kernel for 5x5 Laws Filters

Name	Kernel
L5 (Level)	[1 4 6 4 1]
E5 (Edge)	[-1 -2 0 2 1]
S5 (Spot)	[-1 0 2 0 -1]
W5 (Wave)	[-1 2 0 -2 1]
R5 (Ripple)	[1 -4 6 -4 1]

a) Texture Classification – Feature Extraction (15%)

48 images of four types of textures are given for the texture classification task. They are split into two sets, 36 training samples and 12 testing samples. The ground truth labels of the 36 training samples are known, while the testing samples' categories are waiting for you to explore. Samples of these images are shown in Fig. 1.

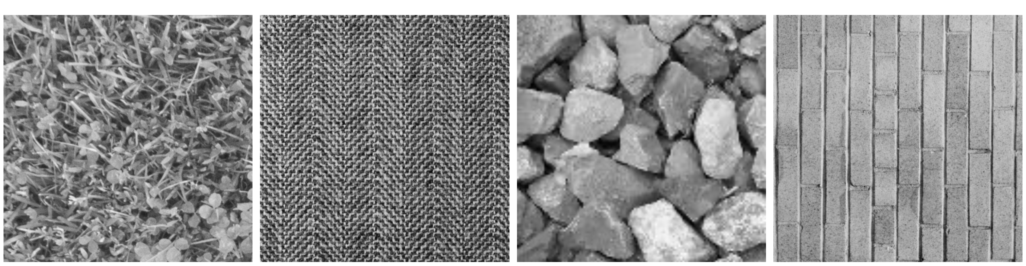


Figure 1: Examples of Grass, Blanket, Stones, Brick [2]

Please follow steps below to extract features for all texture images provided and do analysis:

1. **Filter bank response computation:** Use the twenty-five 5x5 Laws Filters in Table 1 to extract the response vectors from each pixel in the image (use appropriate boundary extensions).
2. **Energy feature averaging:** Compute the energy feature of each element of the response vector. Average the energy feature vectors of all image pixels, leading to a 25-D feature vector for each image. Which feature dimension has the strongest discriminant power? Which has the weakest? Please justify your answer.
3. **Feature reduction:** Reduce the feature dimension from 25 to 3 using the principal component analysis (PCA). Plot the reduced 3-D feature vectors in the 3-D feature space.

Please conduct texture classification using the nearest neighbor rule based on the Mahalanobis distance.

Note: Built-in PCA function can be used.

b) Advanced Texture Classification --- Classifier Exploration (20%)

Based on the 25-D and 3-D feature vectors obtained above, conduct both unsupervised and supervised learning. Please follow the steps below.

1. **Unsupervised:** K-means clustering is a kind of unsupervised learning algorithm which separates the textures into different categories without the help of ground truth labels. It will not directly tell the class for each image but will group similar images together.
   a. Apply the K-means algorithm for test images based on the 25-D feature and the reduced 3-D feature, respectively. Set the hyperparameter *K* (number of clusters) equal to the number of possible classes in the dataset (e.g. *K=4*).
   b. Use the test labels to evaluate the purity of each cluster. Specifically, classify the images in each cluster as the majority class of that cluster. Report the error rate for both methods. Discuss the effectiveness of the feature dimension reduction over the K-means clustering.
2. **Supervised:** Use the 3-D feature of training images to train the Random Forest (RF) and the Support Vector Machine (SVM), respectively. Then predict the test set labels and report the error rate. Compare the two classifiers.

Note: Built-in K-means function, RF and SVM can be used.

Problem 2: Texture Segmentation (30%)

a) Basic Texture Segmentation (20%)

Segment the texture mosaic *Mosaic.raw* in Fig. 2 by following the steps below:

1. **Filter bank response computation:** Use the twenty-five 5x5 Laws Filters in Table 1 to extract the response vectors from each pixel in the image (use appropriate boundary extensions).
2. **Energy feature computation:** Use a window approach to compute the energy measure for each center pixel based on the results from step 1. You may try a couple of different window sizes. After this step, you will obtain 25-D energy feature vector for each pixel.
3. **Energy feature normalization:** All kernels have a zero-mean except for $L5^T L5$. Actually, the feature extracted by the filter $L5^T L5$ is not a useful feature for texture classification and segmentation. Use its energy to normalize all other features at each pixel.
4. **Segmentation:** Discard the feature associated with $L5^T L5$. Use the K-means algorithm to perform segmentation on the composite texture image given in Fig. 2 based on the 24-D energy feature vectors.

If there are K textures in the image, your output image will be of K colors, with each color represents one type of texture. Use the following randomly generated color map to represent the K=6 regions. The ordering does not matter.

