Department of Computer Science

# Filtering Operations Report

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# 1 FILTERING RESULT

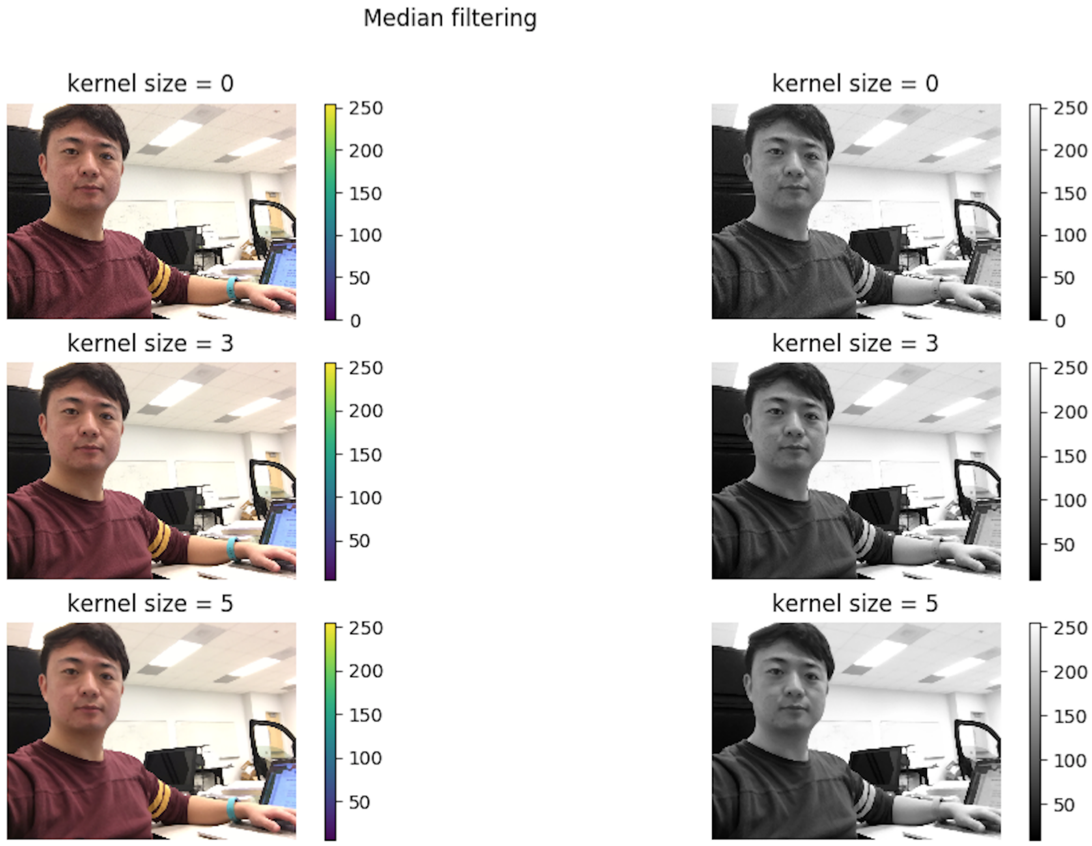



**Figure 1.1:** Median FIltering($5 \times 5$, $3 \times 3$)

## 1.1 MEDIAN FILTERING

The characteristics of Median Filtering.

- Loss of details. The "details" of the image, e.g. the edges, corner points and noises, are blurred out because their values often differs a lot from the median value.
- Kernel size matters. The bigger the kernel size is, the smoother the new image will be, which also means lossing more of locally peculiar points.
- Geometrically local operator. The changes for every pixel are determined only by its geometrical "neighbors", not color space's "neighbors".
- Nonlinear filter. (different from gaussian filtering)

