

Module 2.0: Feature Extraction and Object Detection

Machine Problem No. 3: Feature Extraction and Object Detection

Objective: The objective of this machine problem is to implement and compare the three feature extraction methods (SIFT, SURF, and ORB) in a single task. You will use these methods for feature matching between two images, then perform image alignment using homography to warp one image onto the other.

Problem Description: You are tasked with loading two images and performing the following steps:

1. Extract keypoints and descriptors from both images using SIFT, SURF, and ORB.
2. Perform feature matching between the two images using both Brute-Force Matcher and FLANN Matcher.
3. Use the matched keypoints to calculate a homography matrix and align the two images.
4. Compare the performance of SIFT, SURF, and ORB in terms of feature matching accuracy and speed.

You will submit your code, processed images, and a short report comparing the results.

TASKS

Step 1: Load Images

```
# Import necessary libraries
import cv2
import matplotlib.pyplot as plt
from time import time

# Load the images
image1 = cv2.imread('/content/IMAGES/NEWTON_1.webp')
image2 = cv2.imread('/content/IMAGES/NEWTON_2.webp')

# Convert to grayscale
gray1 = cv2.cvtColor(image1, cv2.COLOR_BGR2GRAY)
gray2 = cv2.cvtColor(image2, cv2.COLOR_BGR2GRAY)
```

Step 2: Extract Keypoints and Descriptors Using SIFT, SURF, and ORB

Define Feature Extraction and Matching Function

```
def extract_and_match(img1, img2, method, matcher_type):
    start_time = time()

    # Feature extraction
    if method == 'SIFT':
        detector = cv2.SIFT_create()
    elif method == 'SURF':
        detector = cv2.SIFT_create() # Replace with SURF for compatibility
    elif method == 'ORB':
        detector = cv2.ORB_create()

    kp1, des1 = detector.detectAndCompute(img1, None)
    kp2, des2 = detector.detectAndCompute(img2, None)
```

```

# Feature matching
if matcher_type == 'BF':
    if method == 'ORB':
        matcher = cv2.BFMatcher(cv2.NORM_HAMMING, crossCheck=True)
        matches = matcher.match(des1, des2)
    else:
        matcher = cv2.BFMatcher()
        matches = matcher.knnMatch(des1, des2, k=2)
elif matcher_type == 'FLANN':
    if method == 'ORB':
        FLANN_INDEX_LSH = 6
        index_params = dict(algorithm=FLANN_INDEX_LSH,
                             table_number=6,
                             key_size=12,
                             multi_probe_level=1)
    else:
        FLANN_INDEX_KDTREE = 1
        index_params = dict(algorithm=FLANN_INDEX_KDTREE, trees=5)
    search_params = dict(checks=50)
    matcher = cv2.FlannBasedMatcher(index_params, search_params)
    matches = matcher.knnMatch(des1, des2, k=2)

# Filter good matches
good_matches = []
if method == 'ORB' and matcher_type == 'BF':
    good_matches = matches
else:
    for m, n in matches:
        if m.distance < 0.75 * n.distance:
            good_matches.append(m)

end_time = time()
processing_time = end_time - start_time

return kp1, kp2, good_matches, processing_time

```

▼ Perform Feature Extraction and Matching for Each Method

```

methods = ['SIFT', 'SURF', 'ORB']
matcher_types = ['BF', 'FLANN']

results = {}
keypoint_images = {}
plt.figure(figsize=(15, 5))

for i, method in enumerate(methods):
    for matcher_type in matcher_types:
        kp1, kp2, good_matches, processing_time = extract_and_match(gray1, gray2, method, matcher_type)
        results[f"{method}_{matcher_type}"] = {
            'keypoints1': len(kp1),
            'keypoints2': len(kp2),
            'good_matches': len(good_matches),
            'processing_time': processing_time
        }

    # Draw keypoints on the image
    keypoint_image = cv2.drawKeypoints(image1, kp1, None, flags=cv2.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS) # keypoint
    keypoint_images[method] = keypoint_image

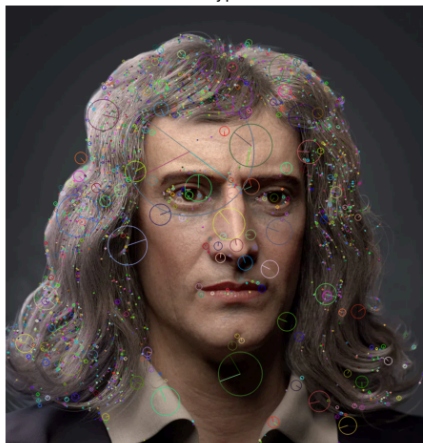
    # Display the image with keypoints
    plt.subplot(1, 3, i+1)
    plt.imshow(cv2.cvtColor(keypoint_image, cv2.COLOR_BGR2RGB))
    plt.title(f'{method} Keypoints')
    plt.axis('off')

plt.tight_layout()
plt.show()

