2023-2 공학설계

4주차 주간 보고

11조

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프로젝트 진행 상황

W3 (11/7 - 13)

- Median Filter 최적화
- Gaussian Filter 최적화

W4 (11/14 - 20)

- Bilateral Filter 구현
- Bilateral Filter 최적화

W5 (11/21 - 27)

- Non-local Means Filter 구현

Salt and Pepper Noise

Median Filter

ALGORITHM 5.11 Perform median filtering on an image

MEDIANFILTER (I, w)

Input: grayscale image I, width w of square window for computing median
Output: median-filtered image

$\tilde{w} \leftarrow \lfloor (w-1)/2 \rfloor$ ▷ Determine half-width.
for $y \leftarrow 0$ **to** $height - 1$ **do**
    $\mathcal{W} \leftarrow \{(-\tilde{w}, -\tilde{w}), \ldots, (\tilde{w}, \tilde{w})\}$ ▷ 2D window of pixel coordinates.
    $h \leftarrow$ HISTOGRAM $(I(\mathcal{W}))$ ▷ Compute graylevel histogram over window.
    $med \leftarrow$ MEDIAN(h) ▷ Compute the median of the pixels.
    $n_m \leftarrow \sum_{i=0}^{med} h[i]$ ▷ Number of pixels whose gray level is less than or equal to *med*.
    for $x \leftarrow 0$ **to** $width - 1$ **do**
        $I'(x, y) \leftarrow med$ ▷ Set output pixel to the median value.
        for $y' \leftarrow -\tilde{w}$ **to** $\tilde{w}$ **do**
            $v \leftarrow I(x - \tilde{w}, y + y')$ ▷ Update histogram by removing pixels along left edge.
            $h[v] \leftarrow_{-} 1$; **if** $v \le med$ **then** $n_m \leftarrow_{-} 1$
            $v \leftarrow I(x + \tilde{w} + 1, y + y')$ ▷ Update histogram by adding pixels along right edge.
            $h[v] \leftarrow_{+} 1$; **if** $v \le med$ **then** $n_m \leftarrow_{+} 1$
        while $n_m < \lfloor w * w/2 \rfloor$ **do** ▷ Update the median.
            $med \leftarrow_{+} 1$; $n_m \leftarrow_{+} h[med]$
        while $n_m > \lfloor w * w/2 \rfloor$ **do**
            $n_m \leftarrow_{-} h[med]$; $med \leftarrow_{-} 1$
return I'

이미지의 각 픽셀에 대해 주변 픽셀의 중앙값을 계산하여 노이즈를 줄이는 기법

Salt and Pepper Noise

Median Filter 구현

```
def median_filter(img, filter_size=(3, 3), stride=1):
    img_shape = np.shape(img)
    result_shape = tuple(np.int64((np.array(img_shape[:2]) - np.array(filter_size)) / stride) + 1) + (img_shape[2],)
    result = np.zeros(result_shape)

    for h in range(0, result_shape[0], stride):
        for w in range(0, result_shape[1], stride):
            for c in range(img_shape[2]):
                tmp = img[h:h + filter_size[0], w:w + filter_size[1], c].ravel()
                tmp = np.sort(tmp)
                result[h, w, c] = tmp[int(len(tmp) / 2)]

    return result
```

각 영상 픽셀에 대해 Median Filter 적용

Salt and Pepper Noise

Median Filter 최적화

1. 커널 사이즈 및 stride에 따른 PSNR 값 비교

```
stride 1, filter size : 3
k size : 3,  sigma = 1
PSNR : 26.865229883265556
stride 1, filter size : 3
k size : 3,  sigma = 4
PSNR : 26.914981703598002
stride 1, filter size : 3
k size : 3,  sigma = 7
PSNR : 26.916010196318577
stride 1, filter size : 3
k size : 5,  sigma = 1
PSNR : 27.092299276174035
stride 1, filter size : 3
k size : 5,  sigma = 4
PSNR : 27.161295722165132
stride 1, filter size : 3
k size : 5,  sigma = 7
PSNR : 27.148359033237472
stride 1, filter size : 3
k size : 7,  sigma = 1
PSNR : 27.12090264185008
stride 1, filter size : 3
k size : 7,  sigma = 4
PSNR : 27.10715949657424
stride 1, filter size : 3
k size : 7,  sigma = 7
PSNR : 27.054817893227217
stride 1, filter size : 5
k size : 3,  sigma = 1
PSNR : 26.860851454047612
stride 1, filter size : 5
k size : 3,  sigma = 4
PSNR : 26.8587488536939
stride 1, filter size : 5
k size : 3,  sigma = 7
PSNR : 26.85823743806598
stride 1, filter size : 5
k size : 5,  sigma = 1
PSNR : 26.938089508391954
stride 1, filter size : 5
k size : 5,  sigma = 4
PSNR : 26.96127622960564
stride 1, filter size : 5
k size : 5,  sigma = 7
PSNR : 26.9569790978835
stride 1, filter size : 5
k size : 7,  sigma = 1
PSNR : 26.947103701589366
stride 1, filter size : 5
k size : 7,  sigma = 4
PSNR : 26.909635207122978
stride 1, filter size : 5
k size : 7,  sigma = 7
PSNR : 26.88270836092078
stride 1, filter size : 7
k size : 3,  sigma = 1
PSNR : 26.645330842325325
stride 1, filter size : 7
k size : 3,  sigma = 4
PSNR : 26.619319798832745
stride 1, filter size : 7
k size : 3,  sigma = 7
PSNR : 26.61796068027901
stride 1, filter size : 7
k size : 5,  sigma = 1
PSNR : 26.670853406495745
stride 1, filter size : 7
k size : 5,  sigma = 4
PSNR : 26.625964355886303
stride 1, filter size : 7
k size : 5,  sigma = 7
PSNR : 26.620557366465725
```

