Project

First, we have an image with width=850 and height=567:



Figure 1: A simple image

1 CPU implementation

1.1 Logic steps

There were five steps that I did in this project:

• Pad the image based on the window's size.

- Convert the image from RGB to HSV.
- For each pixel, extract its corresponding four windows.
- Calculate the standard deviation of each window based on the V channels using numpy.std.
- Assign R, G, B values for each pixel based on the mean value of the windows (numpy.mean) with the smallest standard deviation.

1.2 Implementation steps

1.2.1 Pad the image based on the window's size

```
1 h pad = args.window size // 2
 2 \text{ w pad} = \text{args.window size} // 2
3 \text{ image} = \text{np.pad}(
 4
        image,
        pad width=(
5
6
             (h_pad, h_pad),
 7
             (w_pad, w_pad),
8
             (0, 0),
9
        ),
10
        mode="constant",
        constant_values=0,
11
12)
```

1.2.2 Convert the image from RGB to HSV

```
9
               if delta == 0:
10
                   h value = 0
               elif max_value = image[i, j, 0]:
11
12
                   h_value = 60 * (((image[i, j, 1] - image[i, j, 2]) /
      delta) % 6)
13
               elif max value = image[i, j, 1]:
14
                   h_value = 60 * (((image[i, j, 2] - image[i, j, 0]) /
      delta + 2
15
               elif max_value = image[i, j, 2]:
16
                   h_value = 60 * (((image[i, j, 0] - image[i, j, 1]) /
      delta) + 4
17
               if \max value == 0:
18
                   s value = 0
19
20
               else:
                   s_value = delta / max_value
21
22
               v value = max value
               output[i, j, 0] = h value
23
24
               output[i, j, 1] = s_value
               output[i, j, 2] = v_value
25
26
      return output
```

1.2.3 Extract four corresponding windows

```
1 def extract window(img, top, height, left, width):
       return img[top : top + height, left : left + width]
3
4 window coordinates = [
6
      h - small window height + 1,
7
      small window height,
      w - small window width + 1,
8
9
      small window width,
10],
11 [
12
      h - small window height + 1,
      small window height,
13
14
      w,
15
      small\_window\_width,
```

```
16 ],
17 [
18
      h,
19
      small_window_height,
      w - small window width + 1,
20
21
      small window width,
22 ],
23 [h, small window height, w, small window width],
24
25
26 window1 = extract window(image v, *window coordinates[0])
27 window2 = extract window(image v, *window coordinates[1])
28 window3 = extract window(image v, *window coordinates[2])
29 window4 = extract window(image v, *window coordinates[3])
```

1.2.4 Calculate the standard deviation of each window

```
1 std_dev1 = np.std(window1)
2 std_dev2 = np.std(window2)
3 std_dev3 = np.std(window3)
4 std_dev4 = np.std(window4)
5 min_std = min(std_dev1, std_dev2, std_dev3, std_dev4)
```

1.2.5 Assign the corresponding R, G, and B values for each pixel

```
1 if std dev1 = min std:
      mean r = np.mean(extract window(image r, *window coordinates[0]))
3
      mean g = np.mean(extract window(image g, *window coordinates[0]))
      mean b = np.mean(extract window(image b, *window coordinates[0]))
5 \text{ elif std dev2} = \min \text{ std}:
      mean r = np.mean(extract window(image r, *window coordinates[1]))
6
7
      mean_g = np.mean(extract_window(image_g, *window_coordinates[1]))
      mean b = np.mean(extract window(image b, *window coordinates[1]))
8
9 elif std dev3 == min std:
10
      mean r = np.mean(extract window(image r, *window coordinates[2]))
11
      mean g = np.mean(extract window(image g, *window coordinates[2]))
      mean_b = np.mean(extract_window(image_b, *window_coordinates[2]))
12
13 \text{ elif std dev4} = \min \text{ std}:
14
      mean r = np.mean(extract window(image r, *window coordinates[3]))
```

```
mean_g = np.mean(extract_window(image_g, *window_coordinates[3]))
mean_b = np.mean(extract_window(image_b, *window_coordinates[3]))
image_output[
    h - small_window_height + 1, w - small_window_height + 1, 0
    ] = mean_r
    image_output[
    h - small_window_height + 1, w - small_window_height + 1, 1
    ] = mean_g
    image_output[
    h - small_window_height + 1, w - small_window_height + 1, 1
    ] = mean_g
    image_output[
    h - small_window_height + 1, w - small_window_height + 1, 2
    ] = mean_b
```

