9. Image Matching

Table of Contents

Importing Libraries

In [ ]:
```
import cv2
import matplotlib.pyplot as plt
import numpy as np
```

ORB (Oriented FAST and Rotated BRIEF)

- Developed at OpenCV labs by Ethan Rublee, Vincent Rabaud, Kurt Konolige, and Gary R. Bradski in 2011
- Efficient and viable alternative to SIFT and SURF (patented algorithms)
- ORB is free to use
- Feature detection
- ORB builds on FAST keypoint detector + BRIEF descriptor

In [ ]:
```
#reading image
img = cv2.imread('data/elon_1.jpg')
img_color = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
img_gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

plt.figure(figsize=(15, 8))
plt.subplot(1, 2, 1)
plt.imshow(img_color)
```

```
plt.subplot(1, 2, 2)
plt.imshow(img_gray, cmap="gray")
```

Out[ ]: <matplotlib.image.AxesImage at 0x14c3005f0>

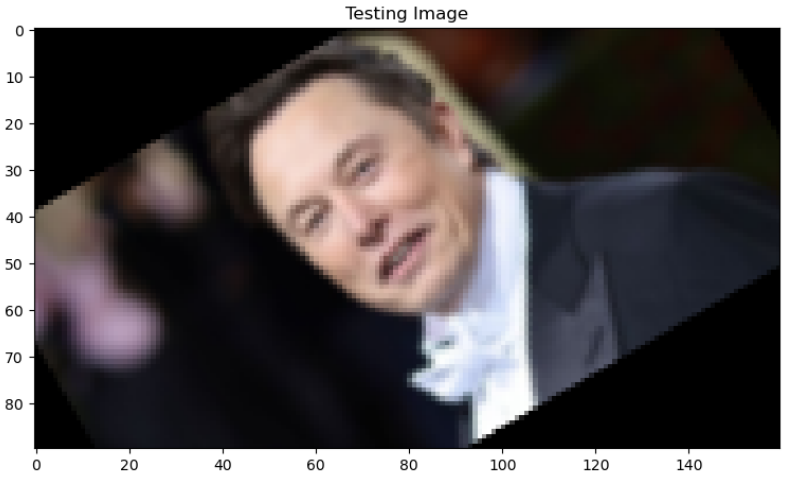
Create test image by adding Scale Invariance and Rotational Invariance

In [ ]:
```
test_image = cv2.pyrDown(img_color)
test_image = cv2.pyrDown(test_image)
num_rows, num_cols = test_image.shape[:2]

rotation_matrix = cv2.getRotationMatrix2D((num_cols/2, num_rows/2), 30, 1)
test_image = cv2.warpAffine(test_image, rotation_matrix, (num_cols, num_rows))

test_gray = cv2.cvtColor(test_image, cv2.COLOR_RGB2GRAY)
```

Display traning image and testing image

In [ ]:
```
fx, plots = plt.subplots(1, 2, figsize=(20,10))

plots[0].set_title("Training Image")
plots[0].imshow(img_color)

plots[1].set_title("Testing Image")
plots[1].imshow(test_image)
```

Out[ ]: <matplotlib.image.AxesImage at 0x14ccd1790>



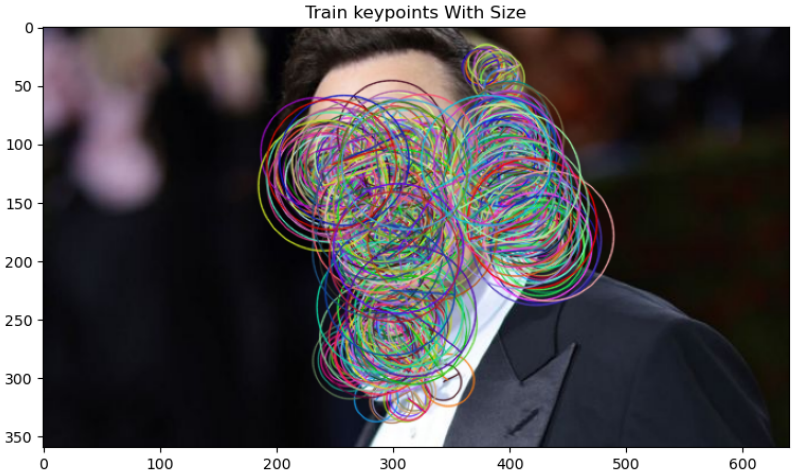
ORB

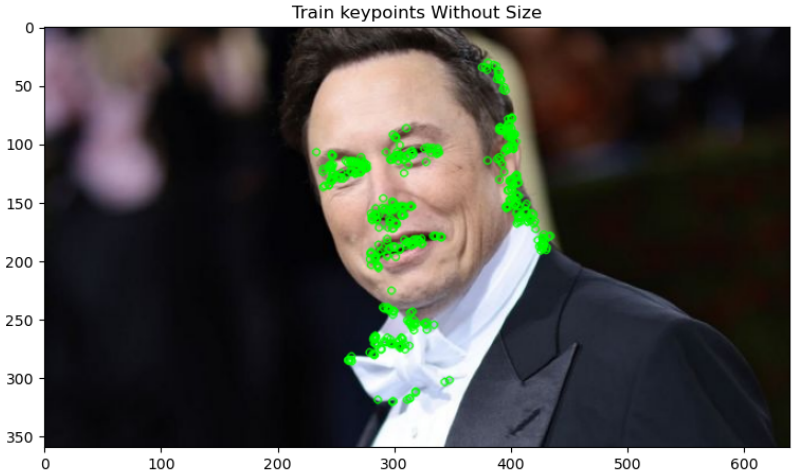
In [ ]:
```
orb = cv2.ORB_create()
```

In [ ]:
```
train_keypoints, train_descriptor = orb.detectAndCompute(img_color, None)
test_keypoints, test_descriptor = orb.detectAndCompute(test_gray, None)

keypoints_without_size = np.copy(img_color)
keypoints_with_size = np.copy(img_color)

cv2.drawKeypoints(img_color, train_keypoints, keypoints_without_size, color = (0, 255, 0))

cv2.drawKeypoints(img_color, train_keypoints, keypoints_with_size, flags = cv2.DRAW_MATCHES_FLAGS_DRAW_RICH

# Display image with and without keypoints size
fx, plots = plt.subplots(1, 2, figsize=(20,10))

plots[0].set_title("Train keypoints With Size")
plots[0].imshow(keypoints_with_size, cmap='gray')

plots[1].set_title("Train keypoints Without Size")
plots[1].imshow(keypoints_without_size, cmap='gray')

# Print the number of keypoints detected in the training image
```

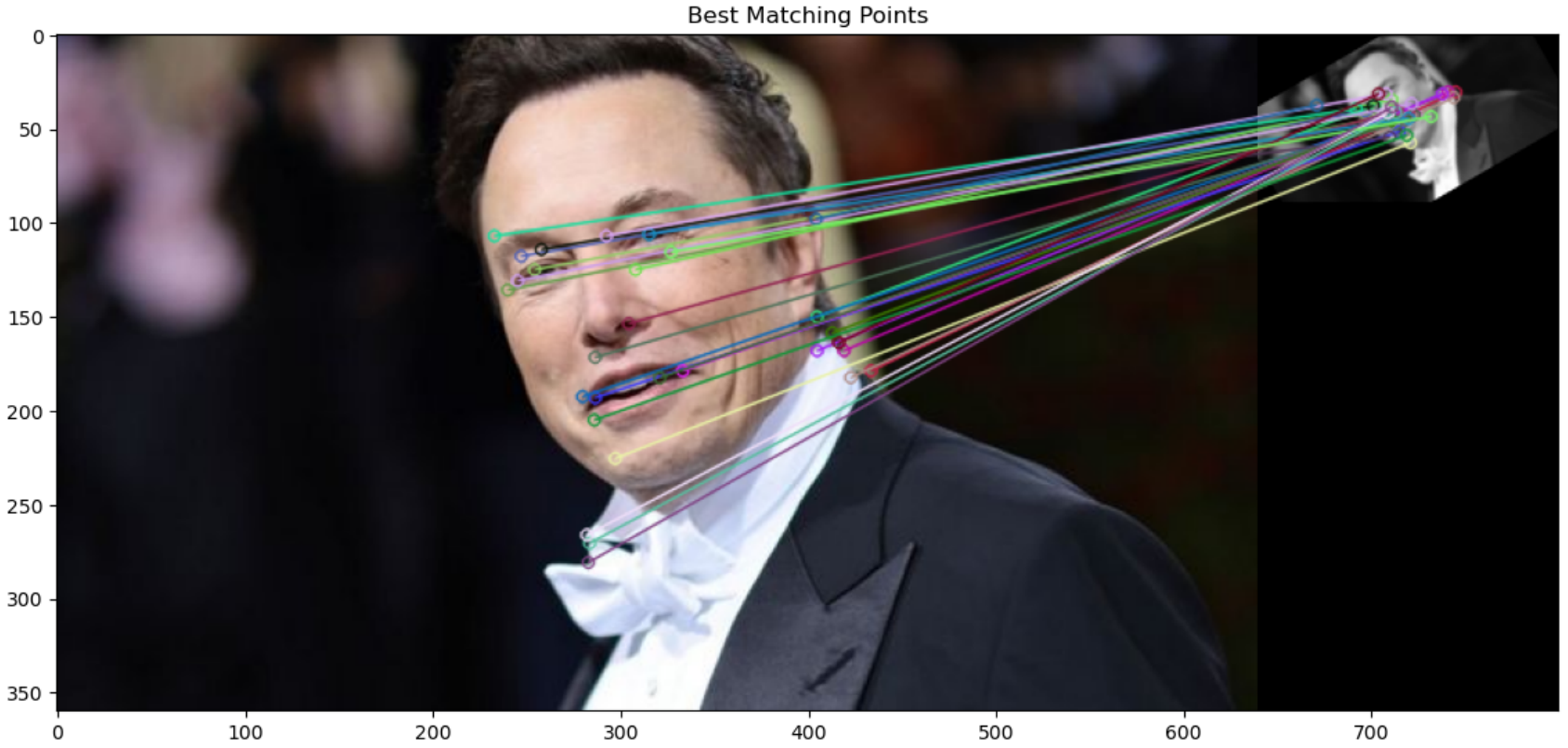
```
print("Number of Keypoints Detected In The Training Image: ", len(train_keypoints))

# Print the number of keypoints detected in the query image
print("Number of Keypoints Detected In The Query Image: ", len(test_keypoints))
```

```
Number of Keypoints Detected In The Training Image:  500
Number of Keypoints Detected In The Query Image:  42
```





