National University
Of Computer and Emerging Sciences

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Computer Vision

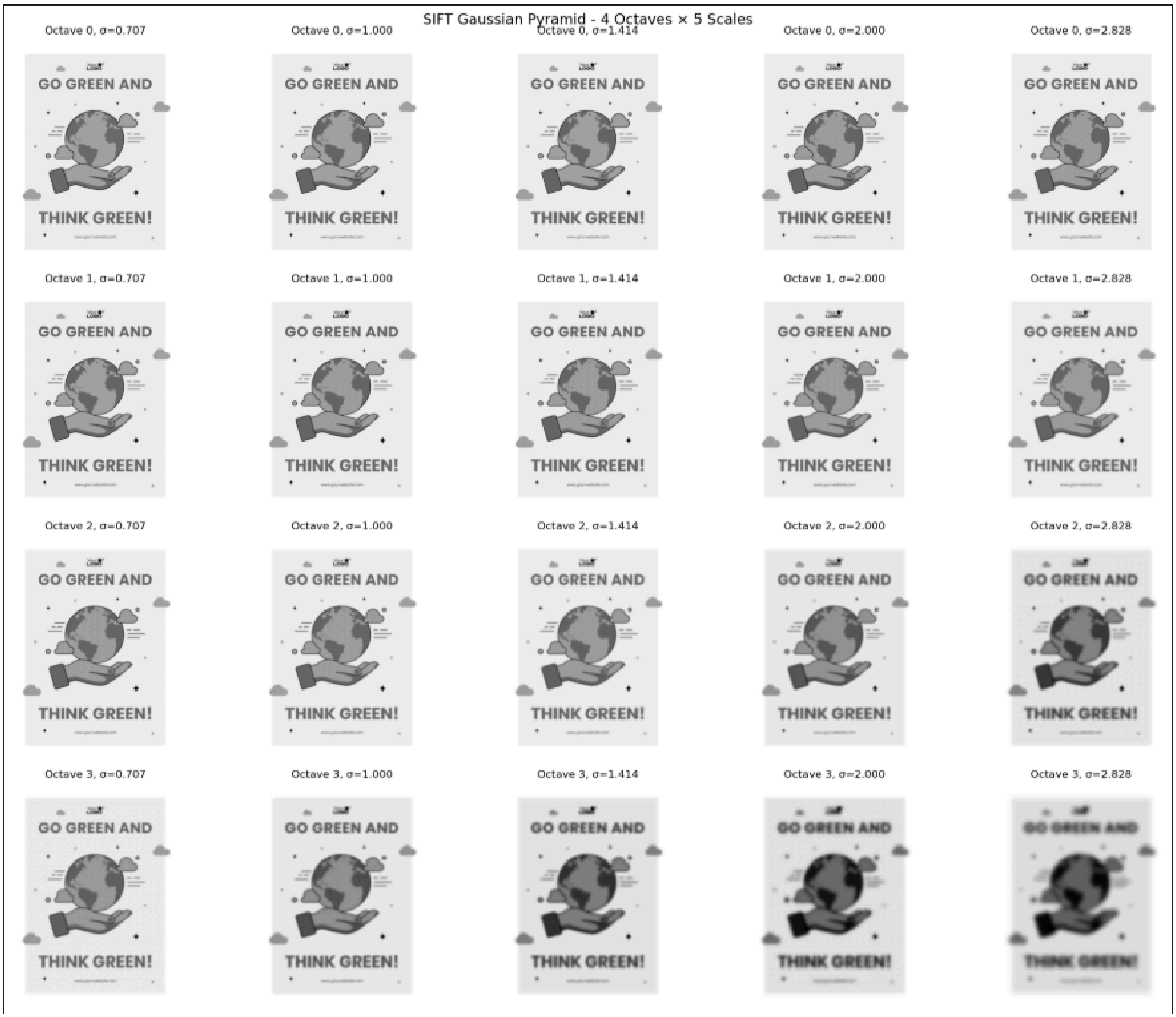
Lab 6 &7: SIFT

Lab Task 1 – Scale-Space and Difference-of-Gaussians (DoG) Construction

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

# %%
img = cv2.imread('green.jpg', cv2.IMREAD_GRAYSCALE)

image_h, image_w = img.shape

sigma_base = 0.707
k = np.sqrt(2)
octaves = []

