

1 Written Part

1(a) K^2HW

If the filter is not separable, then the process of performing a convolution requires $K \cdot K$ operations per pixel, and since the image has $H \cdot W$ pixels in total, so the number of operations would be K^2HW .

1(b) $2KHW$

If the filter is separable, this operation could be speed up by first performing a $1D$ horizontal convolution followed by a $1D$ vertical convolution, then the process of performing a convolution requires $K + K$ operations per pixel, and since the image has $H \cdot W$ pixels in total, so the number of operations would be $2KHW$.

2(a) A vertical derivative, $\frac{\partial G(x,y)}{\partial y}$, of a Gaussian filter G is a separable filter for both isotropic and anisotropic cases.

2(a).01 isotropic Gaussian filter

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

$$\frac{\partial G(x,y)}{\partial y} = -\frac{y}{2\pi\sigma^4} e^{-\frac{x^2+y^2}{2\sigma^2}} = \left[-\frac{1}{\sigma^2\sqrt{2\pi}} e^{-\frac{x^2}{2\sigma^2}} \right] \cdot \left[\frac{y}{\sigma^2\sqrt{2\pi}} e^{-\frac{y^2}{2\sigma^2}} \right]$$

Since the above function could be converted into $f(x) \cdot f(y)$, so it's a separable filter.

2(a).02 anisotropic Gaussian filter

$$G(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} e^{-\left(\frac{x^2}{2\sigma_x^2} + \frac{y^2}{2\sigma_y^2}\right)}$$

$$\frac{\partial G(x,y)}{\partial y} = -\frac{y}{2\pi\sigma_x\sigma_y^3} e^{-\left(\frac{x^2}{2\sigma_x^2} + \frac{y^2}{2\sigma_y^2}\right)} = \left[-\frac{1}{\sigma_x\sqrt{2\pi}} e^{-\frac{x^2}{2\sigma_x^2}} \right] \cdot \left[\frac{y}{\sigma_y^3\sqrt{2\pi}} e^{-\frac{y^2}{2\sigma_y^2}} \right]$$

Since the above function could be converted into $f(x) \cdot f(y)$, so it's a separable filter.

2(b) A Laplacian of Gaussians (LoG) is NOT a separable filter.

The LoG is the sum of the second derivatives of the Gaussian, $LoG = \frac{\partial^2 G}{\partial x^2} + \frac{\partial^2 G}{\partial y^2}$, which could not be directly separated into two $1D$ kernels, thus it is not a separable filter.

2(c) We could apply the singular value decomposition (SVD) on this 3×3 filter and get $F = U\Sigma V^\top$, which as a sum of matrix multiplications, each of a single row/column from the $U \in \mathbb{R}^{3 \times 3}$ and $V \in \mathbb{R}^{3 \times 3}$, multiplied by the diagonal entry from $\Sigma \in \mathbb{R}^{3 \times 3}$. The matrix Σ contains entries, which called “singular values”, on the diagonal only and they are sorted from the highest to the lowest value. If only one singular value is non-zero, which means that it is a rank 1 matrix and then this filter is separable.

3 Cross correlation is NOT commutative.

Proof:

By the definition of cross correlation, we have:

$$\text{Corr}[f, g]_t = \text{Corr}[g, f]_{-t}$$

$$\text{which means } f(t) * g(t) = [g(\bar{t}) * f(\bar{t})](-t)$$

but it needs to satisfy $f(t) * g(t) = g(t) * f(t)$ to be commutative,
so that the cross correlation is not commutative.

4 Convolve the image with a Gaussian filter with $\sigma = \sqrt{5}$

$$\sigma = \sqrt{\sigma_1^2 + \sigma_2^2} = \sqrt{1^2 + 2^2} = \sqrt{5}$$

Proof:

$$\text{Want to show that } G(x, y|\sigma) = G(x, y|\sqrt{\sigma_1^2 + \sigma_2^2}) = G(x, y|\sigma_1) \cdot G(x, y|\sigma_2)$$