In [ ]:
```
# Create a Brute Force Matcher object.
bf = cv2.BFMatcher(cv2.NORM_HAMMING, crossCheck = True)

# Perform the matching between the ORB descriptors of the training image and the test image
matches = bf.match(train_descriptor, test_descriptor)

# The matches with shorter distance are the ones we want.
matches = sorted(matches, key = lambda x : x.distance)

result = cv2.drawMatches(img_color, train_keypoints, test_gray, test_keypoints, matches, test_gray, flags =

# Display the best matching points
plt.rcParams['figure.figsize'] = [14.0, 7.0]
plt.title('Best Matching Points')
plt.imshow(result)
plt.show()

# Print total number of matching points between the training and query images
print("\nNumber of Matching Keypoints Between The Training and Query Images: ", len(matches))
```




```
Number of Matching Keypoints Between The Training and Query Images:  30
```

SIFT Matching (Scale Invariant Feature Transform)

In [ ]:
```python
img1 = cv2.imread('data/elon_1.jpg')
gray1 = cv2.cvtColor(img1, cv2.COLOR_BGR2GRAY)

#keypoints
sift = cv2.SIFT_create()
keypoints_1, descriptors_1 = sift.detectAndCompute(img1,None)

img_1 = cv2.drawKeypoints(gray1,keypoints_1,img1)
plt.imshow(img_1)
```

Out[ ]:
```
<matplotlib.image.AxesImage at 0x14cdf48c0>
```

Matching different images

In [ ]:
```
# read images
img1 = cv2.imread('data/elon_1.jpg')
img2 = cv2.imread('data/elon_2.png')

img1 = cv2.cvtColor(img1, cv2.COLOR_BGR2GRAY)
img2 = cv2.cvtColor(img2, cv2.COLOR_BGR2GRAY)

figure, ax = plt.subplots(1, 2, figsize=(16, 8))
```

```
ax[0].imshow(img1, cmap='gray')
ax[1].imshow(img2, cmap='gray')
```

Out[ ]: <matplotlib.image.AxesImage at 0x14bac0410>

Extracting Keypoints with SIFT

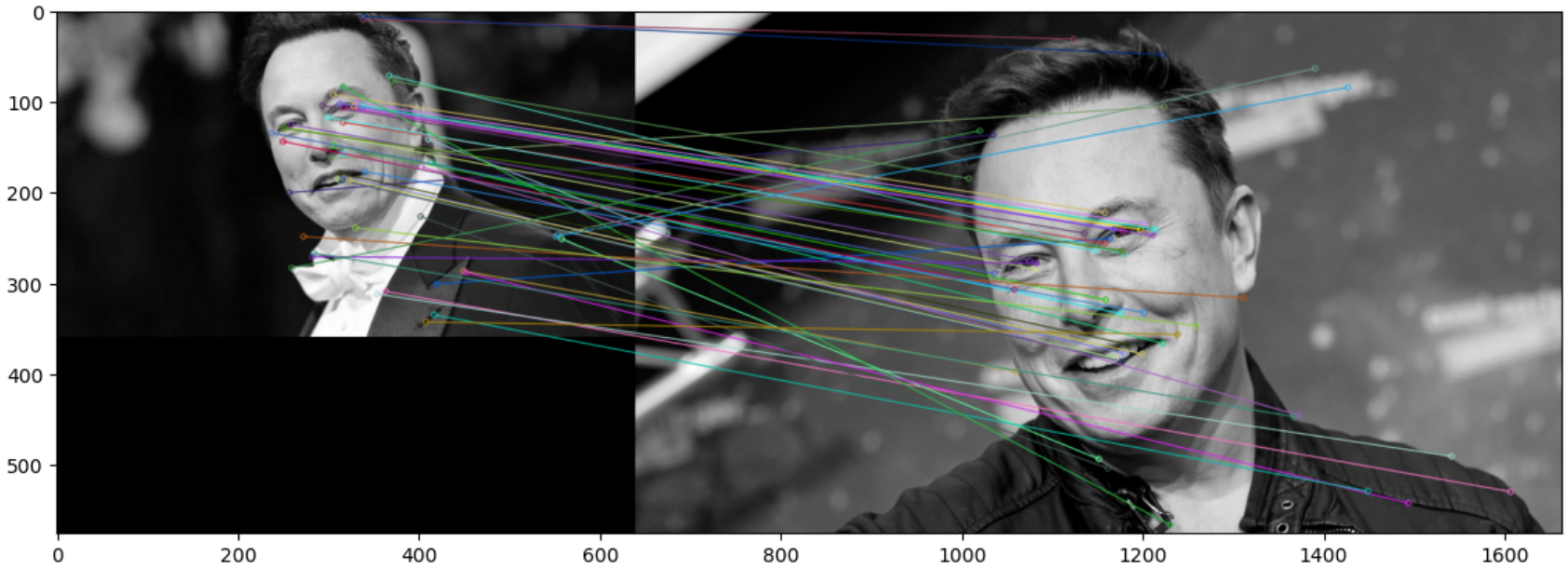
In [ ]:
```
#sift
sift = cv2.SIFT_create()

keypoints_1, descriptors_1 = sift.detectAndCompute(img1,None)
keypoints_2, descriptors_2 = sift.detectAndCompute(img2,None)

len(keypoints_1), len(keypoints_2)
```

Out[ ]: (291, 734)

Feature Matching

In [ ]:
```
#feature matching
bf = cv2.BFMatcher(cv2.NORM_L1, crossCheck=True)

matches = bf.match(descriptors_1,descriptors_2)
matches = sorted(matches, key = lambda x:x.distance)
```

```
img3 = cv2.drawMatches(img1, keypoints_1, img2, keypoints_2, matches[:50], img2, flags=2)
plt.imshow(img3),plt.show()
```



Out[ ]: (<matplotlib.image.AxesImage at 0x14caea210>, None)

Homework

We'll analyze different scenarios for the feature matches outside a human face, which was already showcased in the notebook. We'll use the following samples:

1. A car (same model in different scenarios).
2. A city skyline (different angles, useful to detect places).
3. A church (a highly recognized and famous place).

In [ ]:
```
def applyORB(img):
    img_color = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    img_gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

    test_image = cv2.pyrDown(img_color)
    test_image = cv2.pyrDown(test_image)
```

```
num_rows, num_cols = test_image.shape[:2]

rotation_matrix = cv2.getRotationMatrix2D((num_cols/2, num_rows/2), 30, 1)
test_image = cv2.warpAffine(test_image, rotation_matrix, (num_cols, num_rows))

test_gray = cv2.cvtColor(test_image, cv2.COLOR_RGB2GRAY)

fx, plots = plt.subplots(1, 2, figsize=(20,10))

plt.figure(figsize=(14, 4))
plots[0].set_title("Training Image")
plots[0].imshow(img_color)
plots[1].set_title("Testing Image")
plots[1].imshow(test_image)
plt.show()

orb = cv2.ORB_create()

train_keypoints, train_descriptor = orb.detectAndCompute(img_color, None)
test_keypoints, test_descriptor = orb.detectAndCompute(test_gray, None)

keypoints_without_size = np.copy(img_color)
keypoints_with_size = np.copy(img_color)

cv2.drawKeypoints(img_color, train_keypoints, keypoints_without_size, color = (0, 255, 0))

cv2.drawKeypoints(img_color, train_keypoints, keypoints_with_size, flags = cv2.DRAW_MATCHES_FLAGS_DRAW_

# Display image with and without keypoints size
plt.figure(figsize=(14, 4))
fx, plots = plt.subplots(1, 2, figsize=(20,10))
plots[0].set_title("Train keypoints With Size")
plots[0].imshow(keypoints_with_size, cmap='gray')
plots[1].set_title("Train keypoints Without Size")
plots[1].imshow(keypoints_without_size, cmap='gray')
plt.show()

# Print the number of keypoints detected in the training image
print("Number of Keypoints Detected In The Training Image: ", len(train_keypoints))

# Print the number of keypoints detected in the query image
print("Number of Keypoints Detected In The Query Image: ", len(test_keypoints))
```

```
    # Create a Brute Force Matcher object.
    bf = cv2.BFMatcher(cv2.NORM_HAMMING, crossCheck = True)

    # Perform the matching between the ORB descriptors of the training image and the test image
    matches = bf.match(train_descriptor, test_descriptor)

    # The matches with shorter distance are the ones we want.
    matches = sorted(matches, key = lambda x : x.distance)

    result = cv2.drawMatches(img_color, train_keypoints, test_gray, test_keypoints, matches, test_gray, fla

    # Display the best matching points
    plt.figure(figsize=(18, 8))
    plt.rcParams['figure.figsize'] = [14.0, 7.0]
    plt.title('Best Matching Points')
    plt.imshow(result)
    plt.show()

    # Print total number of matching points between the training and query images
    print("\nNumber of Matching Keypoints Between The Training and Query Images: ", len(matches))
```

