Assignment 1:

Scale Invariant Feature Detection and Image Filtering

Computer Vision NTU, Spring 2022

Announced: 111/03/04 (Fri.)

Due: 111/03/24 (Thur.) 23:59



Outline

Part 1: Scale Invariant Feature Detection

• Implement Difference of Gaussian

Part 2: Image Filtering

- Implement bilateral filter
- Advanced color-to-gray conversion



Part 1:

Difference of Gaussian



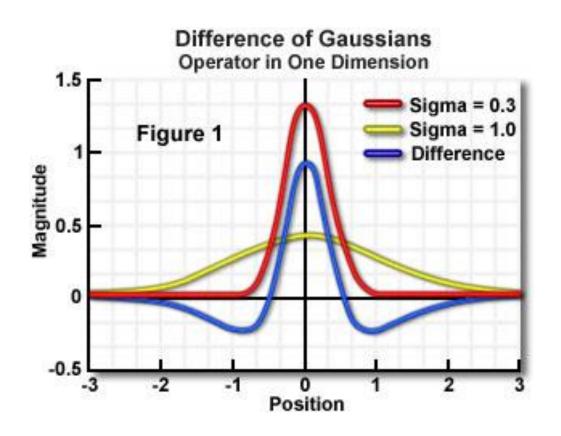
Gaussian Blur





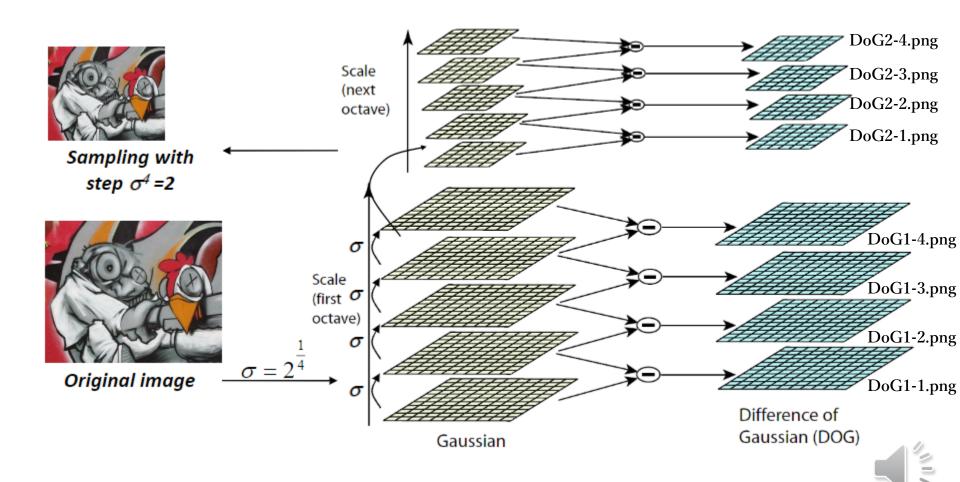


Difference of Gaussian Filter

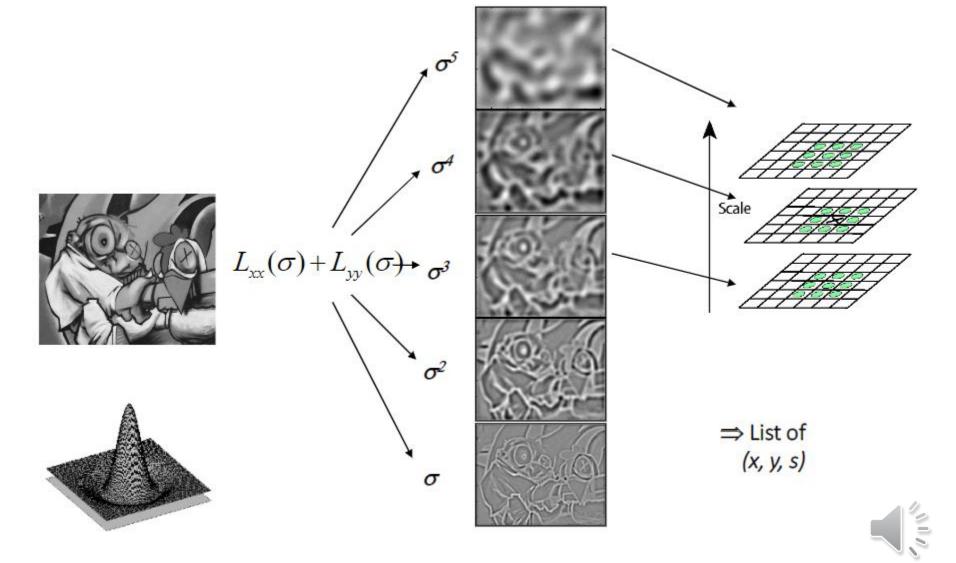




Gaussian Pyramid



Find local extremum



Implementation

In DoG.py

```
# Step 1: Filter images with different sigma values (5 images per octave, 2 octave in total)
# - Function: cv2.GaussianBlur (kernel = (0, 0), sigma = self.sigma**___)
```

• You should do gaussian blur with corresponding sigma value. In the second octave, you should down sample the forth blurred image (fifth image) in the first octave as the base image.

```
# Step 2: Subtract 2 neighbor images to get DoG images (4 images per octave, 2 octave in total)
# - Function: cv2.subtract(second_image, first_image)
```

• You should subtract the second image (less blurred one) to the first image (more blurred one) to get DoG

```
# Step 3: Thresholding the value and Find local extremum (local maximun and local minimum)

# Keep local extremum as a keypoint
```

Threshold the pixel value and find the local extremum

```
# Step 4: Delete duplicate keypoints
# - Function: np.unique
```