커널 사이즈: 3, stride: 1일 때 가장 높은 PSNR 값 도출

2. 필터 적용 횟수에 따른 PSNR 값 비교

```
median filtering : 1

PSNR : 27.161295722165132

median filtering : 2

PSNR : 26.927550862087138

median filtering : 3

PSNR : 26.552685933516592

median filtering : 4

PSNR : 26.13068250021685

median filtering : 5

PSNR : 25.701710413533124
```

필터 한 번만 적용했을 때 가장 높은 PSNR 값 도출

White Gaussian Noise

Gaussian Filter

ALGORITHM 5.4 Create a 1D Gaussian kernel

CreateGaussianKernel(σ)

Input: floating-point standard deviation σ
Output: 1D Gaussian kernel (as an array with w elements)

$\tilde{w} \leftarrow$ GetKernelHalfWidth(σ) ➤ Determine a reasonable halfwidth $\tilde{w}$, using, e.g., Algorithm 5.5.
$w \leftarrow 2\tilde{w} + 1$ ➤ Compute the (odd) width w from the halfwidth $\tilde{w}$.
$norm \leftarrow 0$ ➤ Initialize the normalization factor to zero.
for $i \leftarrow 0$ **to** $w - 1$ **do** ➤ Construct the w-element kernel by sampling the continuous Gaussian function, while keeping track of the normalization factor.
    $gauss[i] \leftarrow \exp(-(i - \tilde{w}) * (i - \tilde{w})/(2 * \sigma * \sigma))$
    $norm \leftarrow_{+} gauss[i]$
for $i \leftarrow 0$ **to** $w - 1$ do ➤ Apply the normalization factor to ensure that $\sum_{i=0}^{w-1} gauss[i] = 0$.
    $gauss[i] \leftarrow_{/} norm$
return $gauss$