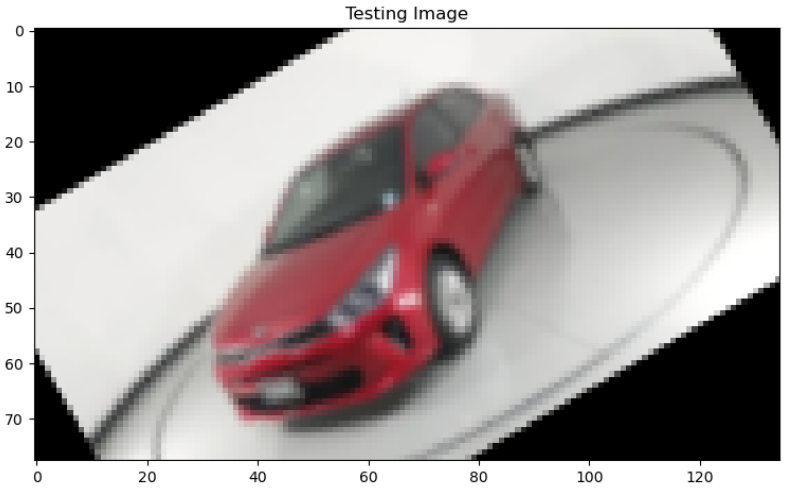
In [ ]:
```
def applySIFT(img, img_test):
    img1 = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
    img2 = cv2.cvtColor(img_test, cv2.COLOR_BGR2GRAY)

    plt.figure(figsize=(14, 4))
    plt.suptitle('Original images to match with SIFT:', fontsize=16)

    ax1 = plt.subplot(1, 2, 1)
    ax2 = plt.subplot(1, 2, 2)

    ax1.imshow(cv2.cvtColor(img, cv2.COLOR_BGR2RGB), cmap='gray')
    ax2.imshow(cv2.cvtColor(img_test, cv2.COLOR_BGR2RGB), cmap='gray')

    plt.show()

    sift = cv2.SIFT_create()

    keypoints_1, descriptors_1 = sift.detectAndCompute(img1, None)
    keypoints_2, descriptors_2 = sift.detectAndCompute(img2, None)
```

```
    plt.figure(figsize=(18, 6))
    plt.suptitle('Keypoints detected:', fontsize=16)
    plt.imshow(cv2.drawKeypoints(img1,keypoints_1,img))
    plt.show()

    bf = cv2.BFMatcher(cv2.NORM_L1, crossCheck=True)

    matches = bf.match(descriptors_1, descriptors_2)
    matches = sorted(matches, key=lambda x: x.distance)

    img3 = cv2.drawMatches(img1, keypoints_1, img2, keypoints_2, matches[:70], img2, flags=2)

    plt.title('SIFT applied:')
    plt.imshow(img3)
    plt.show()
```

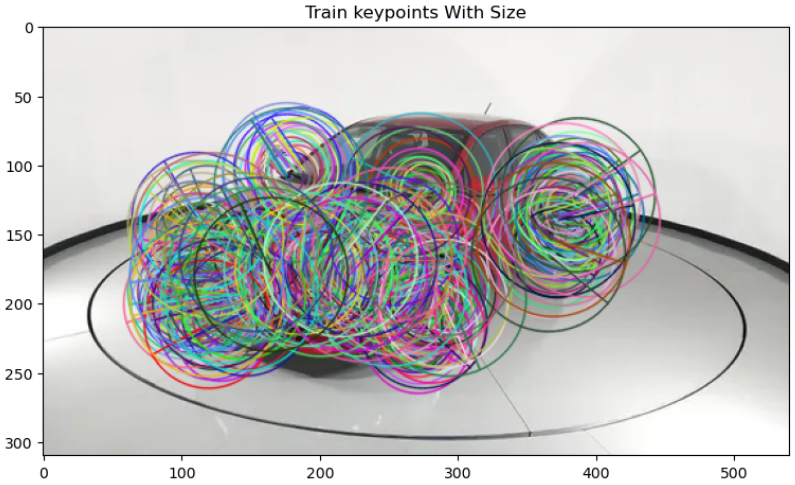
Car matching:

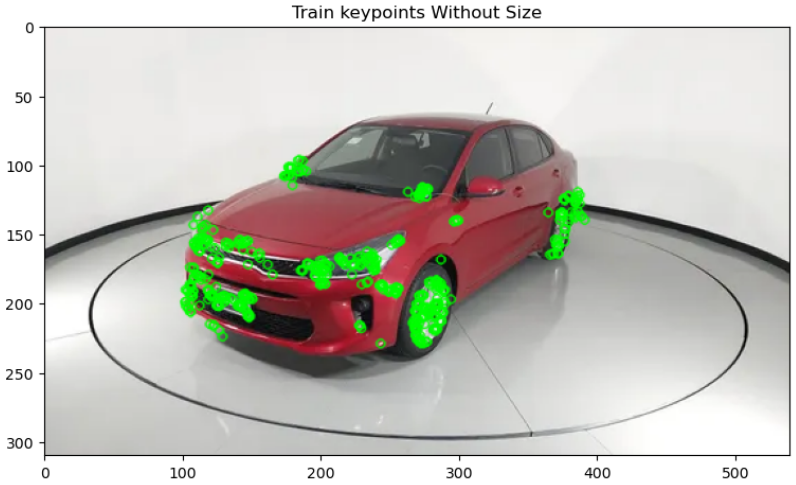
ORB:

In [ ]:
```
applyORB(cv2.imread('data/homework/image_matching/car_1.jpeg'))
```

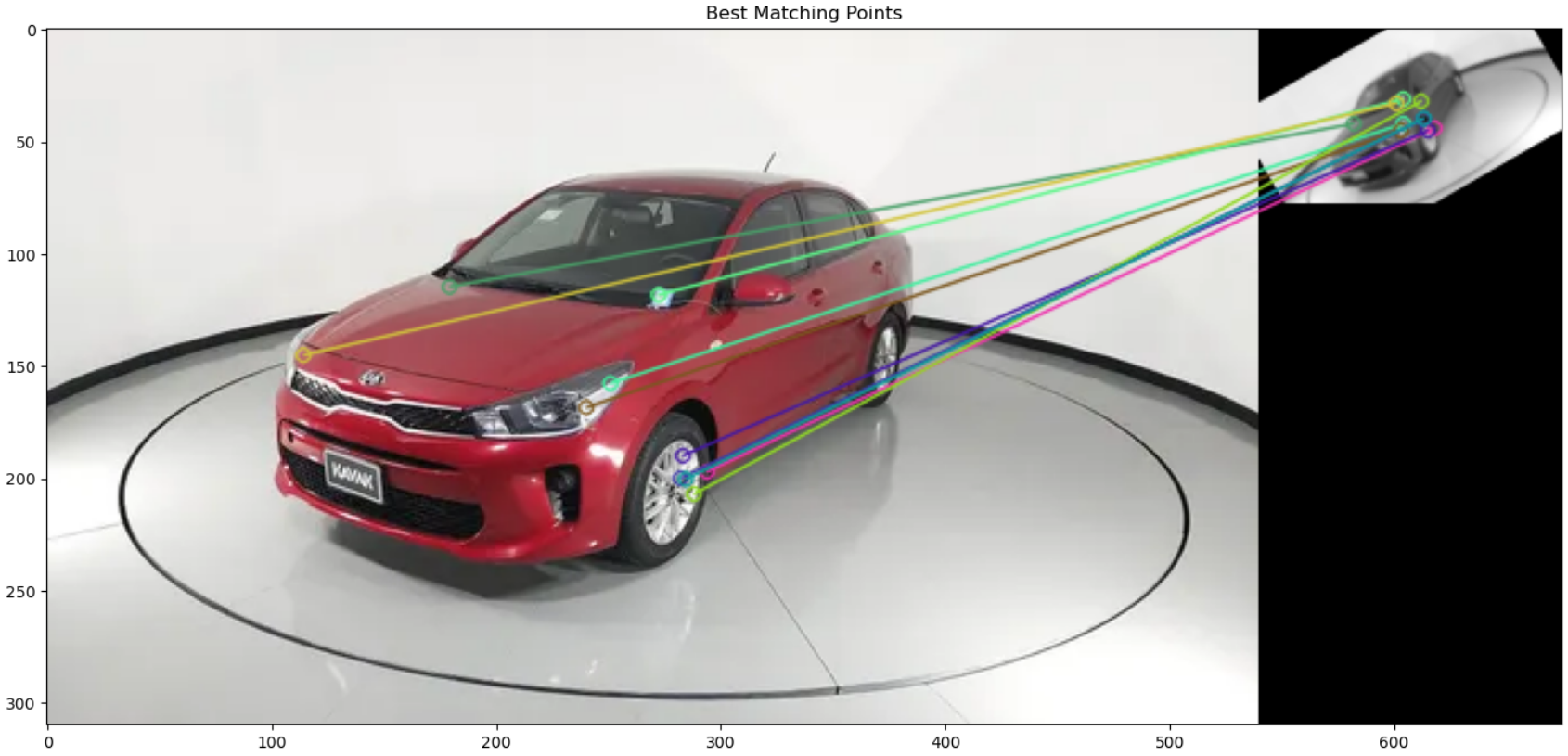



```
<Figure size 1400x400 with 0 Axes>
<Figure size 1400x400 with 0 Axes>
```