1.2.6 Result

We have the resulting image:



Figure 2: Applying Kuwahara filter on the image using CPU

2 GPU implementation (without shared memory)

2.1 Logic steps

There were five steps that I did in this project:

- Pad the image based on the window's size.
- Convert the image from RGB to HSV.
- For each pixel, extract its corresponding four windows.
- Calculate the standard deviation of each window based on the V channels (from scratch).
- Assign R, G, and B values for each pixel based on the mean value of the windows (from scratch) that has the smallest standard deviation.

2.2 Implementation steps

2.2.1 Pad the image based on the window's size

This step is the same as in the CPU

2.2.2 Convert the image from RGB to HSV

```
1 @cuda.jit
2 def rgb to hsv(src, dst):
3
        x, y = \text{cuda.grid}(2)
4
        if y < dst.shape[0] and x < dst.shape[1]:
             \max_{\text{value}} = \max(\text{src}[y, x, 0], \text{src}[y, x, 1], \text{src}[y, x, 2])
5
6
             \min_{\text{value}} = \min_{\text{value}} (\operatorname{src}[y, x, 0], \operatorname{src}[y, x, 1], \operatorname{src}[y, x, 2])
7
             delta = max value - min value
8
             if delta == 0:
9
                  h value = 0
             elif max_value = src[y, x, 0]:
10
                  h_value = 60 * (((src[y, x, 1] - src[y, x, 2]) / delta) % 6)
11
             elif max_value = src[y, x, 1]:
12
13
                  h_value = 60 * (((src[y, x, 2] - src[y, x, 0]) / delta) + 2)
```

```
14
            elif max value = src[y, x, 2]:
                h_value = 60 * (((src[y, x, 0] - src[y, x, 1]) / delta) + 4)
15
16
17
            if \max_{\text{value}} = 0:
18
                s value = 0
19
           else:
20
                s value = delta / max value
21
           v value = max value
           dst[y, x, 0] = h value
22
23
           dst[y, x, 1] = s_value
24
           dst[y, x, 2] = v_value
```

2.2.3 Extract four corresponding windows

This step is a bit different from the CPU version. Instead of having four windows with specific sizes, I just calculate their coordinates(top, left, width, and height)

```
1 tops = cuda.local.array(4, numba.int64)
 2 heights = cuda.local.array(4, numba.int64)
 3 \text{ lefts} = \text{cuda.local.array}(4, \text{ numba.int}64)
 4 widths = cuda.local.array(4, numba.int64)
 6 \text{ tops} [0] = y - \text{small window height} + 1
 7 \text{ tops}[1] = y - \text{small window height} + 1
 8 \text{ tops}[2] = y
 9 \text{ tops} [3] = y
10
11 \text{ heights} [0] = \text{small window height}
12 heights [1] = small_window_height
13 heights [2] = small window height
14 heights [3] = small_window_height
15
16 \operatorname{lefts} [0] = x - \operatorname{small} \operatorname{window} \operatorname{width} + 1
17 \, lefts[1] = x
18 \operatorname{lefts}[2] = x - \operatorname{small} \operatorname{window} \operatorname{width} + 1
19 \, \text{lefts} \, [3] = x
20
21 \text{ widths } [0] = \text{small window width}
22 widths[1] = small window width
23 \text{ widths} [2] = \text{small window width}
```

