9. Image Matching

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Importing Libraries

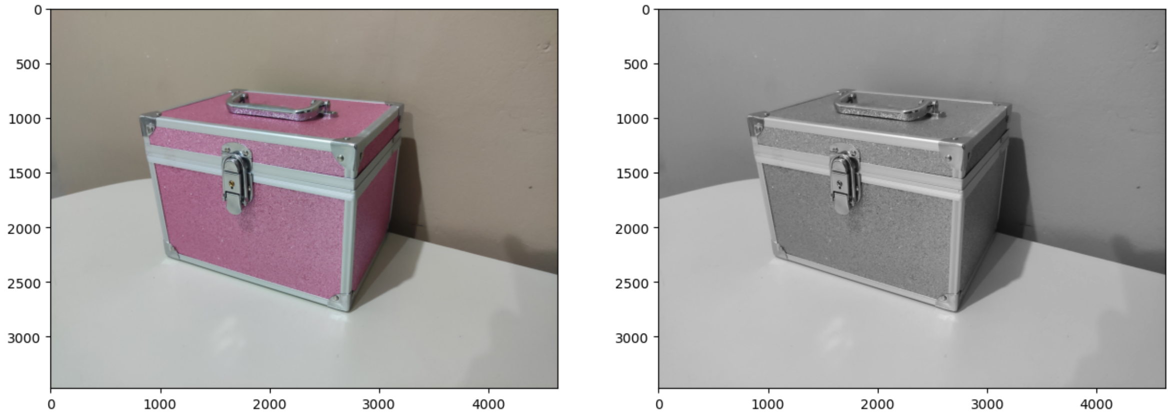
In [14]:
```
import cv2
import matplotlib.pyplot as plt
import numpy as np
```

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 [15]:
```
#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[15]: <matplotlib.image.AxesImage at 0x7fcf65b40ad0>



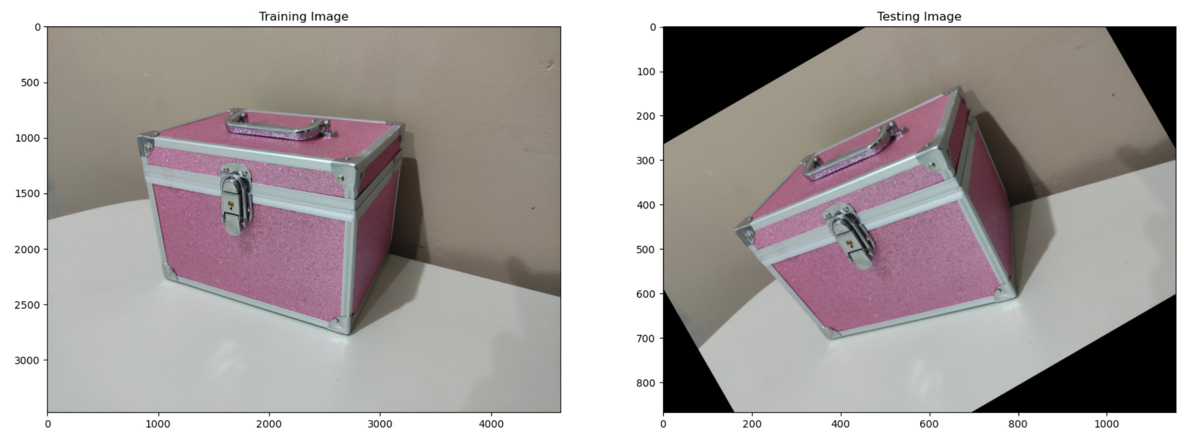
Create test image by adding Scale Invariance and Rotational Invariance

In [16]:
```
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_r