- part1/eval.py
 - TA will run this code to evaluation your result.
 - DO NOT Modify!
- part1/main.py
 - Read image, execute DoG, visualize results for report, · · · etc.
- part1/DoG.py
 - Follow the instructions and implement Difference of Gaussian.
 - The output format should be np.array with its shape (x, 2)



- Recommended steps
 - Implement Difference of Gaussian in DoG.py
 - Use eval.py to evaluate your DoG.py
 - By \$ python3 eval.py --image_path '1.png' --gt_path '1_gt.npy'
 - Your Result needs to match Ground truth [Info] All keypoints match.
 - Finish remaining code in main.py if needed



Supplementary:

Advanced Color-to-Gray Conversion



Color Conversion

- RGB2YUV
 - Read https://en.wikipedia.org/wiki/YUV for more details

$$\begin{bmatrix} Y' \\ U \\ V \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ -0.14713 & -0.28886 & 0.436 \\ 0.615 & -0.51499 & -0.10001 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix},$$

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 1 & 0 & 1.13983 \\ 1 & -0.39465 & -0.58060 \\ 1 & 2.03211 & 0 \end{bmatrix} \begin{bmatrix} Y' \\ U \\ V \end{bmatrix}.$$

• Many vision systems only take the Y channel (luminance) as input to reduce computations



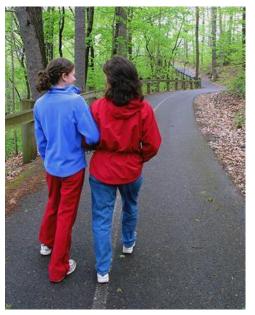
RGB to Gray



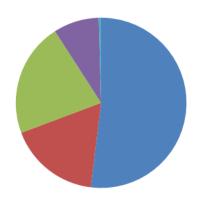




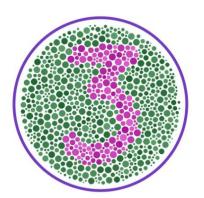
Problems

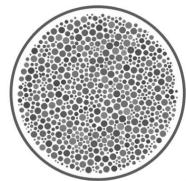












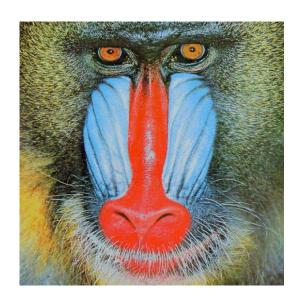


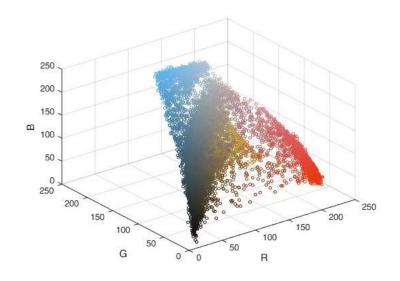
What happened?