Note that if X_1, X_2 are two independent random variables and $X_1 \sim N(0, \sigma_1^2 I)$ and $X_2 \sim N(0, \sigma_2^2 I)$ with two probability density functions G_1 and G_2 respectively, then $X = X_1 + X_2$ would have a density function $G = G_1 \cdot G_2$. And given that $X \sim N(0, (\sigma_1^2 + \sigma_2^2)I)$, we have the probability density function (PDF) of variable X:

$$\begin{aligned} f_X(X) &= \frac{1}{2\pi\sqrt{|\Sigma|}} \exp\left\{-\frac{1}{2}X^\top \Sigma^{-1} X\right\} \\ &= \frac{1}{2\pi(\sigma_1^2 + \sigma_2^2)} \exp\left\{-\frac{X^\top X}{2(\sigma_1^2 + \sigma_2^2)}\right\} \\ &= \frac{1}{2\pi(\sigma_1^2 + \sigma_2^2)} \exp\left\{-\frac{x^2 + y^2}{2(\sigma_1^2 + \sigma_2^2)}\right\} \\ &= G(x, y|\sqrt{\sigma_1^2 + \sigma_2^2}) \\ &= G(x, y|\sigma) \end{aligned}$$

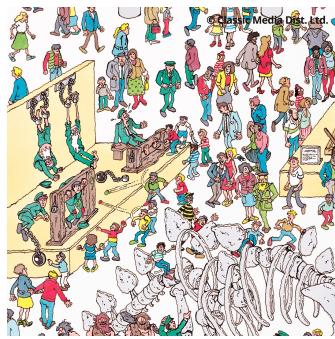
$$\text{where } |\Sigma| = |(\sigma_1^2 + \sigma_2^2)I| = (\sigma_1^2 + \sigma_2^2)^2, X = (x, y)$$

$$\text{Therefore, we've proved that } \sigma = \sqrt{\sigma_1^2 + \sigma_2^2}.$$

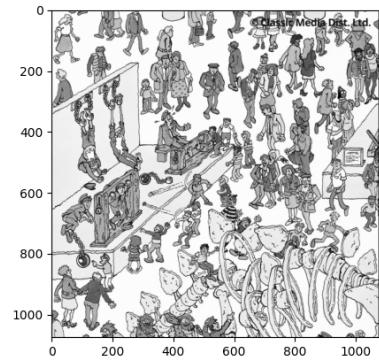
2 Coding Part

1(a)

the original image



the image after convolution

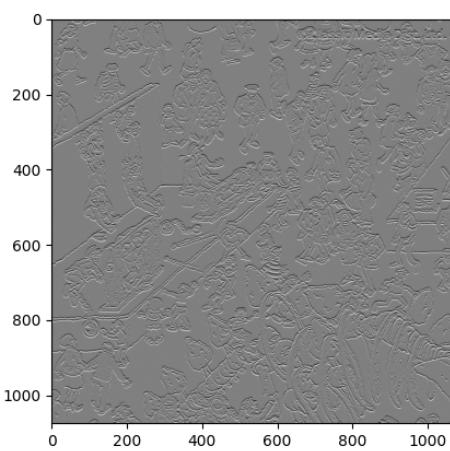


1(b)

Function implement refers to the script appendix.
Found that the above given filter is NOT separable.

1(c) Since the given filter is not separable,
so I chose another separable filter.

$$\begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix}$$



time comparison:

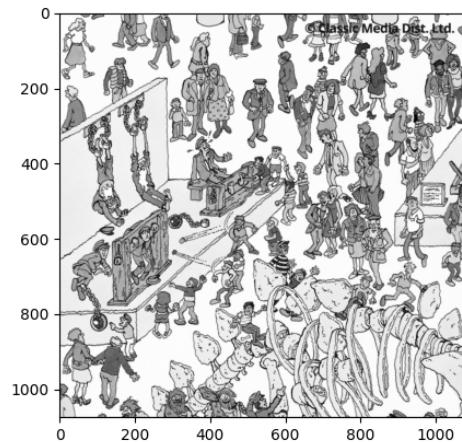
--- convolution takes 2.8190128803253174 seconds ---

--- faster convolution takes 0.12801790237426758 seconds ---

Thus, the faster convolution with the separable filter cost less time.

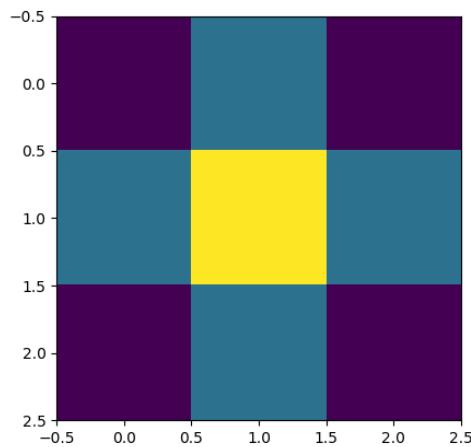
3 Coding Part Continued

1(d)

