

Project
Advanced Programming for HPC
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1 Input

I have used an original image with width=1280 and height=960



Figure 1: The original image

2 Implementation

To implement the Kuwahara filter, I have executed the main following four steps.

- Step 1: Convert RGB to HSV.
- Step 2: Calculate the mean and variance for each channel of four corners.
- Step 3: Determine the quadrant with the minimum variance.
- Step 4: Set the pixel value to the mean of the channel in the minimum variance quadrant.

2.1 Program

1. Step 1: Convert RGB to HSV.

```
1 @cuda.jit
2 def rgb_to_hsv(src, dst):
3     x, y = cuda.grid(2)
4     if y < dst.shape[0] and x < dst.shape[1]:
5         max_value = max(src[y, x, 0], src[y, x, 1], src[y, x, 2])
6         min_value = min(src[y, x, 0], src[y, x, 1], src[y, x, 2])
7         delta = max_value - min_value
8         if delta == 0:
9             h_value = 0
10        elif max_value == src[y, x, 0]:
11            h_value = 60 * (((src[y, x, 1] - src[y, x, 2]) / delta)
12            % 6)
13        elif max_value == src[y, x, 1]:
14            h_value = 60 * (((src[y, x, 2] - src[y, x, 0]) / delta)
15            + 2)
16        elif max_value == src[y, x, 2]:
17            h_value = 60 * (((src[y, x, 0] - src[y, x, 1]) / delta)
18            + 4)
19        if max_value == 0:
20            s_value = 0
21        else:
22            s_value = delta / max_value
```

```

21         v_value = max_value
22         dst[y, x, 0] = h_value
23         dst[y, x, 1] = s_value
24         dst[y, x, 2] = v_value
25

```

2. Step 2: Calculate the mean and variance for each channel of four corners.

```

1  for c in range(0,3):
2      channel_values = neighborhood[:, :, c]
3      channel_values_rgb = neighborhood_rgb[:, :, c]
4      mean = 0.0
5      mean_rgb = 0.0
6      variance = 0.0
7      size = neighborhood.shape[0]*neighborhood.shape[1]
8      # Calculate the mean
9      for i in range(neighborhood.shape[0]):
10         for j in range(neighborhood.shape[1]):
11             mean += channel_values[i, j]
12     mean /= size
13
14     for i in range(neighborhood_rgb.shape[0]):
15         for j in range(neighborhood_rgb.shape[1]):
16             mean_rgb += channel_values_rgb[i, j]
17     mean_rgb /= size
18
19     # Calculate the variance
20     for i in range(neighborhood.shape[0]):
21         for j in range(neighborhood.shape[1]):
22             variance += (channel_values[i, j] - mean) ** 2
23
24     variance /= size
25     mean_variances[q, c] = variance
26     mean_variances[q, c + 3] = mean
27     mean_variances[q, c + 6] = mean_rgb
28

```

3. Step 3: Determine the quadrant with the minimum variance.

```

1  min_variance_quadrant = 0

```

```

2 min_variance =math.sqrt( mean_variances[0, 0] + mean_variances[0,
    1] + mean_variances[0, 2])
3
4 for q in range(1, 4):
5     nn =math.sqrt( mean_variances[q, 0] + mean_variances[q, 1] +
    mean_variances[q, 2])
6     if nn < min_variance:
7         min_variance_quadrant = q
8         min_variance = nn
9

```

4. Step 4: Set the pixel value to the mean of the channel in the minimum variance quadrant.

```

1 output_image[x, y, 0] = mean_variances[min_variance_quadrant, 6]
2 output_image[x, y, 1] = mean_variances[min_variance_quadrant, 7]
3 output_image[x, y, 2] = mean_variances[min_variance_quadrant, 8]
4

```

2.2 Result

The output images on CPU and GPU with shared memory and without shared memory are as below.



Figure 2: The output image **in CPU** - window size 8



Figure 3: The output image **in GPU** - window size 8 with shared memory



Figure 4: The output image **in GPU** - window size 8 without shared memory

2.3 Execution time

	Window size 5	Window size 6	Window size 7	Window size 8
CPU	433.6351	571.8690	735.6915	918.3598

Table 1: Execution time in **CPU** on different window sizes

	Window size 5	Window size 6	Window size 7	Window size 8
GPU Block size (2,2)	1.2011	0.0012	0.0006	0.0011
GPU Block size (4,4)	0.0011	0.0011	0.0011	0.0010
GPU Block size (8,8)	0.0010	0.0012	0.0049	0.0010

Table 2: Execution time in **GPU without shared memory** on different window sizes and block sizes

	Window size 5	Window size 6	Window size 7	Window size 8
GPU Block size (2,2)	0.8776	0.0011	0.0045	0.0012
GPU Block size (4,4)	0.0013	0.0004	0.0011	0.0009
GPU Block size (8,8)	0.0022	0.0004	0.0010	0.0011

Table 3: Execution time in **GPU with shared memory** on different window sizes and block sizes

3 Discussion

I have tried to implement in CPU and GPU with different block sizes and different window sizes in several time and have the following summarise.

- In CPU, it takes a lot of time to process large size images. Especially, when we increase the window sizes, the execution time also increases. Therefore, we should think about the solution in GPU. It can improve the speed a lot.
- In GPU, the first time is always slower than the next times because it takes a lot of time for initiation.
- In GPU, the speed increases if we increase the block sizes.
- In GPU with this filter, the speed with shared memory and without shared memory are almost the same.
- In GPU, when we increase the window size, the speed does not change a lot. However, the output images have more efficiency on Kuwahara filter.

4 Future work

There are two things that have been left for the future due to lack of time.

- In CPU, explanation why the output images have black border on two edges (above and left sight).
- In GPU, optimization.