Dimensionality reduction

$$Y = 0.299R + 0.587G + 0.114B$$

- Another view:
 - The conversion is actually a plane equation! All colors on the same plane are converted to the same grayscale value.







Finding a better conversion

• The general form of linear conversion:

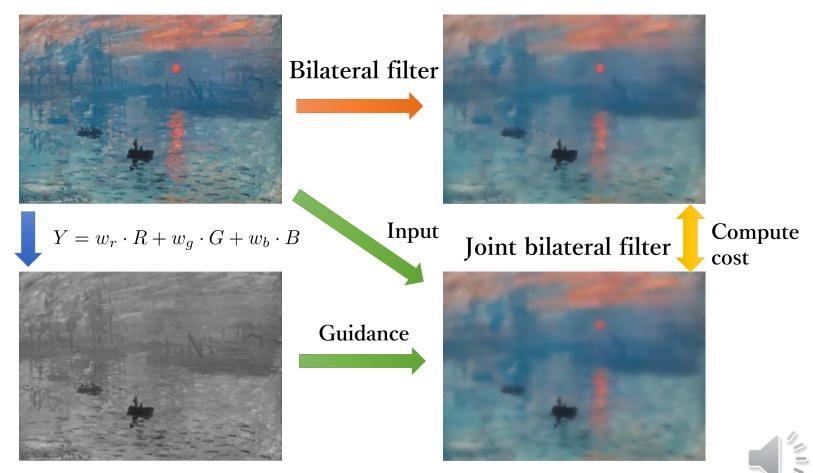
$$Y = w_r \cdot R + w_g \cdot G + w_b \cdot B$$
$$w_r, w_g, w_b >= 0$$
$$w_r + w_g + w_b = 1$$

- Let's consider the quantized weight space $w \in \{0, 0.1, 0.2, ..., 1\}$
 - For example: $(w_r, w_g, w_b) = (0, 0, 1)$ $(w_r, w_g, w_b) = (0, 0.1, 0.9)$
 - Given a color image, a set of weight combination corresponds to a grayscale image candidate.
 - We are going to identify which candidate is better!