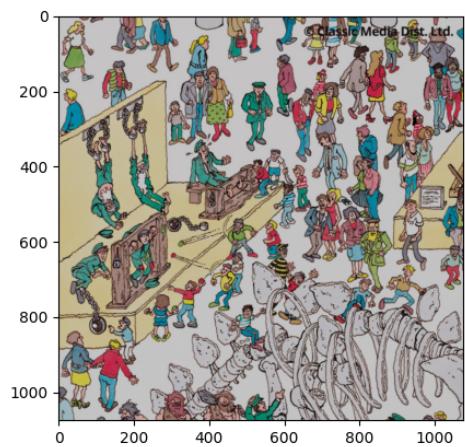


- 2 Convolve the attached waldo.png with a 2D Gaussian filter with sigma of 1 and kernel size of 3.

display the filter



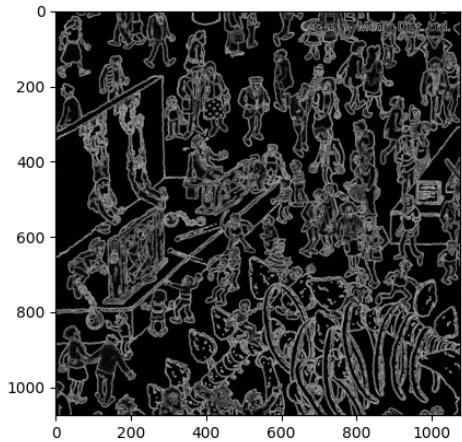
display the convolution



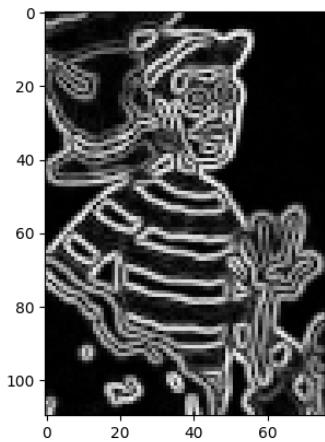
3 Coding Part Continued

3(a) Compute magnitude of gradients for the attached images

waldo.png

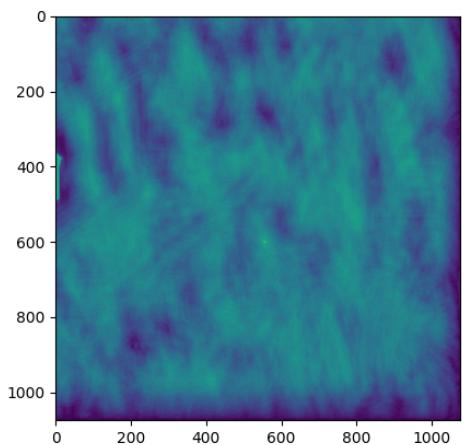


template.png

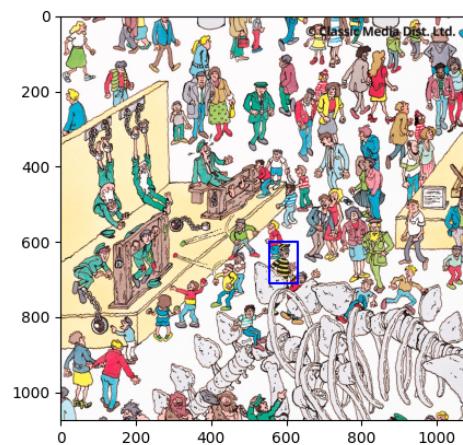


3(b)

