全景图拼接

实验目的

1. 熟悉 Harris 角点检测器的原理和基本使用
2. 熟悉 RANSAC 抽样一致方法的使用场景
3. 熟悉 HOG 描述子的基本原理

实验要求

1. 提交实验报告，要求有适当步骤说明和结果分析、对比
2. 将代码和结果打包提交
3. 实验可以使用现有的特征描述子实现

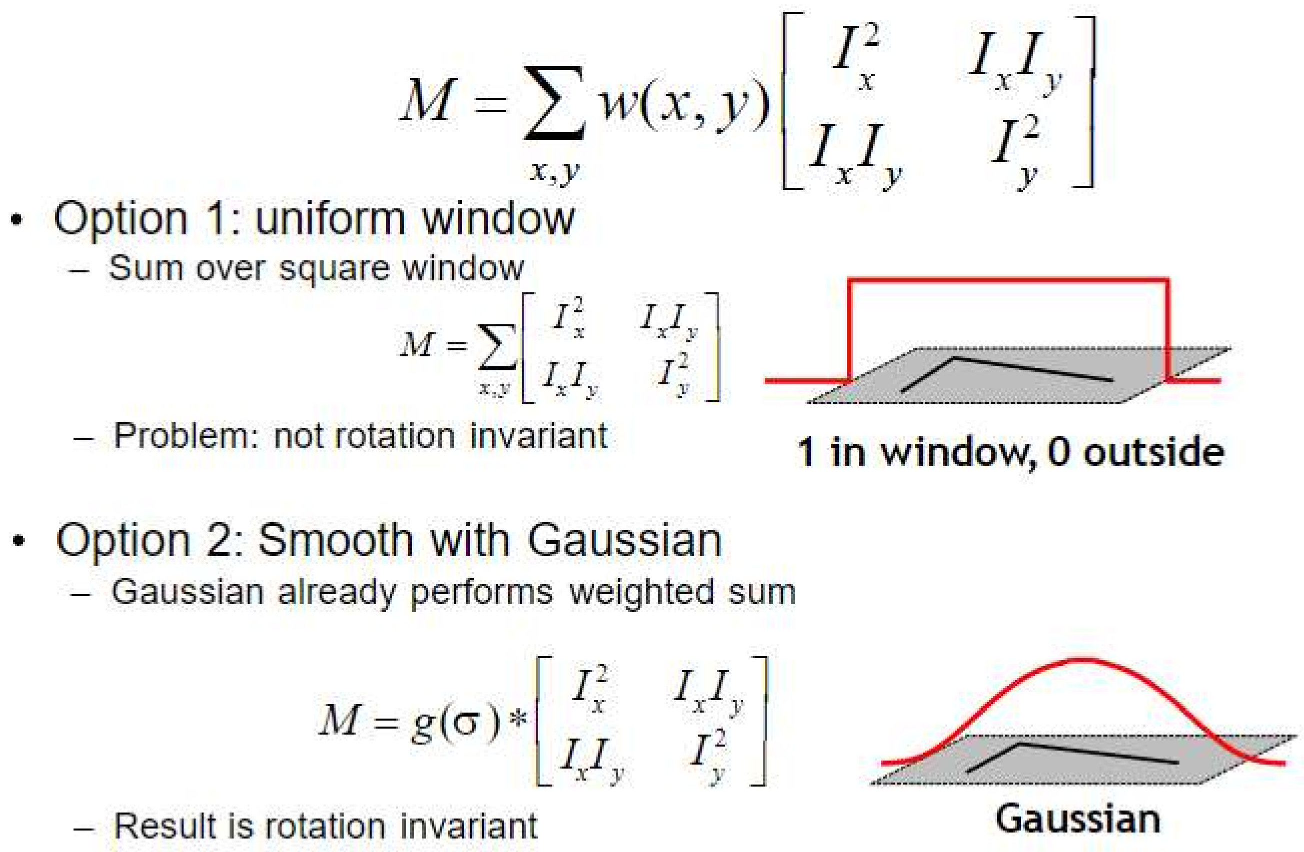
实验内容

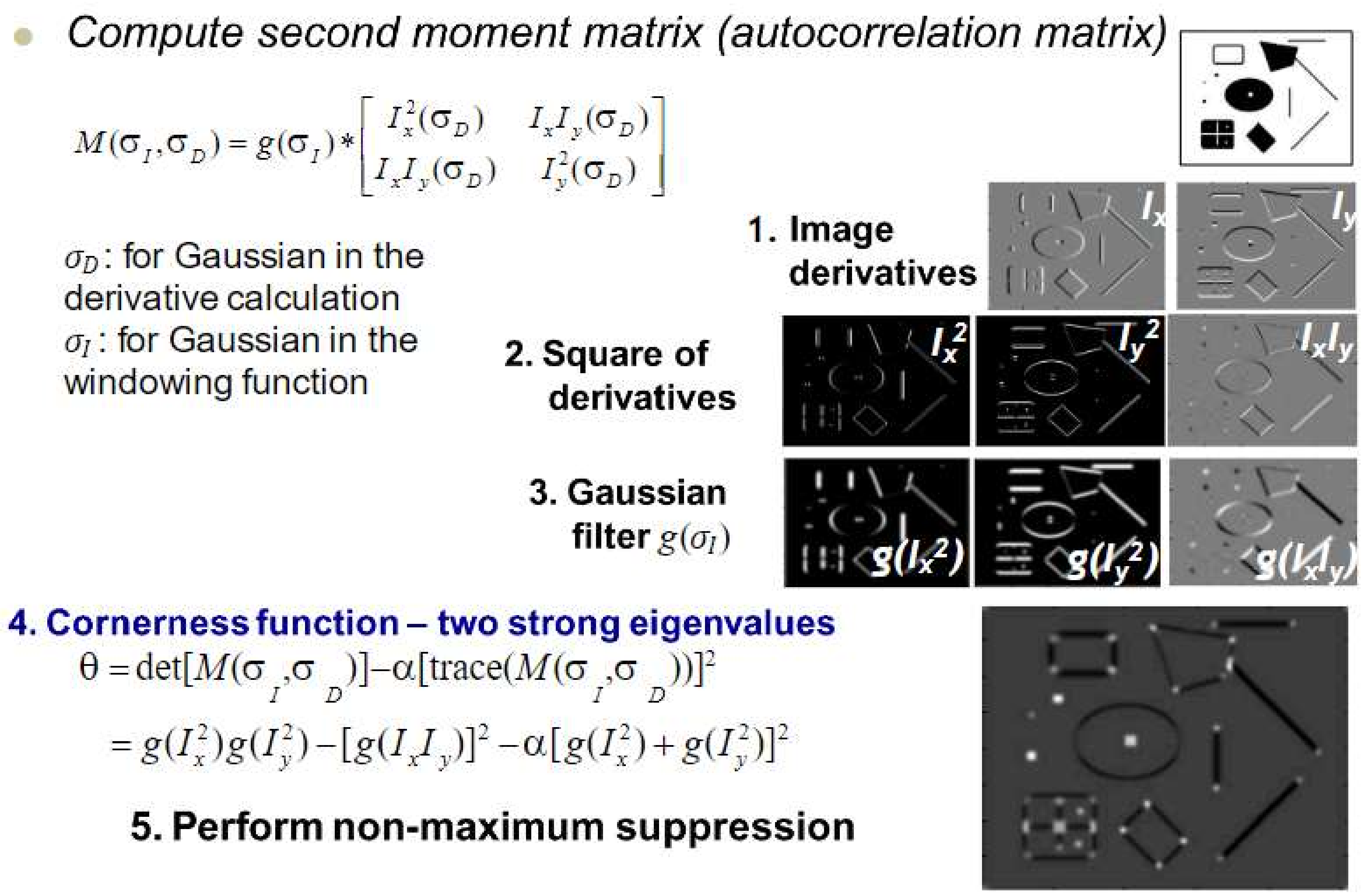
1. 使用 Harris 角点检测器寻找关键点。
2. 构建描述算子来描述图中的每个关键点，比较两幅图像的两组描述子，并进行匹配。
3. 根据一组匹配关键点，使用 RANSAC 进行仿射变化矩阵的计算。
4. 将第二幅图变换过来并覆盖在第一幅图上，拼接形成一个全景图像。
5. 实现不同的描述子，并得到不同的拼接效果。

实验过程

Harris 角点算法

Harris 角点算法的原理如下：





下面是 Harris 角点检测的代码实现：

- Harris 算法只需要处理亮度信息，因此我们读取图像后将其转换为灰度图。

```
img = cv2.imread(img_path)
gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
```

- 使用3x3的Sobel算子计算x方向以及y方向的梯度。

```
Ix = cv2.Sobel(gray, cv2.CV_64F, 1, 0, ksize=3)
Iy = cv2.Sobel(gray, cv2.CV_64F, 0, 1, ksize=3)
```

- 分别计算I_x^2、I_y^2、I_{xy}，并使用高斯函数进行平滑处理。

```
window_size = 3
Ix2 = cv2.GaussianBlur(Ix**2, (window_size, window_size), 0)
Iy2 = cv2.GaussianBlur(Iy**2, (window_size, window_size), 0)
Ixy = cv2.GaussianBlur(Ix * Iy, (window_size, window_size), 0)
```

- 计算Harris响应函数$R=\det(M)-\alpha\cdot\mathrm{trace}(M)^2$。

```
k = 0.04 # Harris parameter α
det = Ix2 * Iy2 - Ixy**2
trace = Ix2 + Iy2
R = det - k * trace**2
```