이미지 중심과의 거리에 따라 가중치를 다르게 하여 영상 내 노이즈를 줄이는 기법

White Gaussian Noise

Gaussian Filter 구현

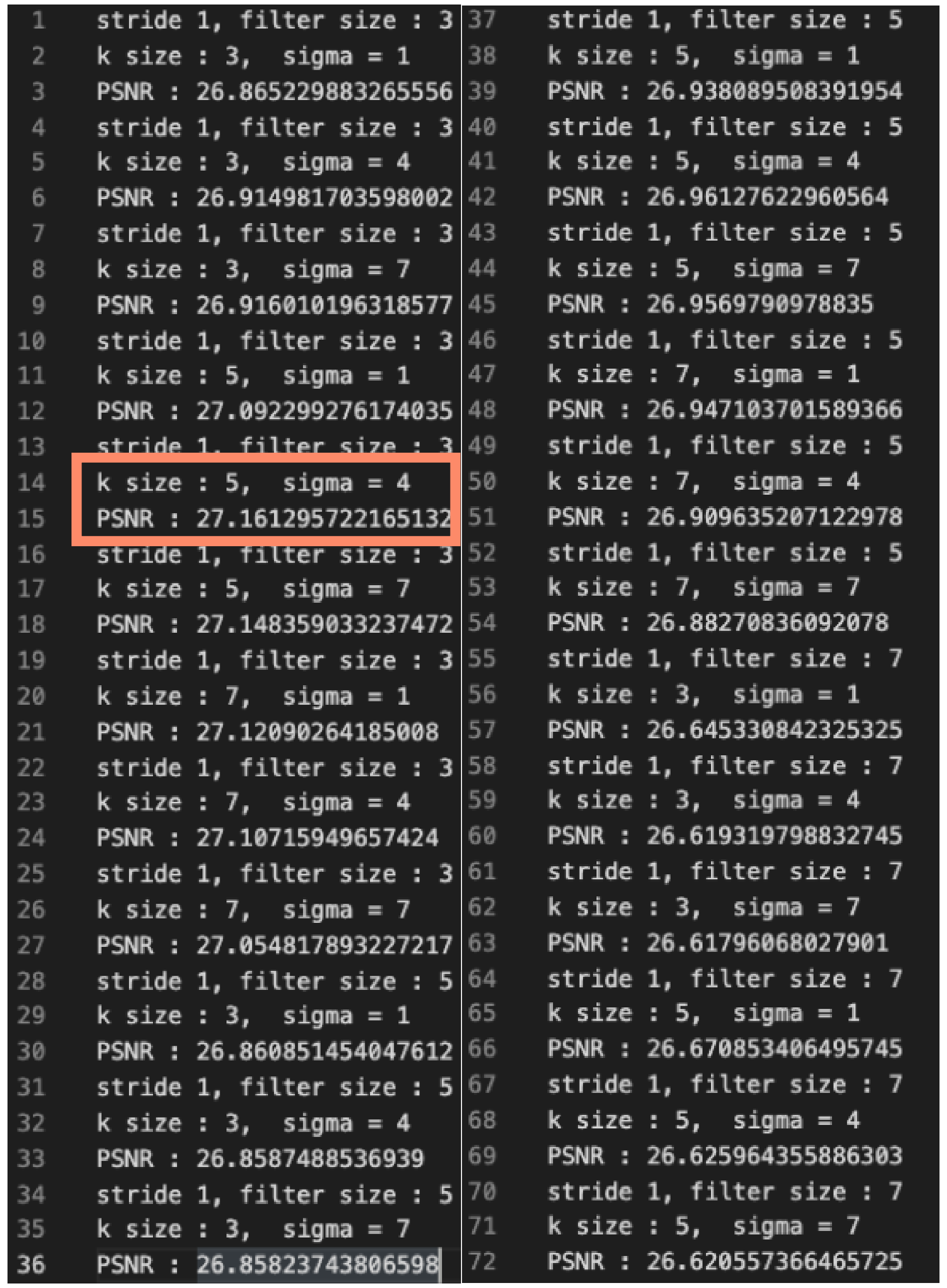
```python
def gaussian_kernel(k_size, sigma):
    size = k_size//2
    y, x = np.ogrid[-size:size+1, -size:size+1]
    filter = 1/(2*np.pi * (sigma**2)) * np.exp(-1 *(x**2 + y**2)/(2*(sigma**2)))
    sum = filter.sum()
    filter /= sum
    return filter

def padding(img, k_size):
    pad_size = k_size//2
    h, w, ch = img.shape

    res = np.zeros((h + (2*pad_size), w+(2*pad_size), ch), dtype=np.float)

    if pad_size == 0:
        res = img.copy()
    else:
        res[pad_size:-pad_size, pad_size:-pad_size] = img.copy()
    return res
```

```python
def gaussian_filtering(img, k_size=5,sigma=4):
    h, w, ch = img.shape
    filter = gaussian_kernel(k_size, sigma)
    pad_img = padding(img,k_size)
    filtered_img = np.zeros((h, w, ch), dtype=np.float32)

    for ch in range(0, ch):
        for i in range(h):
            for j in range(w):
                filtered_img[i, j, ch] = np.sum(filter * pad_img[i:i+k_size, j:j+k_size, ch])

    return filtered_img
```