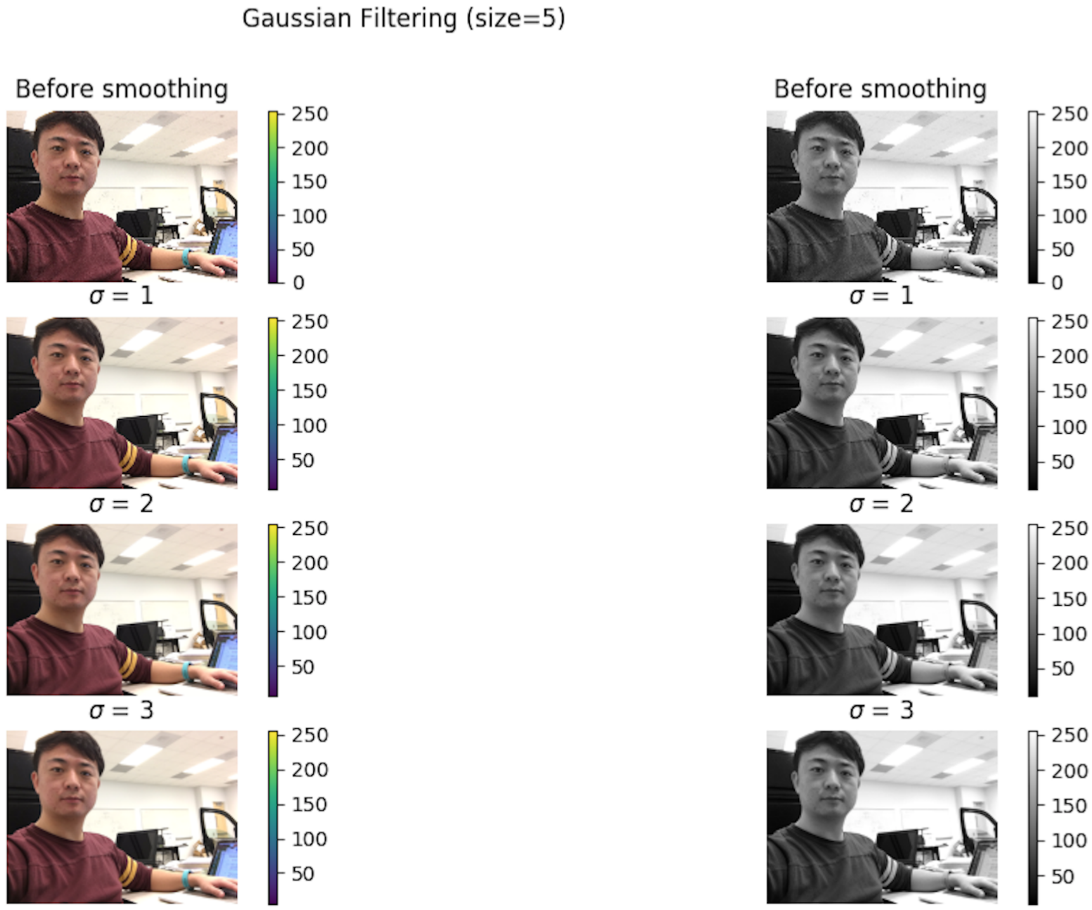



**Figure 1.2:** Gaussian FIltering($size = 5, \quad \sigma = 1, \quad 2, \quad 3$)

### 1.2 GAUSSIAN SMOOTHING

The characteristics of Gaussian smoothing.

- Loss of details.
- Kernel size and variance matter. The greater the standard deviation $\sigma$ is, the smoother the new image will be, which also means lossing more of locally special points.
- Geometrically local operator.
- Linear filter. The new value of a pixel is the output of a linear combination of its neighbors' values and its own.

