trabalho1

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1 1º Trabalho de avaliação de visão computacional

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1.1 Requisitos

- pip
- pipenv
- ipykernel *(para a execução do notebook)*

É necessário o arquivo Pipfile do repositório para possibilitar a instalação das dependências.

1.2 Repositório do projeto

- https://github.com/guilherme1guy/computer_vision

1.3 Execução:

Execute as células do Jupyter Notebook

Instalar dependências e importar pacotes:

[ ]:
```
%%capture
# Instalar dependências
! pip install pipenv
! pipenv install

# Importar pacotes

import numpy as np
import scipy
from PIL import Image
from glob import glob
import matplotlib as mpl
import matplotlib.pyplot as plt
import skimage
from numba import jit, njit, prange
```

Funções auxiliares:

[ ]:
```python
# Funções gerais

def show_image(image: np.ndarray):
    # show grayscale image as actually a grayscale image
    plt.imshow(image, cmap='gray', vmin=0, vmax=255)

def show_images(images: np.ndarray):
    for image in images:
        show_image(image)
        plt.show()

def show_images_side_by_side(*images: np.ndarray, graph_titles: list[str] = []):

    # auto generate graph titles if none are provided
    if len(graph_titles) == 0:
        graph_titles = [f"Image {i}" for i in range(0, len(images))]

    if len(graph_titles) != len(images):
        raise ValueError('graph_titles must have the same length as images')

    # show images side by side
    _, axs = plt.subplots(1, len(images), figsize=(20, 20))

    for i in range(0, len(images)):
        axs[i].imshow(images[i], cmap='gray', vmin=0, vmax=255)
        axs[i].set_title(graph_titles[i])

    plt.show()

def show_multiple_intensity_graphs(*images: np.ndarray, graph_titles: list[str]␣
↪= []):
    # show intensity histograms on different figures, stacked

    # auto generate graph titles if none are provided
    if len(graph_titles) == 0:
        graph_titles = [f"Intensity Histogram {i}" for i in range(0,␣
↪len(images))]

    if len(graph_titles) != len(images):
        raise ValueError('graph_titles must have the same length as images')

    for i, image in enumerate(images):
        show_intensity_graph(image, graph_titles[i])

def show_intensity_graph(image: np.ndarray, graph_title: str = "Intensity␣
↪Histogram"):
    display_height = image.shape[0] // 2
```

```
    plt.figure(figsize=(10, 2))

    # plot instensity value along a line
    plt.bar(
        range(0, image.shape[1]),
        image[display_height, :]
    )

    # value is not 255 to show a bit of blank space on top
    # of the graph
    plt.ylim((0, 255 + 20))

    plt.title(graph_title)

    plt.xlabel('Pixel')
    plt.ylabel('Intensity Value')
    plt.show()

def show_intensity_graph_side_by_side(images: list[np.ndarray], graph_titles):
    _, axs = plt.subplots(1, len(images), figsize=(20, 5))

    for i in range(0, len(images)):
        axs[i].bar(
            range(0, images[i].shape[1]),
            images[i][images[i].shape[0] // 2, :]
        )

        axs[i].set_ylim(0, 255 + 20)

        axs[i].set_title(graph_titles[i])

    plt.show()

# plot intensity graph and std_deviation line graph

def plot_intensity_graph_with_std_deviation(image: np.ndarray, std_deviation:␣
 ↪np.ndarray):
    display_height = image.shape[0] // 2

    # plot instensity value along a line
    fig, ax = plt.subplots()
    ax.plot(image[display_height, :], color='green')

    # get transparent red color
    red = (1, 0, 0, 0.3)
```

```
    ax.plot(image[display_height, :] + std_deviation[display_height, :],␣
↪color=red)
    ax.plot(image[display_height, :] - std_deviation[display_height, :],␣
↪color=red)

    # value is not 255 to show a bit of blank space on top
    # of the graph
    plt.ylim((0, 255 + 20))

    # set size of graph
    fig.set_figheight(4)
    fig.set_figwidth(15)

    # add labels
    plt.title("Intensity Graph with Standard Deviation")
    plt.xlabel('Pixel')

    plt.show(fig)


def plot_all_intensity_graph_with_std_deviation(images: np.ndarray,␣
↪std_deviation: np.ndarray, avg_img: np.ndarray):
    display_height = images.shape[1] // 2

    # plot instensity value along a line
    fig, ax = plt.subplots()
    blue = (0, 0, 1, 0.1)
    for i in range(0, len(images)):
        ax.plot(images[i][display_height, :], color=blue)

    ax.plot(avg_img[display_height, :], color='green')

    # get transparent red color
    red = (1, 0, 0, 0.5)
    ax.plot(avg_img[display_height, :] + std_deviation[display_height, :],␣
↪color=red)
    ax.plot(avg_img[display_height, :] - std_deviation[display_height, :],␣
↪color=red)

    # value is not 255 to show a bit of blank space on top
    # of the graph
    plt.ylim((0, 255 + 20))

    # set size of graph
    fig.set_figheight(4)
    fig.set_figwidth(15)
```

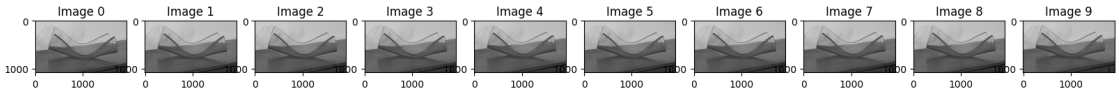
```
    # add labels
    plt.title("Intensity Graph with Standard Deviation")
    plt.xlabel('Pixel')

    plt.show(fig)


def load_images(pattern: str):
    files = sorted(glob(pattern))
    images = []
    for f in files:
        image = Image.open(f)
        image = image.convert('L')
        images.append(np.array(image))
    images = np.array(images)

    return images
```

2 Questão 1.a

Estime o ruído de seu sistema de aquisição de imagens (pode ser uma webcamera ou qualquer outra) usando os passos propostos no algoritmo EST_NOISE e AUTO_COVARIANCE, expostos nos slides em sala de aula. Você precisará capturar diversas imagens da mesma cena estática, em um ambiente sem variações de iluminação (lâmpadas fluorescentes afetam a iluminação das imagens), plotando depois o gráfico da intensidade da imagem ao longo de uma linha e a variação produzida pelo ruído. Esta variação deverá ser pequena, da ordem de menos de 5% em geral, dependendo da qualidade da câmera.

Imagens a serem analisadas:

[ ]:
```
# LOAD IMAGES AS HSV
IMAGES_1A = load_images('trab1/imgs/a/*.jpg')
show_images_side_by_side(*IMAGES_1A)
```



Uma observação sobre o conjunto de imagens é que foi utilizado um recorte da foto original, por conta do tamanho da imagem gerada pela câmera, que torna o tempo de execução dos algoritmos muito grande. Por isso um recorte de aproximadamente 1920x1080 pixels foi feito, e a partir dele foram geradas as imagens a serem analisadas, mostradas anteriormente.

[ ]:
```
@njit
def average_image(images: np.ndarray):
```

```python
    avg_img = np.zeros(images.shape[1:])
    for i in range (0, images.shape[0]):
        avg_img += images[i]

    avg_img /= images.shape[0]

    return avg_img

@njit
def std_deviation_image(images: np.ndarray, avg_im: np.ndarray = None):

    if avg_im is None:
        avg_im = average_image(images)

    n_samples = images.shape[0]
    std_im = np.zeros(images.shape[1:])
    for i in range(0, n_samples):
        std_im += (images[i] - avg_im)**2

    std_im /= n_samples
    std_im = np.sqrt(std_im)

    return std_im


@njit
def est_noise(images: np.ndarray):

    # Imagem = Imagem_pura + ruido
    # O ruído pode ser quantificado como: SNR = media_sinal/desvio_padrao_ruido
    average = average_image(images)
    std_dev = std_deviation_image(images, average)

    SNR = np.where(std_dev == 0, 0, average / std_dev)

    return SNR

@njit
def auto_covariance(images: np.ndarray, avg_im: np.ndarray = None):

        if avg_im is None:
            avg_im = average_image(images)

        n_samples = images.shape[0]
        auto_cov = np.zeros(images.shape[1:])
        for i in range(0, n_samples):
            auto_cov += (images[i] - avg_im)**2
```

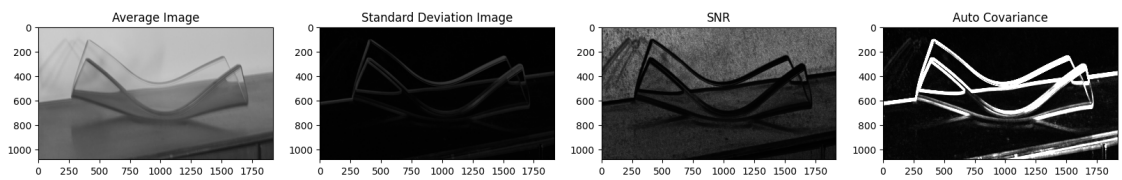
```
        auto_cov /= n_samples

        return auto_cov
```

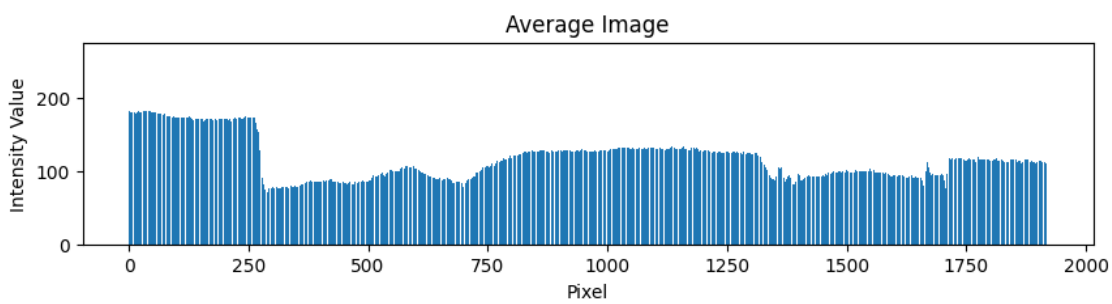
Faz o cálculo e exibe os resultados:

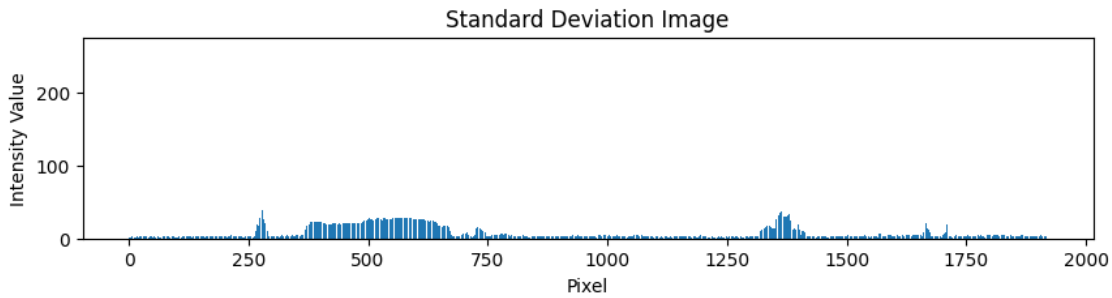
[ ]:
```
avg_im = average_image(IMAGES_1A)
std_dev_im = std_deviation_image(IMAGES_1A, avg_im)
snr = est_noise(IMAGES_1A)
auto_cov = auto_covariance(IMAGES_1A, avg_im)
```

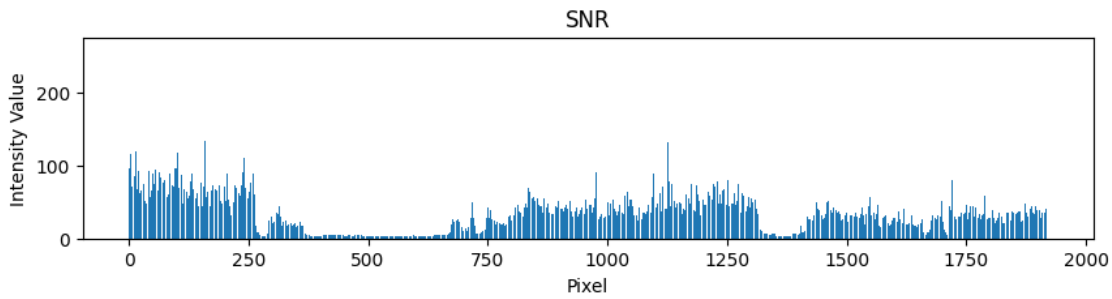
As seguintes imagens representam o cálculo destes valores no conjunto de imagens analisadas. E os gráficos mostram o valor de intensidade ao longo de uma linha da imagem.