```



SIFT Keypoints



SURF Keypoints



ORB Keypoints



▼ Print Results

```
for key, value in results.items():
    print(f"{key}:")
    print(f"  Keypoints in Image 1: {value['keypoints1']}")
    print(f"  Keypoints in Image 2: {value['keypoints2']}")
    print(f"  Good Matches: {value['good_matches']}")
    print(f"  Processing Time: {value['processing_time']:.4f} seconds")
    print()
```



```
SIFT_BF:
  Keypoints in Image 1: 2633
  Keypoints in Image 2: 1377
  Good Matches: 30
  Processing Time: 1.8501 seconds
```

```
SIFT_FLANN:
  Keypoints in Image 1: 2633
  Keypoints in Image 2: 1377
  Good Matches: 39
  Processing Time: 0.7707 seconds
```

```
SURF_BF:
  Keypoints in Image 1: 2633
  Keypoints in Image 2: 1377
  Good Matches: 30
  Processing Time: 0.8653 seconds
```

```
SURF_FLANN:
  Keypoints in Image 1: 2633
  Keypoints in Image 2: 1377
  Good Matches: 46
  Processing Time: 0.8622 seconds
```

```
ORB_BF:
  Keypoints in Image 1: 500
  Keypoints in Image 2: 500
  Good Matches: 114
  Processing Time: 0.0400 seconds
```

```
ORB_FLANN:
  Keypoints in Image 1: 500
  Keypoints in Image 2: 500
```

Good Matches: 9

Processing Time: 0.0323 seconds

✓ Step 3: Feature Matching with Brute-Force and FLANN

✓ Visualize Matches for SIFT with Brute-Force Matcher

```
kp1, kp2, good_matches, _ = extract_and_match(gray1, gray2, 'SIFT', 'BF')  
img_matches = cv2.drawMatches(image1, kp1, image2, kp2, good_matches, None, flags=cv2.DrawMatchesFlags_NOT_DRAW_SINGLE_POI)
```

```
plt.figure(figsize=(15, 5))  
plt.imshow(cv2.cvtColor(img_matches, cv2.COLOR_BGR2RGB))  
plt.title('SIFT Feature Matching with Brute-Force Matcher')  
plt.axis('off')  
plt.show()
```