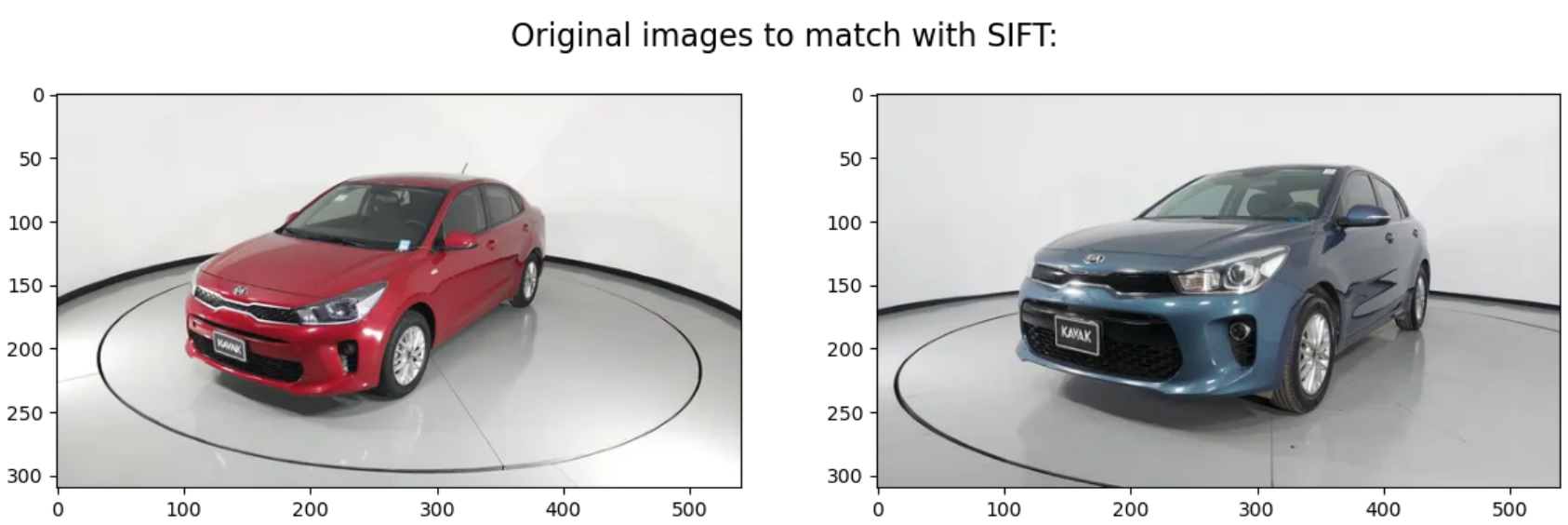
Number of Keypoints Detected In The Training Image: 500
Number of Keypoints Detected In The Query Image: 14

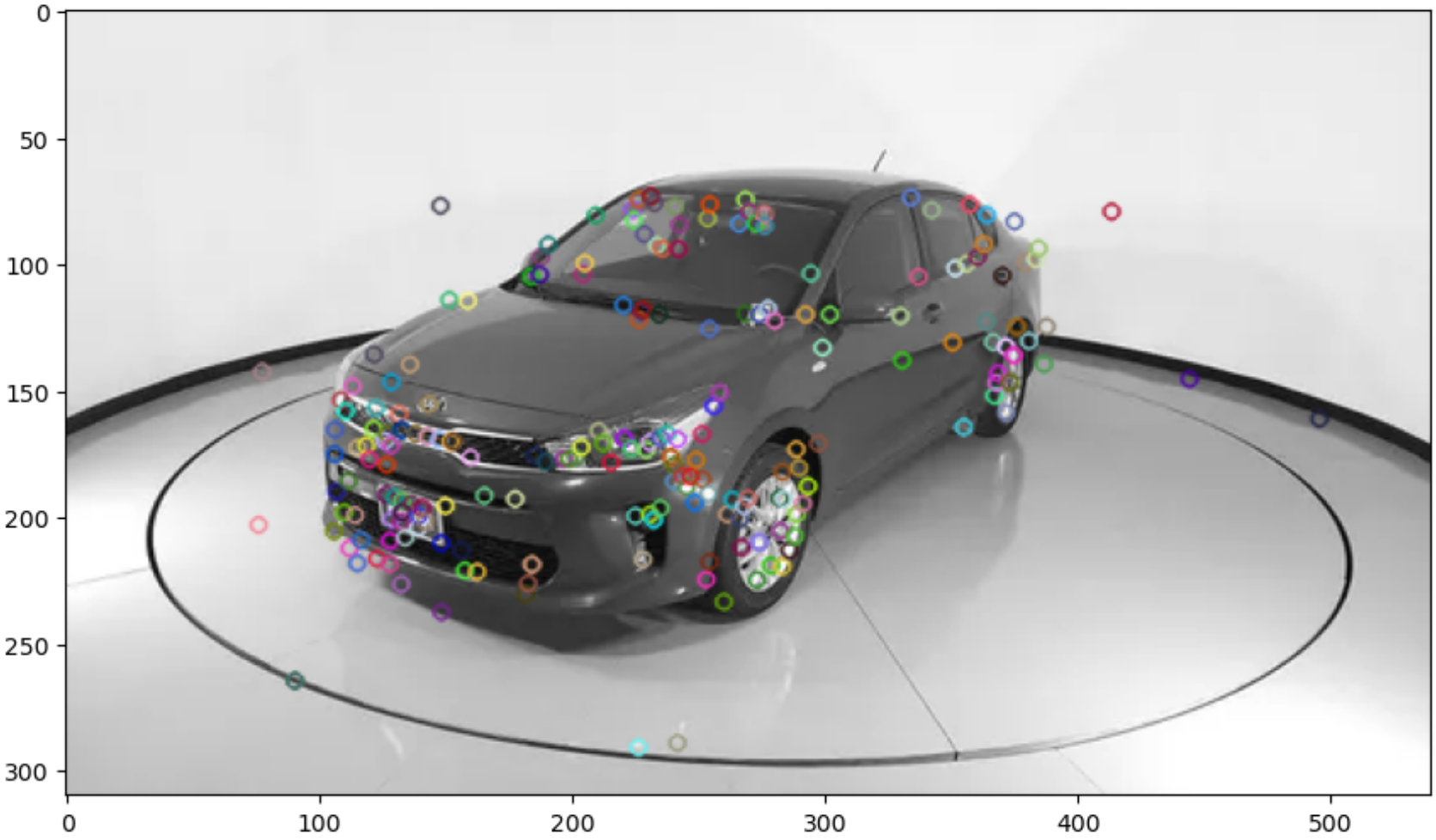


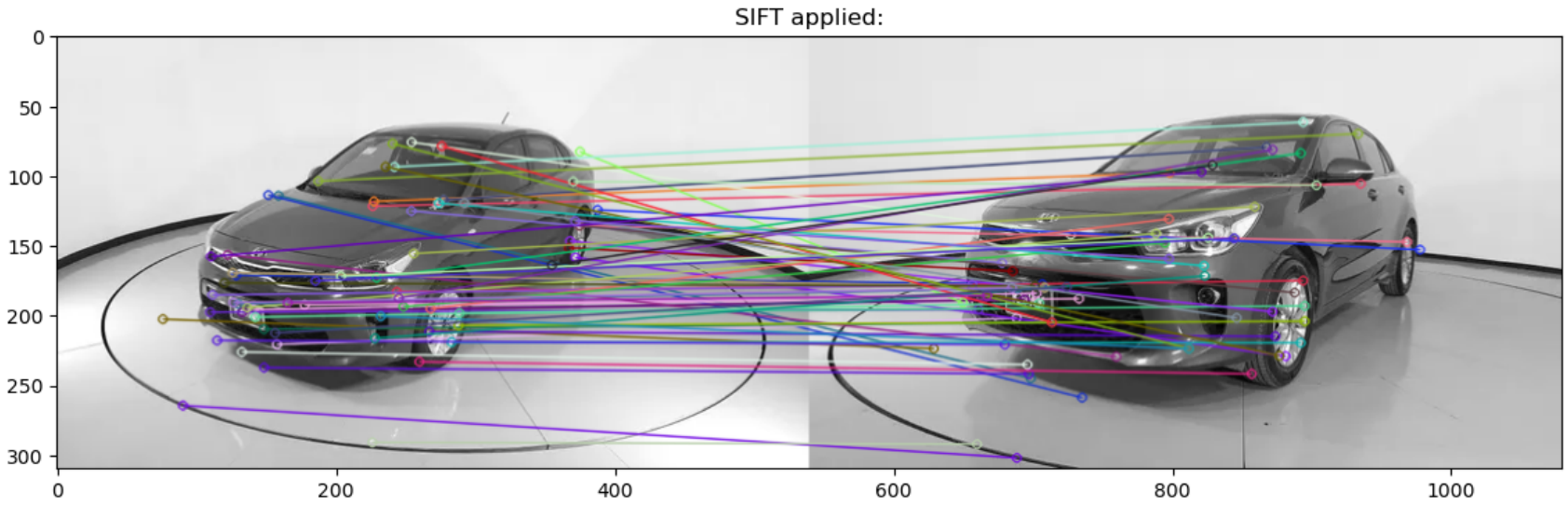
Number of Matching Keypoints Between The Training and Query Images: 10

SIFT:

In [ ]:
```
applySIFT(
    cv2.imread('data/homework/image_matching/car_1.jpeg'),
    cv2.imread('data/homework/image_matching/car_2.jpeg')
)
```




Keypoints detected:
0
50
100
150
200
250
300
0
100
200
300
400
500



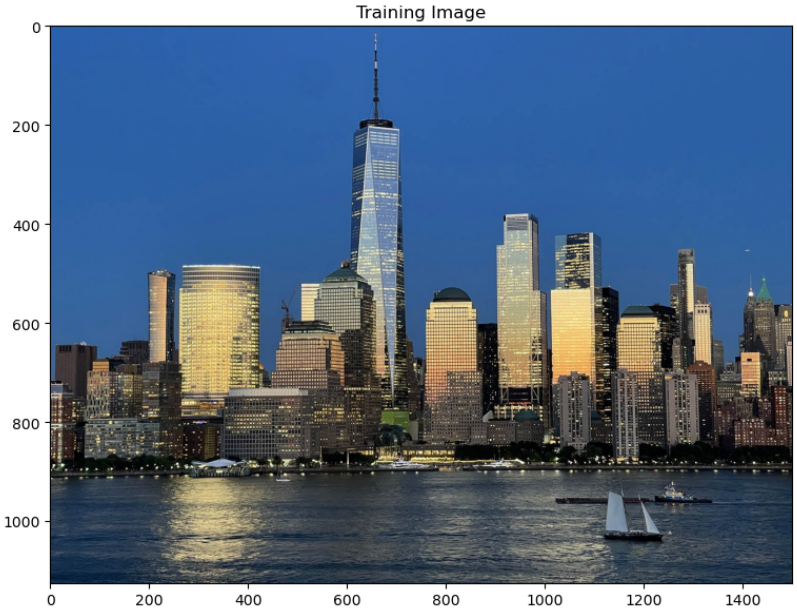
For this car images from a Kavak listing, it was observed that SIFT exhibited suboptimal performance compared to ORB. Despite expectations, SIFT failed to detect sufficient keypoints on the relatively uniform surface of the car, whereas ORB demonstrated efficiency and robustness, particularly in scenarios with limited texture variation.