Result of normalized cross-correlation

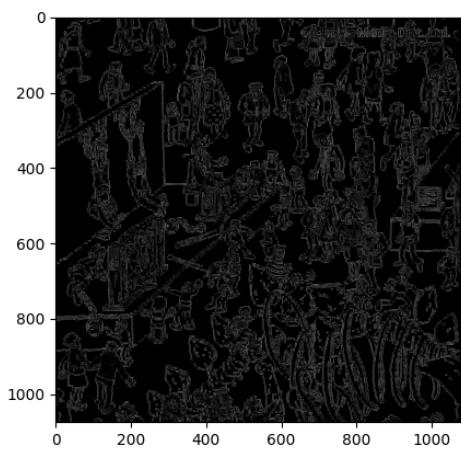


Result of localizing the template



3 Coding Part Continued

4. Visualize the Canny edge detector results on waldo.png



```

1 import numpy as np
2 from skimage import io
3 from matplotlib import pyplot as plt
4 import time
5
6
7 def convolution(img, filter_matrix):
8     """
9         Write a function for computing convolution of the 2D (grayscale) image
10        and a 2D filter.
11    """
12
13    # flip the filter vertically and horizontally
14    filter_matrix = filter_matrix[::-1, ::-1]
15    filter_shape = filter_matrix.shape[0]
16    padding = filter_shape - 1
17
18    # zero padding
19    padded = np.zeros((img.shape[0] + padding, img.shape[1] + padding))
20
21    # copy in the image matrix between the padding in the matrix
22    for row in range(padding//2, padded.shape[0] - (padding//2)):
23        for col in range(padding//2, padded.shape[1] - (padding//2)):
24            padded[row, col] = img[row - (padding//2), col - (padding//2)]
25
26    # make the output matrix be the same size as the input image
27    result = np.zeros(img.shape)
28
29    for row in range(result.shape[0]):
30        for col in range(result.shape[1]):
31            img_section = padded[row: (row + filter_shape),
32                                  col: (col + filter_shape)]
33            # convolution calculation
34            result[row, col] = img_section.flatten().dot(filter_matrix.flatten())
35
36    return result
37
38
39 if __name__ == '__main__':
40     start_time = time.time()
41
42     input_filter = np.array([[0, 0.125, 0], [0.5, 0.5, 0.125], [0, 0.5, 0]])
43     input_img = io.imread('waldo.png', as_gray=True)
44     output = convolution(input_img, input_filter)
45
46     print("--- convolution takes %s seconds ---" % (time.time() - start_time))
47
48     plt.imshow(output, cmap='gray')
49     plt.show()
50

```

```
1 import numpy as np
2
3
4 def separable(input_filter):
5     """
6         Write a function to verify the input filter is separable or not.
7         """
8
9     # apply SVD
10    u, sigma, v = np.linalg.svd(input_filter)
11    print(sigma)
12
13    # Check if the 2nd diagonal element of the Sigma matrix is zero,
14    # considering rounding errors, choose to round to 14 digits
15    if round(sigma[1], 14) == 0:
16        print("This is a separable filter")
17        return True
18    print("This is NOT a separable filter")
19    return False
20
21
22 if __name__ == '__main__':
23     filter_input = np.array([[0, 0.125, 0], [0.5, 0.5, 0.125], [0, 0.5, 0]])
24     separable(filter_input)
25
```

```
1 import numpy as np
2 from scipy import ndimage
3 from skimage import io
4 from matplotlib import pyplot as plt
5 import time
6
7
8 def faster_convolution(img, filter_matrix):
9     """
10     Write a faster convolution function Leveraging the fact that
11     the filter is separable.
12     """
13
14     # apply SVD to the filter
15     u, sigma, v = np.linalg.svd(filter_matrix)
16
17     # The separated horizontal vertical filters
18     horizontal = np.sqrt(sigma[0]) * np.asmatrix(u[:, 0])
19     vert = np.sqrt(sigma[0]) * np.asmatrix(v[0])
20
21     # convolve image by the horizontal filter
22     horizontal_output = ndimage.convolve(img, horizontal)
23     # convolve image by the vertical filter.
24     result = ndimage.convolve(horizontal_output, vert.T)
25
26     return result
27
28
29 if __name__ == '__main__':
30     start_time = time.time()
31
32     # choose a separable filter
33     input_filter = np.array([[1, 0, -1], [2, 0, -2], [1, 0, -1]])
34     input_img = io.imread('waldo.png', as_gray=True)
35     output = faster_convolution(input_img, input_filter)
36
37     print("---- faster convolution takes %s seconds ---" %
38          (time.time() - start_time))
39
40     plt.imshow(output, cmap='gray')
41     plt.show()
42
```

```

1 import numpy as np
2 from skimage import io
3 from matplotlib import pyplot as plt
4
5
6 def cross_correlation(image, filter_matrix):
7     """
8         Implement cross-correlation.
9     """
10
11    height, width = image.shape
12    frame, col_pad, row_pad = zero_pad(image, filter_matrix)
13
14    result = np.empty_like(frame)
15    # traverse all pixels and calculate the correlation
16    for i in range(col_pad, col_pad + height):
17        for j in range(row_pad, row_pad + width):
18            result[i, j] = correlation(frame, filter_matrix, i, j)
19
20    return result[col_pad: col_pad + height, row_pad: row_pad + width]
21
22
23 def correlation(image, filter_matrix, i, j):
24     """
25         Implement correlation.
26     """
27
28    height, width = filter_matrix.shape
29
30    m = int((height - 1) / 2)
31    n = int((width - 1) / 2)
32
33    img = image[i - m: i + m + 1, j - n: j + n + 1].flatten()
34    filter_matrix = filter_matrix.flatten()
35
36    return np.dot(img, filter_matrix)
37
38 def zero_pad(img, fil):
39     """
40         Helper function to apply zero padding
41     """
42
43    i, j = fil.shape
44
45    pad_axis_1 = (i, i)
46    pad_axis_2 = (j, j)
47
48    padding = (pad_axis_1, pad_axis_2)
49    frame = np.pad(img, padding, mode='constant', constant_values=0)
50
51    return frame, i, j
52
53 if __name__ == '__main__':
54     input_filter = np.array([[0, 0.125, 0], [0.5, 0.5, 0.125], [0, 0.5, 0]])
55     input_img = io.imread('waldo.png', as_gray=True)
56     output = cross_correlation(input_img, input_filter)
57
58     plt.imshow(output, cmap='gray')
59     plt.show()
60