for octave_i in range(4):

   if octave_i == 0:
       current_img = img
   else:
```

```
        current_img = cv2.resize(current_img, (current_img.shape[1]//2,
current_img.shape[0]//2), interpolation=cv2.INTER_LINEAR)

    sigma_values = []
    gaussian_images = []

    # Keep 5 scales as original
    for scale_i in range(5):
        current_sigma = sigma_base * (k ** scale_i)
        sigma_values.append(current_sigma)

        blurred_img = cv2.GaussianBlur(current_img, (0, 0),
sigmaX=current_sigma, sigmaY=current_sigma, borderType=cv2.BORDER_DEFAULT)
        gaussian_images.append(blurred_img)

    octaves.append({
        'gaussian_images': gaussian_images,
        'sigma_values': sigma_values,
        'shape': current_img.shape
    })

# %%
# Visualize Gaussian Pyramid
fig, axes = plt.subplots(4, 5, figsize=(20, 16))
fig.suptitle('SIFT Gaussian Pyramid - 4 Octaves × 5 Scales', fontsize=16)

for octave_i in range(4):
    for scale_i in range(5):
        ax = axes[octave_i, scale_i]
        img_to_show = octaves[octave_i]['gaussian_images'][scale_i]
        sigma_val = octaves[octave_i]['sigma_values'][scale_i]

        ax.imshow(img_to_show, cmap='gray')
        ax.set_title(f'Octave {octave_i}, σ={sigma_val:.3f}')
        ax.axis('off')
```

```
plt.tight_layout()
plt.show()
```



```
dog_octaves = []

for octave_i in range(4):
   dog_images = []

   for scale_i in range(4):  # 5 Gaussians → 4 DoGs
       img1 =
octaves[octave_i]['gaussian_images'][scale_i].astype(np.float32)
       img2 = octaves[octave_i]['gaussian_images'][scale_i +
1].astype(np.float32)

       # Normalize to [0, 1] range
       dog = (img2 - img1) / 255.0
       dog_images.append(dog)

   dog_octaves.append({
       'dog_images': dog_images,
       'shape': octaves[octave_i]['shape']
   })

# %%
# Visualize DoG
fig, axes = plt.subplots(4, 4, figsize=(16, 16))
fig.suptitle('Difference of Gaussians (DoG) - 4 Octaves × 4 DoG Images',
fontsize=16)

for octave_i in range(4):
   for dog_i in range(4):
       ax = axes[octave_i, dog_i]
       dog_img = dog_octaves[octave_i]['dog_images'][dog_i]

       ax.imshow(dog_img, cmap='gray')
       ax.set_title(f'Octave {octave_i}, DoG {dog_i}')
       ax.axis('off')
```