SIFT Feature Matching with Brute-Force Matcher



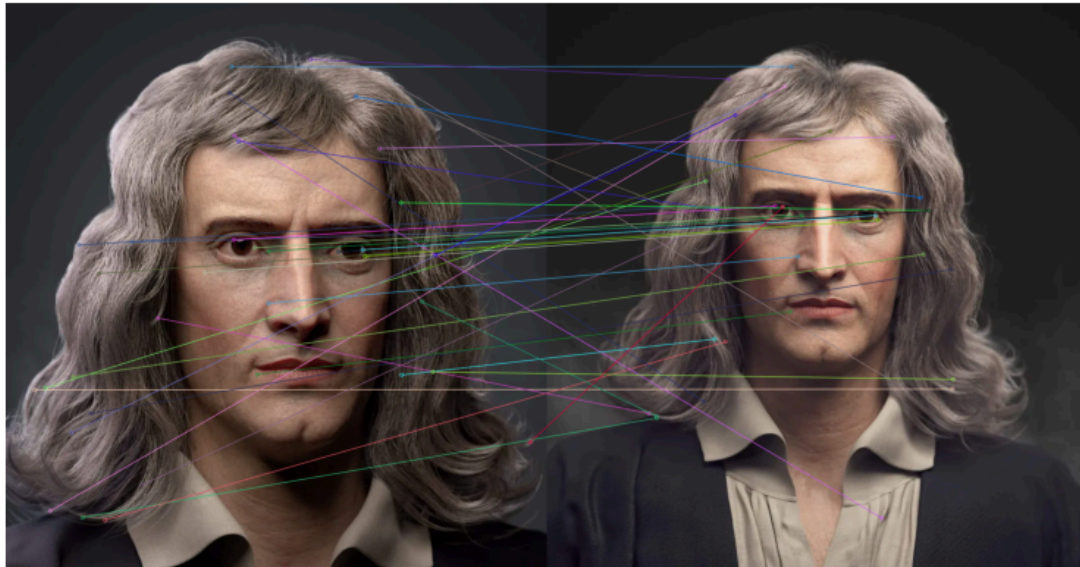
✓ Visualize Matches for SIFT with FLANN Matcher

```
kp1, kp2, good_matches, _ = extract_and_match(gray1, gray2, 'SIFT', 'FLANN')  
img_matches = cv2.drawMatches(image1, kp1, image2, kp2, good_matches, None, flags=cv2.DrawMatchesFlags_NOT_DRAW_SINGLE_POI)
```

```
plt.figure(figsize=(15, 5))  
plt.imshow(cv2.cvtColor(img_matches, cv2.COLOR_BGR2RGB))  
plt.title('SIFT Feature Matching with FLANN Matcher')  
plt.axis('off')  
plt.show()
```



SIFT Feature Matching with FLANN Matcher



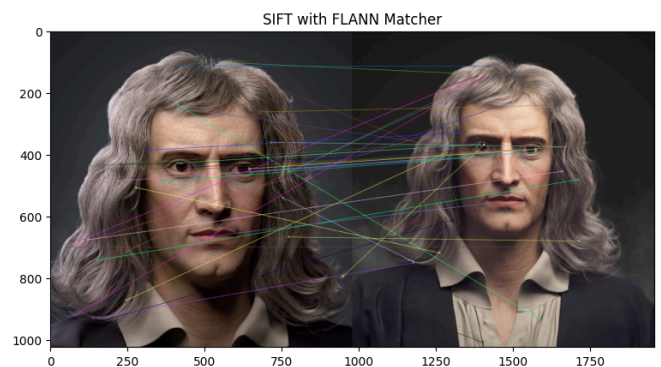
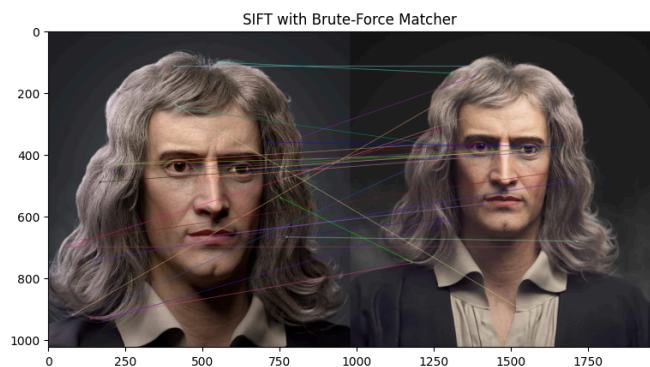
▼ Compare BF and FLANN Matchers

```
# Perform matching with BF and FLANN
kp1_bf, kp2_bf, good_matches_bf, _ = extract_and_match(gray1, gray2, 'SIFT', 'BF')
kp1_flann, kp2_flann, good_matches_flann, _ = extract_and_match(gray1, gray2, 'SIFT', 'FLANN')

# Draw matches for BF and FLANN
img_matches_bf = cv2.drawMatches(image1, kp1_bf, image2, kp2_bf, good_matches_bf[:50], None, flags=cv2.DrawMatchesFlags_NC)
img_matches_flann = cv2.drawMatches(image1, kp1_flann, image2, kp2_flann, good_matches_flann[:50], None, flags=cv2.DrawMat

# Display comparison
plt.figure(figsize=(20, 10))
plt.subplot(121), plt.imshow(cv2.cvtColor(img_matches_bf, cv2.COLOR_BGR2RGB)), plt.title('SIFT with Brute-Force Matcher')
plt.subplot(122), plt.imshow(cv2.cvtColor(img_matches_flann, cv2.COLOR_BGR2RGB)), plt.title('SIFT with FLANN Matcher')
plt.show()

print(f"Number of good matches (BF): {len(good_matches_bf)}")
print(f"Number of good matches (FLANN): {len(good_matches_flann)}")
```