2.2.4 Calculate the standard deviation of each window and get the coordinate of the window that has the smallest deviation

```
1 smallest std window = np.inf
2 \text{ smallest window idx} = -1
3 for window in range(4):
       total sum window = 0
       top = tops[window]
5
       left = lefts [window]
6
       height = heights [window]
7
       width = widths [window]
8
9
       for i in range(top, top + height):
10
           for j in range(left, left + width):
11
               total_sum_window += image_v[i, j]
12
       mean window = total sum window / (width * height)
13
14
       sum of squared diff window = 0
15
16
       for i in range(top, top + height):
           for j in range(left, left + width):
17
18
               diff = image v[i, j] - mean window
19
               sum of squared diff window += diff * diff
20
21
       std window = math.sqrt(sum of squared diff window / (width * height)
      )
       if std window < smallest std window:
22
23
           smallest std window = std window
24
           smallest window idx = window
26 top = tops[smallest window idx]
27 left = lefts[smallest window idx]
28 height = heights [smallest window idx]
29 width = widths [smallest window idx]
```

2.2.5 Assign the corresponding R, G, and B values for each pixel

```
1 \text{ total\_sum\_window\_r} = 0.0
 2~total\_sum\_window\_g~=~0.0
 3~total\_sum\_window\_b~=~0.0
 4
 5 for i in range (top, top + 4):
 6
         for j in range(left, left + 4):
               total\_sum\_window\_r \; +\!\!= \; src\_rgb \left[ \; i \; , \; \; j \; , \; \; 0 \right]
 7
 8
               total\_sum\_window\_g \ += \ src\_rgb\left[ \ i \ , \ \ j \ , \ \ 1 \right]
               total\_sum\_window\_b \; +\!\!= \; src\_rgb\left[\,i \;, \;\; j \;, \;\; 2\,\right]
 9
10
11 dst[y, x, 0] = total_sum_window_r / (width * height)
12 dst[y, x, 1] = total_sum_window_g / (width * height)
13 \ dst \left[ y, \ x, \ 2 \right] \ = \ total\_sum\_window\_b \ / \ (width \ * \ height)
```

We have the resulting image:



Figure 3: Applying Kuwahara filter on the image using GPU (without shared memory)

3 GPU implementation (with shared memory)

3.1 Logic steps

There were five steps that I did in this project:

- Pad the image based on the window's size.
- Convert the image from RGB to HSV.
- For each pixel, extract its corresponding four windows.
- Calculate the standard deviation of each window based on the V channels (from scratch).
- Assign R, G, and B values for each pixel based on the mean value of the windows (from scratch) with the smallest standard deviation.

3.2 Implementation steps

3.2.1 Pad the image based on the window's size

I pad the image so that the image's width and height are divisible by 8.

```
1 def pad image to divisible by 8 (image, n):
2
       padded height = image.shape[0] + 2 * n
3
      padded width = image.shape[1] + 2 * n
4
      left pad = top pad = n
5
6
      right_pad = bottom_pad = n
7
8
       if padded width \% 8 != 0:
           additional width = 8 - (padded width \% 8)
9
10
           left pad += additional width // 2
           right\_pad += additional\_width - (additional\_width // 2)
11
12
13
       if padded height % 8 != 0:
           additional height = 8 - (padded height % 8)
14
           top pad += additional_height // 2
15
           bottom_pad += additional_height - (additional_height // 2)
16
```

