Computer Vision and Pattern Recognition

CS 4243

S1-Y2022/23

NUS National University of Singapore | School of Computing

6 questions, 6 CA marks

Due date: Check Luminus

Coursework 3

Lessons 5 & 6

A COLORFUL TEXTURE!

Important …

- Coursework 3 contains 6 questions; and conveys 6 CA marks (1*6=6)
- To find the Due date, please Check the Luminus
- Here, DTR = Discuss The Results
- Submission:
  - Check the best way and proper format of submission with your TA

Coursework 3

1. **Study, Color Spaces, Fill the gaps, please.**
   A. The wavelength of blue color is roughly between …. Nanometer and the wavelength of red color is roughly between …. Nanometer.
   B. The relation between the wavelength (λ) and the frequency (f) of an electromagnetic wave is:

$$\lambda = \frac{\dots}{f}$$

   C. The ….. The frequency of a color spectrum, the higher its rate of absorption in the environment, so the …. the distance it can travel.
   D. Therefore, we can see a …. Light from a much further distance, compared to a same power …. Light.

Coursework 3

2. Gold color: Use gold1.bmp and gold2.bmp, and fill up the table below.

- You may compute the average of each value over all the pixels of your image.
- You can use the OpenCV functions.

Image:	**Gold1.bmp**		**HSV**		**Lab**	
R	G	B	H	S	a	b
Image:	**Gold2.bmp**		**HSV**		**Lab**	
R	G	B	H	S	a	b

Coursework 3

3. Refer to the face portraits directory, faces,

1. For all 4 portraits there, convert them to HSV color space.
2. Find a range of **H** and a range of **S** that can cover a good majority of the face pixels. (for each image separately)
3. Use that ranges and reject all other pixels using an **H-S** select filter. (for each image separately)
4. Show the results. What will be the applications?
5. Can we develop a general **H-S** filter for face segmentation in all possible portraits that exist on the Web? Discuss your answer.

Coursework 3

3. (continued) Refer to the face portraits directory, faces,

- How to do that? Possibly the best way is random sampling.
- So, for each image, randomly select a face pixel, save its {R,G,B}, find its {H,S}, and repeat that for 10 to 20 face pixels.
- Now you have got random samples of face pixels' H and. So, you can easily compute a reasonable range for that face's H and S.
- Complete the next table, as well as provide the answers for the last page questions.
- Those portraits are nobody. I generated them using a GAN deep neural network.

Coursework 3

3. (continued) Refer to the face portraits directory, faces,

Image	Min H	Max H	Min S	Max S
m2_samples_533_4.png				
m2_samples_563_0.png				
m2_samples_565_3.png				
m2_samples_615_1.png				

Coursework 3

4. Local Binary Patterns:

1. Develop a function to extract the local binary pattern of any given gray level image.
2. Your function should get a gray level image matrix as the input parameter, and return the LBP matrix, its histogram, and the LBP matrix power, e.g.:

def lbp(image):

Usage:

Lbp_mat , lbp_hist , lbp_power = lbp(imag)

3. Test your function with the test images mentioned and complete the next table.

Coursework 3

4. (continued) Local Binary Patterns:

image	LBP Power
Gold1.bmp	
diag_texture.bmp	
IMG_0054q.JPG	

4. We don’t use padding here. The LBP matrix size will be equal to your image size. The first/last row/column of the LBP matrix is 0. So, if your image is NxN, the LBP will be computed for pixels between [1:N-1 , 1:N-1]

Coursework 3

5. Gray Level Co-Occurrence Matrices:

1. Develop a function to extract (to compute) the GLCM of any given gray level image and return the GLCM matrix. The input is the gray level image matrix, number of gray levels, and distance and Θ parameters, while the output is the GLCM of that image for that d and Θ.

def glcm(imag, GL, dist, theta):

Usage:

mycm = glcm(a , 64 , 1 , 0)

- Here, my image, **a**, has got **64** gray levels.
- dist can be any integer number in the image size range
- Theta only can be {0 or 45 or 90 or 135}

Coursework 3

5. (continued) Gray Level Co-Occurrence Matrices:

2. Develop a function to compute the *Maximum, Energy, and Inertia* of the input GLCM matrix.

def glcm_features(mycm):

Usage:

Mxx , enrg , inrt = glcm_features(mycm)

3. Test your functions with the test images mentioned and complete the next table.

Coursework 3

5. (continued) Gray Level Co-Occurrence Matrices:

image	dist, theta	Maximum	Energy	Inertia
Gold1.bmp	1,0			
	1,90			
diag_texture.bmp	1,0			
	1,90			
IMG_0054q.JPG	1,0			
	1,90			
IMG_8636q.JPG	1,0			
	1,90			

Coursework 3

6. Study: Texture Analytics, please fill up the gaps.

A. In MSMD algorithms, Scale is indeed …. …. .

B. Apart from Deep Learning methods, the best known texture analytics algorithms use the …. approach.

C. In Wavelet analysis, the Gaussian pyramid contains …. Frequency features of the image, whereas the Laplacian pyramid contains ….. Frequency features.

D. KLT/ eignfiltering …. employ a fixed filter bank.

E. Eigenvalues show the …. or ….. of the eigenfilters and detail images in the configuration of the input image.

That’s It…

COURSEWORK 3 IS OVER