- 设置自适应阈值，这里取R的最大值的0.01倍，用于过滤弱响应点。然后应用阈值，将小于阈值的点置为0，保留强响应点。

```
threshold = 0.01 * R.max()
R[R < threshold] = 0
```

- 对响应图进行膨胀操作，将强响应点连接起来。

```
R = cv2.dilate(R, None)
```

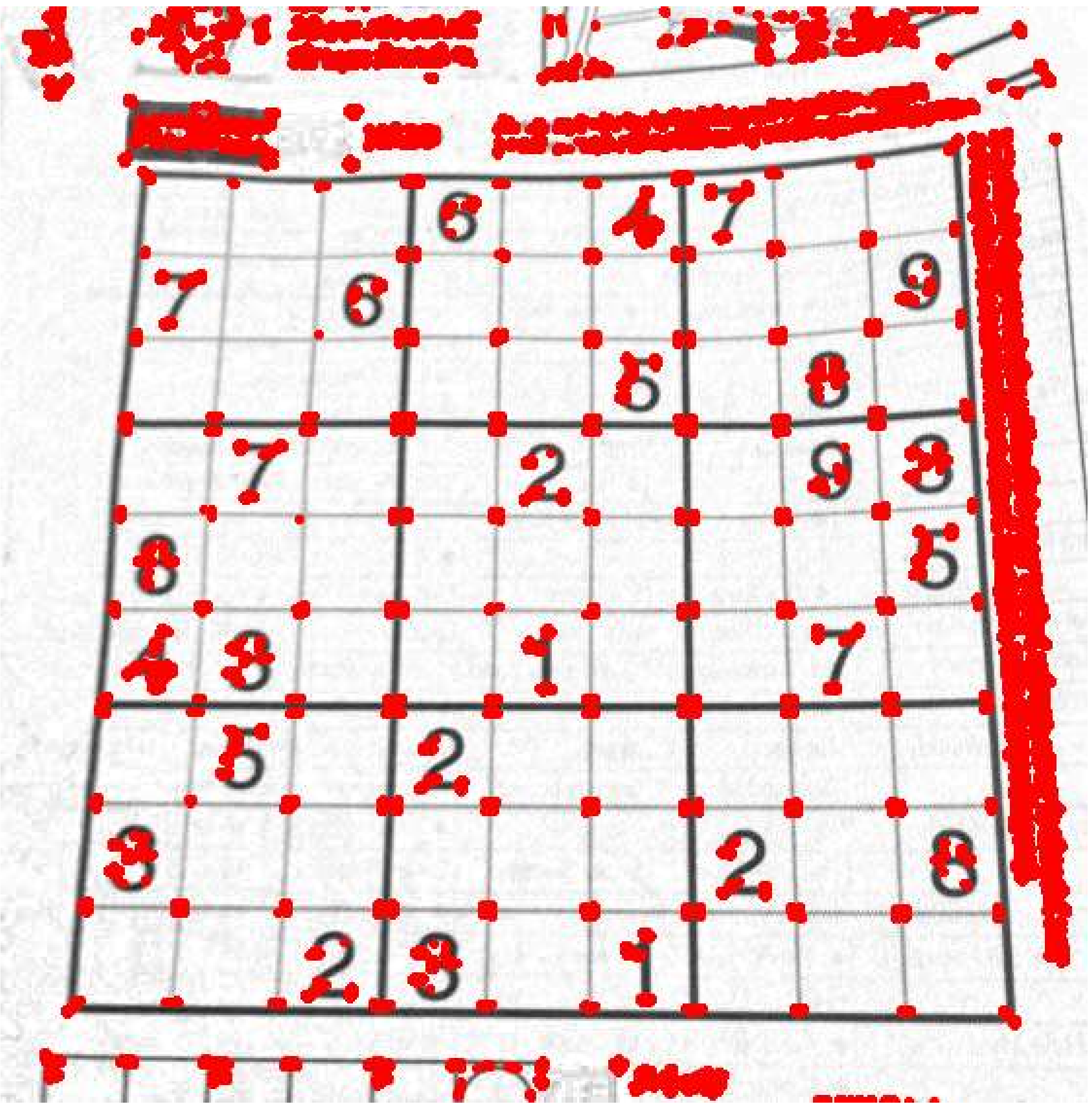
- 最后，获取强响应点的坐标。

```
keypoints = np.argwhere(R > 0)
```