```
plt.tight_layout()
plt.show()
```

Lab Task 2 – Keypoint Detection and Refinement

Objective: Detect and filter keypoints using DoG extrema and local gradient analysis.

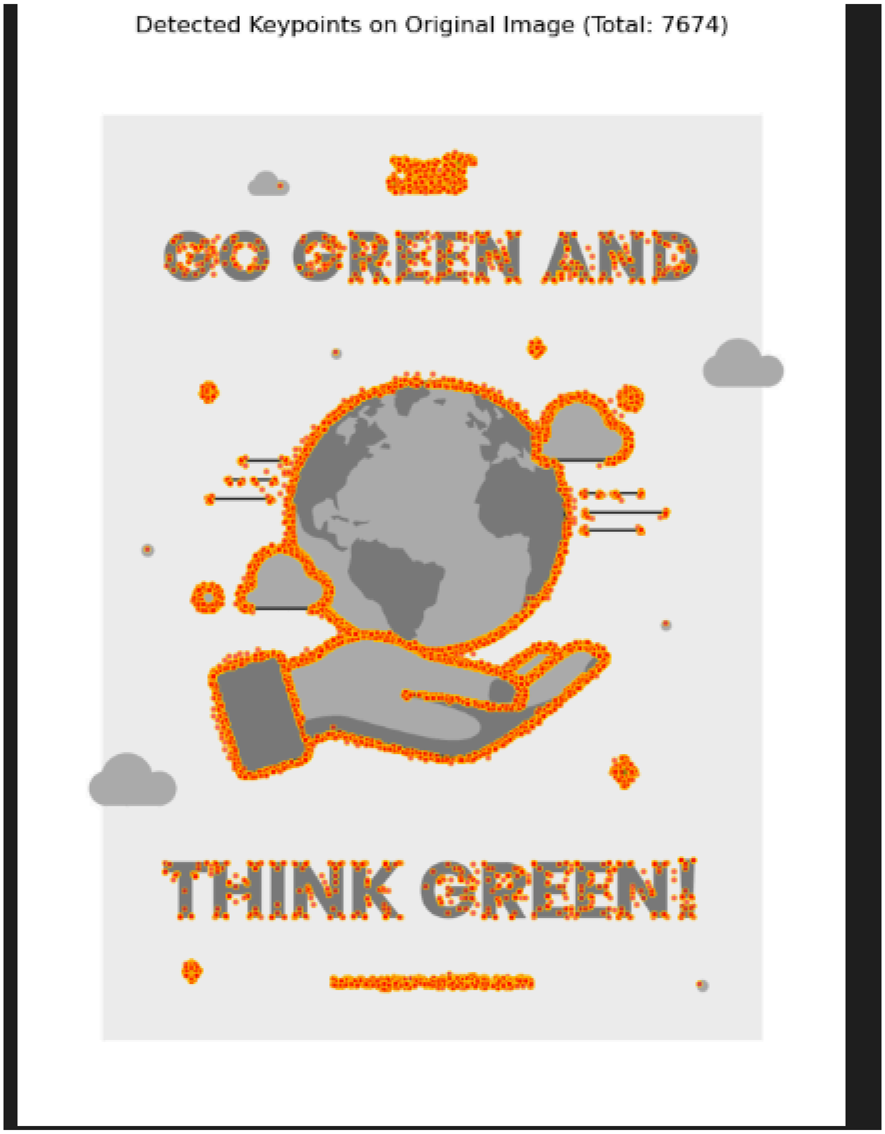
Steps:

1. Identify potential keypoints by checking local extrema in 3×3×3 neighborhoods across DoG images.
2. Eliminate low-contrast points (e.g., |DoG| < 0.04).
3. Remove edge-like points using the principal curvature ratio (Hessian test).
4. Visualize detected keypoints on the original image using cv2.circle() or plt.scatter().

```
for octave_i, octave_data in enumerate(dog_octaves):
   print(f"\nOctave {octave_i}:")
   print(f"  Shape: {octave_data['shape']}")

edge_threshold = 10
contrast_threshold = 0.03
keypoints = []

for octave_i in range(4):
   dog_images = dog_octaves[octave_i]['dog_images']
   sigma_values = octaves[octave_i]['sigma_values']
   h, w = dog_octaves[octave_i]['shape']


   for dog_i in range(1, 3):
       prev_dog = dog_images[dog_i - 1]
       current_dog = dog_images[dog_i]
       next_dog = dog_images[dog_i + 1]

       for y in range(1, h - 1):
           for x in range(1, w - 1):
```

```
                center_value = current_dog[y, x]


                cube = np.stack([
                    prev_dog[y-1:y+2, x-1:x+2],
                    current_dog[y-1:y+2, x-1:x+2],
                    next_dog[y-1:y+2, x-1:x+2]
                ])


                 if (center_value == cube.max() or center_value == cube.min())
and abs(center_value) > contrast_threshold:


                        Dxx = current_dog[y, x+1] + current_dog[y, x-1] - 2 *
center_value
                        Dyy = current_dog[y+1, x] + current_dog[y-1, x] - 2 *
center_value
                    Dxy = (current_dog[y+1, x+1] - current_dog[y+1, x-1]
                          - current_dog[y-1, x+1] + current_dog[y-1, x-1]) /
4.0

                    detH = Dxx * Dyy - Dxy**2
                    traceH = Dxx + Dyy

                    if detH > 0:
                        r = (traceH**2) / detH
                        r_thresh = ((edge_threshold + 1)**2) / edge_threshold
                        if r < r_thresh:

                            sigma = sigma_values[dog_i + 1]
                            x_real = x * (2 ** octave_i)
                            y_real = y * (2 ** octave_i)
```

```
                            keypoints.append((x_real, y_real, sigma, octave_i,
dog_i))


   octave_kp_count = sum(1 for kp in keypoints if kp[3] == octave_i)
   print(f"Octave {octave_i}: {octave_kp_count} keypoints")

print(f"\nTotal keypoints detected: {len(keypoints)}")

print("\nSample keypoints (x, y, σ, octave, dog, response):")
for i, (x, y, sigma, octave, dog) in enumerate(keypoints[:10]):
    print(f"   KP {i+1}: x={x:.1f}, y={y:.1f}, σ={sigma:.3f}, oct={octave},
dog={dog}")
```



Lab Task 3 – Orientation Assignment and Descriptor Generation

Objective: Compute orientation and generate 128-dimensional SIFT descriptors.

Steps:

1. For each keypoint, compute gradient magnitude and orientation within a circular window.
2. Construct an orientation histogram (36 bins, 10° each) weighted by gradient magnitude and Gaussian distance.
3. Assign one or more dominant orientations to each keypoint.
4. Divide the local patch into 4×4 subregions; compute an 8-bin orientation histogram for each region.

5. Flatten, normalize, and visualize the descriptor.
6. Compare the output with cv2.SIFT_create() for validation.

Expected Output:

- Keypoints with orientations drawn as arrows or lines.
- Descriptor arrays printed or visualized as histograms.
- Side-by-side comparison with OpenCV's SIFT results.

```
def compute_gradient_magnitude_orientation(image):
   Gx = cv2.Sobel(image.astype(np.float64), cv2.CV_64F, 1, 0, ksize=3)
   Gy = cv2.Sobel(image.astype(np.float64), cv2.CV_64F, 0, 1, ksize=3)
   magnitude = np.sqrt(Gx**2 + Gy**2)
   orientation = (np.degrees(np.arctan2(Gy, Gx)) + 360) % 360
   return magnitude, orientation


def assign_orientation_to_keypoints(octaves, dog_octaves, keypoints,
num_bins=36):

   oriented_keypoints = []
   bin_width = 360 / num_bins

   for (x_real, y_real, sigma, octave_i, dog_i) in keypoints:

       scale_factor = 2 ** octave_i
       x = int(x_real / scale_factor)
       y = int(y_real / scale_factor)


       gaussian_image = octaves[octave_i]['gaussian_images'][dog_i + 1]
       magnitude, orientation =
compute_gradient_magnitude_orientation(gaussian_image)


       dog_image = dog_octaves[octave_i]['dog_images'][dog_i]
       response = abs(dog_image[y, x])
```

```
    h, w = gaussian_image.shape
    radius = int(round(1.5 * sigma))


    if x < radius or y < radius or x >= (w - radius) or y >= (h - radius):
        continue


    patch_mag = magnitude[y - radius:y + radius + 1,
                          x - radius:x + radius + 1]
    patch_ori = orientation[y - radius:y + radius + 1,
                            x - radius:x + radius + 1]


    y_grid, x_grid = np.ogrid[-radius:radius+1, -radius:radius+1]
    gaussian_weight = np.exp(-(x_grid**2 + y_grid**2) / (2 * (1.5 *
sigma)**2))