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

Display traning image and testing image

In [17]:
```
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[17]: <matplotlib.image.AxesImage at 0x7fcf65bf5a10>



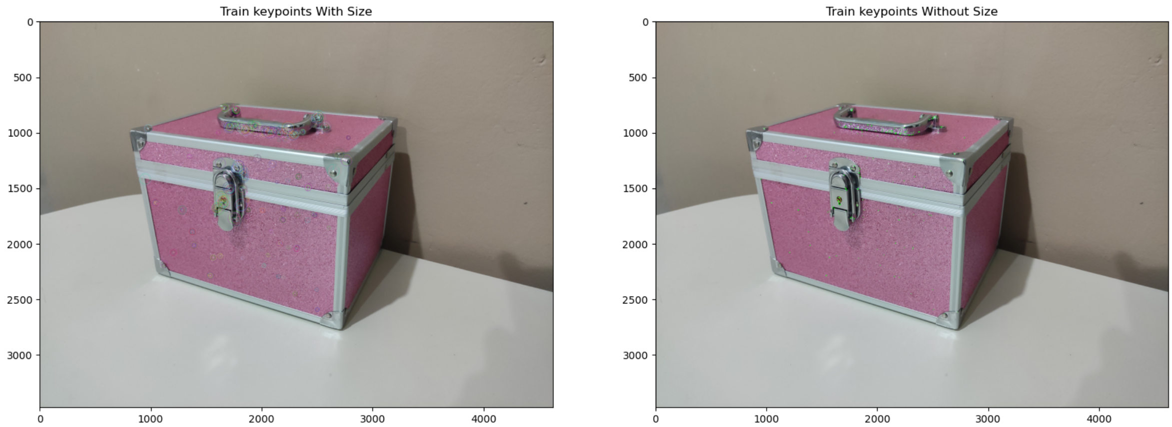
ORB

In [18]:
```
orb = cv2.ORB_create()
```

In [19]:
```
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, col

cv2.drawKeypoints(img_color, train_keypoints, keypoints_with_size, flags

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

plots[0].set_title("Train keypoints With Size")
```

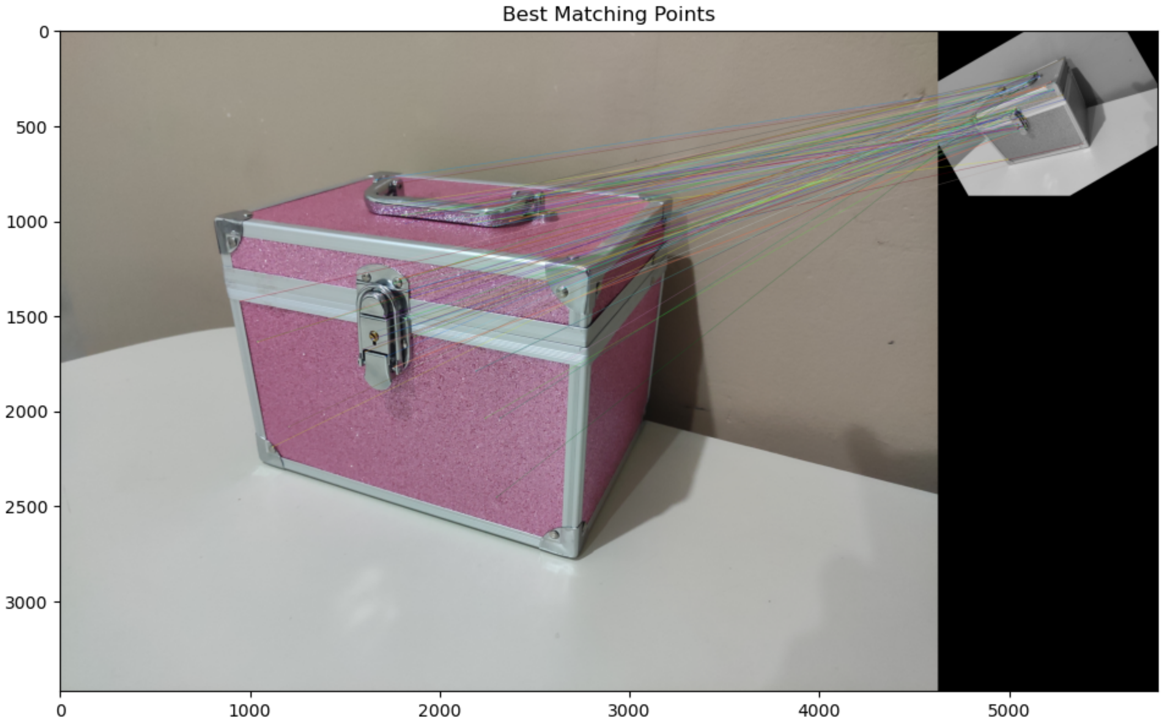
```
plots[0].imshow(keypoints_with_size, cmap='gray')