	0	**1**	**2**	**3**	**4**	**5**
R	107	114	175	167	144	157
G	143	99	128	57	147	189
B	159	107	74	32	104	204

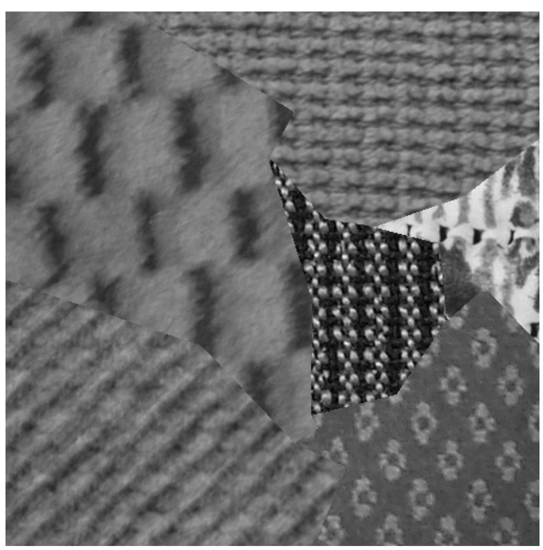


Figure 2: Texture mosaic image. [3]

b) Advanced Texture Segmentation (10%)

You may not get good segmentation results for the complicated texture mosaic image in Fig. 2. Please develop some techniques to improve your segmentation result. Several ideas are sketched below.

1. Use the PCA for feature reduction. Use the dimension reduced features to do texture segmentation of Fig. 2.
2. Develop a post-processing technique to merge small holes.
3. Enhance the boundary of two adjacent regions by focusing on the texture properties in these two regions only.

Problem 3: SIFT and Image Matching (35%)

Image feature extractors are useful for representing the image information in a low dimensional form.

(a) Salient Point Descriptor (Basic: 10%)

SIFT is an effective tool to extract salient points in an image. Read the paper in [1] and answer the following questions.

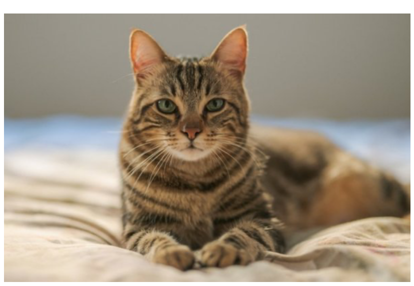
1. From the paper abstract, the SIFT is robust to what geometric modifications?
2. How does SIFT achieve its robustness to each of them?
3. How does SIFT enhance its robustness to illumination change?
4. What are the advantages of using Difference of Gaussians (DoG) instead of Laplacian of Gaussians (LoG) in SIFT?
5. What is the SIFT's output vector size in its original paper?

(b) Image Matching (Basic: 15%)

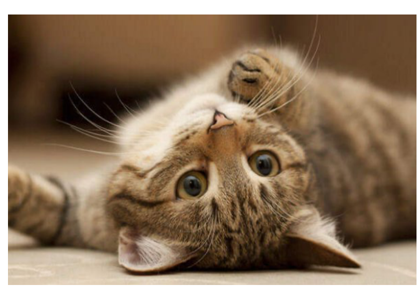
You can apply SIFT to image matching. Extract and show SIFT features.

1. Find key-points of the Cat_1 and Cat_Dog images in Fig. 3. Pick the key-point with the largest scale in Cat_1 and find its closest neighboring key-point in Cat_Dog. You can do nearest neighbor search in the searching database for the query image Cat_1 which is represented as a SIFT extracted feature vector. Discuss your results, especially the orientation of each key-point. Show the corresponding SIFT pairs between Cat_1 and Cat_Dog.
2. Perform the same processing with the following three image pairs: a) Dog_1 and Cat_Dog, b) Cat_1 vs Cat_2, c) Cat_1 vs Dog_1. The matching may not work well between different objects or against the same object but with a large viewing angle difference. Show and comment on the matching results. Explain why it works or fails in some cases.

You are allowed to use open source library (OpenCV or VLFeat) to extract features.



(a) Cat_1



(b) Cat_2

(c) Dog_1 (d) Cat_Dog

Figure 3: Images for image matching. [4]

(c) Bag of Words (10%)

If we create a codebook with K codewords representing K types of key patterns, each image can be represented by the codewords. A histogram can be calculated to reflect the occurrence of each codeword in an image. This representation is called the Bag of Words (BoW).

Apply the K-means clustering to the extracted SIFT features from the four images in part (b) to form a codebook with K=8 codewords. Each codeword is characterized by the centroid of the SIFT feature vectors. Generate the BoW representations for Cat_1, Dog_1 and Dog_2 provided in the materials. Match Dog_2's BoW representation with Cat_1 and Dog_1, respectively. Which one gives you the better matching? Show the histograms of these three images and discuss your observations.

Figure 4: Dog_2 image. [4]

Appendix:

Problem 1: Texture Analysis

48 texture images (**./train and ./test**)	128x128	8-bit	grayscale

Problem 2: Texture Segmentation

Mosaic.raw	512x512	8-bit	grayscale

Problem 3: Image Feature Extractors

Cat_1.raw	600x400	24-bit	Color (RGB)
Cat_2.raw	600x400	24-bit	Color (RGB)

Cat_Dog.raw	600x400	24-bit	Color (RGB)
Dog_1.raw	600x400	24-bit	Color (RGB)
Dog_2.raw	600x400	24-bit	Color (RGB)

Reference Images

Images in this homework are taken from SIPI Image Database [2], Prague dataset [3] and Google images [4].

References

[1] David G. Lowe, “Distinctive image features from scale-invariant keypoints,” International Journal of Computer Vision, 60(2), 91-110, 2004

[2] https://sipi.usc.edu/database/

[3] https://mosaic.utia.cas.cz/

[4] [Online] http://images.google.com/