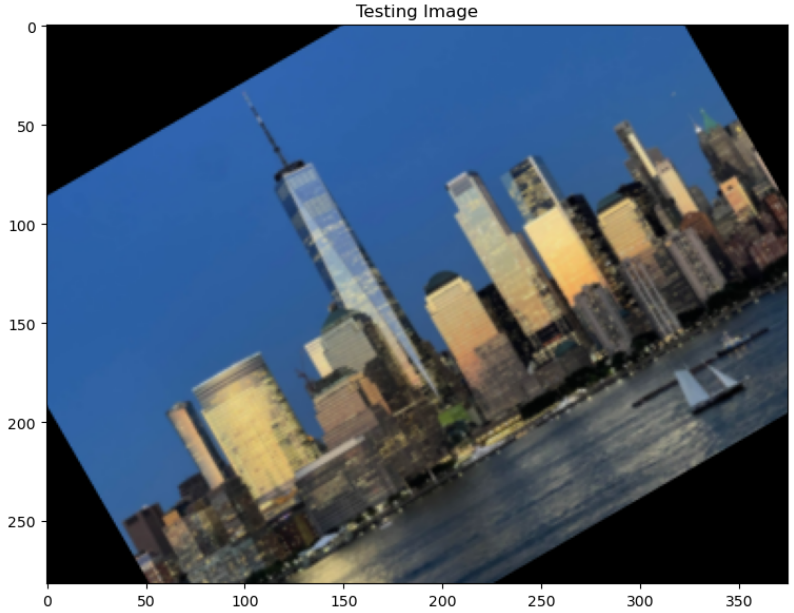
The superior performance of ORB over SIFT can be attributed to the nature of the object and the characteristics of the algorithms. ORB, known for its efficiency and robustness in scenarios with limited texture variation, effectively detected and matched keypoints on the relatively smooth surface of the car. In contrast, SIFT, renowned for its prowess in capturing detailed texture information, struggled to discern prominent keypoints on the car's surface due to the lack of intricate texture. Consequently, ORB's efficiency in detecting keypoints and matching descriptors made it better suited for accurately mapping the features of the car image.

City skyline:

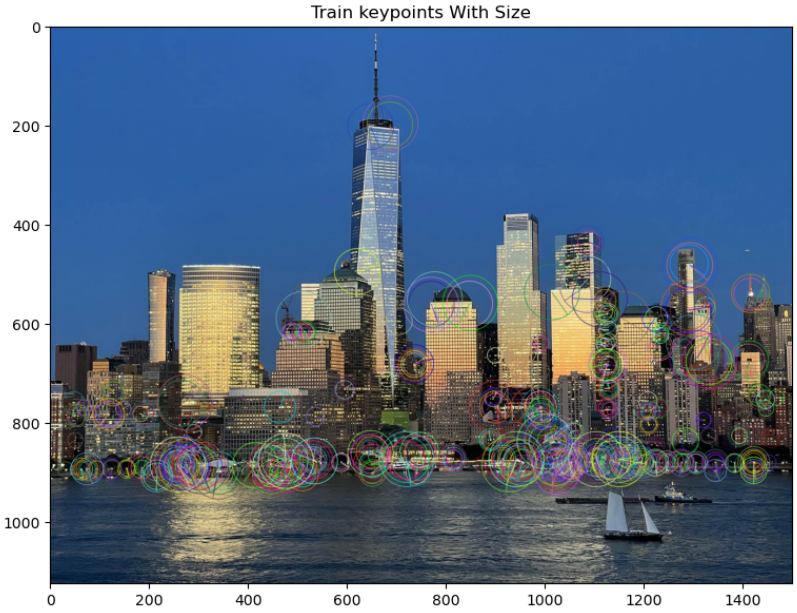
ORB:

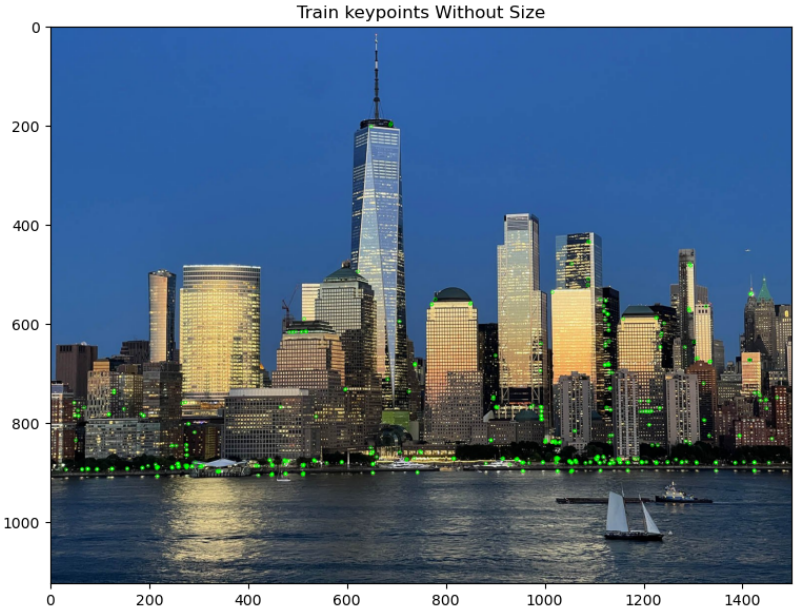
In [ ]:
```
applyORB(cv2.imread('data/homework/image_matching/skyline_1.jpeg'))
```



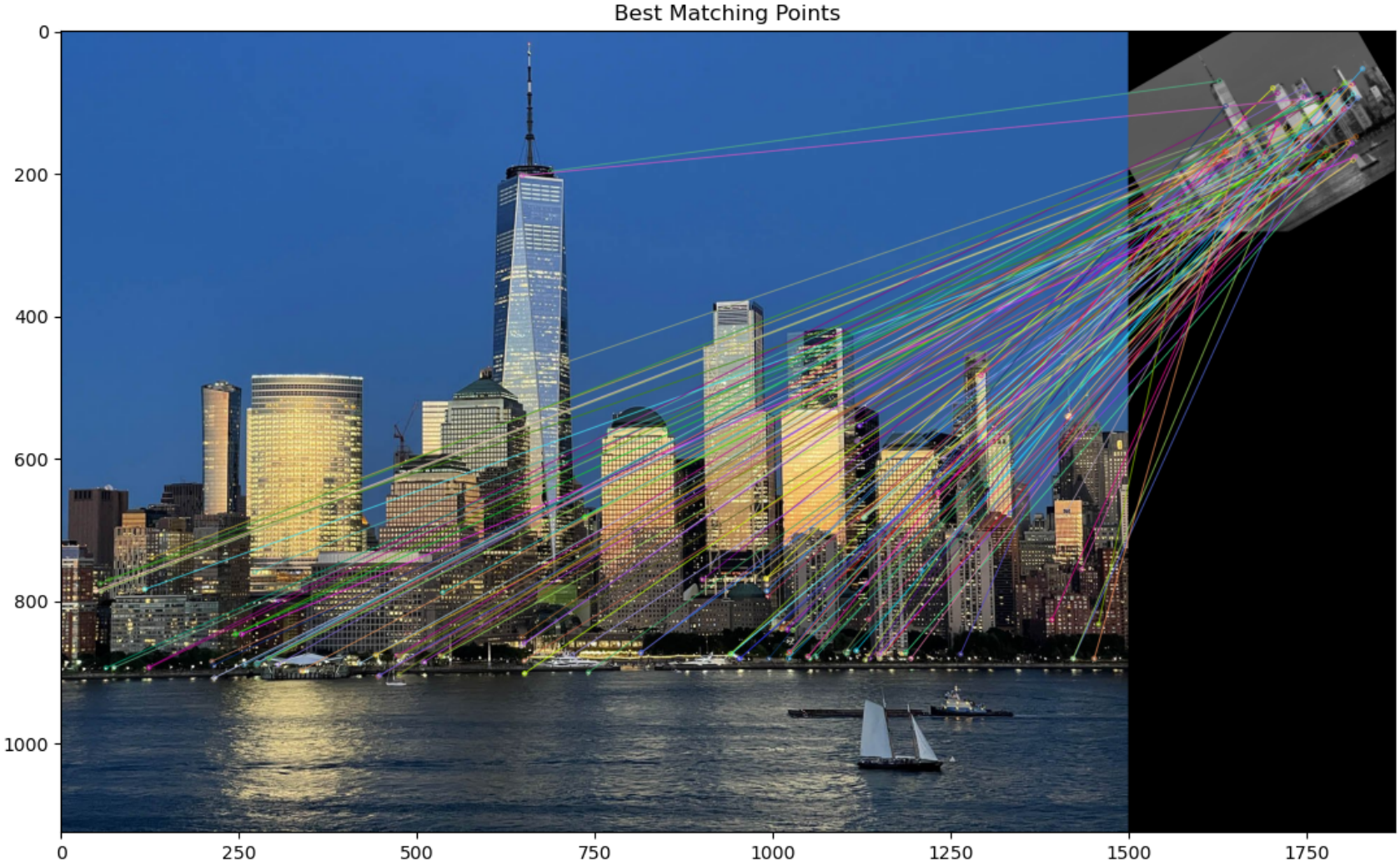



```
<Figure size 1400x400 with 0 Axes>
<Figure size 1400x400 with 0 Axes>
```






```
Number of Keypoints Detected In The Training Image:  500
Number of Keypoints Detected In The Query Image:  489
```