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_k

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

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



In [20]:

```
# 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
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_keyp

# 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 im
print("\nNumber of Matching Keypoints Between The Training and Query Imag
```

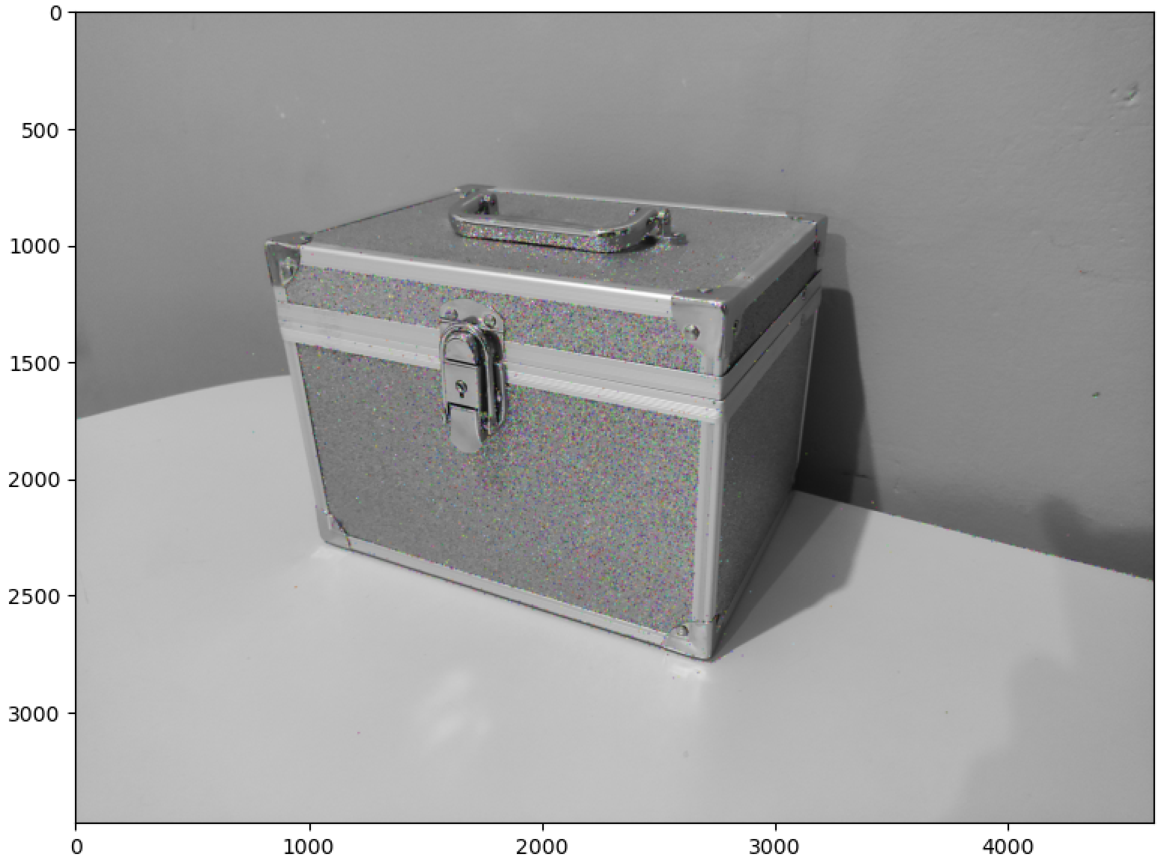



```
Number of Matching Keypoints Between The Training and Query Images:  115
```

SIFT Matching (Scale Invariant Feature Transform)