## 2 DERIVATIVE RESULT

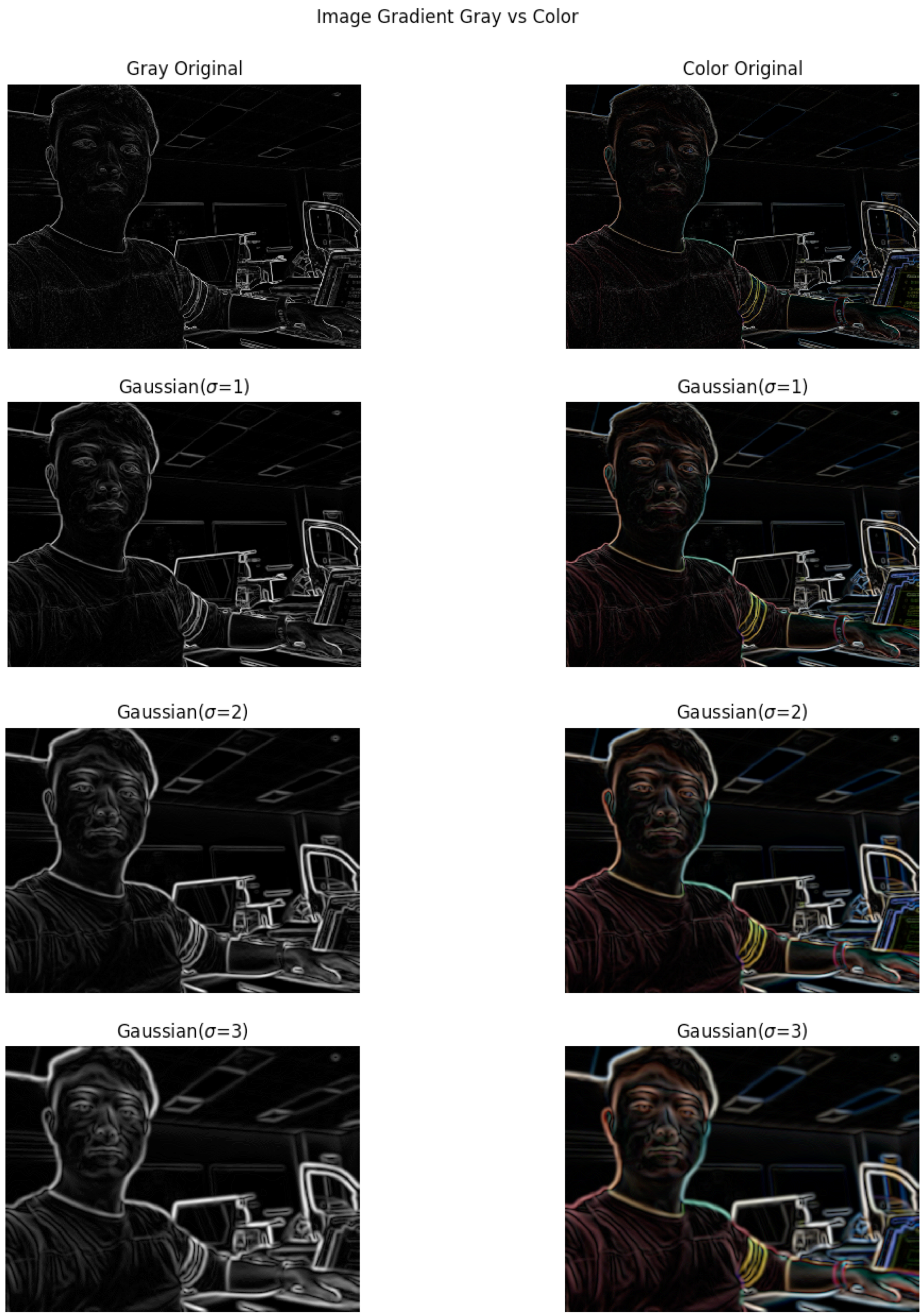


Image Gradient Gray vs Color
Gray Original
Color Original
Gaussian(σ=1)
Gaussian(σ=1)
Gaussian(σ=2)
Gaussian(σ=2)
Gaussian(σ=3)
Gaussian(σ=3)

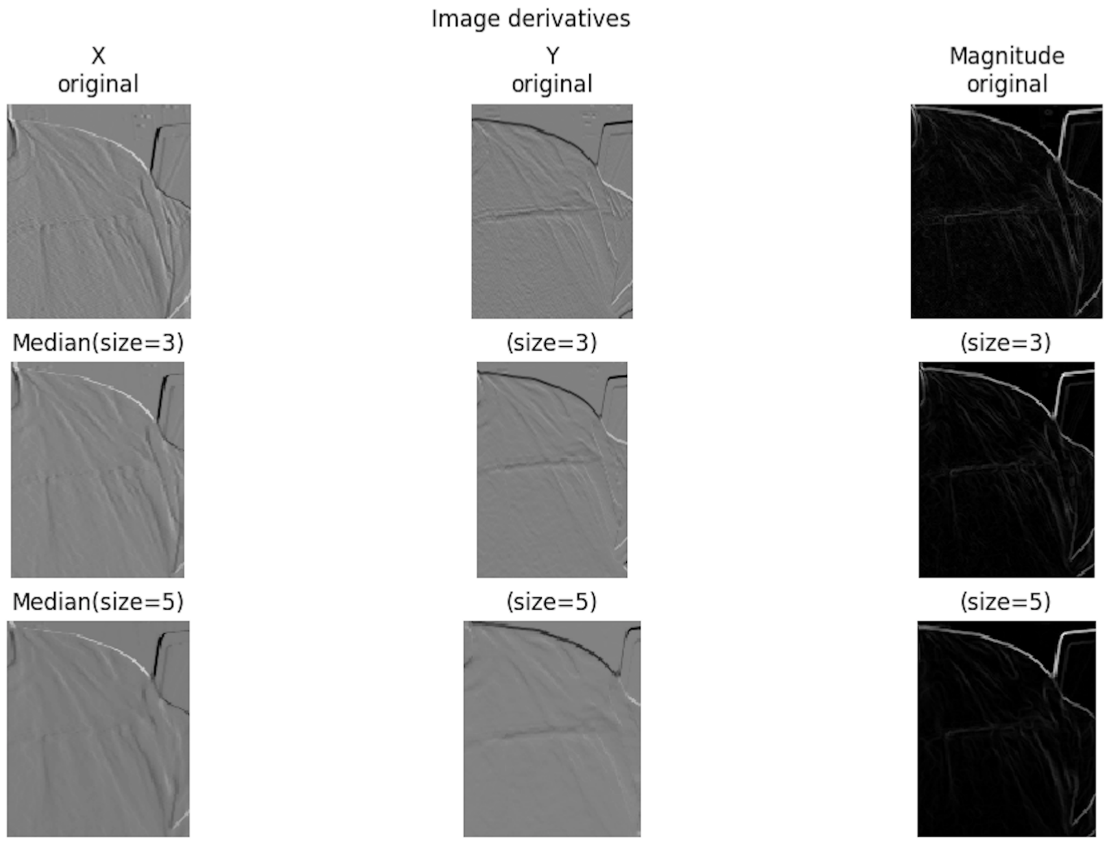
**Figure 2.1:** Image Derivatives($X$, $Y$, $Gradient$)

