CV TA-2

Name : Yash.S.Gajjalwar

Section: A

Roll No.: 68

1.Implement the SIFT algorithm to detect and match key points between two images.

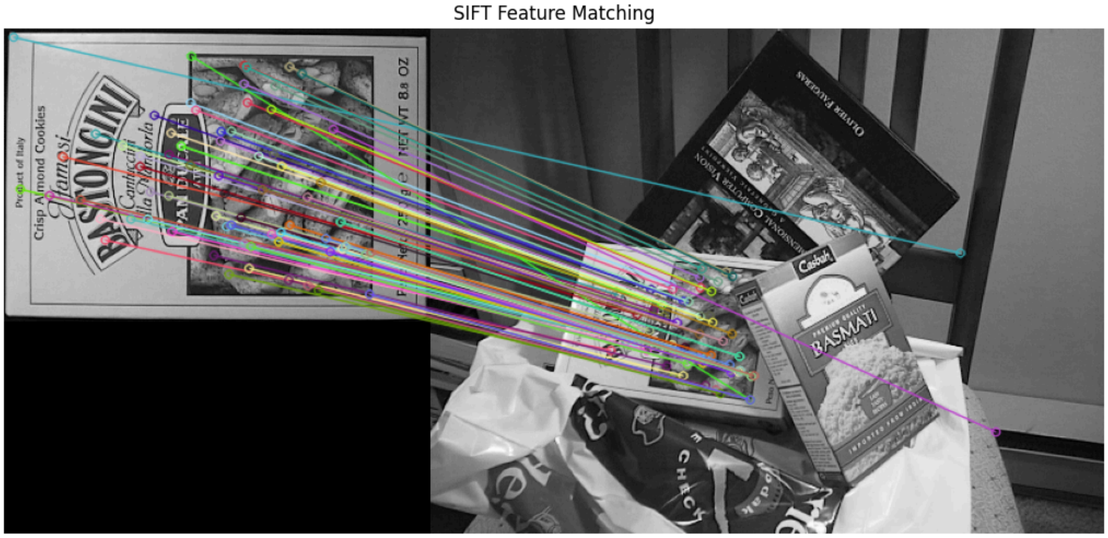
```
import cv2
import numpy as np
from matplotlib import pyplot as plt

img1 = cv2.imread('/content/box.png', cv2.IMREAD_GRAYSCALE)
img2 = cv2.imread('/content/box_in_scene.png', cv2.IMREAD_GRAYSCALE)

plt.figure(figsize=(6,6))
plt.imshow(img1, cmap='gray')
plt.title("Image 1")
plt.axis('off')
plt.show()

plt.figure(figsize=(6,6))
plt.imshow(img2, cmap='gray')
plt.title("Image 2")
plt.axis('off')
plt.show()

sift = cv2.SIFT_create()

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

bf = cv2.BFMatcher()
matches = bf.knnMatch(des1, des2, k=2)

good_matches = []
for m, n in matches:
```

```python
    if m.distance < 0.75 * n.distance:
        good_matches.append([m])

matched_img = cv2.drawMatchesKnn(img1, kp1, img2, kp2, good_matches,
None, flags=2)

plt.figure(figsize=(15, 6))
plt.imshow(cv2.cvtColor(matched_img, cv2.COLOR_BGR2RGB))
plt.title("SIFT Feature Matching")
plt.axis('off')
plt.show()
```

Image 1

Image 2

SIFT Feature Matching



SIFT (Scale-Invariant Feature Transform): SIFT was successfully applied to detect and describe keypoints in two different images. The algorithm demonstrated its robustness by accurately identifying matching features despite changes in scale, rotation, and slight perspective differences. It effectively extracted invariant features that are useful for object recognition tasks.