完整的函数实现如下:

```
def harris_corner_detection(img_path):
    img = cv2.imread(img_path)
    gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

    Ix = cv2.Sobel(gray, cv2.CV_64F, 1, 0, ksize=3)
    Iy = cv2.Sobel(gray, cv2.CV_64F, 0, 1, ksize=3)

    window_size = 3
    k = 0.04 # Harris parameter α

    Ix2 = cv2.GaussianBlur(Ix**2, (window_size, window_size), 0)
    Iy2 = cv2.GaussianBlur(Iy**2, (window_size, window_size), 0)
    Ixy = cv2.GaussianBlur(Ix * Iy, (window_size, window_size), 0)

    det = Ix2 * Iy2 - Ixy**2
    trace = Ix2 + Iy2
    R = det - k * trace**2

    threshold = 0.01 * R.max()
    R[R < threshold] = 0
    R = cv2.dilate(R, None)
    keypoints = np.argwhere(R > 0)
    return keypoints
```

处理sudoku.png效果如下:



关键点描述与匹配

SIFT 描述子

SIFT 描述子的实现如下（具体含义见代码注释）：

```python
def match_sift_features(img1_path, img2_path):
    # 读取图像，并将图像转换为灰度图
    img1 = cv2.imread(img1_path)
    img2 = cv2.imread(img2_path)
    gray1 = cv2.cvtColor(img1, cv2.COLOR_BGR2GRAY)
    gray2 = cv2.cvtColor(img2, cv2.COLOR_BGR2GRAY)

    # 使用OpenCV内置的SIFT检测器，检测关键点并计算描述子
    sift = cv2.SIFT_create()
    keypoints1, descriptors1 = sift.detectAndCompute(gray1, None)
    keypoints2, descriptors2 = sift.detectAndCompute(gray2, None)

    # 使用暴力匹配器进行特征匹配
    bf = cv2.BFMatcher(cv2.NORM_L2, crossCheck=True)
    matches = bf.match(descriptors1, descriptors2)

    # 按照距离排序
    matches = sorted(matches, key=lambda x: x.distance)

    # 绘制前50个最佳匹配
    match_img = cv2.drawMatches(img1, keypoints1, img2, keypoints2, matches[:50], None,
                                flags=cv2.DrawMatchesFlags_NOT_DRAW_SINGLE_POINTS)

    return keypoints1, keypoints2, descriptors1, descriptors2, matches, match_img
```

HOG 描述子

HOG 描述子的实现如下（具体含义见代码注释）：

```python
def match_hog_features(img1_path, img2_path):
    # 读取图像，并将图像转换为灰度图
    img1 = cv2.imread(img1_path)
    img2 = cv2.imread(img2_path)
    gray1 = cv2.cvtColor(img1, cv2.COLOR_BGR2GRAY)
    gray2 = cv2.cvtColor(img2, cv2.COLOR_BGR2GRAY)

    # 使用OpenCV内置的SIFT检测器，检测关键点并计算描述子
    # （虽然这里用我实现的Harris检测器也可以，但可惜我的实现比cv2中SIFT的实现运行速度差了一大截，
    # 为了方便后续做运行时间对比，这里使用cv2中的SIFT检测器）
    # detector = cv2.SIFT_create(nfeatures=100)
    detector = cv2.SIFT_create()
    keypoints1 = detector.detect(gray1, None)
    keypoints2 = detector.detect(gray2, None)

    hog_params = dict(orientations=8, pixels_per_cell=(4, 4), cells_per_block=(2, 2), visualize=False)

    # 计算HOG描述子
    def compute_hog_descriptors(image, keypoints, params):
        descriptors = []
        valid_kps = []
        for kp in keypoints:
            x, y = int(kp.pt[0]), int(kp.pt[1])
            if 8 <= x < image.shape[1]-8 and 8 <= y < image.shape[0]-8:
                window = image[y-8:y+8, x-8:x+8]
                desc = hog(window, **params)
                descriptors.append(desc)
                valid_kps.append(kp)
        return np.array(descriptors, dtype=np.float32), valid_kps

    descriptors1, valid_keypoints1 = compute_hog_descriptors(gray1, keypoints1, hog_params)
    descriptors2, valid_keypoints2 = compute_hog_descriptors(gray2, keypoints2, hog_params)

    # 使用暴力匹配器进行特征匹配
    bf = cv2.BFMatcher(cv2.NORM_L2, crossCheck=True)
    matches = bf.match(descriptors1, descriptors2)

    # 按照距离排序
    matches = sorted(matches, key=lambda x: x.distance)

    # 绘制前50个最佳匹配
    match_img = cv2.drawMatches(img1, valid_keypoints1, img2, valid_keypoints2,
                                matches[:50], None,
                                flags=cv2.DrawMatchesFlags_NOT_DRAW_SINGLE_POINTS)

    return valid_keypoints1, valid_keypoints2, descriptors1, descriptors2, matches, match_img
```