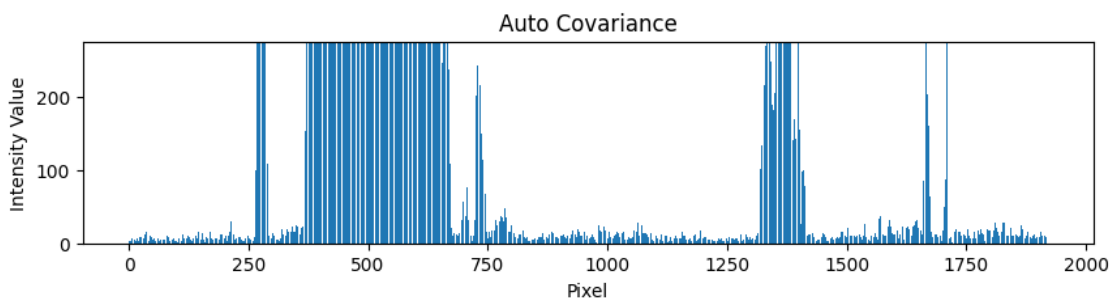
[ ]:
```
titles = ["Average Image", "Standard Deviation Image", "SNR", "Auto Covariance"]

show_images_side_by_side(avg_im, std_dev_im, snr, auto_cov, graph_titles=titles)
show_multiple_intensity_graphs(
    avg_im, std_dev_im, snr, auto_cov,
    graph_titles=titles
)
```











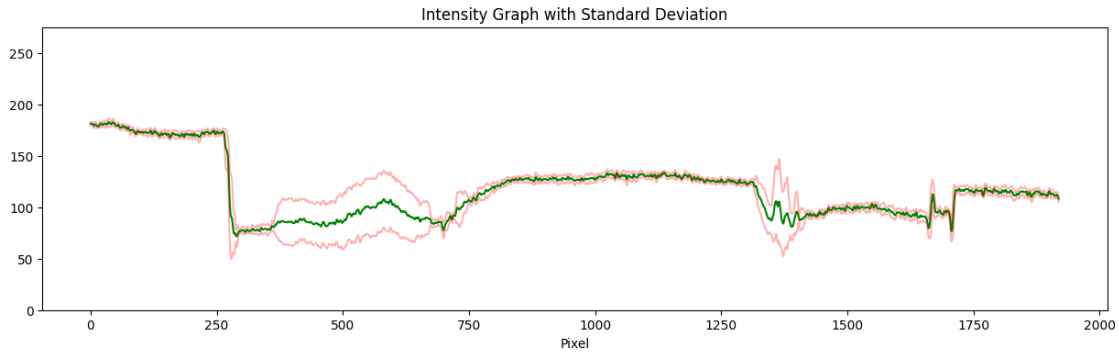
Podemos observar que em momentos em que o desvio padrão é maior, a variação da intensidade da imagem é maior, o que indica que o ruído é maior. O que é confirmado ao observar o SNR.

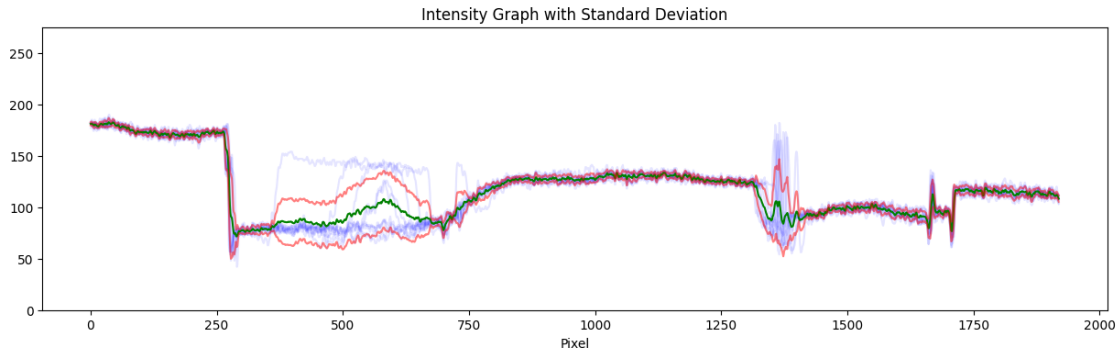
[ ]:
```
averages = {
    'SNR': np.mean(snr),
    'Average Image Intensity': np.mean(avg_im),
    'Standard Deviation Images': np.mean(std_dev_im),
    'Auto Covariance': np.mean(auto_cov)
}

print(f"Averages:")
for key, value in averages.items():
```

```
    print(f"* {key}: {value}")
```

```
Averages:
* SNR: 50.92969842698794
* Average Image Intensity: 132.05843354552476
* Standard Deviation Images: 5.963709570797012
* Auto Covariance: 113.96605972222221
```

[ ]:
```
plot_intensity_graph_with_std_deviation(avg_im, std_dev_im)
plot_all_intensity_graph_with_std_deviation(IMAGES_1A, std_dev_im, avg_im)
```





Os gráficos acima mostram a intensidade ao longo de uma linha horizontal no meio da imagem, em verde a imagem média, em vermelho o desvio padrão em relação à média e em azul todo o conjunto de imagens.

Existem dois pontos de ruído alto na imagem. Entre, aproximadamente, os pixeis 300 e 680 e 1300 e 1400. Esse nível de ruído pode surgir por conta de a imagem ser um recorte, ou pequenos tremores da câmera na captura da imagem.

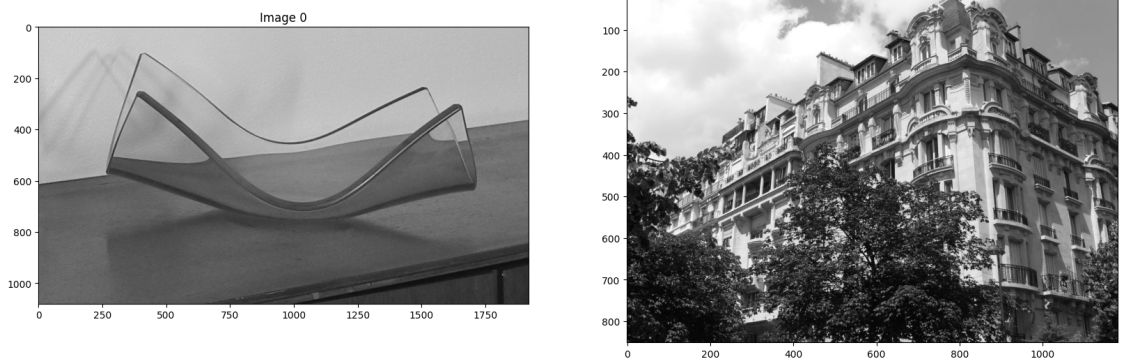
3 Questão 1.b

Escreva rotinas para inserção de ruído gaussiano e do tipo sal-e-pimenta e, após, implemente um filtro de ruídos Gaussiano e Mediano e aplique sobre as imagens, mostrando o resultado da aplicação dos dois filtros sobre as duas imagens. O código deve permitir a especificação da largura do filtro, para percepção dos resultados. Mostre as imagens e discuta os resultados.

Carrega as imagens:

[ ]:
```
# Carrega imagem
IMAGES_1B = load_images('trab1/imgs/b/*.jpg')
show_images_side_by_side(*IMAGES_1B)
```

```
/tmp/ipykernel_91677/2573833541.py:146: VisibleDeprecationWarning: Creating an
ndarray from ragged nested sequences (which is a list-or-tuple of lists-or-
tuples-or ndarrays with different lengths or shapes) is deprecated. If you meant
to do this, you must specify 'dtype=object' when creating the ndarray.
  images = np.array(images)
```



Código dos filtros e geradores de ruído:

[ ]:
```
def gaussian_noise(image: np.ndarray, mean: float = 0, std: float = 1):
    noise = np.random.normal(mean, std, image.shape)
    return image + noise

def salt_pepper_noise(image: np.ndarray, epsilon: float = 0.90, intensity_min:␣
 ↪int = 0, intensity_max: int = 255):

    random_x = np.random.random(image.shape)
    random_y = np.random.random(image.shape)

    intensity_delta = intensity_max - intensity_min

    noise = np.where(
```

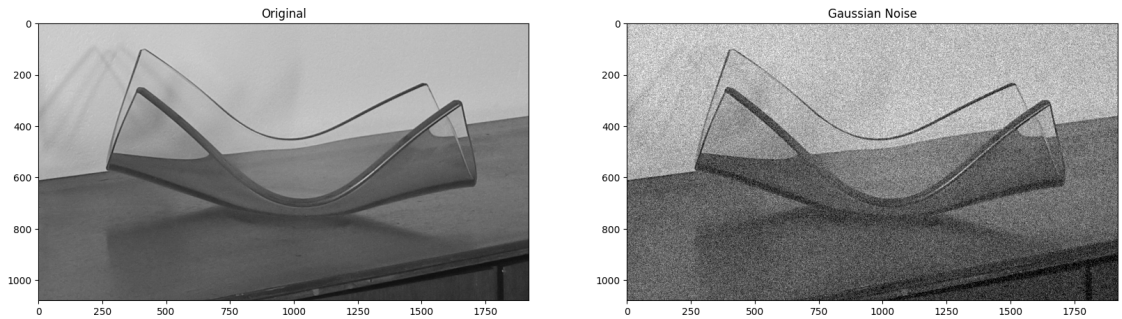
```
        random_x >= epsilon, intensity_min + random_y * intensity_delta,
        0
    )

    return image + noise

def linear_filter(image: np.ndarray, kernel: np.ndarray):

    # scipy automatically chooses fft or direct convolution
    # based on the size of inputs to use the most efficient

    return scipy.signal.convolve(image, kernel, mode='same')

def avg_filter(image: np.ndarray, kernel_size: int = 3):

    kernel = np.ones((kernel_size, kernel_size)) / (kernel_size ** 2)

    return linear_filter(image, kernel)

def gaussian_kernel(kernel_size: int = 50, sigma: float = 5):

    kernel = np.outer(
        scipy.signal.windows.gaussian(kernel_size, sigma),
        scipy.signal.windows.gaussian(kernel_size, sigma),
    )

    kernel /= 2 * np.pi * sigma ** 2

    return kernel

def gaussian_filter(image: np.ndarray, kernel_size: int = 50, sigma: int = 5):
    return linear_filter(
        image,
        gaussian_kernel(kernel_size, sigma)
    )

@njit(parallel=True)
def median_filter(image: np.ndarray, kernel_size: int = 10):

    image_filtered = np.zeros(image.shape)

    kernel_size = kernel_size // 2

    for i in prange(0, image.shape[0]):
        for j in prange(0, image.shape[1]):

            begin_i = max(0, i - kernel_size)
```