White Gaussian Noise

Gaussian Filter 최적화

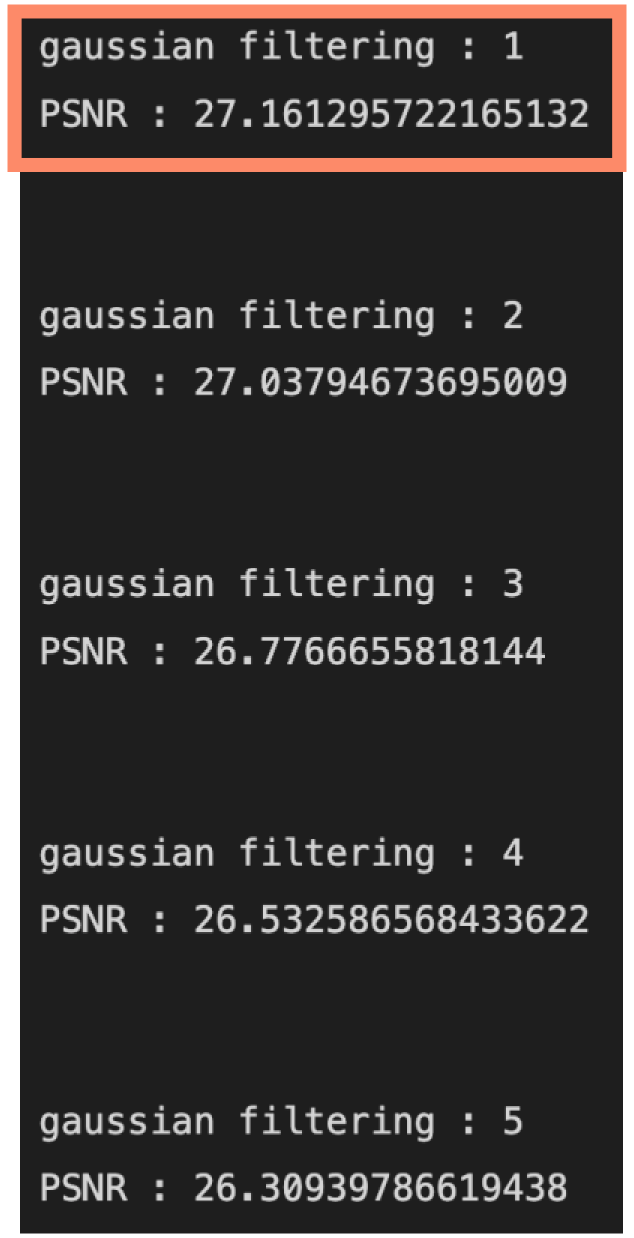
1. 커널 사이즈 및 표준 편차에 따른 PSNR 값 비교



```
stride 1, filter size : 3
k size : 3,  sigma = 1
PSNR : 26.865229883265556
stride 1, filter size : 3
k size : 3,  sigma = 4
PSNR : 26.914981703598002
stride 1, filter size : 3
k size : 3,  sigma = 7
PSNR : 26.916010196318577
stride 1, filter size : 3
k size : 5,  sigma = 1
PSNR : 27.092299276174035
stride 1, filter size : 3
k size : 5,  sigma = 4
PSNR : 27.161295722165132
stride 1, filter size : 3
k size : 5,  sigma = 7
PSNR : 27.148359033237472
stride 1, filter size : 3
k size : 7,  sigma = 1
PSNR : 27.12090264185008
stride 1, filter size : 3
k size : 7,  sigma = 4
PSNR : 27.10715949657424
stride 1, filter size : 3
k size : 7,  sigma = 7
PSNR : 27.054817893227217
stride 1, filter size : 5
k size : 3,  sigma = 1
PSNR : 26.860851454047612
stride 1, filter size : 5
k size : 3,  sigma = 4
PSNR : 26.8587488536939
stride 1, filter size : 5
k size : 3,  sigma = 7
PSNR : 26.85823743806598
stride 1, filter size : 5
k size : 5,  sigma = 1
PSNR : 26.938089508391954
stride 1, filter size : 5
k size : 5,  sigma = 4
PSNR : 26.96127622960564
stride 1, filter size : 5
k size : 5,  sigma = 7
PSNR : 26.9569790978835
stride 1, filter size : 5
k size : 7,  sigma = 1
PSNR : 26.947103701589366
stride 1, filter size : 5
k size : 7,  sigma = 4
PSNR : 26.909635207122978
stride 1, filter size : 5
k size : 7,  sigma = 7
PSNR : 26.88270836092078
stride 1, filter size : 7
k size : 3,  sigma = 1
PSNR : 26.645330842325325
stride 1, filter size : 7
k size : 3,  sigma = 4
PSNR : 26.619319798832745
stride 1, filter size : 7
k size : 3,  sigma = 7
PSNR : 26.61796068027901
stride 1, filter size : 7
k size : 5,  sigma = 1
PSNR : 26.670853406495745
stride 1, filter size : 7
k size : 5,  sigma = 4
PSNR : 26.625964355886303
stride 1, filter size : 7
k size : 5,  sigma = 7
PSNR : 26.620557366465725
```