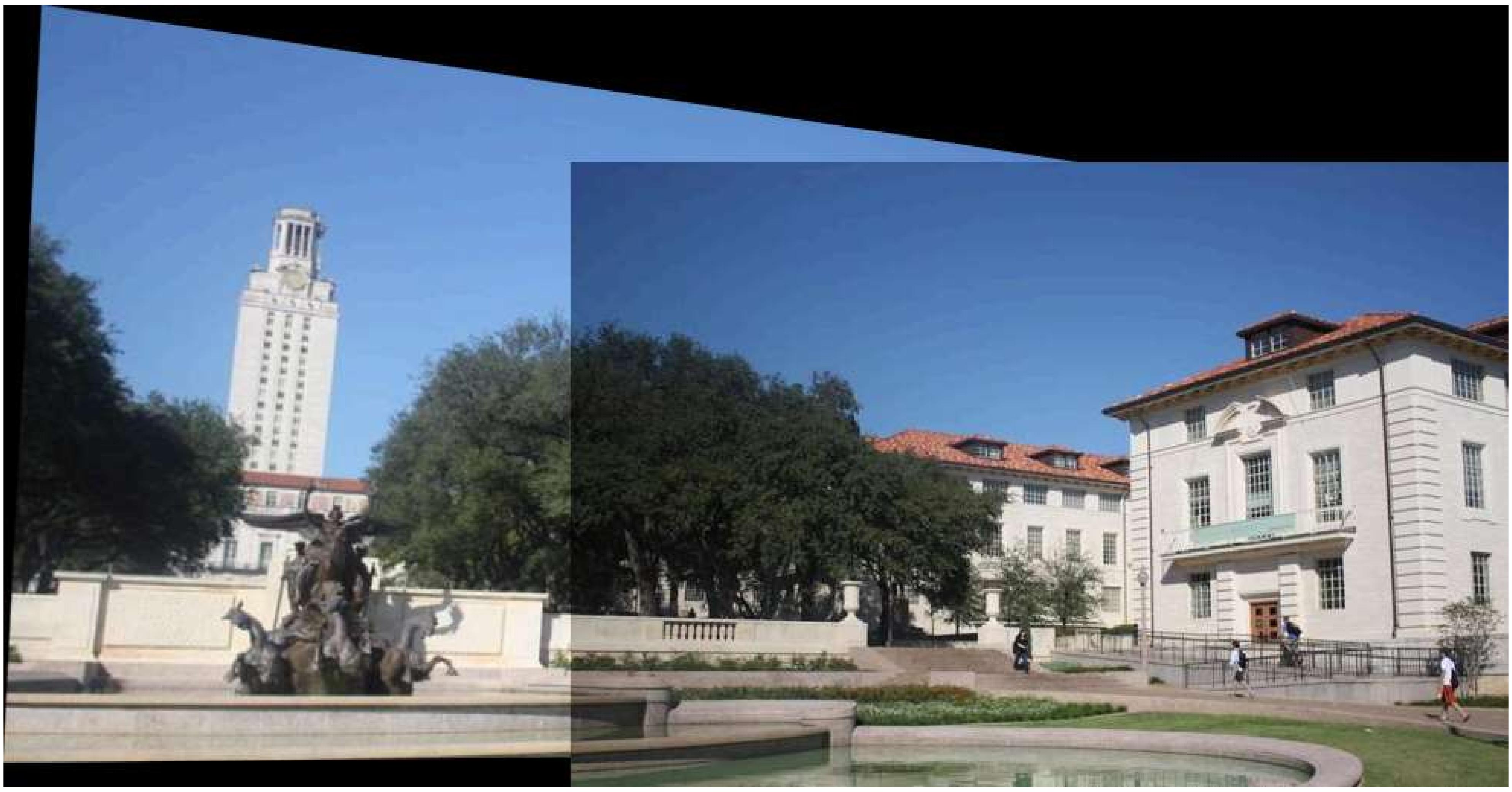
使用 RANSAC 求解仿射变换矩阵，并实现图像拼接

在实现了 SIFT 和 HOG 描述子后，我们就可以使用 RANSAC 算法求解仿射变换矩阵，并实现图像拼接。

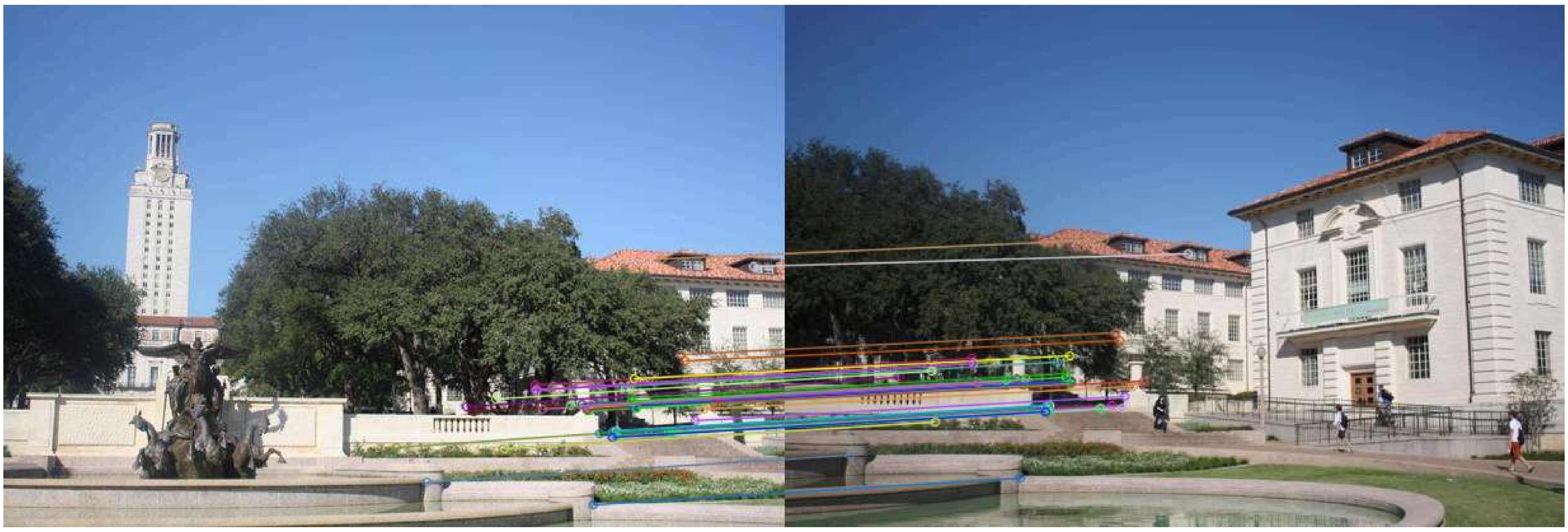
```python
def stitch_images_with_ransac(img1, keypoints1, img2, keypoints2, matches):
    # 获取匹配点坐标
    src_pts = np.float32([keypoints1[m.queryIdx].pt for m in matches]).reshape(-1, 1, 2)
    dst_pts = np.float32([keypoints2[m.trainIdx].pt for m in matches]).reshape(-1, 1, 2)

    # 使用RANSAC方法估计单应性矩阵
    M, mask = cv2.findHomography(src_pts, dst_pts, cv2.RANSAC, 5.0)

    # 获取图像尺寸
    h1, w1 = img1.shape[:2]
    h2, w2 = img2.shape[:2]

    # 计算变换后的图像边界
    pts = np.float32([[0, 0], [0, h1-1], [w1-1, h1-1], [w1-1, 0]]).reshape(-1, 1, 2)
    dst = cv2.perspectiveTransform(pts, M)

    # 计算拼接图像的尺寸
    min_x = min(0, dst[0][0][0], dst[1][0][0], dst[2][0][0], dst[3][0][0])
    min_y = min(0, dst[0][0][1], dst[1][0][1], dst[2][0][1], dst[3][0][1])
    max_x = max(w2, dst[0][0][0], dst[1][0][0], dst[2][0][0], dst[3][0][0])
    max_y = max(h2, dst[0][0][1], dst[1][0][1], dst[2][0][1], dst[3][0][1])

    # 调整变换矩阵以适应新的图像尺寸
    translation_matrix = np.array([
        [1, 0, -min_x],
        [0, 1, -min_y],
        [0, 0, 1]
    ])
    M_translated = translation_matrix.dot(M)

    # 创建拼接图像
    stitched_width = int(max_x - min_x)
    stitched_height = int(max_y - min_y)
    stitched_img = np.zeros((stitched_height, stitched_width, 3), dtype=np.uint8)

    # 将第一张图像变换到拼接图像上
    cv2.warpPerspective(img1, M_translated, (stitched_width, stitched_height), stitched_img)

    # 将第二张图像添加到拼接图像上
    stitched_img[-int(min_y):h2-int(min_y), -int(min_x):w2-int(min_x)] = img2

    return stitched_img
```