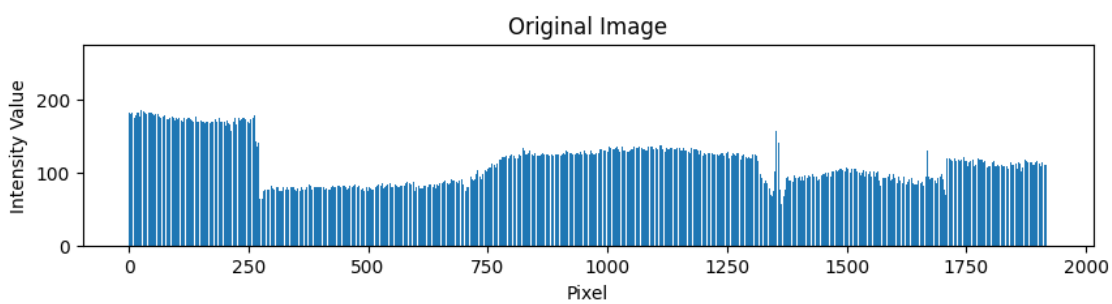
```
            end_i = min(i + kernel_size, image.shape[0])
            begin_j = max(0, j - kernel_size)
            end_j = min(j + kernel_size, image.shape[1])

            region = image[begin_i:end_i, begin_j:end_j]

            image_filtered[i, j] = np.median(region)

    return image_filtered


# Função auxiliar para plotar gráficos e exibir resultados
def apply_filter_show_graphs(filter_func, filter_name: str, *args, **kwargs):
    for idx, image in enumerate(IMAGES_1B):
        filtered_imgs = [
            filter_func(image, *args, **kwargs),
            filter_func(gaussian_imgs[idx], *args, **kwargs),
            filter_func(salt_pepper_imgs[idx], *args, **kwargs)
        ]

        show_images_side_by_side(
            image, gaussian_imgs[idx], salt_pepper_imgs[idx],
            graph_titles=["Original", "Gaussian Noise", "Salt & Pepper Noise"]
        )

        show_images_side_by_side(
            *filtered_imgs,
            graph_titles=[f"Original ({filter_name})", f"Gaussian Noise␣
↪({filter_name})", f"Salt & Pepper Noise ({filter_name})"]
        )

        show_intensity_graph_side_by_side(
            [image, gaussian_imgs[idx], salt_pepper_imgs[idx]],
            graph_titles=["Original", "Gaussian Noise", "Salt & Pepper Noise"]
        )

        show_intensity_graph_side_by_side(
            filtered_imgs,
            graph_titles=[f"Original ({filter_name})", f"Gaussian Noise␣
↪({filter_name})", f"Salt & Pepper Noise ({filter_name})"]
        )
```

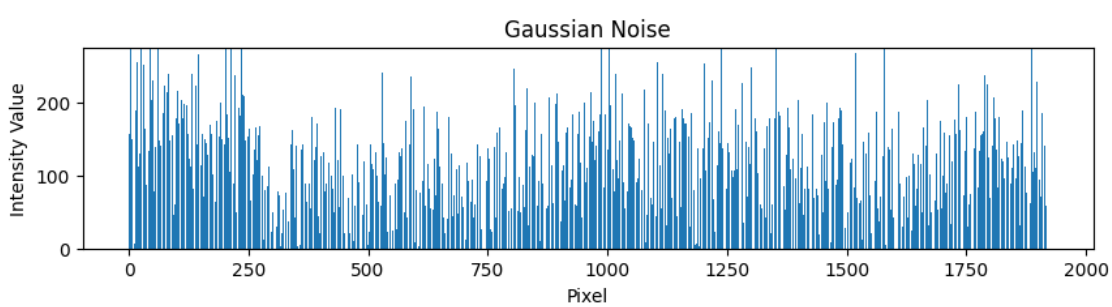
3.1 Ruídos

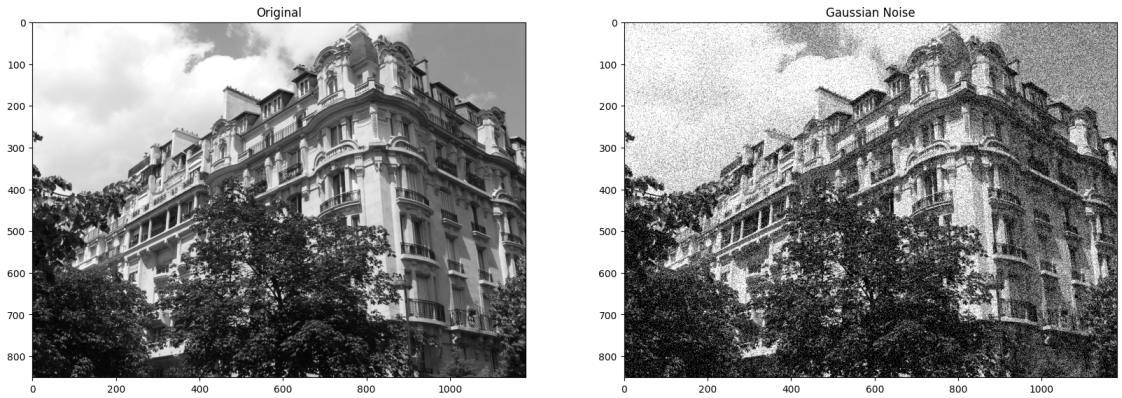
3.1.1 Ruído gaussiano:

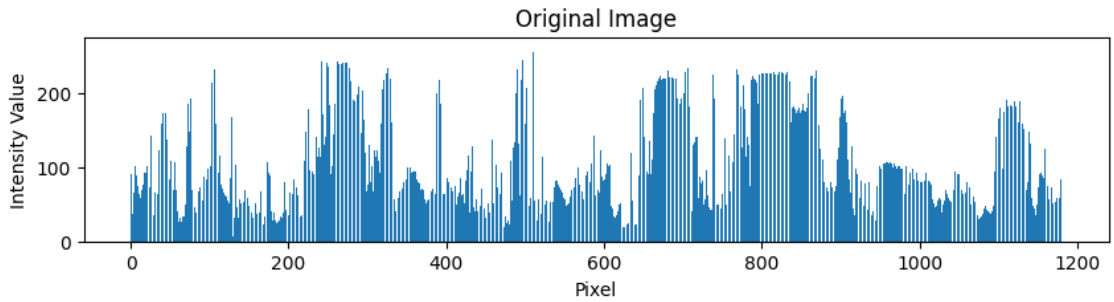
[ ]:
```
gaussian_imgs = []

for image in IMAGES_1B:
    gaussian_img = gaussian_noise(image, mean=0, std=255//4)
    gaussian_imgs.append(gaussian_img)
    show_images_side_by_side(image, gaussian_img, graph_titles=["Original",␣
 ↪"Gaussian Noise"])
    show_multiple_intensity_graphs(
        image, gaussian_img,
        graph_titles=["Original Image", "Gaussian Noise"])
```

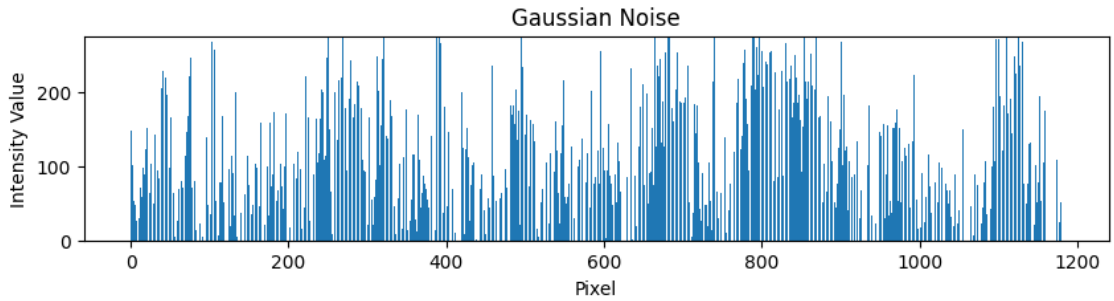








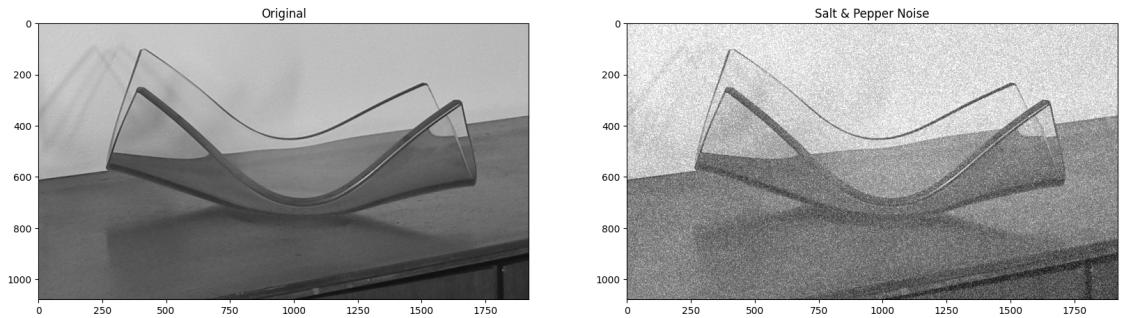


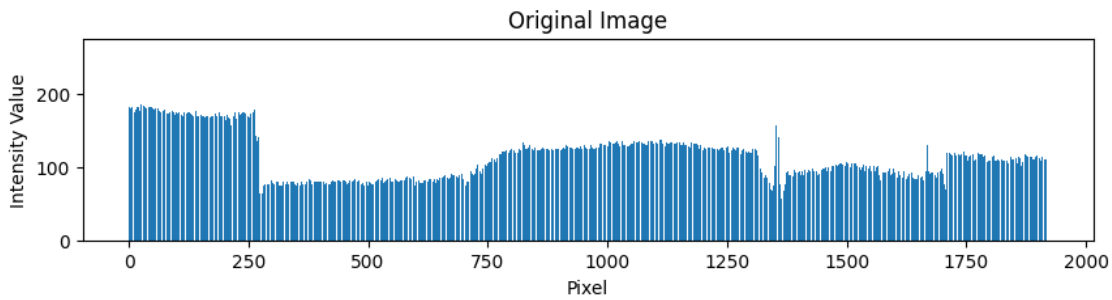


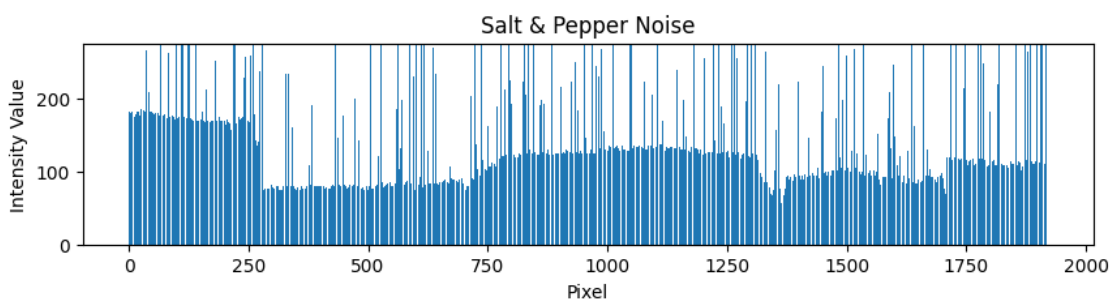
3.1.2 Ruído sal e pimenta:

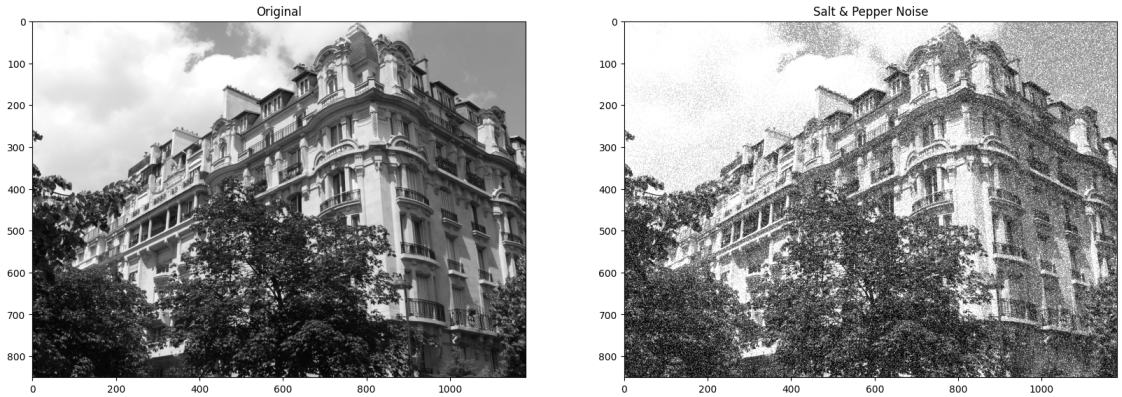
[ ]:
```
salt_pepper_imgs = []

for image in IMAGES_1B:
    salt_pepper_img = salt_pepper_noise(image, epsilon=0.75)
    salt_pepper_imgs.append(salt_pepper_img)
```