2. Use RANSAC to remove outlier key point matches and fit a transformation model between two images.

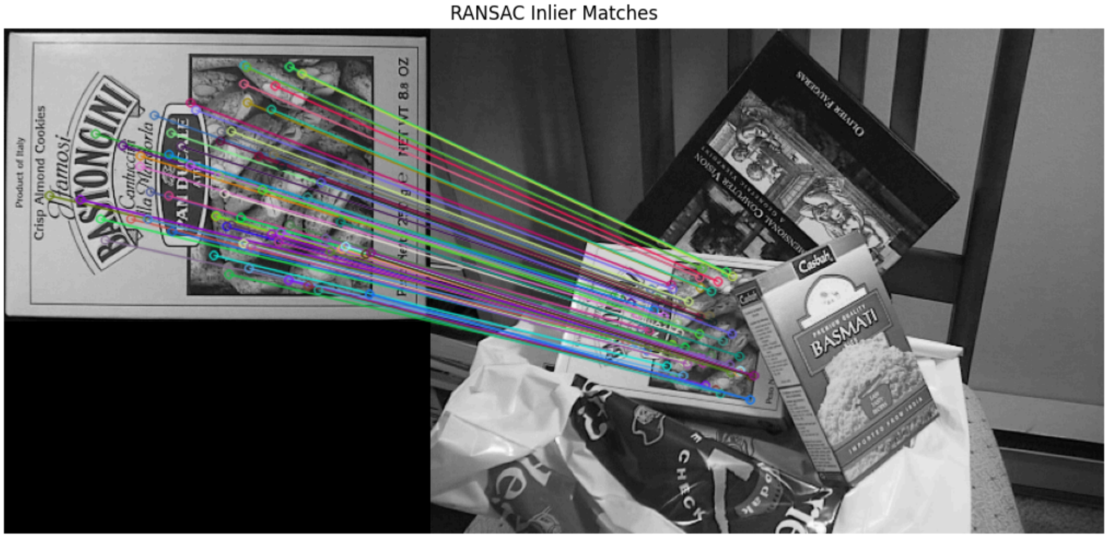
```
import cv2
import numpy as np
from matplotlib import pyplot as plt

img1 = cv2.imread('/content/box.png', cv2.IMREAD_GRAYSCALE)
img2 = cv2.imread('/content/box_in_scene.png', cv2.IMREAD_GRAYSCALE)

plt.figure(figsize=(6,6))
plt.imshow(img1, cmap='gray')
plt.title("Image 1")
plt.axis('off')
plt.show()

plt.figure(figsize=(6,6))
plt.imshow(img2, cmap='gray')
plt.title("Image 2")
plt.axis('off')
plt.show()

sift = cv2.SIFT_create()
kp1, des1 = sift.detectAndCompute(img1, None)
kp2, des2 = sift.detectAndCompute(img2, None)

bf = cv2.BFMatcher()
matches = bf.knnMatch(des1, des2, k=2)

good_matches = []
for m, n in matches:
    if m.distance < 0.75 * n.distance:
        good_matches.append(m)

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)
matchesMask = mask.ravel().tolist()

inlier_matches = [good_matches[i] for i in range(len(good_matches)) if
matchesMask[i]]
```

```python
ransac_result = cv2.drawMatches(img1, kp1, img2, kp2, inlier_matches,
None, flags=2)

plt.figure(figsize=(15, 6))
plt.imshow(cv2.cvtColor(ransac_result, cv2.COLOR_BGR2RGB))
plt.title("RANSAC Inlier Matches")
plt.axis('off')
plt.show()
```

Image 1

Image 2

RANSAC Inlier Matches



RANSAC (Random Sample Consensus): To improve the reliability of feature matching, RANSAC was used to eliminate outliers from the initial SIFT matches. By estimating a homography between the two sets of matched points, RANSAC preserved only the inlier matches that agreed with the transformation model. This step significantly enhanced match accuracy and robustness, especially in the presence of noise or false matches.

3. Implement the Harris corner detector to find and visualize corners in a grayscale image.

```
import cv2
import numpy as np
from matplotlib import pyplot as plt

img = cv2.imread('/content/building.jpg')
gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

plt.figure(figsize=(6,6))
plt.imshow(cv2.cvtColor(img, cv2.COLOR_BGR2RGB))
plt.title("Input Image")
plt.axis('off')
plt.show()

gray = np.float32(gray)
dst = cv2.cornerHarris(gray, blockSize=2, ksize=3, k=0.04)

dst = cv2.dilate(dst, None)

img_with_corners = img.copy()
img_with_corners[dst > 0.01 * dst.max()] = [0, 0, 255]

plt.figure(figsize=(6,6))
plt.imshow(cv2.cvtColor(img_with_corners, cv2.COLOR_BGR2RGB))
plt.title("Harris Corners Detected")
plt.axis('off')
plt.show()
```

Input Image

Harris Corners Detected

Harris Corner Detection: Harris Corner Detection was implemented to identify strong corner features in grayscale images. The algorithm detected prominent corners based on gradient changes and worked particularly well on structured images like boxes, buildings, and checkerboard patterns. This technique provides a foundational understanding of corner-based feature extraction.

Conclusion :

SIFT (Scale-Invariant Feature Transform)

- Observation: SIFT effectively detected and matched keypoints between two images even under scale, rotation, and lighting changes.
- Strength: It extracts robust and distinctive local features, making it ideal for tasks like object recognition, image stitching, and matching.
- Limitation: Computationally more expensive than simpler detectors; performance may vary on textureless or repetitive regions.

RANSAC (Random Sample Consensus)

- Observation: RANSAC improved the accuracy of SIFT matching by filtering out noisy/outlier matches using geometric consistency.
- Strength: It robustly estimates a transformation (e.g., homography) between images and keeps only the inliers — ensuring more reliable matching.
- Limitation: It may discard good matches if thresholds aren't tuned properly, and its results can vary depending on randomness.

Harris Corner Detection

- Observation: Harris successfully identified prominent corners in structured images (e.g., buildings, boxes, chessboards) with sharp edges.
- Strength: It's computationally simple and provides a strong base for tracking and corner-based algorithms.
- Limitation: Sensitive to scale and rotation; struggles in textured or curved regions compared to modern descriptors like SIFT or ORB.

Final Insights :

All three algorithms are powerful tools in computer vision for different stages of feature-based image analysis.

SIFT + RANSAC together form a highly reliable pipeline for object recognition and image alignment.

Harris provides a simpler, yet effective, method for detecting corners which can be used in tracking and motion analysis tasks.