3.2.2 Convert the image from RGB to HSV

```
1 x, y = \text{cuda.grid}(2)
 2 tx = cuda.threadIdx.x
 3 \text{ ty} = \text{cuda.threadIdx.y}
 4 shared hsv = cuda.shared.array(shape=(8, 8, 3), dtype=numba.float32)
 6 \hspace{0.1cm} if \hspace{0.1cm} y \hspace{0.1cm} < \hspace{0.1cm} dst.\hspace{0.1cm} shape\hspace{0.1cm} [\hspace{0.1cm} 0\hspace{0.1cm}] \hspace{0.1cm} and \hspace{0.1cm} x \hspace{0.1cm} < \hspace{0.1cm} dst.\hspace{0.1cm} shape\hspace{0.1cm} [\hspace{0.1cm} 1\hspace{0.1cm}] \hspace{0.1cm} \colon \hspace{0.1cm} \\
          for i in range(3):
                shared_hsv[ty, tx, i] = src[y, x, i]
9 cuda.syncthreads()
10 if ty < 8 and tx < 8:
11
          \max \text{ value} = \max(
12
                shared hsv[ty, tx, 0], shared hsv[ty, tx, 1], shared hsv[ty, tx,
          2]
13
14
          \min \text{ value} = \min (
15
                shared hsv[ty, tx, 0], shared hsv[ty, tx, 1], shared hsv[ty, tx,
          2]
16
          )
17
          delta = max value - min value
          if delta = 0:
18
                h value = 0
19
          elif max value == shared_hsv[ty, tx, 0]:
20
21
                h \text{ value} = 60 * (
                       ((shared_hsv[ty, tx, 1] - shared_hsv[ty, tx, 2]) / delta) %
22
         6
```

```
23
           )
24
       elif max_value == shared_hsv[ty, tx, 1]:
           h_value = 60 * (
25
26
                ((shared_hsv[ty, tx, 2] - shared_hsv[ty, tx, 0]) / delta) +
27
           )
28
       elif max value = shared hsv[ty, tx, 2]:
           h \text{ value} = 60 * (
29
                ((shared_hsv[ty, tx, 0] - shared_hsv[ty, tx, 1]) / delta) +
30
31
           )
32
       if \max value == 0:
33
           s value = 0
34
35
       else:
36
           s_value = delta / max_value
37
       v value = max value
38
39
       dst[y, x, 0] = h value
       dst[y, x, 1] = s_value
40
41
       dst[y, x, 2] = v value
42 cuda.syncthreads()
```

3.2.3 Extract four corresponding windows

This step is a bit different from the CPU version. Instead of having four windows with specific sizes, I just calculate the coordinates of them (top, left, width, and height)

```
1 tx = cuda.threadIdx.x
2 ty = cuda.threadIdx.y
3 shared_hsv = cuda.shared.array(shape=(26, 26, 1), dtype=numba.float32)
4 shared_rgb = cuda.shared.array(shape=(26, 26, 3), dtype=numba.float32)
5 if (
6
      x < src hsv.shape[1]
      and y < src hsv.shape[0]
7
8):
      shared_hsv[ty, tx] = src_hsv[
9
10
          y - 3,
          x - 3
11
12
```

```
13
       shared hsv[ty + 6, tx] = src hsv[
            y + 3,
14
            x - 3,
15
16
17
       shared hsv[ty, tx + 6] = src hsv[
18
            y - 3,
19
            x + 3,
20
       shared_hsv[ty + 6, tx + 6] = src_hsv[
21
22
            y + 3,
            x + 3,
23
24
25
26 if (
27
       x < src rgb.shape[1]
       and y < src rgb.shape[0]
28
29 ):
        for i in range(3):
30
31
            \operatorname{shared\_rgb}[\operatorname{ty}, \operatorname{tx}, i] = \operatorname{src\_rgb}[y - 3, x - 3, i]
32
            shared_rgb[ty + 6, tx, i] = src_rgb[y + 3, x - 3, i]
            shared \operatorname{rgb}[ty, tx + 6, i] = \operatorname{src} \operatorname{rgb}[y - 3, x + 3, i]
33
            shared\_rgb[ty + 6, tx + 6, i] = src\_rgb[y + 3, x + 3, i]
34
35
36 cuda.syncthreads()
37 if (
38
       x < src hsv.shape[1]
       and y < src hsv.shape[0]
39
40 ):
41
        tops = cuda.local.array(4, numba.int64)
        heights = cuda.local.array(4, numba.int64)
42
43
        lefts = cuda.local.array(4, numba.int64)
        widths = cuda.local.array(4, numba.int64)
44
45
46
        tops[0] = ty
47
        tops[1] = ty
        tops[2] = ty + small window height - 1
48
49
        tops[3] = ty + small window height - 1
50
       heights [0] = small_window_height
51
52
        heights [1] = small window height
```

```
53
       heights [2] = small window height
54
       heights [3] = small window height
55
56
       lefts[0] = tx
57
       lefts[1] = tx + small window width - 1
       lefts[2] = tx
58
       lefts[3] = tx + small window width - 1
59
60
       widths[0] = small window width
61
       widths [1] = small window width
62
       widths [2] = small window width
63
       widths [3] = small window width
64
```