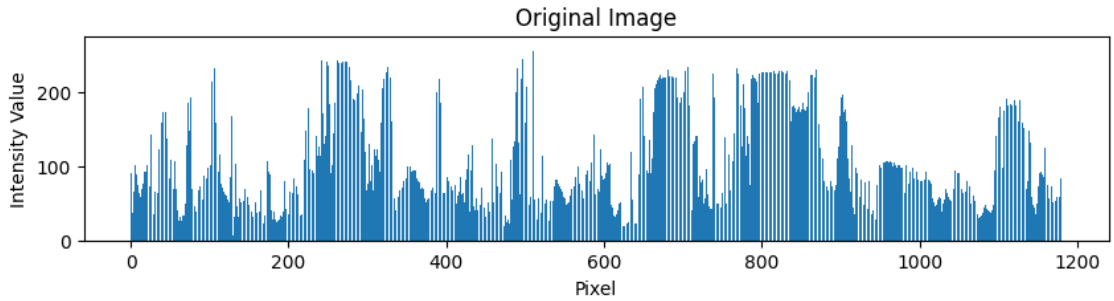
```
show_images_side_by_side(image, salt_pepper_img, graph_titles=["Original",␣
↪"Salt & Pepper Noise"])
show_multiple_intensity_graphs(
    image, salt_pepper_img,
    graph_titles=["Original Image", "Salt & Pepper Noise"])
```

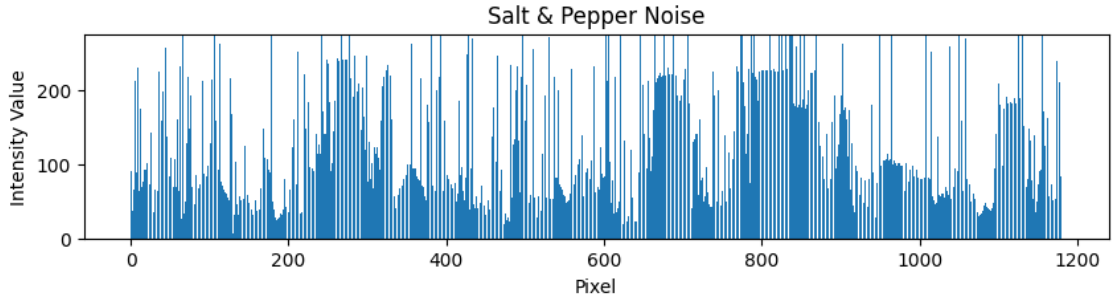










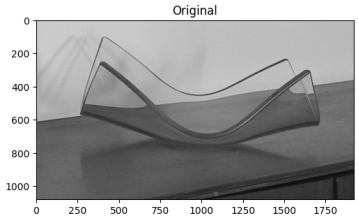


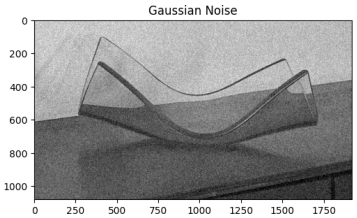
3.2 Filtros

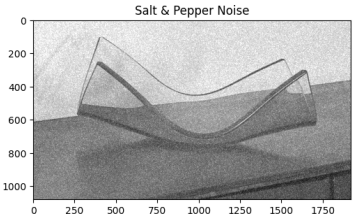
3.2.1 Filtro Média

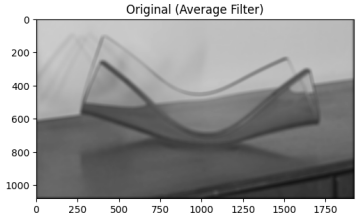
Não estava na questão, mas acabei fazendo para testar

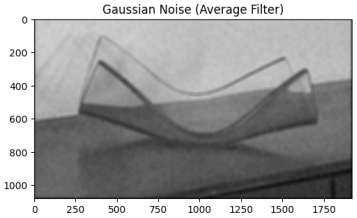
[ ]:
```
apply_filter_show_graphs(avg_filter, "Average Filter", kernel_size=25)
```

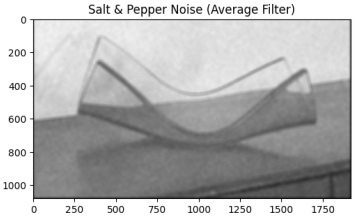

Original

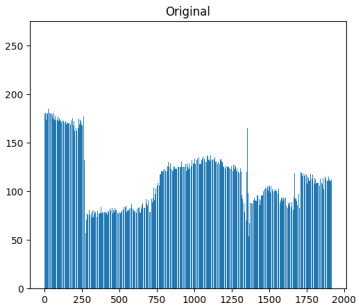

Gaussian Noise

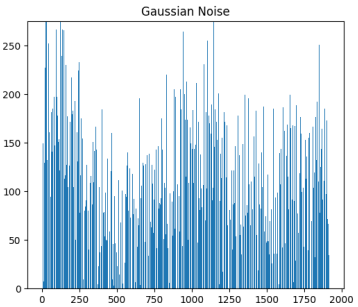

Salt & Pepper Noise

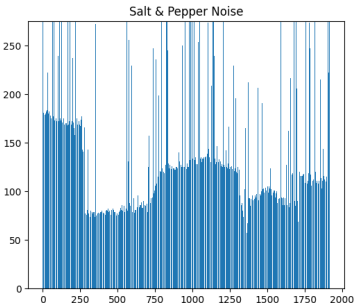

Original (Average Filter)

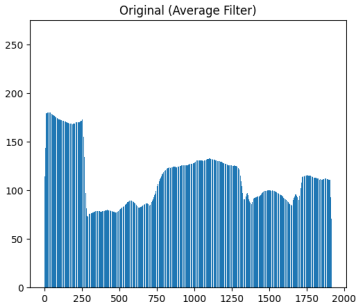

Gaussian Noise (Average Filter)

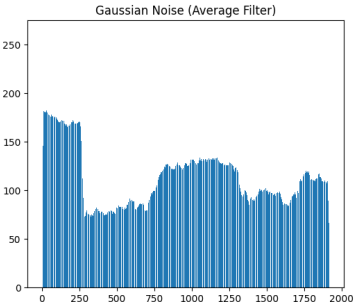

Salt & Pepper Noise (Average Filter)

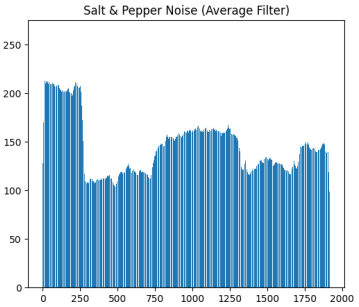

Original

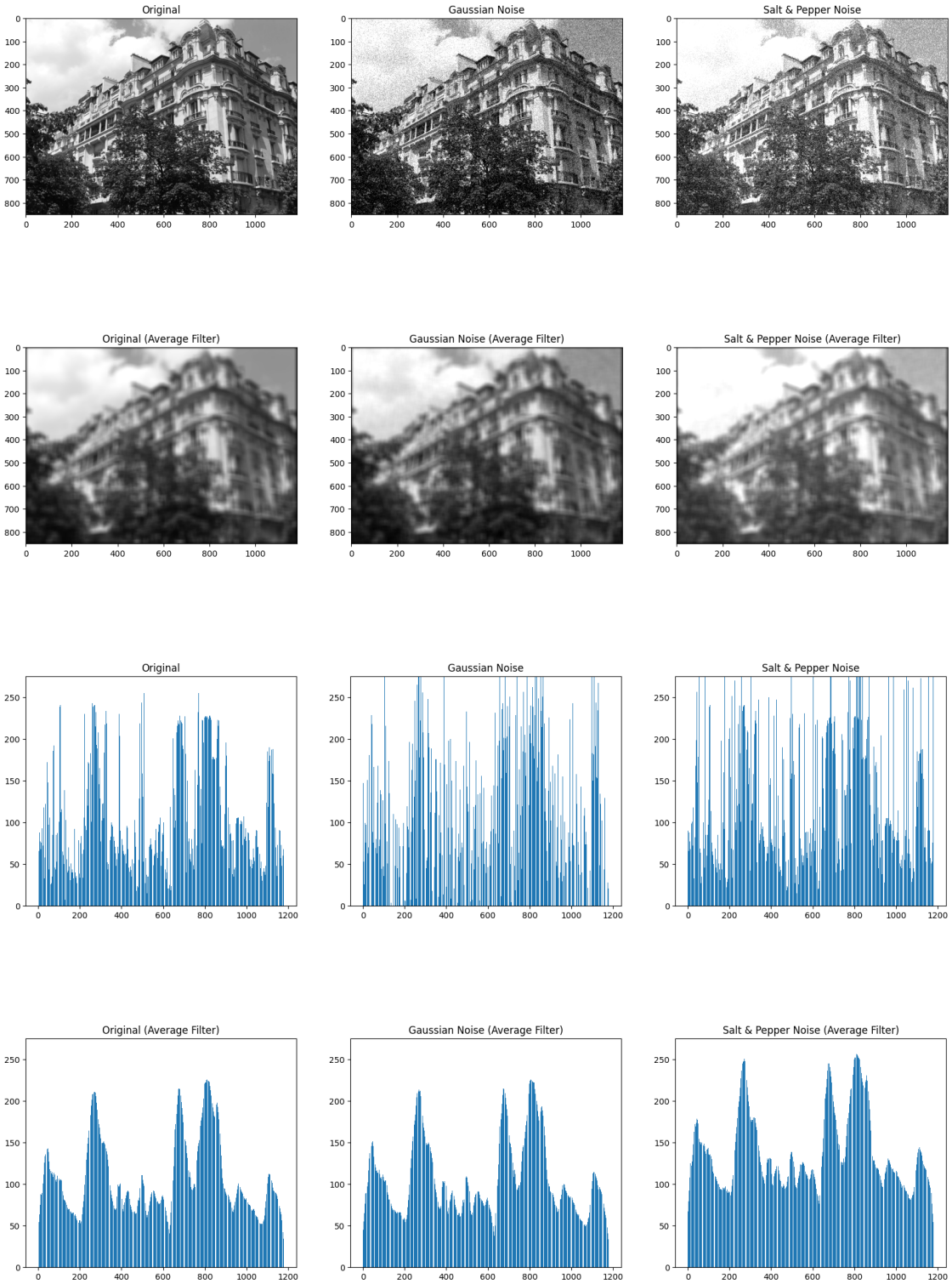

Gaussian Noise


Salt & Pepper Noise


Original (Average Filter)