커널 사이즈: 5, 표준 편차: 4일 때 가장 높은 PSNR 값 도출

2. 필터 적용 횟수에 따른 PSNR 값 비교

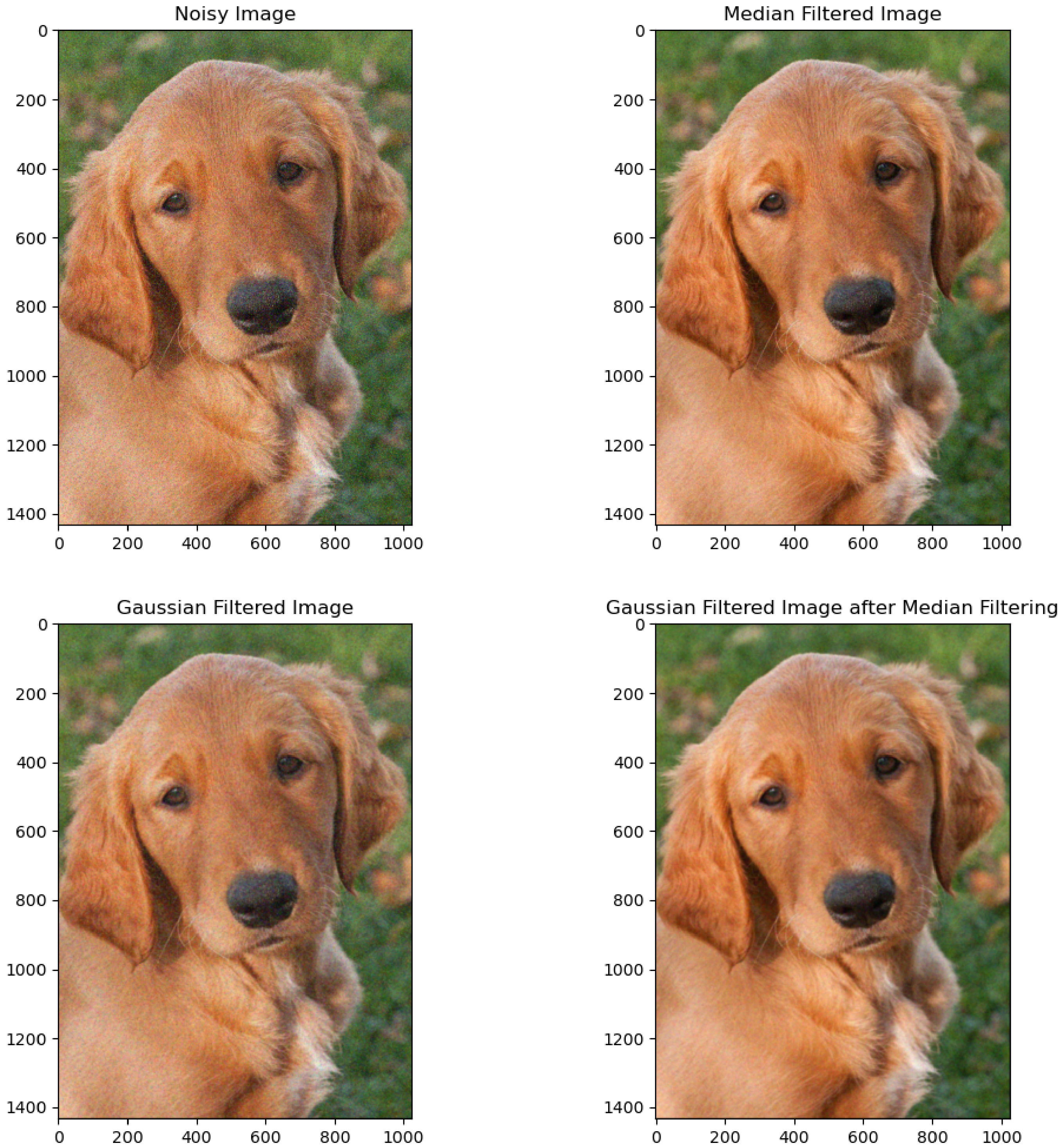


```
gaussian filtering : 1
PSNR : 27.161295722165132

gaussian filtering : 2
PSNR : 27.03794673695009

gaussian filtering : 3
PSNR : 26.7766655818144

gaussian filtering : 4
PSNR : 26.532586568433622

gaussian filtering : 5
PSNR : 26.30939786619438
```