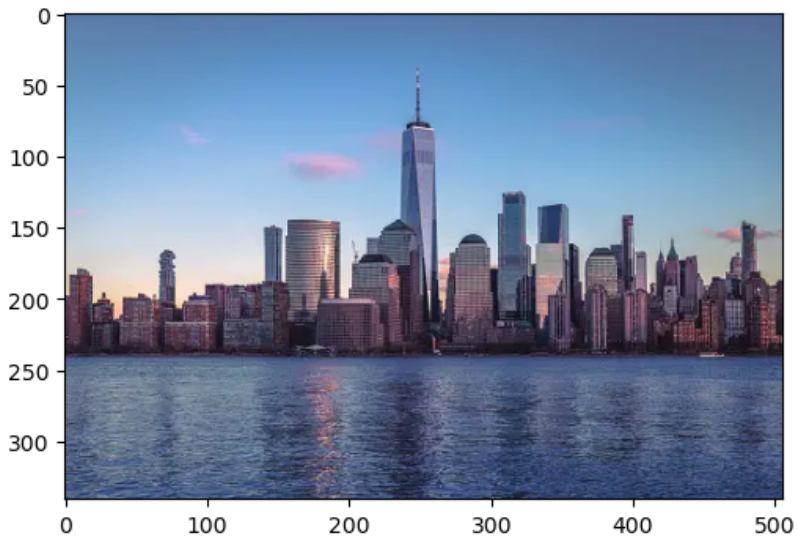


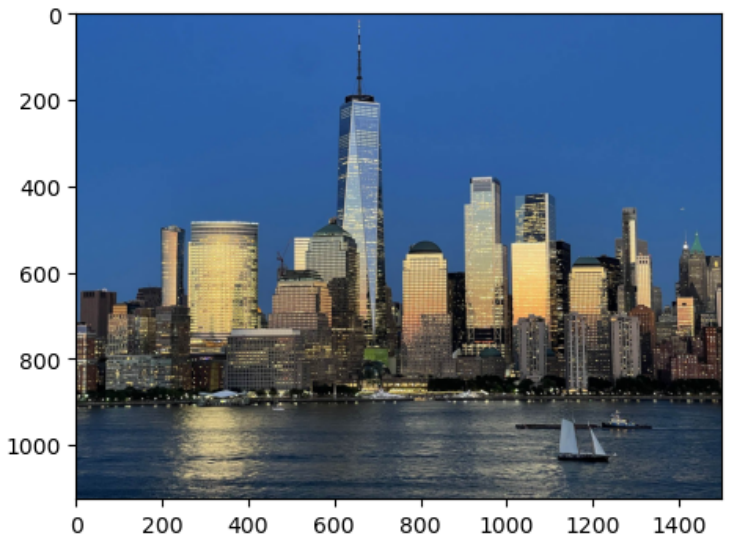

```
Number of Matching Keypoints Between The Training and Query Images:  136
```

SIFT:

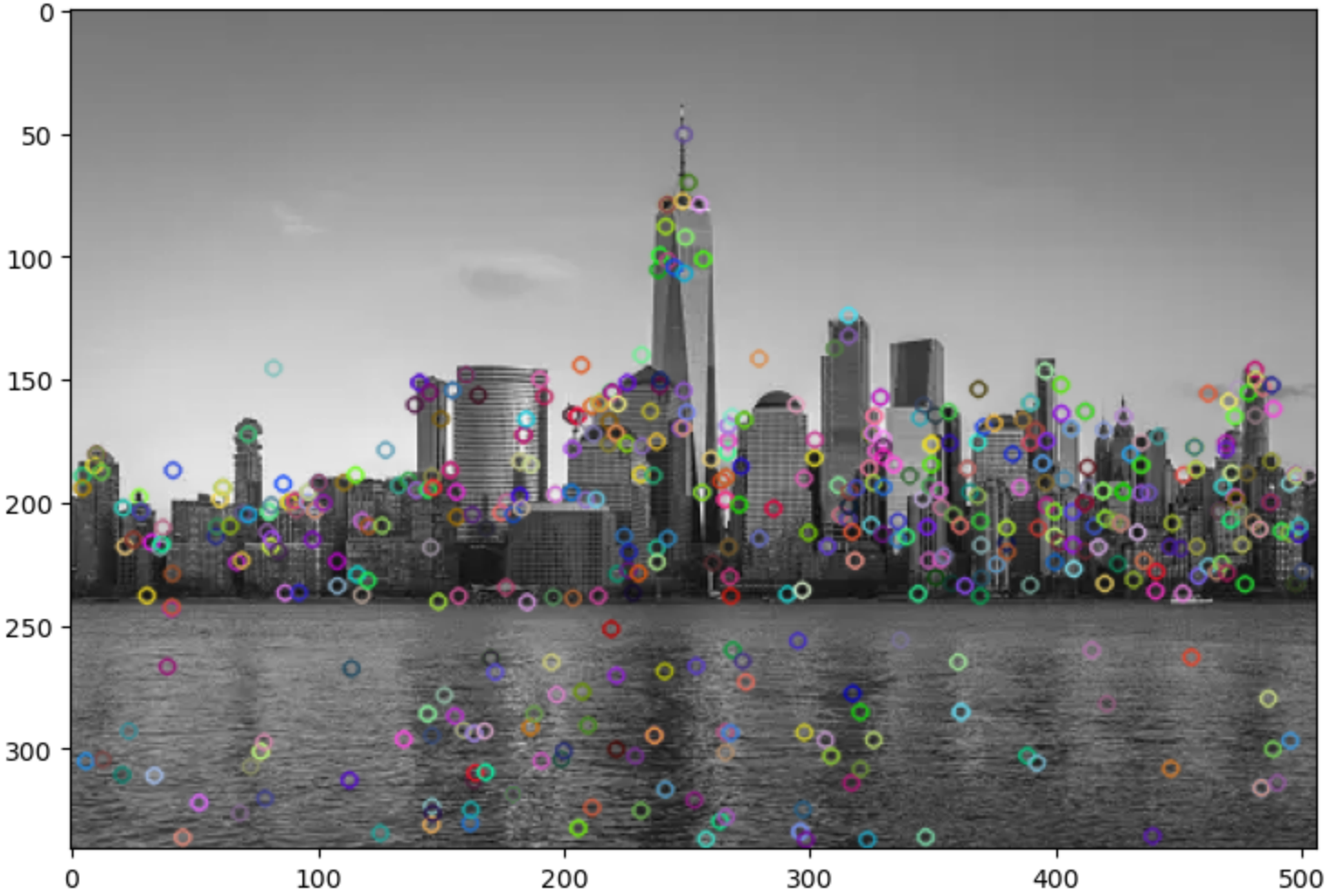
In [ ]:
```
applySIFT(
    cv2.imread('data/homework/image_matching/skyline_2.jpeg'),
    cv2.imread('data/homework/image_matching/skyline_1.jpeg')
)
```

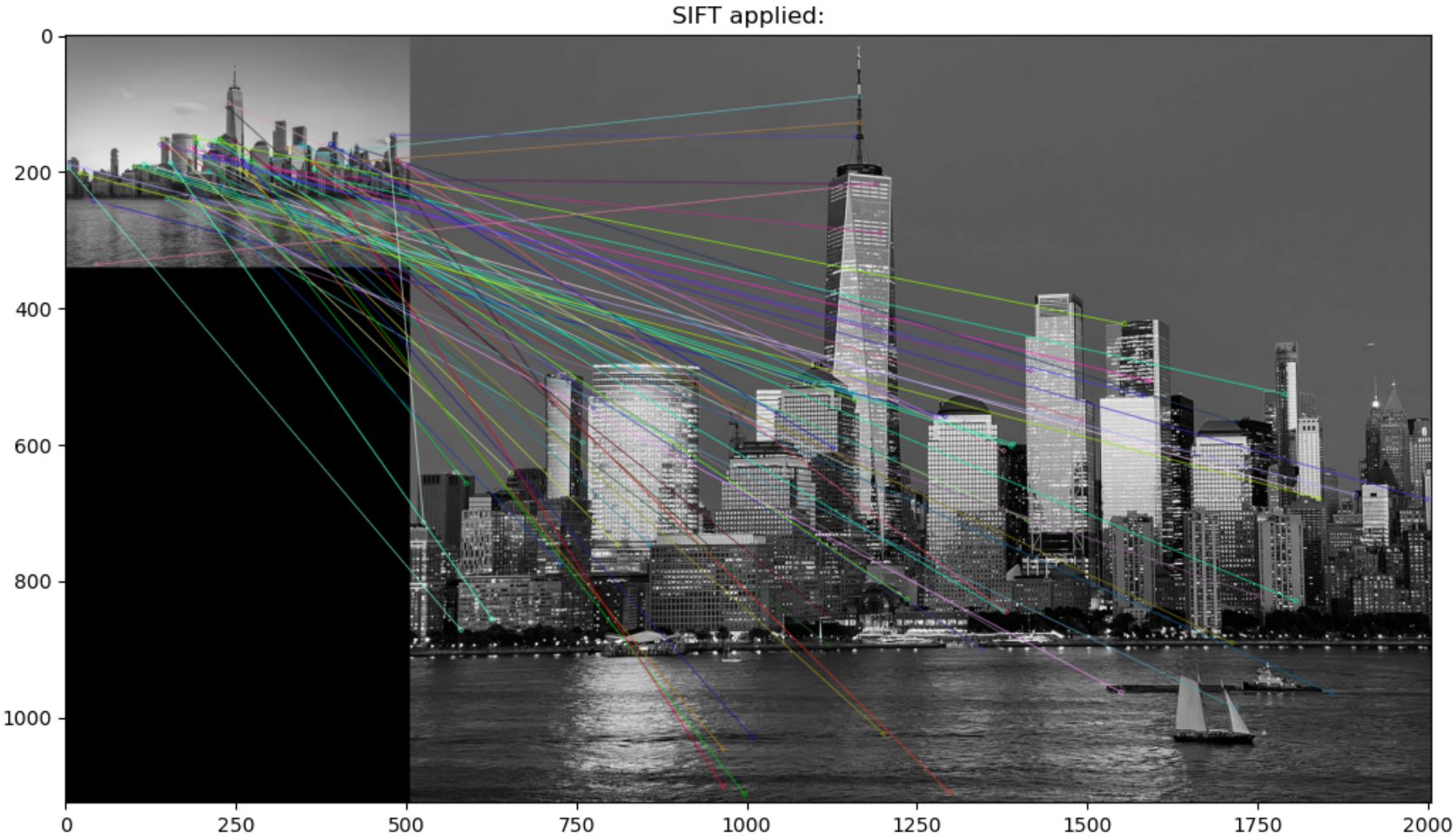
Original images to match with SIFT:





Keypoints detected:





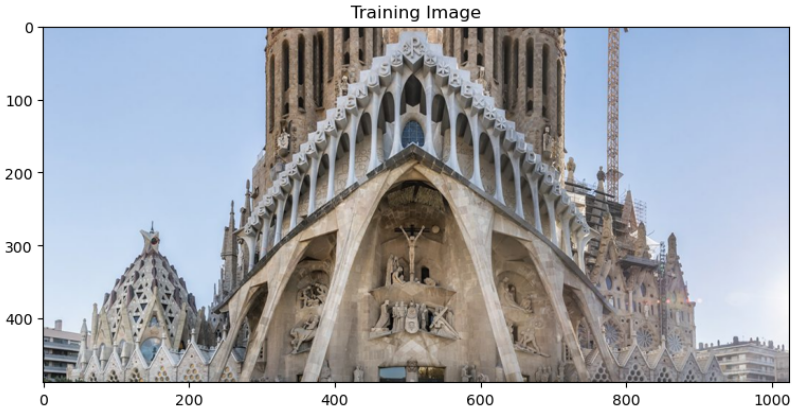
In the context of the city skyline image, it was noted that ORB outperformed SIFT.

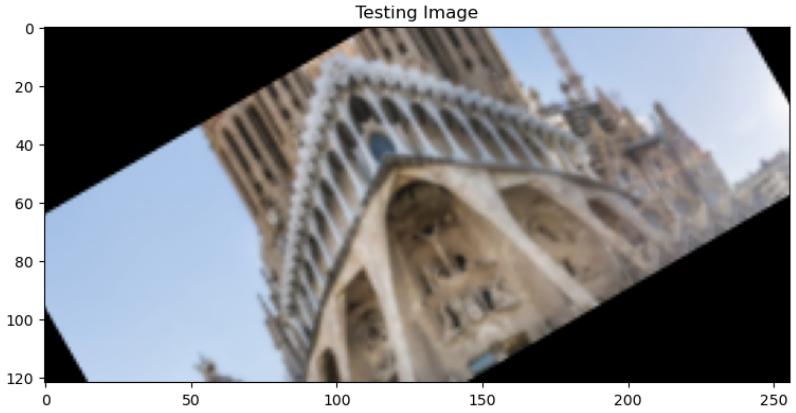
ORB's dominance over SIFT can be explained by the complexity and density of the structures present. The intricate details and densely packed nature of the skyline posed a challenge for SIFT, resulting in mixed and imprecise mappings of individual buildings. In contrast, ORB's efficiency in detecting keypoints allowed it to effectively handle the complexities of the skyline, accurately identifying and mapping the distinct structures with greater precision.

Church:

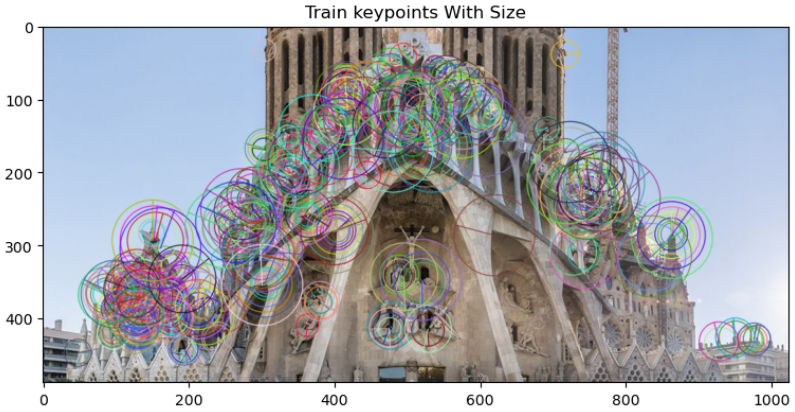
ORB:

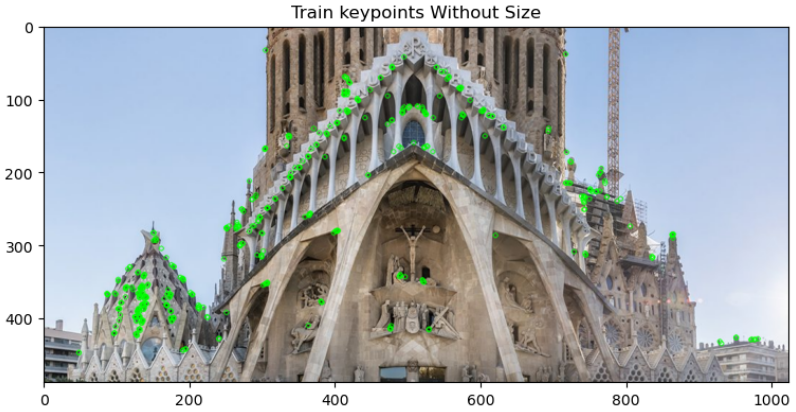
In [ ]:
```
applyORB(cv2.imread('data/homework/image_matching/church_1.jpeg'))
```



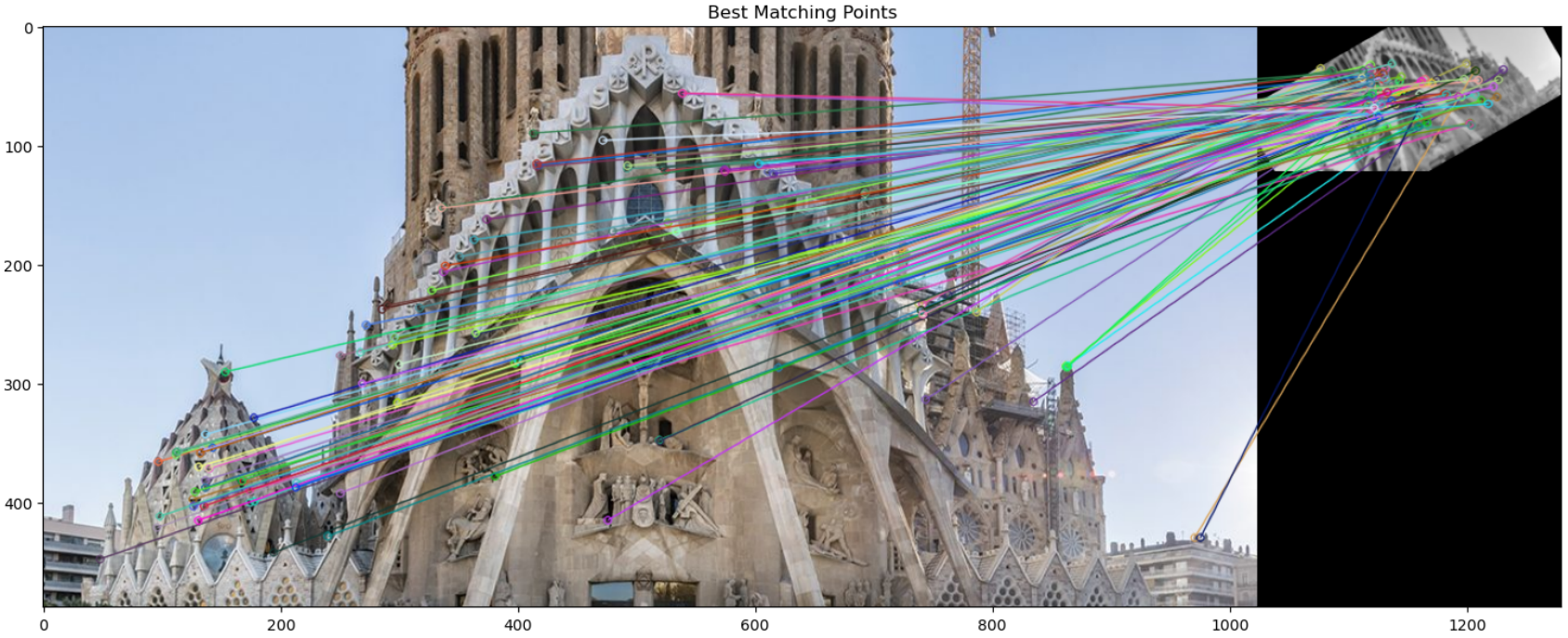



```
<Figure size 1400x400 with 0 Axes>
<Figure size 1400x400 with 0 Axes>
```






```
Number of Keypoints Detected In The Training Image:  500
Number of Keypoints Detected In The Query Image:  294
```