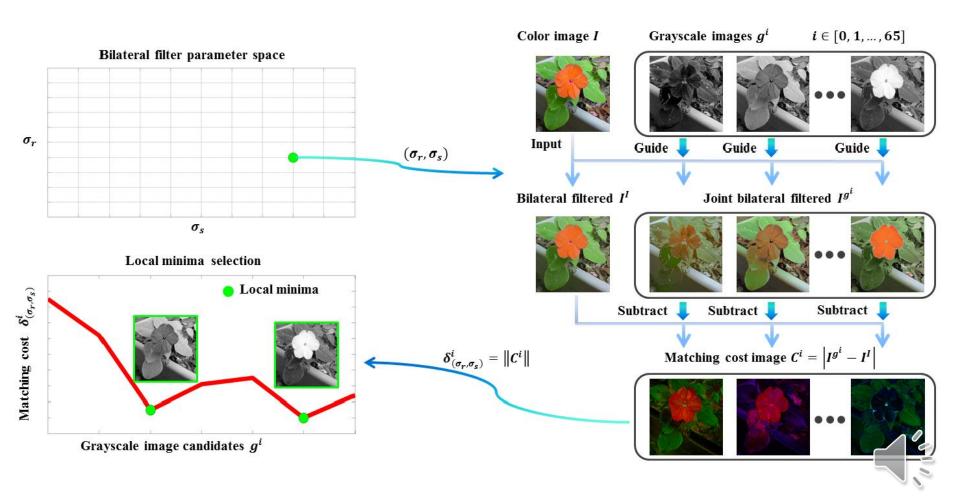
Measuring the perceptual similarity

• Joint bilateral filter (JBF) as the similarity measurement



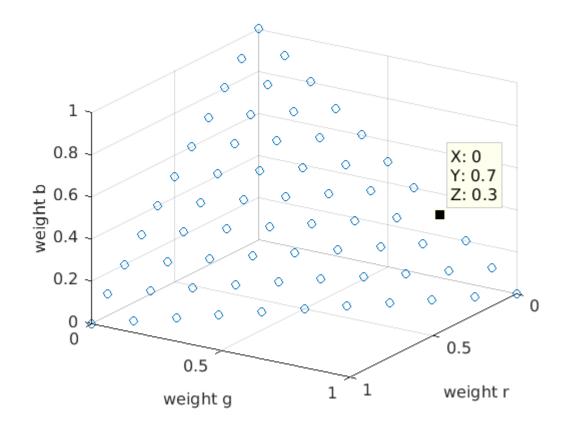
Measuring the perceptual similarity

• Joint bilateral filter (JBF) as the similarity measurement



Measuring the perceptual similarity

- Find local minimum
 - The actual weight space looks like this:



$$w_r, w_g, w_b >= 0$$
$$w_r + w_g + w_b = 1$$



Part 2: Image Filtering



Bilateral Filter

• Given input image *I* and guidance *T*, the bilateral filter is written as:

$$I_p' = \frac{\sum_{q \in \Omega_p} G_S(p, q) \cdot G_r(T_p, T_q) \cdot I_q}{\sum_{q \in \Omega_p} G_S(p, q) \cdot G_r(T_p, T_q)}$$

- I_p : Intensity of pixel p of original image I
- I'_p : Intensity of pixel p of filtered image I'
- T_p : Intensity of pixel p of guidance image T
- Ω_p : Window centered in pixel p
- G_s : Spatial kernel
- G_r : Range kernel



Bilateral Filter

• For the spatial kernel G_s :

$$G_s(p,q) = e^{-\frac{(x_p - x_q)^2 + (y_p - y_q)^2}{2\sigma_s^2}}$$

- For the range kernel G_r :

• If T is a single-channel image:
$$G_r(T_p,T_q)=e^{-\frac{(T_p-T_q)^2}{2\sigma_r^2}}$$

• If *T* is a color image:

$$G_r(T_p, T_q) = e^{-\frac{(T_p^r - T_q^r)^2 + (T_p^g - T_q^g)^2 + (T_p^b - T_q^b)^2}{2\sigma_r^2}}$$

• Pixel values should be normalized to [0, 1] (divided by 255) to construct range kernel.



- part2/main.py
 - Read image, execute joint bilateral filter, read setting file, select the best grayscale conversion… etc.
- part2/JBF.py
 - Implement joint bilateral filter

- part2/eval.py (DO NOT Modify!)
 - Evaluate the correctness of the output of joint bilateral filter

```
def main():
   parser = argparse.ArgumentParser(description='evaluation function of joint bilateral filter')
   parser.add_argument('--sigma_s', default=3, type=int, help='sigma of spatial kernel')
   parser.add argument('--sigma r', default=0.1, type=float, help='sigma of range kernel')
   parser.add_argument('--image_path', default='./testdata/ex.png', help='path to input image')
   parser.add_argument('--gt_bf_path', default='./testdata/ex_gt_bf.png', help='path to ground truth bf image')
   parser.add argument('--gt jbf path', default='./testdata/ex gt jbf.png', help='path to ground trut jbf image')
   args = parser.parse_args()
   img = cv2.imread(args.image_path)
                                                   We will test your inference
   img_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
   img_gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
                                                  duration of joint bilateral filter.
   JBF = Joint_bilateral_filter(args.sigma_s, args.sigma_r)
   bf_out = JBF.joint_bilateral_filter(img_rgb, img_rgb).astype(np.uint8)
   t0 = time.time()
   jbf_out = JBF.joint_bilateral_filter(img_rgb,_img_gray).astype(np.uint8)
   print('[Time] %.4f sec'%(time.time()-t0))
```

- TAs will run this file to score upload code.
- When testing your code, we will assign different arguments, like σ_s and σ_r , and corresponding ground truth file.