## 2.1 IMAGE DERIVATIVES

The characteristics of image derivatives.

- Derivatives are directional. X derivatives only detect the changes of value along X direction. So the edges(lines in the ceiling) that have the close direction with X are unnoticeable.
- Just the gradient over 2D representation. Since gradient seizes rate of change, the magnitude graph grasps all the salient points and edges.
- Smoothing affects output. The greater the kernel and the greater the variance is, the more detail we lose in derivative graph. For example, the folds of clothes are hard to recognize in the more smoothed derivative images. Figure 2.2
- Geometrically local operator. The operators here still only describe the relationship between one point and its neighbors.

**Image derivatives in Zoom-In mode**



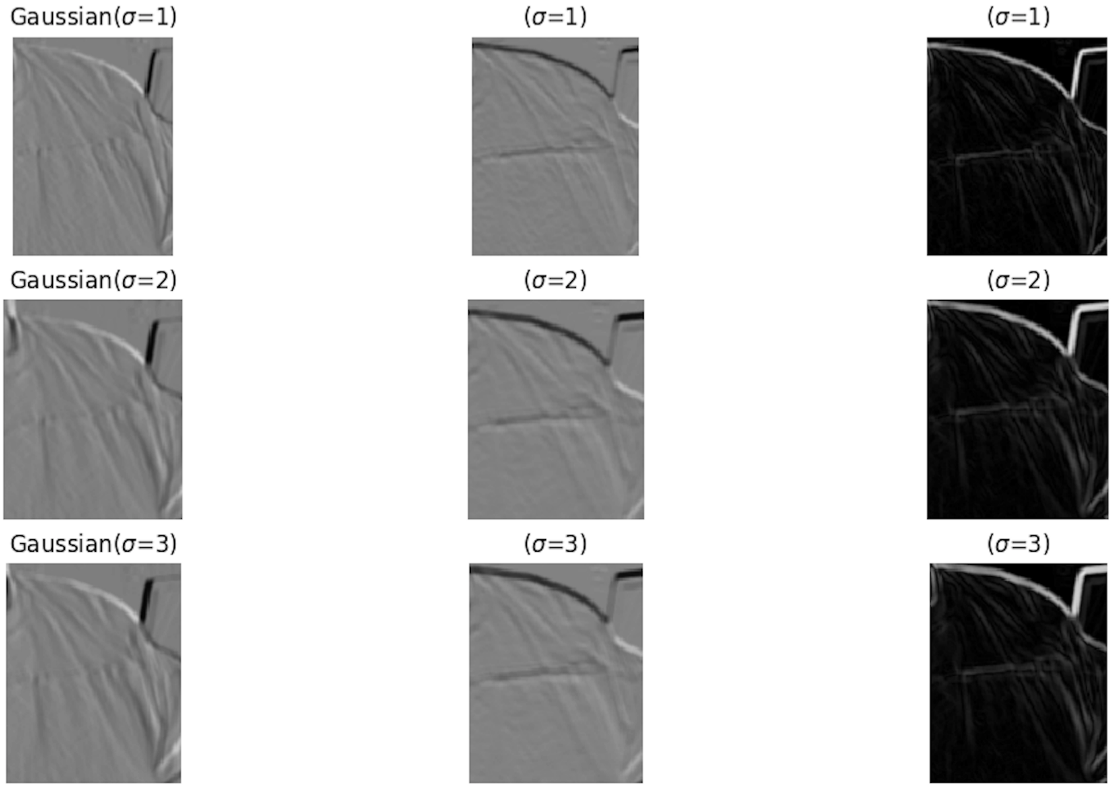



**Figure 2.2:** Image Derivatives of Folds on Clothes($X$, $Y$, $Gradient$)

# 3 Color Image Gradient (additional methods)

## 3.1 Method

The steps of computing color image gradient.

- Apply respectively X and Y derivative kernels on color image.
- Maximum absolute value selection. Select for each pixel on derivative images the value with the highest absolute value among its RGB values.
- Compute magnitude image based on the new X and Y derivative images.

## 3.2 Analysis

The characteristics of color image gradient method.

- It seems in the experiment to catch all the details that gray image gradient method has. This can be inferred by the fact that high intensity contrast often comes from high contrast on some color space.

- Furthermore, it also finds some edges which gray image gradient method doesn't Figure 3.2. One explanation for this is that high color contrast may sometimes leads to low intensity contrast. For example, for two neighboring pixels one with much higher value in red space though much lower value in green space than the other must appear different to each other, though may have the same intensity(value in gray image).