    hist = np.zeros(num_bins)
    for i in range(patch_ori.shape[0]):
        for j in range(patch_ori.shape[1]):
            angle = patch_ori[i, j]
            bin_idx = int(angle // bin_width) % num_bins
            hist[bin_idx] += patch_mag[i, j] * gaussian_weight[i, j]


    hist_padded = np.concatenate([hist[-3:], hist, hist[:3]])
    kernel = np.array([1, 4, 6, 4, 1]) / 16.0
    hist_smooth = np.convolve(hist_padded, kernel, mode='valid')


    max_val = np.max(hist_smooth)
    if max_val == 0:
```

```
            continue


        dominant_bins = np.where(hist_smooth >= 0.8 * max_val)[0]

        for b in dominant_bins:

            prev_val = hist_smooth[(b - 1) % num_bins]
            curr_val = hist_smooth[b]
            next_val = hist_smooth[(b + 1) % num_bins]

            interp_offset = 0.5 * (prev_val - next_val) / (prev_val - 2*curr_val + next_val + 1e-10)
            bin_refined = (b + interp_offset) % num_bins
            theta = bin_refined * bin_width

            oriented_keypoints.append((x_real, y_real, sigma, octave_i, dog_i, theta, response))

    return oriented_keypoints


def non_maximum_suppression(oriented_keypoints, radius=10):

    if len(oriented_keypoints) == 0:
        return []


    sorted_kps = sorted(oriented_keypoints, key=lambda x: x[6], reverse=True)

    filtered = []

    for kp in sorted_kps:
        x, y, sigma, octave, dog, theta, response = kp
```

```
        too_close = False
        for (x2, y2, sigma2, _, _, _, _) in filtered:
            dist = np.sqrt((x - x2)**2 + (y - y2)**2)

            min_sigma = min(sigma, sigma2)
            if dist < radius * min_sigma:
                too_close = True
                break

        if not too_close:
            filtered.append(kp)

    return filtered



def compute_sift_descriptors(octaves, oriented_keypoints):

    descriptors = []
    valid_keypoints = []

    for (x_real, y_real, sigma, octave_i, dog_i, theta, response) in
oriented_keypoints:

        scale_factor = 2 ** octave_i
        x = int(x_real / scale_factor)
        y = int(y_real / scale_factor)


        gaussian_image = octaves[octave_i]['gaussian_images'][dog_i + 1]
        magnitude, orientation =
compute_gradient_magnitude_orientation(gaussian_image)

        h, w = gaussian_image.shape
```

```
    patch_radius = 8

    if x < patch_radius or y < patch_radius or x >= (w - patch_radius) or y
>= (h - patch_radius):
        continue


    patch_mag = magnitude[y - patch_radius:y + patch_radius,
                          x - patch_radius:x + patch_radius]
    patch_ori = orientation[y - patch_radius:y + patch_radius,
                            x - patch_radius:x + patch_radius]

    if patch_mag.shape[0] != 16 or patch_mag.shape[1] != 16:
        continue


    rel_ori = (patch_ori - theta + 360) % 360


    y_grid, x_grid = np.ogrid[-patch_radius:patch_radius,
-patch_radius:patch_radius]
    gaussian_weight = np.exp(-(x_grid**2 + y_grid**2) / (2 * (8)**2))
    weighted_mag = patch_mag * gaussian_weight

    descriptor = []