- part2/testdata/
 - One example image with bf and jbf ground truth
 - Two images with respective setting files



```
R,G,B

0.0,0.0,1.0

0.0,1.0,0.0

0.1,0.0,0.9

0.1,0.4,0.5

0.8,0.2,0.0

sigma_s,2,sigma_r,0.1
```

- Setting file gives σ_s , σ_r and five kinds of gray conversion
- You need to use those five and also original cv2 gray conversions (six in total) as guidance to run joint bilateral filter and compute the perceptual similarity.
 - Refer p24 and p25 for details (we use L1-norm as our cost function).
 - Note: need to cast the image into np.int32 to avoid overflow for subtraction.



- Recommended steps
 - Implement joint bilateral filter in JBF.py
 - Use eval.py to evaluate your JBF.py
 - By

python3 eval.py --image_path './testdata/ex.png' --gt_bf_path './testdata/ex_gt_bf.png' --gt_jbf_path './testdata/ex_gt_jbf.png

- The error of bilateral and joint bilateral filter should be both 0

 [Error] Bilateral: 0

 [Error] Joint bilateral: 0
- Finish remaining code in main.py if needed
- Improve the inference speed of joint bilateral filter



- About the speed test of JBF…
 - For fair comparison, you CAN ONLY use basic functions (e.g. cannot use cv2.filter2D, cv2.GaussianBlur) in JBF.py
 - Cython, multi-thread and GPU acceleration is forbidden.
 - Reference time of TA code on ex.png
 - Intel Core i7-6800K CPU + 128 GB RAM \Rightarrow ~1.28 sec
 - You can also run TA code on your own platform. (TA/JBF.so)
 - Some useful tips
 - Build look-up-table for both spatial and range gaussian kernels
 - Reduce the usage of for-loop to enhance parallel processing
 - We only use one for-loop (in range(1, window_size**2)) in entire bilateral filtering



Package

- Python 3.6+
- Python standard library
- Numpy 1.21.1
- Opency-python 4.5.1
- https://docs.python.org/3.7/library/



Submission

- Directory architecture:
 - + R07654321/
 - DoG.py
 - JBF.py
 - report.pdf
- Put all above files in a directory (named StudentID) and compress the directory into zip file (named StudentID.zip)
 - e.g. After TAs run "unzip R07654321.zip", it should create one directory named "R07654321"
- Submit to NTU COOL
- Deadline: 111/03/24 (Thur.) 23:59
 - Late policy: http://media.ee.ntu.edu.tw/courses/cv/22S/hw/delay_policy.pdf
- Do NOT copy homeworks (code and report) from others



Report

- Your student ID, name
- Part1: Difference of Gaussian
 - Plot 8 DoG images descripted in page.6 with threshold 5 (4%)
 - Use three thresholds (2, 5, 7) on 2.png and plot, then describe the difference (5%)
- Part2: Joint bilateral filter
 - For 1.png and 2.png:
 - Report the cost for each filtered image (by using 6 grayscale images as guidance) (1%+1%)
 - Show original RGB image / two filtered RGB images and two grayscale images with highest and lowest cost (five images in total for each input image) (2%+2%)
 - Describe the difference between those two grayscale images. (5%+5%)
 - Describe how you speed up the implementation of bilateral filter. (5%)



Grading (Total 15%)

- Part 1 Code: 30%
 - 30%, no error (TA will check your answer on 2.png)
 - 0%, others
- Part 2 Code: 30%
 - 30%, runs within 5 mins and no error (both bf and jbf error = 0)
 - 0%, others
- Report : 30%
- Part 2 Inference time: 10%
 - 10%, Top ~ 20%
 - 6%, 20% ~ 50%
 - 3%, 50% ~ 80%
 - 0%, 80% ~



TA information

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