- The test result also gives support to the previous assumptions( Figure 3.1 ). The data here indicates for each pixel in a image, color image derivative has a very high probability to be larger than gray image derivative in both X and Y direction. Compared to color image based gradient, gray image based gradient is just a simplified version of gradient. In conclude, color based image can find more contrast points than gray image based gradient.

**More Experiments**

| | MAX | MIN |
|---|---|---|
| X | 46.0 | 0.0 |
| Y | 43.5 | 0.0 |

**Figure 3.1:** We compute the difference image between the color image derivative(highest absolute value among RGB) and gray image derivative with respect to absolute value. And the table shows the maximum and minimum values in both X and Y direction.

## 3.3 Result

**Image Gradient in Zoom-In mode**

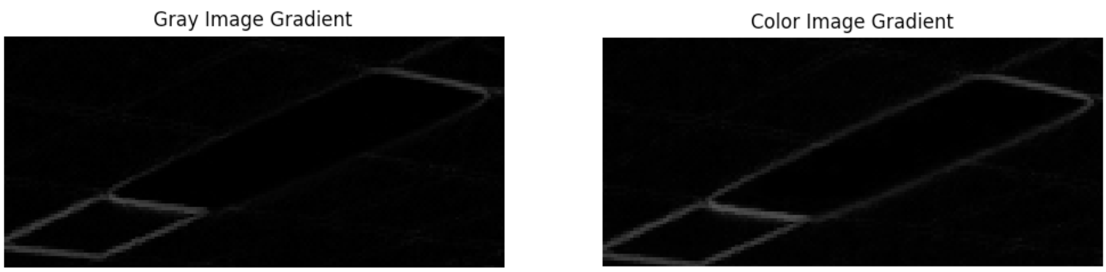



**Figure 3.2:** Image Gradient(Gray vs Color)

# 4 FURTHER DISCUSSION

## 4.1 VECTOR NORM

We notice later that the special result from table Figure 3.1 doesn't come from coincidence. In general, the differences between gray image and color image gradients are only from how differently they compute the distance between two vectors.
**Different ways of computing distance.**

1. Gray image(Opencv uses). $I_g$ is the intensity of grayscale image.

$$D_g = \Delta I_g = 0.299\Delta R + 0.587\Delta G + 0.114\Delta B \tag{4.1}$$

2. Color image(L-$\infty$).

$$D_\infty = \|\mathbf{x}\|_\infty = \max_i |x_i| = \max(\Delta R, \Delta G, \Delta B) \tag{4.2}$$

3. Color image(L-2).

$$D_2 = \|\mathbf{x}\|_2 = \sqrt{\sum_{i=1}^{\infty} |x_i|^2} = \sqrt{DeltaR^2 + \Delta G^2 + \Delta B^2} \tag{4.3}$$

We can easily prove that.

$$D_g <= D_\infty <= D_2 \tag{4.4}$$

The bigger D is, the easier the method can keep edges and salient points. In conclude, gray image based gradient method is very close to other method regarding to edge detection performance, while it is much cheaper computationally.