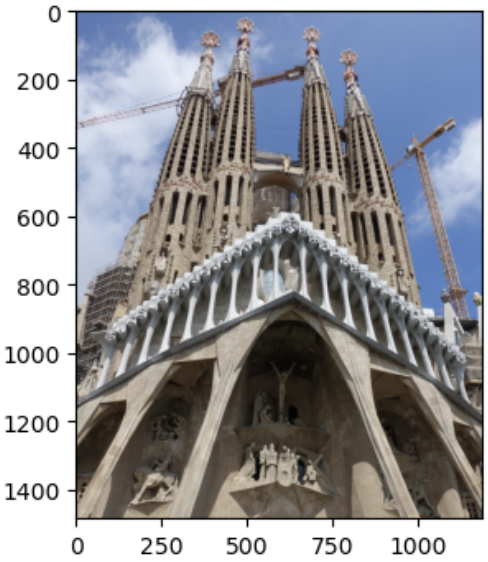


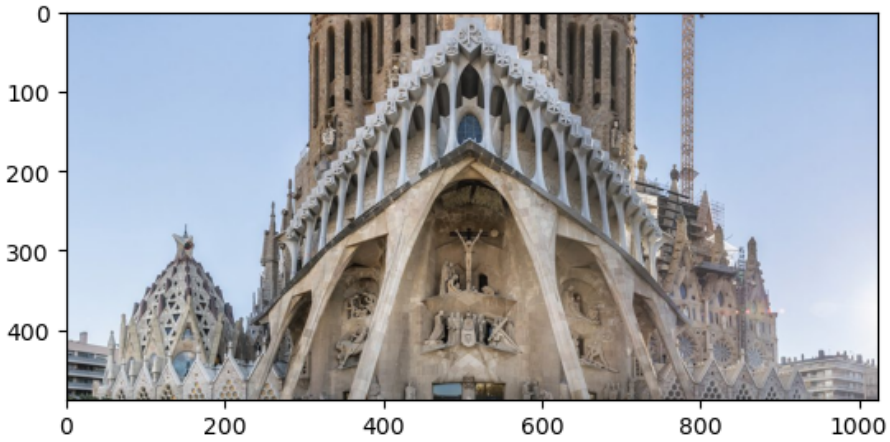

```
Number of Matching Keypoints Between The Training and Query Images:  109
```

SIFT:

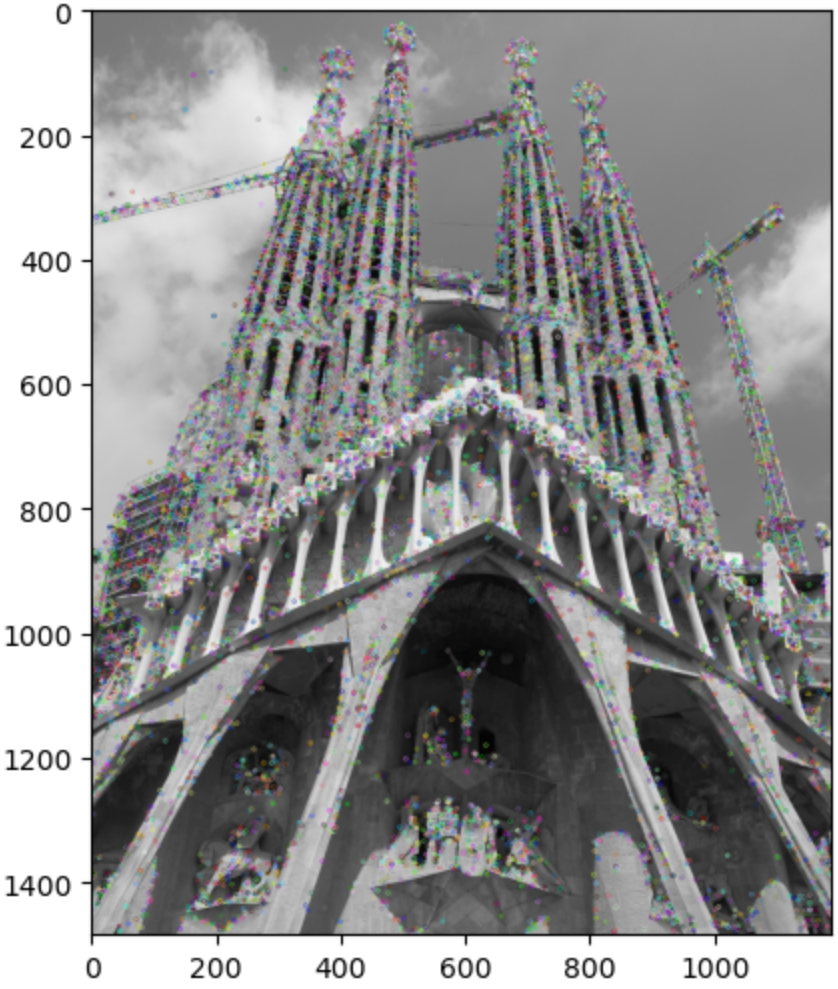
In [ ]:
```
applySIFT(
    cv2.imread('data/homework/image_matching/church_2.jpeg'),
    cv2.imread('data/homework/image_matching/church_1.jpeg')
)
```

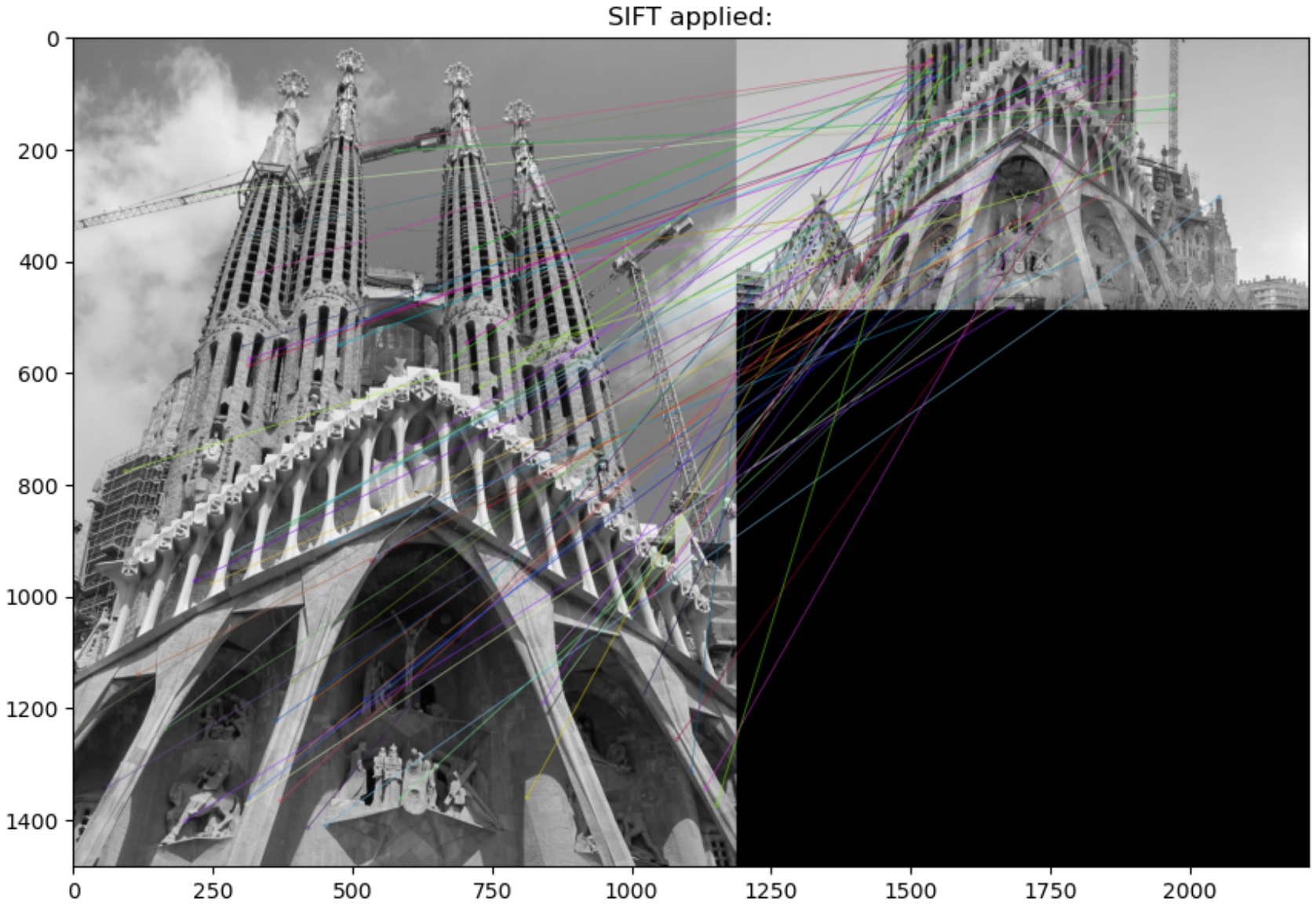
Original images to match with SIFT:





Keypoints detected:




SIFT applied:
0
200
400
600
800
1000
1200
1400
0
250
500
750
1000
1250
1500
1750
2000

Regarding the church image characterized by intricate details, SIFT's outperformance of ORB can be attributed to its adeptness in capturing and matching subtle texture variations, as mentioned in our previous discussion. While ORB struggled to distinguish between finer details, leading to less precise matching results, SIFT excelled in leveraging the rich texture variations present in the church's architecture. This aligns with the observation that SIFT worked better in capturing intricate details, underscoring its suitability for scenarios requiring nuanced texture information.