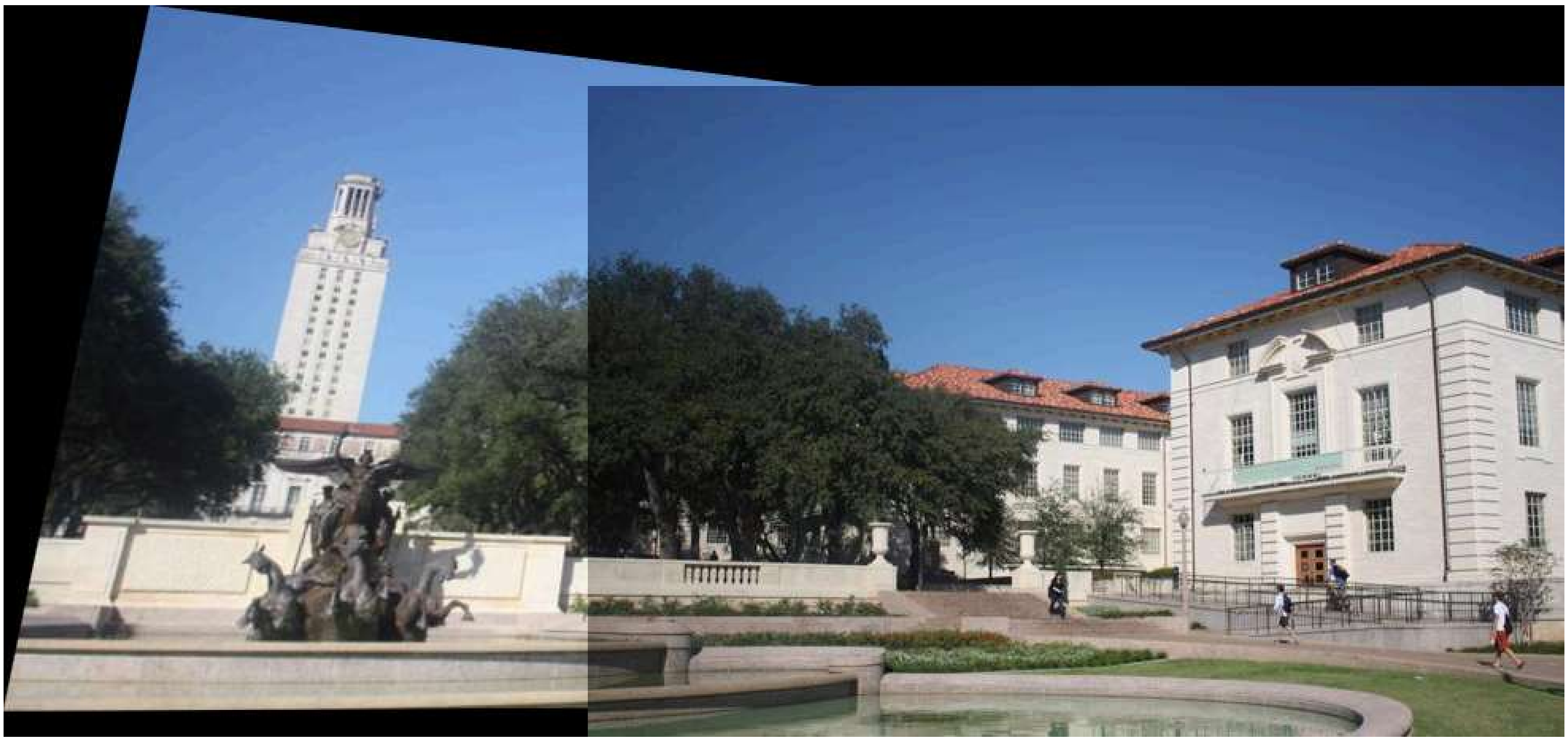
最终实现的拼接效果如下:

SIFT匹配效果



HOG匹配效果





SIFT与HOG特征匹配效果对比分析

通过对比SIFT与HOG特征匹配的结果，可以发现：

1. SIFT特征匹配生成了更多的有效匹配点，且分布更加均匀；HOG特征匹配的点数较少，主要集中在图像的高对比度区域。

2. SIFT特征匹配表现出了更好的视角不变性，即使图像有一定的角度变化，仍然能够找到正确的匹配。
3. 使用SIFT特征的拼接结果更加平滑自然，边缘过渡更加连贯。

理论情况下，HOG特征匹配的计算复杂度更低，然而实际运行时，我发现SIFT特征匹配的计算时间更短。这或许与我实现的HOG的匹配不如cv2中集成的SIFT匹配效果好有关，我尝试通过减少特征点数量来提高匹配速度，但这样将会导致HOG的匹配准确率大幅降低。具体运行时间见下：

```python
    suduku_output = draw_keypoints(suduku_img_path, suduku_keypoints)
    cv2.imwrite('results/sudoku_keypoints.png', suduku_output)

    uttower1_img_path = 'images/uttower1.jpg'
    uttower1_keypoints = harris_corner_detection(uttower1_img_path)
    uttower1_output = draw_keypoints(uttower1_img_path, uttower1_keypoints)
    cv2.imwrite('results/uttower1_keypoints.png', uttower1_output)

    uttower2_img_path = 'images/uttower2.jpg'
    uttower2_keypoints = harris_corner_detection(uttower2_img_path)
    uttower2_output = draw_keypoints(uttower2_img_path, uttower2_keypoints)
    cv2.imwrite('results/uttower2_keypoints.png', uttower2_output)

    # 2. SIFT and HOG feature matching
    uttower1_path = 'images/uttower1.jpg'
    uttower2_path = 'images/uttower2.jpg'

    # SIFT feature matching
    start_time = time.time()
    kp1_sift, kp2_sift, desc1_sift, desc2_sift, matches_sift, match_img_sift = match_sift_features(uttower1_path, uttower2_path)
    end_time = time.time()
    print(f"SIFT feature matching time: {end_time - start_time} seconds")
    if match_img_sift is not None:
        cv2.imwrite('results/uttower_match_sift.png', match_img_sift)

    # HOG feature matching
    start_time = time.time()
    kp1_hog, kp2_hog, desc1_hog, desc2_hog, matches_hog, match_img_hog = match_hog_features(uttower1_path, uttower2_path)
    end_time = time.time()
    print(f"HOG feature matching time: {end_time - start_time} seconds")
    if match_img_hog is not None:
        cv2.imwrite('results/uttower_match_hog.png', match_img_hog)

    # 3. Image stitching
```