```

```
1 import numpy as np
2 from skimage import io
3 from scipy import ndimage
4 from matplotlib import pyplot as plt
5
6
7 def gaussian_filter(size, std):
8     """
9         Generate Gaussian filter with kernel size and std (sigma) as input.
10        """
11
12    # template
13    gauss = np.zeros((size, size))
14    # index of mean
15    mu = (size - 1) / 2
16
17    for row in range(size):
18        for col in range(size):
19            power = np.exp(-((row - mu) ** 2 + (col - mu) ** 2)
20                           / (2 * (std ** 2)))
21            gauss[row, col] = power / (2 * np.pi * (std ** 2))
22
23    return gauss
24
25
26 if __name__ == '__main__':
27     img_matrix = io.imread('waldo.png')
28
29     # use a gaussian filter with kernel size=3 and std=1
30     gauss_filter = gaussian_filter(3, 1)
31     plt.imshow(gauss_filter)
32     plt.show()
33
34     # Convolve each RGB dimension
35     img_matrix[:, :, 0] = ndimage.convolve(img_matrix[:, :, 0], gauss_filter)
36     img_matrix[:, :, 1] = ndimage.convolve(img_matrix[:, :, 1], gauss_filter)
37     img_matrix[:, :, 2] = ndimage.convolve(img_matrix[:, :, 2], gauss_filter)
38
39     plt.imshow(img_matrix)
40     plt.show()
41
```

```

1 import numpy as np
2 from skimage import io
3 from scipy import ndimage
4 from matplotlib import pyplot as plt
5
6
7 def magnitude_gradient(img):
8     """
9         Compute magnitude of gradients for the input image.
10        """
11    img_matrix = io.imread(img, as_gray=True)
12
13    # choose the sobel filter
14    sobel_x = np.array([[-1, 0, 1], [-2, 0, 2], [-1, 0, 1]])
15    sobel_y = np.array([[-1, -2, -1], [0, 0, 0], [1, 2, 1]])
16
17    # use the sobel filter for the horizontal gradient
18    horizontal = ndimage.convolve(img_matrix, sobel_x)
19    # use the sobel filter for the vertical gradient
20    vertical = ndimage.convolve(img_matrix, sobel_y)
21
22    # get square root of the sum of squares of vertical and horizontal gradients
23    result = np.sqrt(horizontal ** 2 + vertical ** 2)
24
25    return result
26
27
28 def grid_localize(filter_img, img):
29     """
30         Write a function that Localizes the input filter image in the input image
31         based on the magnitude of gradients.
32     """
33
34     image = io.imread(img) # colored image
35     # using function from part 3a to compute the gradient magnitudes
36     img_gradient = magnitude_gradient(img)
37     filter_gradient = magnitude_gradient(filter_img)
38
39     frame, col_pad, row_pad = zero_pad(img_gradient, filter_gradient)
40
41     height, width = img_gradient.shape
42     result = np.empty_like(frame)
43
44     for i in range(col_pad, col_pad + height):
45         for j in range(row_pad, row_pad + width):
46             result[i, j] = normalized_correlation(frame, filter_gradient, i, j)
47
48     similarity = result[col_pad: col_pad + height, row_pad: row_pad + width]
49     max_index = similarity.argmax()
50
51     i, j = np.unravel_index(max_index, similarity.shape)
52     corners = np.array([[i, j],
53                         [i + col_pad - 1, j],
54                         [i + col_pad - 1, j + row_pad - 1],
55                         [i, j + row_pad - 1],
56                         [i, j]])
57
58     # visualize the normalized cross-correlation
59     plt.imshow(similarity)
60     plt.show()