필터 한 번만 적용했을 때 가장 높은 PSNR 값 도출

Image Denoising

Filter 적용 순서에 따른 PSNR 비교



이미지에 Median 필터 적용한 뒤 Gaussian 필터를 적용했을 때,
더 높은 PSNR 값 도출

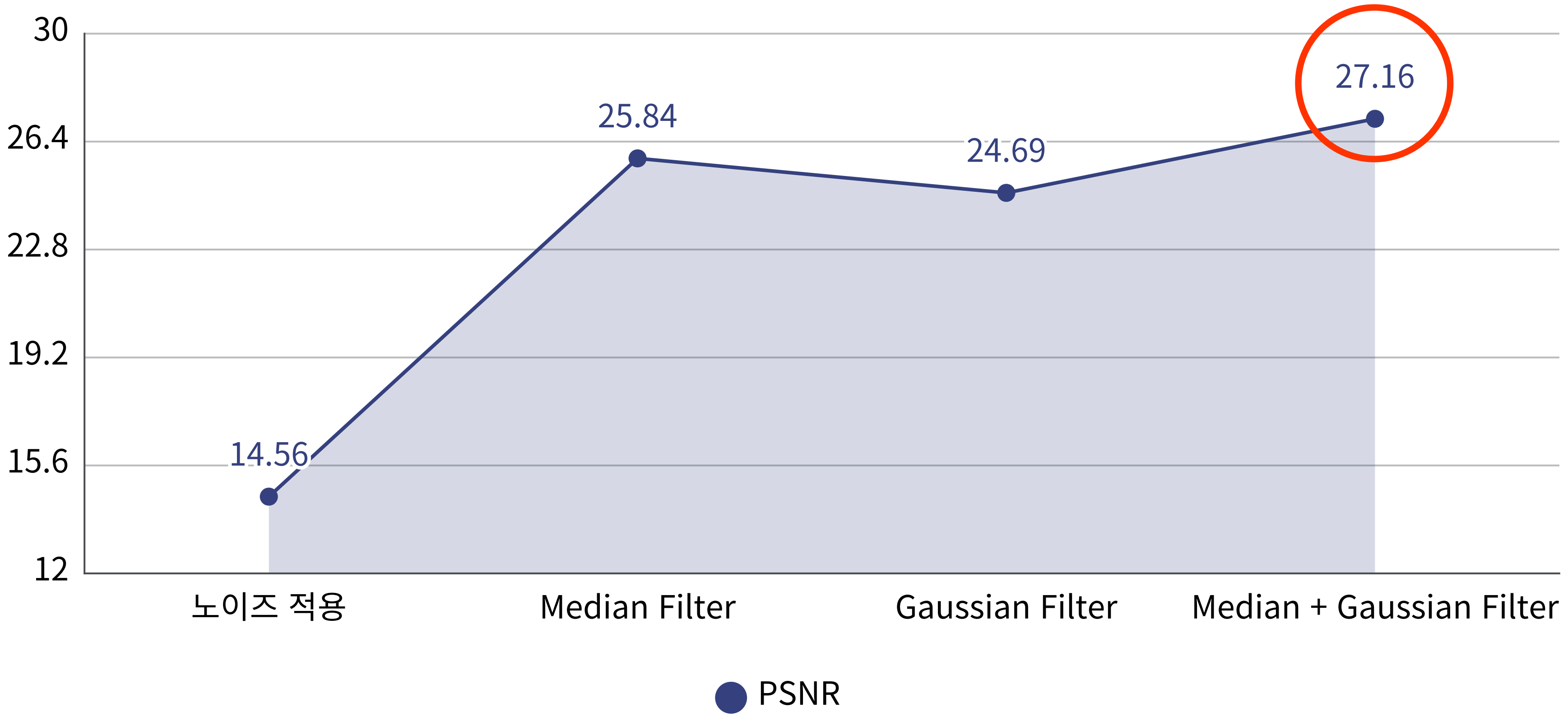


Image Denoising

Bilateral Filter

Gaussian Filter 적용 시,

영상 엣지 부근에서 픽셀 값을 평탄하게 만드는 단점을 보완하기 위해 Bilateral Filter 구현

ALGORITHM 5.13 Perform bilateral filtering on an image

$\textsc{BilateralFilter}(I, \sigma_s, \sigma_r, n_{iter})$

Input: grayscale image I, standard deviations σ_s and σ_r of Gaussian spatial and range kernels, number n_{iter} of iterations

Output: bilateral-filtered image

for $k \leftarrow 1$ **to** n_{iter} **do**	➤ For each iteration,
for $(x, y) \in I$ **do**	and for each pixel in the image,
$val \leftarrow 0$	initialize the value to zero,
$norm \leftarrow 0$	and the normalization factor to zero.
for $(\delta_x, \delta_y) \in \mathcal{W}$ **do**	➤ For each pixel in a $\pm 2.5\sigma_s$ window,
$d_s^2 \leftarrow \delta_x * \delta_x + \delta_y * \delta_y$	compute squared spatial distance,
$d_r \leftarrow I(x, y) - I(x + \delta_x, y + \delta_y)$	and range difference
$w \leftarrow \exp(-d_s^2/(2 * \sigma_s^2)) * \exp(-(d_r * d_r)/(2 * \sigma_r^2))$	to compute weight.
$val \leftarrow_+ w * I(x + \delta_x, y + \delta_y)$	➤ Accumulate weighted sum
$norm \leftarrow_+ w$	and update normalization factor.
$I'(x, y) \leftarrow val/norm$	➤ Set output to normalized weighted sum.
$I \leftarrow I'$	➤ Copy entire output image to input for next iteration.
return I'	

Image Denoising

Bilateral Filter 구현

```python
def bilateral_filter(noisy_img, k_size=5, sigma_space=4, sigma_intensity=0.2):
    h, w, ch = noisy_img.shape
    bilateral_noisy_img = np.zeros((h, w, ch))
    spatial_filter = gaussian_kernel(k_size, sigma_space)
    for c in range(ch):
        for i in range(h):
            for j in range(w):
                intensity_center = noisy_img[i, j, c]
                weighted_sum = 0.0
                normalization_factor = 0.0
                for m in range(-k_size//2, k_size//2 + 1):
                    for n in range(-k_size//2, k_size//2 + 1):
                        i_neighbor = i + m
                        j_neighbor = j + n

                        if 0 <= i_neighbor < h and 0 <= j_neighbor < w:
                            intensity_neighbor = noisy_img[i_neighbor, j_neighbor, c]
                            weight_intensity = np.exp(-(intensity_center - intensity_neighbor)**2 / (2 * sigma_intensity**2))
                            weight_spatial = spatial_filter[m + k_size//2, n + k_size//2]
                            weight = weight_intensity * weight_spatial
                            weighted_sum += intensity_neighbor * weight
                            normalization_factor += weight

                bilateral_noisy_img[i, j, c] = weighted_sum / normalization_factor

    return bilateral_noisy_img
```