3.2.4 Calculate the standard deviation of each window and get the coordinate of the window that has the smallest deviation

```
1 smallest std window = np.inf
2 \text{ smallest window idx} = -1
3
 4 for window in range(4):
       total sum window = np.float32(0)
 5
       top = tops [window]
6
       left = lefts [window]
7
8
       height = heights [window]
       width = widths [window]
9
       for i in range(top, top + height):
10
           for j in range(left, left + width):
11
               total sum window += shared hsv[i, j, 0]
12
       mean_window = total_sum_window / (width * height)
13
       sum of squared diff window = 0
14
15
16
       for i in range(top, top + height):
17
           for j in range(left, left + width):
               diff = shared hsv[i, j, 0] - mean window
18
               sum of squared diff window += diff * diff
19
20
       std window = math.sqrt(sum of squared diff window / (width * height)
21
22
       if std window < smallest std window:
```

```
smallest_std_window = std_window
smallest_window_idx = window
smallest_window_idx = window
top = tops[smallest_window_idx]
left = lefts[smallest_window_idx]
height = heights[smallest_window_idx]
width = widths[smallest_window_idx]
```

3.2.5 Assign the corresponding R, G, and B values for each pixel

```
1 total_sum_window_r = np.float32(0)
2 total_sum_window_g = np.float32(0)
3 total_sum_window_b = np.float32(0)
4
5 for i in range(top, top + 4):
6     for j in range(left, left + 4):
7         total_sum_window_r += shared_rgb[i, j, 0]
8         total_sum_window_g += shared_rgb[i, j, 1]
9         total_sum_window_b += shared_rgb[i, j, 2]
10 dst[y, x, 0] = total_sum_window_r / (width * height)
11 dst[y, x, 1] = total_sum_window_b / (width * height)
12 dst[y, x, 2] = total_sum_window_b / (width * height)
```

We have the resulting image:



Figure 4: Applying Kuwahara filter on the image using GPU (with shared memory)

4 Run time comparison

All experiments are run on Intel(R) Core(TM) i7-9750H CPU @ 2.60GHz and GTX 1650.

	Ws 3	Ws 5	Ws 7	Ws 9
CPU	53.12	56.35	58.46	51.58
GPU (without shared memory)	0.6169	0.5848	0.6291	0.6349
GPU (with shared memory)	0.5844	0.6296	0.5837	0.6678

Table 1: Runtime comparison between 3 different methods on four different window sizes (Ws: window size).

I compare the run time on CPU, GPU (without shared memory), and GPU (with shared memory) with five different window sizes. For the sake of simplicity, I only

compare the runtime of Kuwahara filter and not other functions. The execution of the filter on the CPU is very slow, around 51-60s for different window sizes. I noticed an interesting thing: Large windows size do not always run slower than small windows size. I decrease the run time by nearly 90-100 times when I run the code on GPU (without shared memory). Using shared memory results in nearly the same run times as not using shared memory (same block size = 8).

5 Conclusion and future work

Things that I have done in this project:

- Implementation of Kuwahara filter on CPU, GPU (without shared memory), and GPU (with shared memory).
- No hardcoded of most values (except block size and shared array's shape).

Things that I have not done in this project:

• Optimization of Kuwahara filter on GPU.