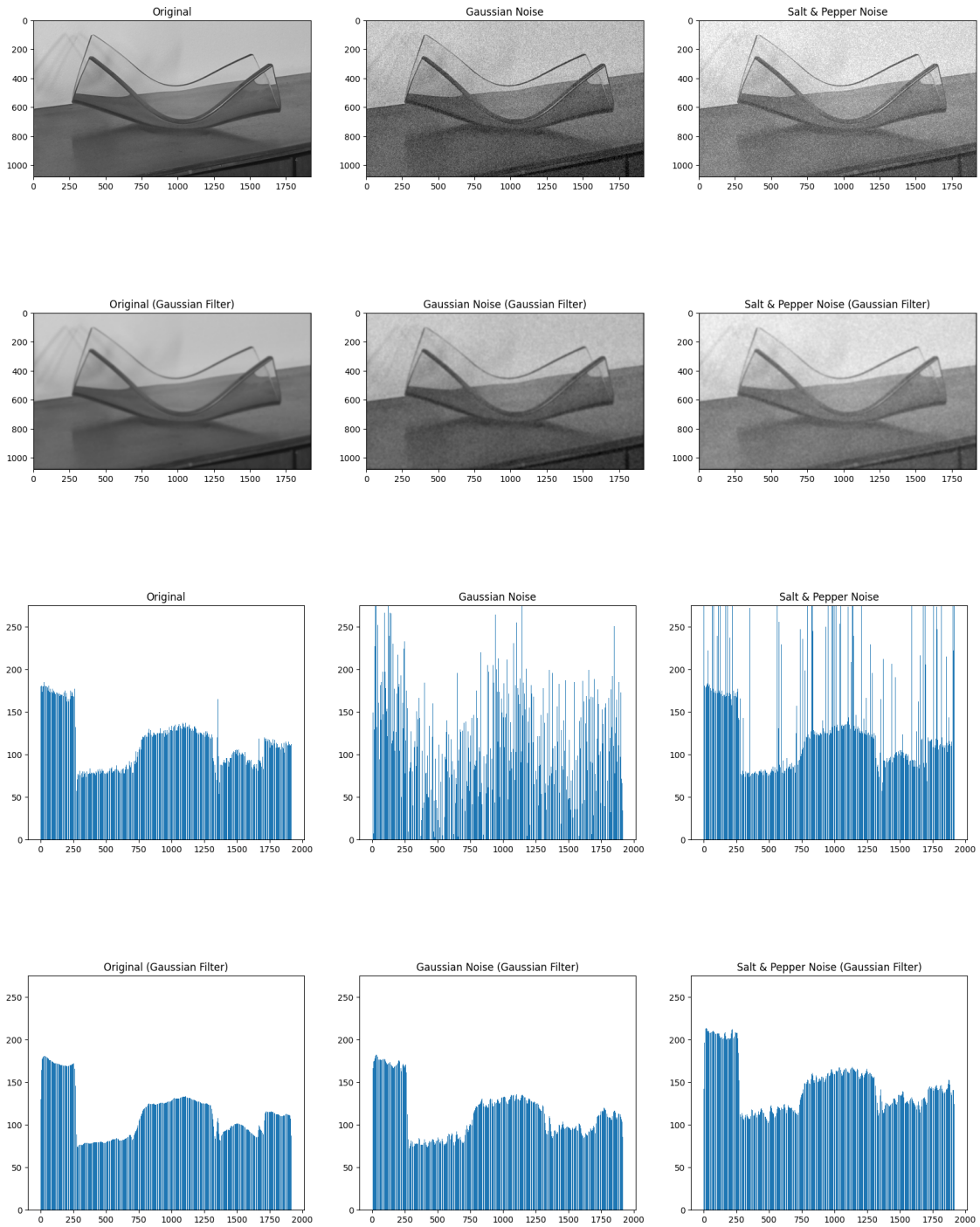

Gaussian Noise (Average Filter)

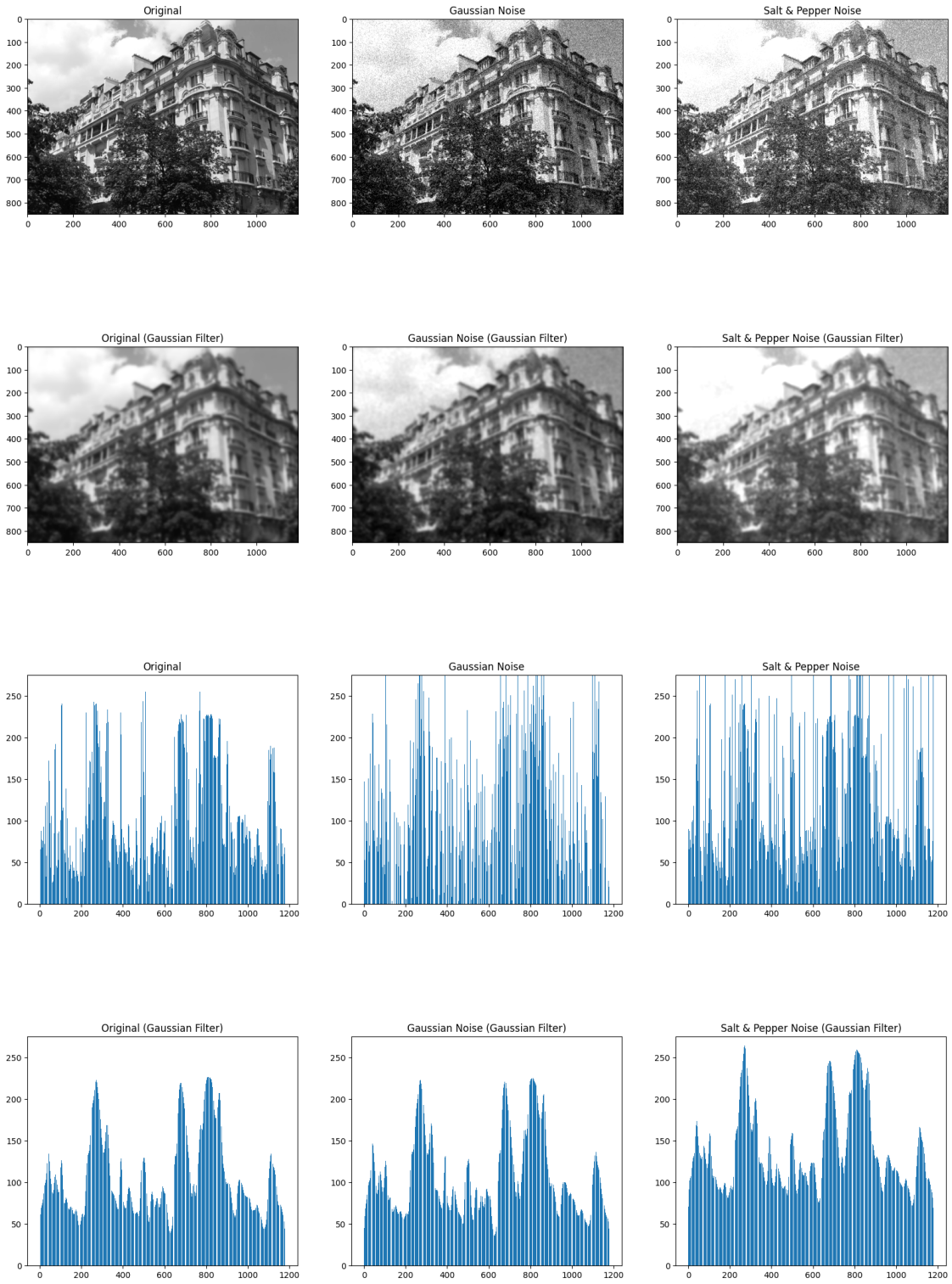

Salt & Pepper Noise (Average Filter)


Original
Gaussian Noise
Salt & Pepper Noise
Original (Average Filter)
Gaussian Noise (Average Filter)
Salt & Pepper Noise (Average Filter)
Original
Gaussian Noise
Salt & Pepper Noise
Original (Average Filter)
Gaussian Noise (Average Filter)
Salt & Pepper Noise (Average Filter)

3.2.2 Filtro Gaussiano

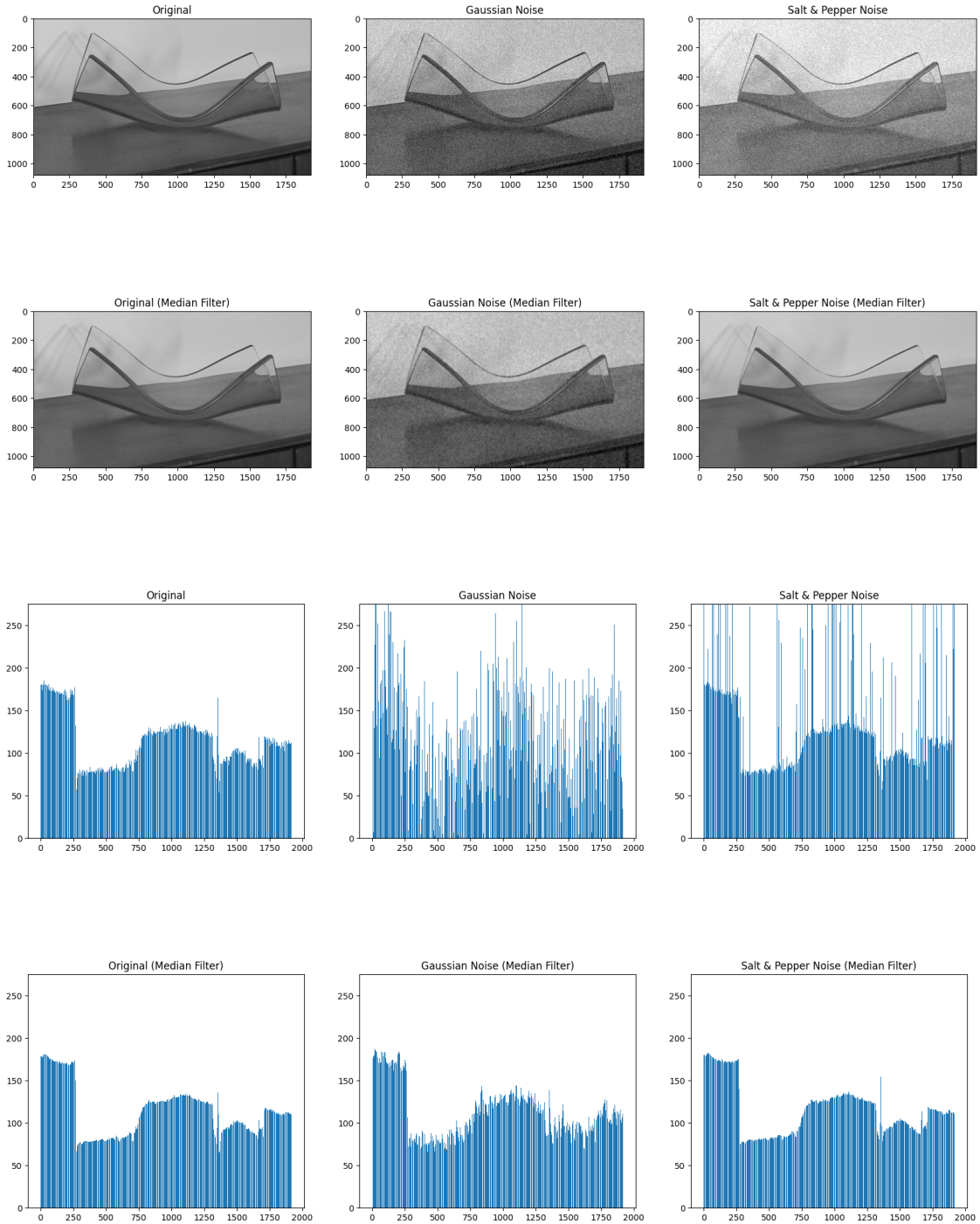
[ ]:
```
apply_filter_show_graphs(
    gaussian_filter,
    "Gaussian Filter",
    kernel_size=50,
    sigma=5
)
```