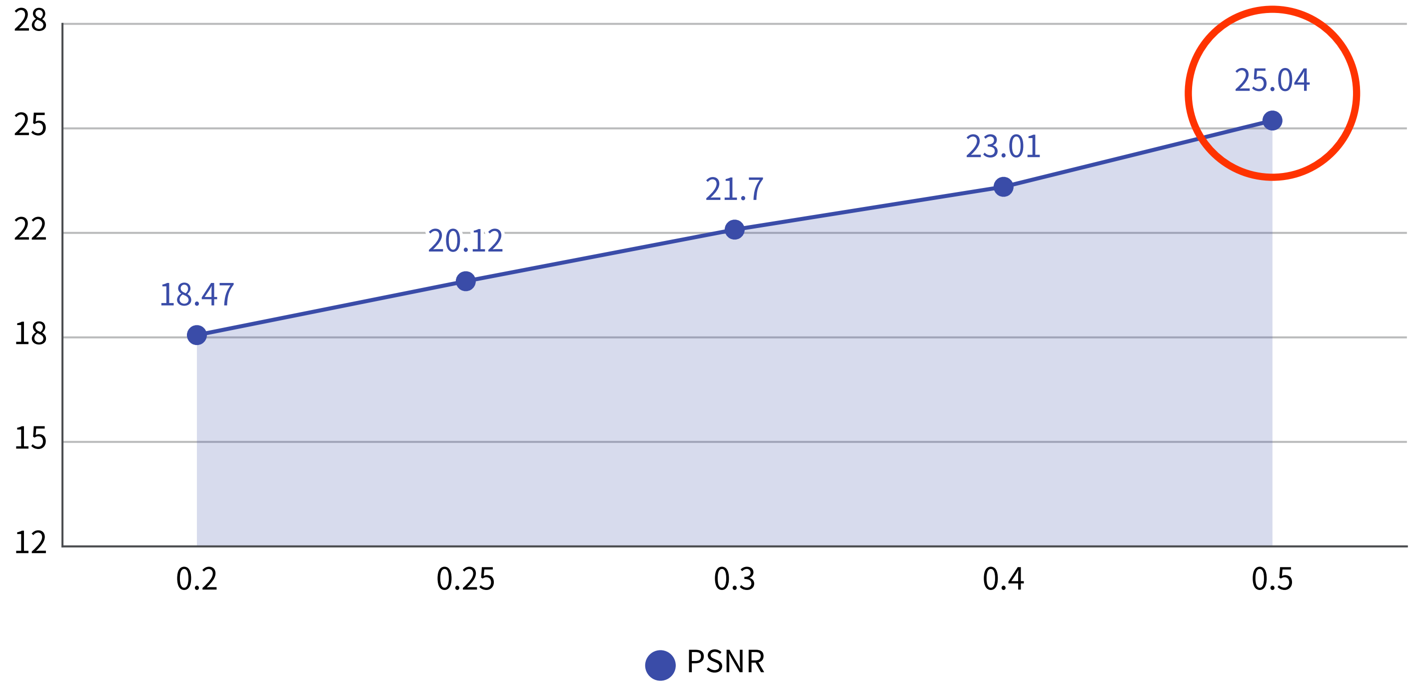
이미지 내 특정 픽셀과 주변 픽셀 간 강도 차이를 고려하여
가중치를 다르게 적용

Image Denoising

Bilateral Filter 최적화 I

- 표준 편차에 따른 PSNR 값 비교

```
sigma_intemsity=0.2 - PSNR: 18.465199371341477
sigma_intemsity=0.25 - PSNR: 20.11810428632533
sigma_intemsity=0.3 - PSNR: 21.69718677355458
sigma_intemsity=0.35 - PSNR: 23.00701856295732
sigma_intemsity=0.4 - PSNR: 23.966817433556663
sigma_intemsity=0.5 - PSNR: 25.0380909386099
```



표준 편차 0.5일 때 가장 높은 PSNR 값 도출

Image Denoising

Bilateral Filter 최적화 II

- vectorization을 통한 실행 시간 단축

기존 코드: 기본 반복문 구조

```python
def bilateral_filter(noisy_img, k_size=5, sigma_space=4, sigma_intensity=0.2):
    h, w, ch = noisy_img.shape
    bilateral_noisy_img = np.zeros((h, w, ch))
    spatial_filter = gaussian_kernel(k_size, sigma_space)
    for c in range(ch):
        for i in range(h):
            for j in range(w):
                intensity_center = noisy_img[i, j, c]
                weighted_sum = 0.0
                normalization_factor = 0.0
                for m in range(-k_size//2, k_size//2 + 1):
                    for n in range(-k_size//2, k_size//2 + 1):
                        i_neighbor = i + m
                        j_neighbor = j + n

                        if 0 <= i_neighbor < h and 0 <= j_neighbor < w:
                            intensity_neighbor = noisy_img[i_neighbor, j_neighbor, c]
                            weight_intensity = np.exp(-(intensity_center - intensity_neighbor)**2 / (2 * sigma_intensity**2))
                            weight_spatial = spatial_filter[m + k_size//2, n + k_size//2]
                            weight = weight_intensity * weight_spatial
                            weighted_sum += intensity_neighbor * weight
                            normalization_factor += weight

                bilateral_noisy_img[i, j, c] = weighted_sum / normalization_factor

    return bilateral_noisy_img
```