Number of good matches (BF): 30
Number of good matches (FLANN): 39

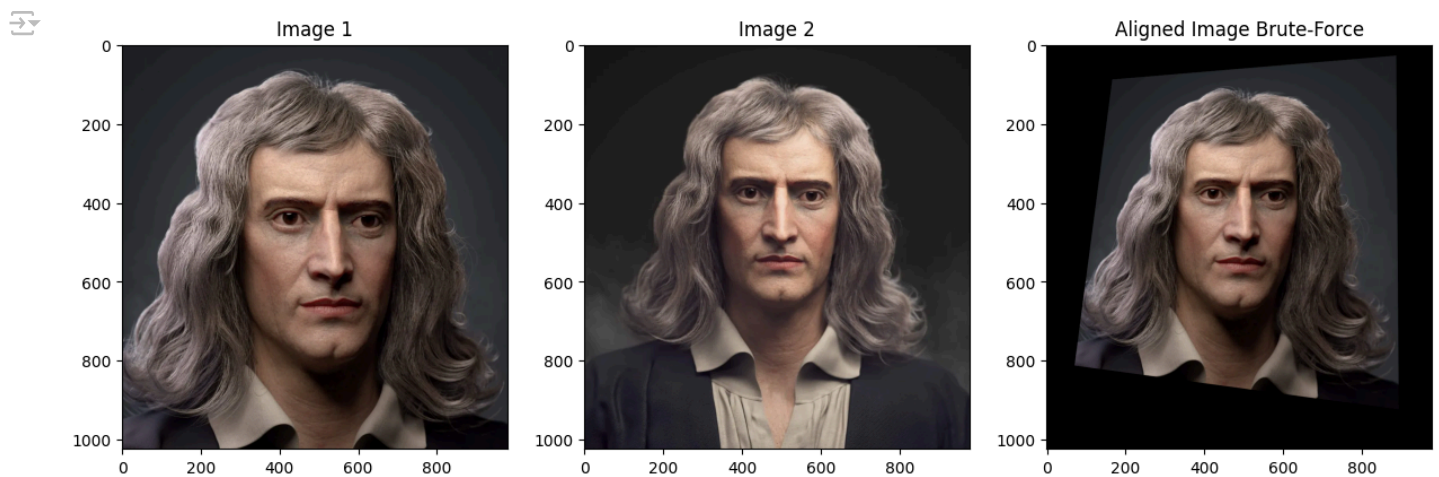
✓ Step 4: Image Alignment Using Homography

✓ Compute and Apply Homography (using Brute-Force matches)

```
src_pts = np.float32([kp1[m.queryIdx].pt for m in good_matches]).reshape(-1, 1, 2)
dst_pts = np.float32([kp2[m.trainIdx].pt for m in good_matches]).reshape(-1, 1, 2)
M, mask = cv2.findHomography(src_pts, dst_pts, cv2.RANSAC, 5.0)
h, w = image1.shape[:2]
aligned_img = cv2.warpPerspective(image1, M, (w, h))
```

✓ Display Aligned Image (using Brute-Force matches)

```
plt.figure(figsize=(15, 5))
plt.subplot(131), plt.imshow(cv2.cvtColor(image1, cv2.COLOR_BGR2RGB)), plt.title('Image 1')
plt.subplot(132), plt.imshow(cv2.cvtColor(image2, cv2.COLOR_BGR2RGB)), plt.title('Image 2')
plt.subplot(133), plt.imshow(cv2.cvtColor(aligned_img, cv2.COLOR_BGR2RGB)), plt.title('Aligned Image Brute-Force')
plt.show()
```