In [21]:
```
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)
```

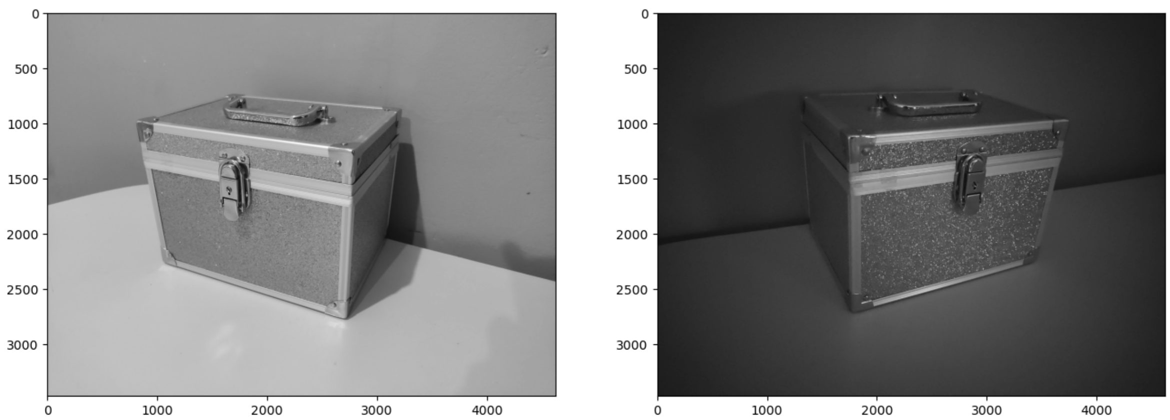
Out[21]:
```
<matplotlib.image.AxesImage at 0x7fcf9b2c2b90>
```



Matching different images

In [22]:
```
# 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[22]: <matplotlib.image.AxesImage at 0x7fcf9b235090>



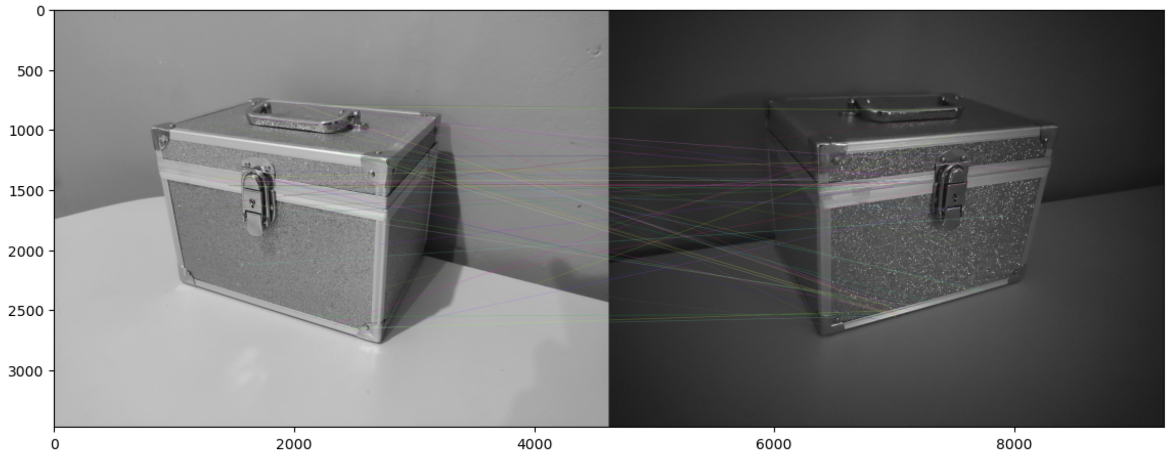
Extracting Keypoints with SIFT

In [23]:
```
#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[23]: (19692, 23868)

Feature Matching

In [24]:
```
#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]
plt.imshow(img3),plt.show()
```



Out[24]: (<matplotlib.image.AxesImage at 0x7fcf9af53250>, None)

En el caso de extracción de keypoints con SIFT la iluminación sí hace un cambio significativo. Probé las imágenes con diferentes tipos de iluminación. Con la iluminación similar, sí se identificaban las características correctamente. Con un cambio significativo de luz hay diferencias significativas.