최적화 코드: Numpy 배열 연산 사용

```python
def fff_bilateral_filter(noisy_img, k_size=5, sigma_space=4, sigma_intensity=0.2):
    h, w, ch = noisy_img.shape
    bilateral_noisy_img = np.zeros((h, w, ch))

    spatial_filter = gaussian_kernel(k_size, sigma_space)

    for c in range(ch):
        intensity_center = noisy_img[:, :, c]
        weighted_sum = np.zeros_like(intensity_center)
        normalization_factor = np.zeros_like(intensity_center)

        for m in range(-k_size//2, k_size//2 + 1):
            for n in range(-k_size//2, k_size//2 + 1):
                i_neighbors = np.clip(np.arange(h) + m, 0, h - 1)
                j_neighbors = np.clip(np.arange(w) + n, 0, w - 1)
                intensity_neighbors = noisy_img[i_neighbors, :, c][:, j_neighbors]
                weight_intensity = np.exp(-(intensity_center - intensity_neighbors)**2 / (2 * sigma_intensity**2))
                weight_spatial = spatial_filter[m + k_size//2, n + k_size//2]
                weighted_sum += intensity_neighbors * weight_intensity * weight_spatial
                normalization_factor += weight_intensity * weight_spatial

        bilateral_noisy_img[:, :, c] = weighted_sum / normalization_factor
    return bilateral_noisy_img
```

Baby_noisy(25.8 MB) 영상의 경우,

기존 코드 실행에 50분 소요되었으나 최적화 이후 2분으로 **실행 시간 감소**

Image Denoising

Bilateral Filter 최적화 II

- 커널 사이즈 및 표준 편차에 따른 PSNR 비교

```
kernel size=5, sigma_space=3, sigma_intemsity=0.1 - PSNR: 15.482560680105301
kernel size=5, sigma_space=3, sigma_intemsity=0.2 - PSNR: 18.392135237237245
kernel size=5, sigma_space=3, sigma_intemsity=0.3 - PSNR: 21.585433732029156
kernel size=5, sigma_space=3, sigma_intemsity=0.4 - PSNR: 23.871470681241483
kernel size=5, sigma_space=3, sigma_intemsity=0.5 - PSNR: 24.974357477097954
kernel size=5, sigma_space=3, sigma_intemsity=0.6 - PSNR: 25.425883603286312
kernel size=5, sigma_space=3, sigma_intemsity=0.7 - PSNR: 25.593061943578054
kernel size=5, sigma_space=3, sigma_intemsity=0.8 - PSNR: 25.642755359154297
kernel size=5, sigma_space=3, sigma_intemsity=0.9 - PSNR: 25.64498497109403
kernel size=5, sigma_space=3, sigma_intemsity=1.0 - PSNR: 25.628996811033005
kernel size=5, sigma_space=4, sigma_intemsity=0.1 - PSNR: 15.509620617675209
kernel size=5, sigma_space=4, sigma_intemsity=0.2 - PSNR: 18.46346220024416
kernel size=5, sigma_space=4, sigma_intemsity=0.3 - PSNR: 21.693411693786757
kernel size=5, sigma_space=4, sigma_intemsity=0.4 - PSNR: 23.961350463343383
kernel size=5, sigma_space=4, sigma_intemsity=0.5 - PSNR: 25.032026330667687
kernel size=5, sigma_space=4, sigma_intemsity=0.6 - PSNR: 25.458961405099252
kernel size=5, sigma_space=4, sigma_intemsity=0.7 - PSNR: 25.609732151321513
kernel size=5, sigma_space=4, sigma_intemsity=0.8 - PSNR: 25.64859932744764
kernel size=5, sigma_space=4, sigma_intemsity=0.9 - PSNR: 25.643513499767497
kernel size=5, sigma_space=4, sigma_intemsity=1.0 - PSNR: 25.622419298357514
kernel size=5, sigma_space=5, sigma_intemsity=0.1 - PSNR: 15.52199519684902
kernel size=5, sigma_space=5, sigma_intemsity=0.2 - PSNR: 18.495943815090857
kernel size=5, sigma_space=5, sigma_intemsity=0.3 - PSNR: 21.741335996969905
kernel size=5, sigma_space=5, sigma_intemsity=0.4 - PSNR: 23.999221820794677
kernel size=5, sigma_space=5, sigma_intemsity=0.5 - PSNR: 25.0544917753176
```

커널 사이즈: 5, 공간 표준편차: 4, 강도 표준편차: 0.8 일 때, 가장 높은 PSNR 도출