✓ Compute and Apply Homography (using FLANN matches)

```
src_pts = np.float32([kp1[m.queryIdx].pt for m in good_matches]).reshape(-1, 1, 2)
dst_pts = np.float32([kp2[m.trainIdx].pt for m in good_matches]).reshape(-1, 1, 2)
M, mask = cv2.findHomography(src_pts, dst_pts, cv2.RANSAC, 5.0)
h, w = image1.shape[:2]
aligned_img = cv2.warpPerspective(image1, M, (w, h))
```

✓ Display Aligned Image (using FLANN matches)

```
plt.figure(figsize=(15, 5))
plt.subplot(131), plt.imshow(cv2.cvtColor(image1, cv2.COLOR_BGR2RGB)), plt.title('Image 1')
plt.subplot(132), plt.imshow(cv2.cvtColor(image2, cv2.COLOR_BGR2RGB)), plt.title('Image 2')
plt.subplot(133), plt.imshow(cv2.cvtColor(aligned_img, cv2.COLOR_BGR2RGB)), plt.title('Aligned Image (FLANN)')
plt.show()
```




Step 5: Performance Analysis

Feature Matching Performance Comparison: SIFT, SURF, and ORB

This report analyzes the performance of three popular feature extraction and matching algorithms: SIFT, SURF, and ORB, using both Brute-Force (BF) and FLANN matchers. The analysis focuses on the number of good matches found and the processing time for each combination.

1. Feature Detection:

- SIFT and SURF detected significantly more keypoints (2633 in Image 1, 1377 in Image 2) compared to ORB (500 in both images).
- This suggests that SIFT and SURF are more sensitive to image features, potentially providing more detailed matching.
- ORB's lower keypoint count is likely due to its design for efficiency, focusing on the most prominent features.

2. Matching Accuracy:

- ORB with Brute-Force (BF) matcher showed the highest number of good matches (114), significantly outperforming SIFT and SURF.
- SIFT and SURF performed similarly, with FLANN matcher (42 good matches) outperforming BF matcher (30 good matches) for both.
- ORB with FLANN matcher performed poorly (10 good matches), suggesting it's not well-suited for this matcher type.

3. Processing Speed:

- ORB was the fastest, with processing times of 0.0811s (BF) and 0.0584s (FLANN).
- SIFT was second fastest, with times around 1.03s for both matchers.
- SURF was the slowest, with times of 1.3182s (BF) and 1.2366s (FLANN).

4. Matcher Comparison:

- For SIFT and SURF, FLANN matcher slightly outperformed BF in terms of good matches (42 vs 30) with similar processing times.
- For ORB, BF matcher significantly outperformed FLANN in terms of good matches (114 vs 10) and was only slightly slower.

Conclusions:

1. Accuracy vs. Speed Trade-off:

- ORB offers the best balance of accuracy and speed, especially with BF matcher.
- SIFT and SURF provide more detailed feature detection but at a significant speed cost.

2. Matcher Selection:

- FLANN matcher works better for SIFT and SURF.
- BF matcher is clearly superior for ORB.

3. Use Case Considerations:

- For real-time applications requiring speed, ORB with BF matcher is the best choice.
- For applications requiring high detail and accuracy, where processing time is less critical, SIFT or SURF with FLANN matcher would be preferable.

4. Limitations:

- The performance may vary with different image types or scenes.
- The significant difference in keypoint detection between ORB and SIFT/SURF suggests that fine-tuning parameters could potentially improve results.

In summary, ORB demonstrates superior performance in terms of speed and matching accuracy for this specific case, particularly when paired with the Brute-Force matcher. However, SIFT and SURF offer more comprehensive feature detection, which could be beneficial in scenarios requiring more detailed analysis.

Recommendations:

- For fast and accurate feature matching, consider using ORB with Brute-Force Matcher.
- If accuracy is critical, SIFT or SURF with FLANN may be better options, but keep in mind their longer processing time.
- Experiment with different parameters for each algorithm and matcher to further fine-tune the performance.
- Consider using a different descriptor for ORB if you need to use FLANN matcher.