Problems Output Debug Console Terminal Test Results Ports GitLens Python Debug

```
\2_Computer_Science\Pattern_Recognition\hw\Homework1\hw.py'
SIFT feature matching time: 0.08462762832641602 seconds
HOG feature matching time: 0.824716329574585 seconds
SIFT + RANSAC stitching time: 0.01467132568359375 seconds
HOG + RANSAC stitching time: 0.014742136001586914 seconds
(cv) [K] 3325.45ms ..\hw\Homework1 $
```

实现基于 SIFT+RANSAC 的多图像拼接

```python
def stitch_multiple_images(image_paths):
    # 读取第一张图像作为初始结果
    result = cv2.imread(image_paths[0])

    # 逐一拼接后续图像
    for i in range(1, len(image_paths)):
        img = cv2.imread(image_paths[i])

        # 使用SIFT提取特征
        sift = cv2.SIFT_create()

        # 转换为灰度图并计算特征
        gray_result = cv2.cvtColor(result, cv2.COLOR_BGR2GRAY)
        gray_img = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

        keypoints1, descriptors1 = sift.detectAndCompute(gray_result, None)
        keypoints2, descriptors2 = sift.detectAndCompute(gray_img, None)

        # 使用FLANN匹配器进行特征匹配
        FLANN_INDEX_KDTREE = 1
        index_params = dict(algorithm=FLANN_INDEX_KDTREE, trees=5)
        search_params = dict(checks=50)
        flann = cv2.FlannBasedMatcher(index_params, search_params)

        matches = flann.knnMatch(descriptors1, descriptors2, k=2)

        # 应用比率测试筛选优质匹配
        good_matches = []
        for m, n in matches:
            if m.distance < 0.7 * n.distance:
                good_matches.append(m)

        # 如果有足够的匹配点，执行拼接
        if len(good_matches) > 10:
            # 获取匹配点坐标
            src_pts = np.float32([keypoints1[m.queryIdx].pt for m in good_matches]).reshape(-1, 1, 2)
            dst_pts = np.float32([keypoints2[m.trainIdx].pt for m in good_matches]).reshape(-1, 1, 2)

            # 使用RANSAC方法估计单应性矩阵
            M, mask = cv2.findHomography(src_pts, dst_pts, cv2.RANSAC, 5.0)

            # 获取图像尺寸
            h1, w1 = result.shape[:2]
            h2, w2 = img.shape[:2]

            # 计算变换后的图像边界
            pts = np.float32([[0, 0], [0, h1-1], [w1-1, h1-1], [w1-1, 0]]).reshape(-1, 1, 2)
            dst = cv2.perspectiveTransform(pts, M)

            # 计算拼接图像的尺寸
            min_x = min(0, dst[0][0][0], dst[1][0][0], dst[2][0][0], dst[3][0][0])
            min_y = min(0, dst[0][0][1], dst[1][0][1], dst[2][0][1], dst[3][0][1])
            max_x = max(w2, dst[0][0][0], dst[1][0][0], dst[2][0][0], dst[3][0][0])
            max_y = max(h2, dst[0][0][1], dst[1][0][1], dst[2][0][1], dst[3][0][1])

            # 调整变换矩阵以适应新的图像尺寸
            translation_matrix = np.array([
                [1, 0, -min_x],
                [0, 1, -min_y],
                [0, 0, 1]
            ])
            M_translated = translation_matrix.dot(M)

            # 创建拼接图像
            stitched_width = int(max_x - min_x)
```

```
        stitched_height = int(max_y - min_y)
        stitched_img = np.zeros((stitched_height, stitched_width, 3), dtype=np.uint8)

        # 将当前结果变换到拼接图像上
        cv2.warpPerspective(result, M_translated, (stitched_width, stitched_height), stitched_img)

        # 将新图像添加到拼接图像上
        stitched_img[-int(min_y):h2-int(min_y), -int(min_x):w2-int(min_x)] = img

        # 更新结果
        result = stitched_img

    return result
```

上面实际上就是之前步骤的拼接，这里不再重复，直接贴效果：