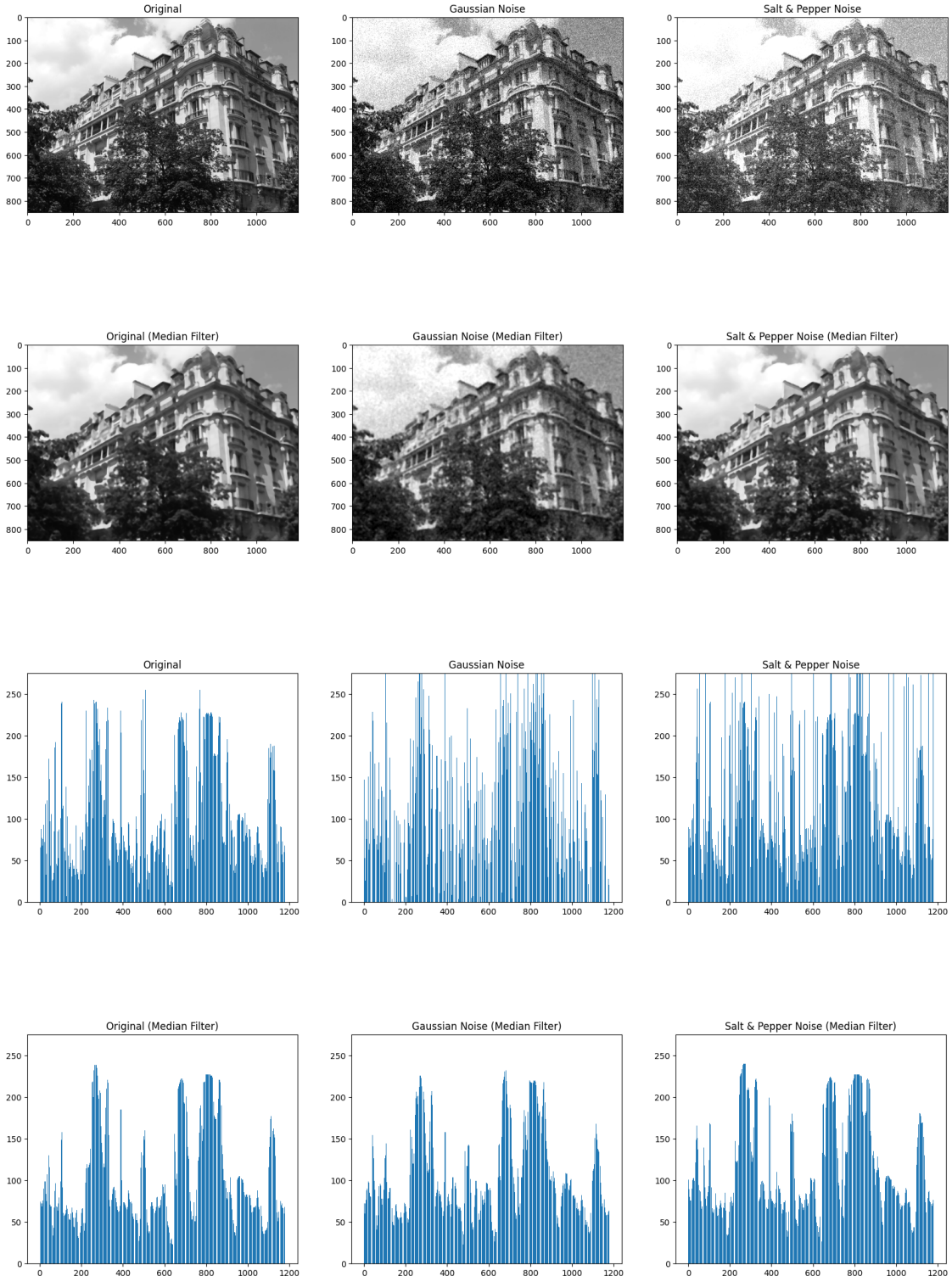



Original
Gaussian Noise
Salt & Pepper Noise
Original (Gaussian Filter)
Gaussian Noise (Gaussian Filter)
Salt & Pepper Noise (Gaussian Filter)
Original
Gaussian Noise
Salt & Pepper Noise
Original (Gaussian Filter)
Gaussian Noise (Gaussian Filter)
Salt & Pepper Noise (Gaussian Filter)

3.2.3 Filtro Mediano

[ ]:
```
apply_filter_show_graphs(
    median_filter,
    "Median Filter",
    kernel_size=10
)
```

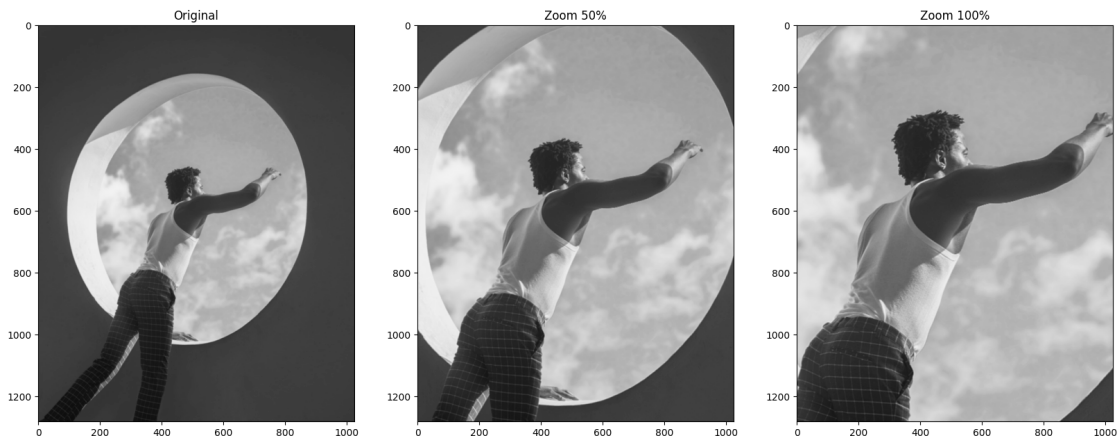



Original
Gaussian Noise
Salt & Pepper Noise
Original (Median Filter)
Gaussian Noise (Median Filter)
Salt & Pepper Noise (Median Filter)
Original
Gaussian Noise
Salt & Pepper Noise
Original (Median Filter)
Gaussian Noise (Median Filter)
Salt & Pepper Noise (Median Filter)

4 Questão 1.c

Use uma rotina qualquer para o algoritmo CANNY e produza diversas imagens indicando os efeitos de escala e os limiares de contraste nos contornos detectados. Implemente os detectores de Robert e Sobel nas mesmas imagens, para uma única escala, e compare os três algoritmos. Sugestão: Use a função icanny fornecida pela Machine Vison ToolBox, que pode ser baixada do site www.petercorke.com

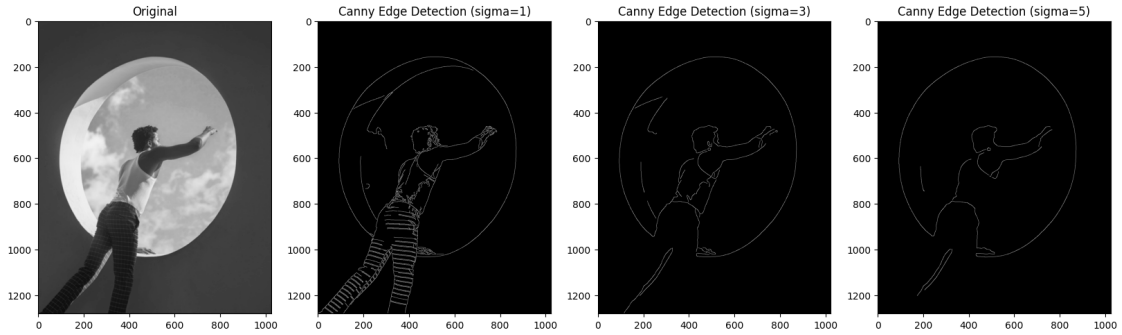
[ ]:
```
RAW_IMAGES_1C = load_images('trab1/imgs/c/*.jpg')
# img source: https://www.pexels.com/pt-br/foto/solitario-no-topo-13747843/
IM_1C_NAMES = ["Original", "Zoom 50%", "Zoom 100%"]

# apply gaussian filter to all images
IMAGES_1C = [scipy.ndimage.gaussian_filter(img, sigma=1) for img in␣
 ↪RAW_IMAGES_1C]

show_images_side_by_side(*IMAGES_1C, graph_titles=IM_1C_NAMES)
```

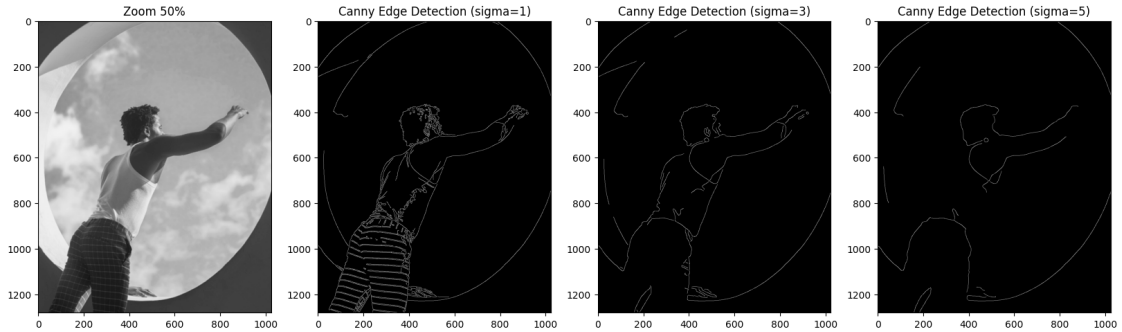


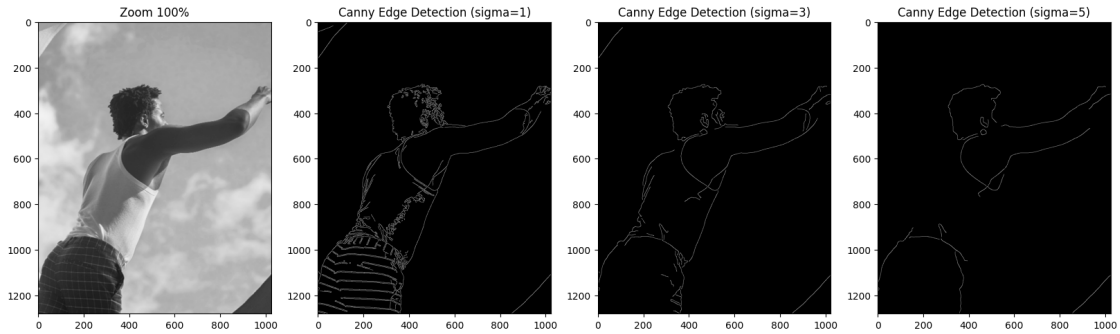
[ ]:
```
def canny_edge_detection(
    image: np.ndarray,
    sigma=1,
    low_threshold=None,
    high_threshold=None
):

    canny_image = skimage.feature.canny(
        image,
        sigma=sigma,
        low_threshold=low_threshold,
        high_threshold=high_threshold)

    return canny_image * 255 # multiply by 255 to make it from 0,1 to 0,255
```

4.0.1 Imagens com diferentes sigmas para Canny Edge Detector

[ ]:
```
for idx, image in enumerate(IMAGES_1C):

    filtered_imgs = [
        image,
        canny_edge_detection(image, sigma=1),
        canny_edge_detection(image, sigma=3),
        canny_edge_detection(image, sigma=5),
    ]

    titles = [
        IM_1C_NAMES[idx],
        "Canny Edge Detection (sigma=1)",
        "Canny Edge Detection (sigma=3)",
        "Canny Edge Detection (sigma=5)",
    ]

    show_images_side_by_side(*filtered_imgs, graph_titles=titles)
```