```

```

61
62     # visualize the template matching
63     plt.plot(corners[:, 1], corners[:, 0], 'b')
64     plt.imshow(image)
65     plt.show()
66
67
68 def normalized_correlation(img, filter_matrix, i, j):
69     """
70     helper function to conduct normalized correlation
71     """
72     height, width = filter_matrix.shape
73
74     # flatten images
75     img = img[i: i+height, j: j+width].flatten()
76     filter_matrix = filter_matrix.flatten()
77
78     dot = np.dot(img, filter_matrix)
79     norm_img = np.linalg.norm(img)
80     norm_filter = np.linalg.norm(filter_matrix)
81
82     if (norm_img * norm_filter) == 0:
83         result = 0
84     else:
85         result = dot/(norm_img * norm_filter)
86
87     return result
88
89
90 def zero_pad(img, fil):
91     """
92     Helper function to apply zero padding
93     """
94     i, j = fil.shape
95
96     pad_axis_1 = (i, i)
97     pad_axis_2 = (j, j)
98
99     padding = (pad_axis_1, pad_axis_2)
100    frame = np.pad(img, padding, mode='constant', constant_values=0)
101
102    return frame, i, j
103
104
105 if __name__ == '__main__':
106
107     # 3a compute and visualize the magnitude of gradients
108     plt.imshow(magnitude_gradient('waldo.png'), cmap='gray')
109     plt.show()
110
111     plt.imshow(magnitude_gradient('template.png'), cmap='gray')
112     plt.show()
113
114     # 3b Localize the template in the image
115     grid_localize('template.png', 'waldo.png')
116

```

```

1 import numpy as np
2 from skimage import io
3 from scipy import ndimage
4 from matplotlib import pyplot as plt
5
6
7 def canny_edge_detector(img):
8     """
9         Implement the Canny edge detector, performing non-maxima suppression.
10    """
11    # Load the image as matrix
12    img_matrix = io.imread(img, as_gray=True)
13
14    # Apply Gaussian filter
15    img_matrix = ndimage.gaussian_filter(img_matrix, sigma=1, order=0)
16
17    # choose the sobel filter
18    sobel_x = np.array([[-1, 0, 1], [-2, 0, 2], [-1, 0, 1]])
19    sobel_y = np.array([[-1, -2, -1], [0, 0, 0], [1, 2, 1]])
20
21    horizontal = ndimage.convolve(img_matrix, sobel_x)
22    vertical = ndimage.convolve(img_matrix, sobel_y)
23
24    # get square root of the sum of squares of vertical and horizontal gradients
25    gradient = np.sqrt(horizontal ** 2 + vertical ** 2)
26
27    # compute angles for each pixel
28    angles = np.zeros(img_matrix.shape)
29
30    for row in range(angles.shape[0]):
31        for col in range(angles.shape[1]):
32            current_angle = np.arctan2(vertical[row, col], horizontal[row, col])
33            # convert to degrees
34            current_angle = current_angle * 180 / np.pi
35            if current_angle < 0:
36                current_angle += 180
37            angles[row, col] = current_angle
38
39    # apply non-maximum suppression
40    non_max = np.zeros(img_matrix.shape)
41    for row in range(1, non_max.shape[0]-1):
42        for col in range(1, non_max.shape[1]-1):
43            # edge direction
44            direction = 45 * round(angles[row, col] / 45)
45            # save the neighbor edge strengths
46            if direction == 0 or direction == 180:
47                left = gradient[row, col - 1]
48                right = gradient[row, col + 1]
49            elif direction == 45:
50                left = gradient[row + 1, col - 1]
51                right = gradient[row - 1, col + 1]
52            elif direction == 90:
53                left = gradient[row - 1, col]
54                right = gradient[row + 1, col]
55            else:
56                left = gradient[row - 1, col - 1]
57                right = gradient[row + 1, col + 1]
58
59            # compare current pixel's edge strengths with neighbors
60            if left < gradient[row, col] and right < gradient[row, col]:

```

```
61         non_max[row, col] = gradient[row, col]
62     else:
63         non_max[row, col] = 0
64
65     return non_max
66
67
68 if __name__ == '__main__':
69     canny_edge = canny_edge_detector('waldo.png')
70     plt.imshow(canny_edge, cmap='gray')
71     plt.show()
72
```