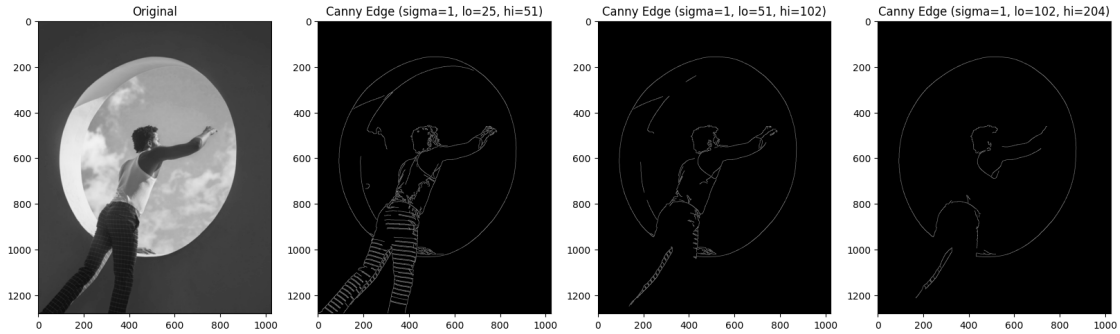


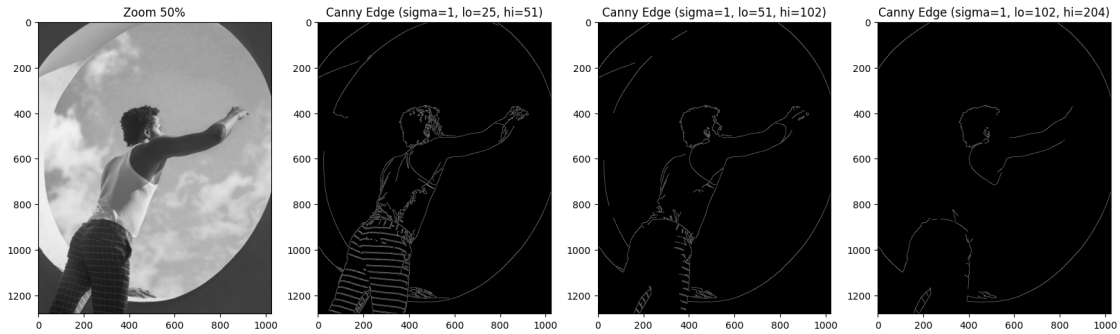


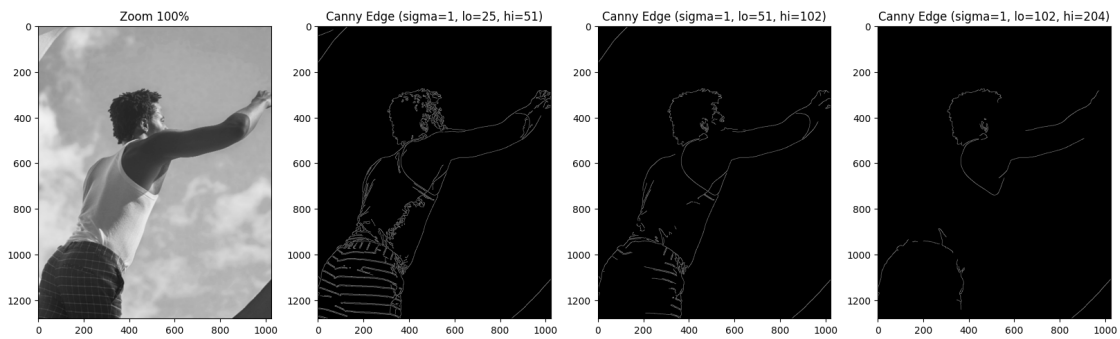


4.0.2 Imagens com diferentes limiares para Canny Edge Detector

[ ]:
```
for idx, image in enumerate(IMAGES_1C):

    filtered_imgs = [
        image,
        canny_edge_detection(image, sigma=1, low_threshold=25,␣
↪high_threshold=51),
        canny_edge_detection(image, sigma=1, low_threshold=51,␣
↪high_threshold=102),
        canny_edge_detection(image, sigma=1, low_threshold=102,␣
↪high_threshold=204),
    ]

    titles = [
        IM_1C_NAMES[idx],
        "Canny Edge (sigma=1, lo=25, hi=51)",
        "Canny Edge (sigma=1, lo=51, hi=102)",
        "Canny Edge (sigma=1, lo=102, hi=204)",
    ]

    show_images_side_by_side(*filtered_imgs, graph_titles=titles)
```







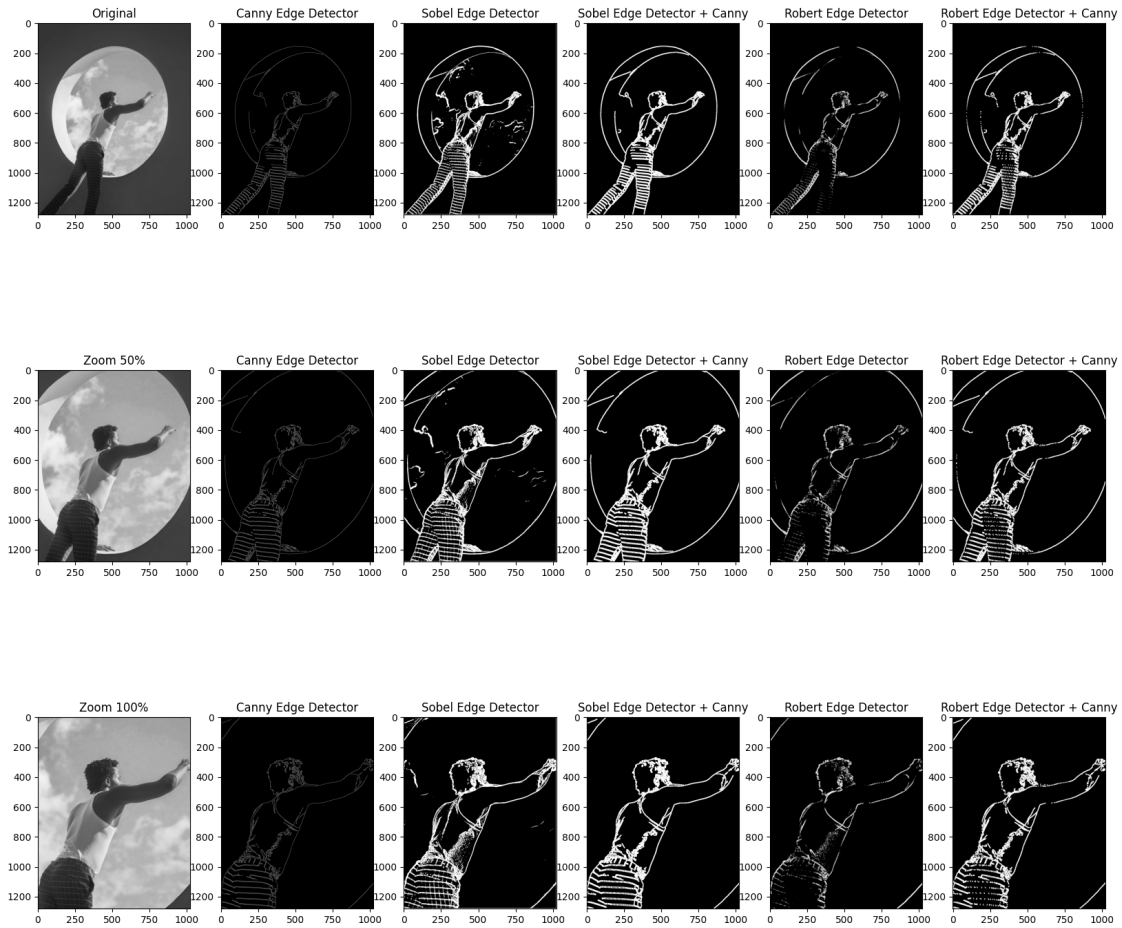
4.1 Canny vs Robert vs Sobel

[ ]:
```
def sobel_edge_detection(image: np.ndarray, threshold=20):

    # apply gaussian filter
    image = gaussian_filter(image, kernel_size=5, sigma=1)

    kernel_1 = np.array([
        [-1, 0, 1],
        [-2, 0, 2],
        [-1, 0, 1]
    ])

    kernel_2 = np.array([
        [-1, -2, -1],
        [0,   0,  0],
        [1,   2,  1]
    ])

    im_1 = linear_filter(image, kernel_1)
    im_2 = linear_filter(image, kernel_2)
```

```
    gradient = np.sqrt(im_1**2 + im_2**2)

    return np.where(gradient > threshold, 255, 0)


    #sobel_image = skimage.filters.sobel(image)
    #return sobel_image * 255 # multiply by 255 to make it from 0,1 to 0,255

def roberts_edge_detection(image: np.ndarray, threshold=2):

    # apply gaussian filter
    image = gaussian_filter(image, kernel_size=5, sigma=1)

    kernel_1 = np.array([
        [1, -1],
        [-1, 1],
    ])

    kernel_2 = np.array([
        [-1, 1],
        [1, -1],
    ])

    im_1 = linear_filter(image, kernel_1)
    im_2 = linear_filter(image, kernel_2)

    gradient = np.sqrt(im_1**2 + im_2**2)

    return np.where(gradient > threshold, 255, 0)

    #roberts_image = skimage.filters.roberts(image)
    #return roberts_image * 255 # multiply by 255 to make it from 0,1 to 0,255
```

[ ]:
```
for idx, image in enumerate(IMAGES_1C):

    canny_img = canny_edge_detection(image)

    filtered_imgs = [
        image,
        canny_img,
        sobel_edge_detection(image),
        sobel_edge_detection(canny_img),
        roberts_edge_detection(image),
        roberts_edge_detection(canny_img),
    ]

    titles = [
```

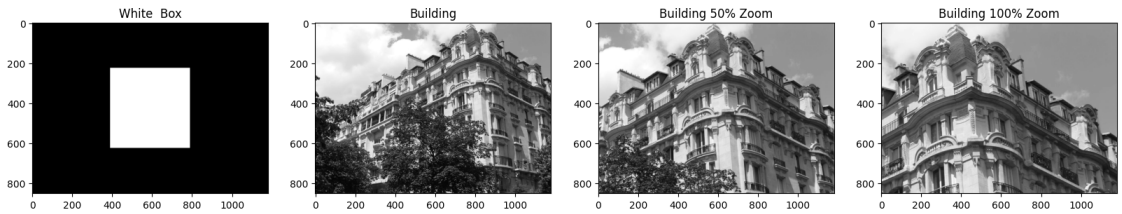
```
        IM_1C_NAMES[idx],
        "Canny Edge Detector",
        "Sobel Edge Detector",
        "Sobel Edge Detector + Canny",
        "Robert Edge Detector",
        "Robert Edge Detector + Canny",
    ]

    show_images_side_by_side(*filtered_imgs, graph_titles=titles)
```



5 Questão 1.d

Implemente o algoritmo CORNERS e use uma interface que mostre os vértices superpostos às imagens originais. Construa uma imagem sintética com um quadrado branco sobre um fundo preto e teste o algoritmo. Em seguida use a imagem disponível no site do curso (building2-1.png). Rode a função icorner no Matlab, fornecida pela Machine Vison ToolBox que pode ser baixada do site www.petercorke.com, sobre a mesma imagem.

[ ]:
```
IMAGES_1D = load_images('trab1/imgs/d/*.jpg')
IM_1D_NAMES = ["White  Box", "Building", "Building 50% Zoom", "Building 100%␣
↪Zoom"]

show_images_side_by_side(*IMAGES_1D, graph_titles=IM_1D_NAMES)
```



[ ]:
```
def corners(image: np.ndarray, threshold: float = 0.25, n: int = 10):
    # developed with the help of https://stackoverflow.com/a/62306124
    size = 2 * n + 1

    # apply gaussian filter
    filtered_image = scipy.ndimage.gaussian_filter(image, sigma=1)

    ex, ey = np.gradient(filtered_image)

    # optimize by already saving squared values
    exex = ex * ex
    eyey = ey * ey
    exey = ex * ey

    # another optimization is to precalculate sums using a kernel
    sum_kernel = np.ones((size, size))
    sum_exex = scipy.ndimage.convolve(exex, sum_kernel)
    sum_eyey = scipy.ndimage.convolve(eyey, sum_kernel)
    sum_exey = scipy.ndimage.convolve(exey, sum_kernel)

    coordinates = []
    lambdas = np.zeros(image.shape)

    for u in range(image.shape[0]):
        for v in range(image.shape[1]):

            # Optimize by not using lingalg to perform the eigenvalue calculation,
            # instead we use a formula for the eigenvalues of a 2x2 matrix
            # based on: https://www.youtube.com/watch?v=e50Bj7jn9IQ

            # original C array
            #C = np.array([
```

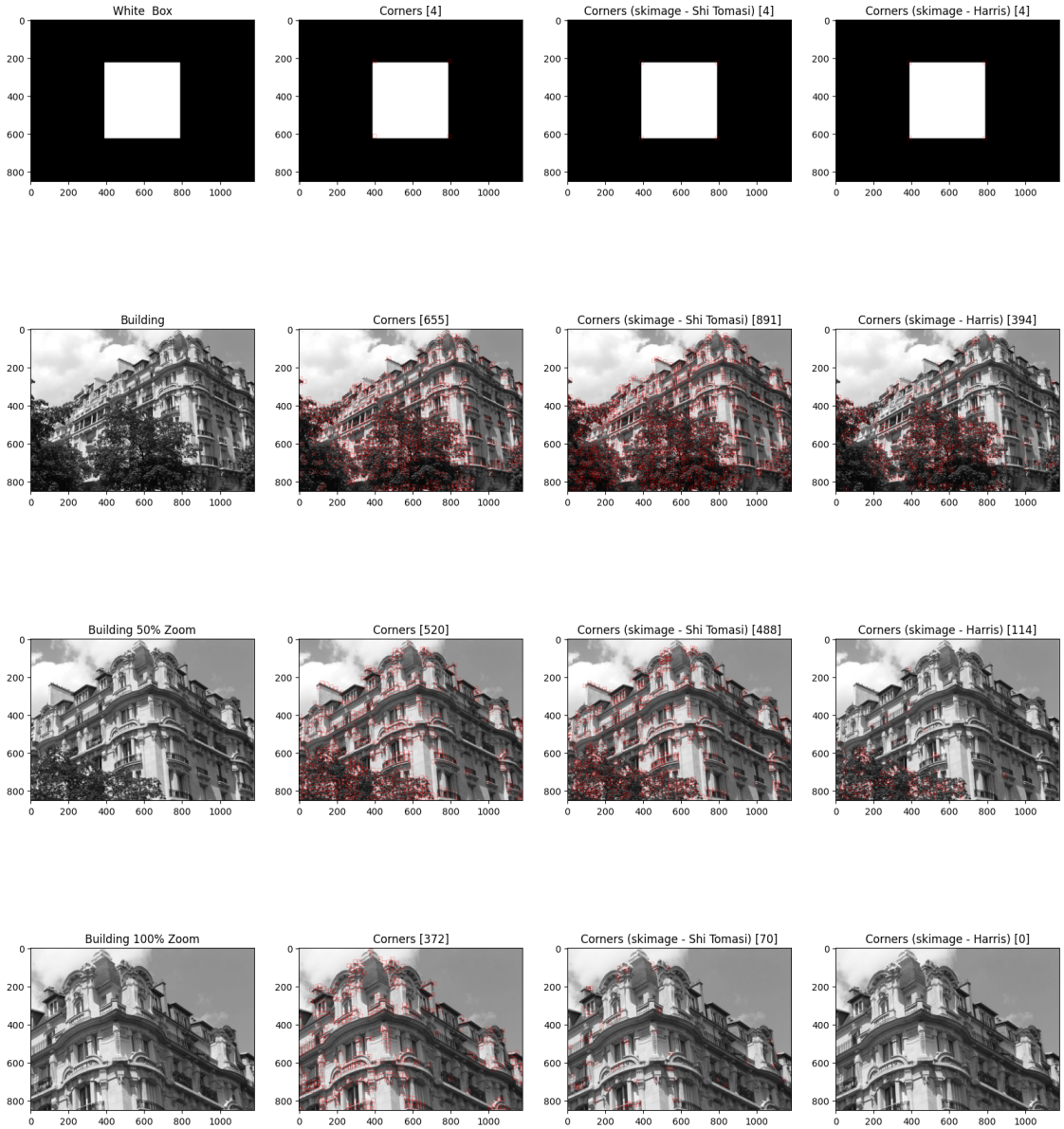
```
        #   [sum_exex[u, v], sum_exey[u, v]],
        #   [sum_exey[u, v], sum_eyey[u, v]],
        #])

        # now lets consider C as:
        # [a b]
        # [c d]

        # calculate lambda values:

        # mean is (a + d)/2
        mean_lambda = (sum_exex[u, v] + sum_eyey[u, v]) / 2

        # the product is ad - bc, since b and c are the same,
        # we can simplify to ad - c^2
        product_lambda = sum_exex[u, v] * sum_eyey[u, v] - sum_exey[u, v] ** 2
        lamda_diff = ((mean_lambda ** 2) - product_lambda) ** 0.5 # sqrt(m^2 -␣
↪p)

        # eigenvalues = mean +/- sqrt(mean^2 - p)
        # eigenvalues = mean +/- lamda_diff

        # we use the minimal eigenvalue
        minimal_lambda = min(
           mean_lambda - lamda_diff,
           mean_lambda + lamda_diff
        )

        lambdas[u, v]  = minimal_lambda

        # instead of selecting lambdas now, we will filter them later based on␣
↪a relative threshold
        #if minimal_lambda > threshold:
        #   coordinates.append((u, v, minimal_lambda))

  # select all values above the relative threshold
  # the relative threshold is calculated by taking the maximum value and␣
↪multiplying it by the threshold
  rel_threshold = np.max(lambdas) * threshold
  coordinates = np.argwhere(lambdas > rel_threshold)

  # sort by the lambda value
  coordinates = sorted(coordinates, key=lambda x: x[-1], reverse=True)
  coordinates = list(map(lambda x: (x[0], x[1]), coordinates))
  coordinate_dict = dict.fromkeys(coordinates)

  # remove corners that are in the region of an already selected corner
```

```
    # we are using a dict to optimize lookup time
    for coordinate in list(coordinate_dict.keys()):
        if coordinate not in coordinate_dict:
            # skip already removed coordinates
            continue

        u, v = coordinate

        # instead of looking through all coordinates
        # we can unconditionally check all coordinates in a 2n+1 x 2n+1 region
        # and remove them from the dict if they had a corner
        # this is much faster than iterating through all the selected corners
        # especially in cases where there are many corners
        for i in range(-size, size + 1):
            for j in range(-size, size + 1):

                if i == 0 and j == 0:
                    # dont self remove
                    continue

                if (u + i, v + j) in coordinate_dict:
                    del coordinate_dict[(u + i, v + j)]

    return list(coordinate_dict.keys())


def draw_corners_to_image(image: np.ndarray, corners: list, n=10):

    size = 2 * n + 1
    offset = size // 2


    # add a colored overlay to black and white image
    image = np.stack([image, image, image], axis=-1)
    image = image.astype(np.float32)

    # paint a square around the corners
    for corner in corners:
        u, v = corner

        min_u = max(0, u - offset)
        max_u = min(image.shape[0], u + offset + 1)
        min_v = max(0, v - offset)
        max_v = min(image.shape[1], v + offset + 1)

        for i in range(min_u, max_u):
            for j in range(min_v, max_v):
```

```
            if i == min_u or i == max_u - 1 or j == min_v or j == max_v - 1:
                image[i, j, 0] = 255
                image[i, j, 1] = 0
                image[i, j, 2] = 0

      image[u, v, 0] = 255
      image[u, v, 1] = 0
      image[u, v, 2] = 0

   return image.astype(np.uint8)
```

[ ]:
```
threshold = 0.15
n = 10

for idx, image in enumerate(IMAGES_1D):

    img_corners = corners(
        image,
        threshold=threshold,
        n=n
    )

    img_corners_lib_shi_tomasi = skimage.feature.peak_local_max(
        skimage.feature.corner_shi_tomasi(image),
        min_distance=n,
        threshold_rel=threshold,
    )

    img_corners_lib_harris = skimage.feature.peak_local_max(
        skimage.feature.corner_harris(image),
        min_distance=n,
        threshold_rel=threshold,
    )


    filtered_imgs = [
        image,
        draw_corners_to_image(image, img_corners),
        draw_corners_to_image(image, img_corners_lib_shi_tomasi),
        draw_corners_to_image(image, img_corners_lib_harris),
    ]

    titles = [
        IM_1D_NAMES[idx],
        f"Corners [{len(img_corners)}]",
        f"Corners (skimage - Shi Tomasi) [{len(img_corners_lib_shi_tomasi)}]",
        f"Corners (skimage - Harris) [{len(img_corners_lib_harris)}]",
```

```
    ]

    show_images_side_by_side(*filtered_imgs, graph_titles=titles)
```



6 Questão 2.1

Explique quais efeitos você observaria em uma imagem caso a distância focal da lente seja alterada para mais ou para menos.

A distância focal altera o campo de visão da imagem, uma distância focal menor aumenta o campo de visão da imagem e uma distância focal maior diminui o campo de visão. Isso dá a impressão de

que um *zoom* ocorra na imagem com uma distância focal maior.

7 Questão 2.2

Explique o conceito de ruído em imagens, como pode ser quantificado, e como pode afetar o processamento das imagens em visão computacional.

O ruído pode ser considerado como qualquer flutuação que ocorra nos valores de uma imagem. Tudo que atrapalhe a aquisição dos dados da imagem ou que não seja necessário para a execução do cálculo.

8 Questão 2.3

Explique porque a precisão de amostragem de um filtro Gaussiano 1-D com = 0,6 não pode ser melhorada utilizando mais de três amostras espaciais (largura espacial maior que 3 píxeis).

Isso acontece porque o valor do desvio padrão e o tamanho da amostra do filtro gaussiano possuem uma relação. Caso o desvio padrão seja alto e o tamanho da amostra pequeno, boa parte da curva gaussiana seria removida, pois não é possível representá-la no espaço de amostragem. Mas fazer um espaço de amostragem muito grande também não é o ideal, pois aumenta o custo computacional da operação.

Por isso se estabelece que uma boa relação entre o desvio padrão e tamanho de amostragem é `amostragem = 5 * desvio padrão`. No caso de um desvio padrão de 0.6, o tamanho da amostragem é de 3 pixeis. Utilizar mais do que isso é desperdício do poder computacional, pois não alterará significativamente o resultado, já que graças a relação previamente mencionada, 98% do espaço gaussiano já está representado na amostra.

9 Questão 2.4

Dadas as definições e classificações de bordas, discuta as diferenças entre bordas em imagens de intensidade e de profundidade. Quais as diferenças nos algoritmos para detectá-las e localizá-las?

Uma diferença fundamental é que as imagens de intensidade são uma superfície, não codificando informação de profundidade, o que faz a análise de bordas se preocupar apenas com um espaço bi-dimensional, com pontos que estão lado a lado. A imagem de profundidade representa um conjunto de pontos, que estão distribuídos diferentes níveis de profundidade diferentes. Numa imagem de intensidade a borda pode ser definida, em termos gerais, como uma diferença de intensidade entre dois pontos. Já em imagens de profundidade se trabalha com a segmentação da imagem em retalhos que representem regiões de superfície homogêneas, analisando com base na proximidade que conjuntos de pontos tem com formas pré-definidas. A comparação é realizada com os dados de curvatura média e também da convexidade de um pedaço de superfície.

10 Questão 2.5

Explique porque a segmentação H-K não pode ser aplicada a imagens de intensidade na expectativa de se encontrarem cenas de superfícies homogêneas.

A segmentação H-K utiliza os valores de profundidade e não do contorno de formas planas. O valor em uma imagem de intensidade difere dos valores que estariam presentes em uma imagem de profundidade. A formação destes dados é completamente diferente e isso impacta no que estes dados representam. Numa imagem de intensidade cada pixel é afetado por elementos da iluminação da cena e representa a luz que chegou ao sensor naquele ponto. Já na imagem de profundidade o dado surge a partir da profundidade real, as variações de intensidade seriam um ruído para o algoritmo H-K.