    for i in range(4):
        for j in range(4):
            y_start = i * 4
            y_end = y_start + 4
            x_start = j * 4
            x_end = x_start + 4
```

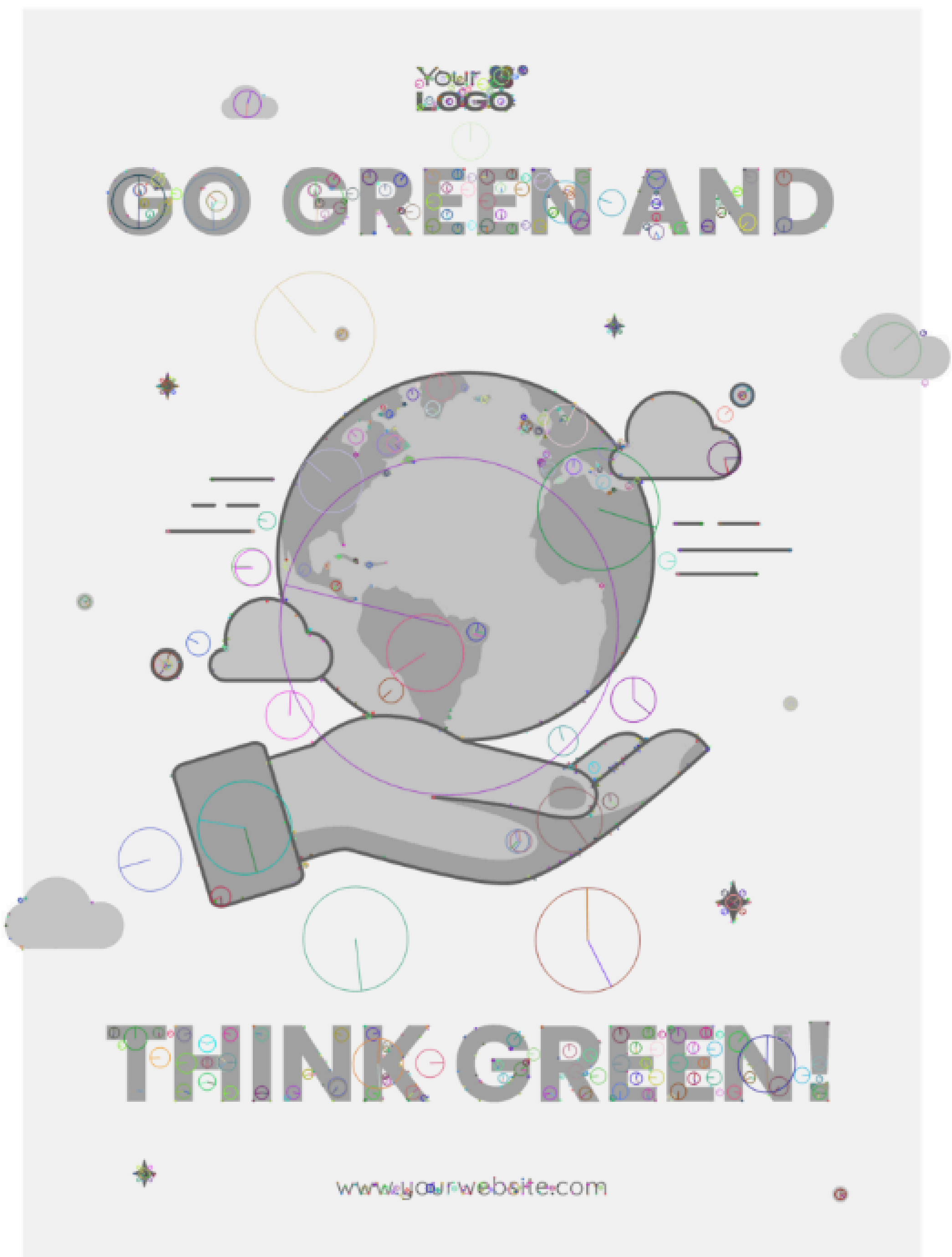
```
        sub_mag = weighted_mag[y_start:y_end, x_start:x_end]
        sub_ori = rel_ori[y_start:y_end, x_start:x_end]


        hist = np.zeros(8)
        bin_width = 360 / 8

        for di in range(4):
            for dj in range(4):
                mag_val = sub_mag[di, dj]
                ori_val = sub_ori[di, dj]


                bin_float = ori_val / bin_width
                bin_low = int(np.floor(bin_float)) % 8
                bin_high = (bin_low + 1) % 8
                weight_high = bin_float - np.floor(bin_float)
                weight_low = 1 - weight_high

                hist[bin_low] += mag_val * weight_low
                hist[bin_high] += mag_val * weight_high

        descriptor.extend(hist)


    descriptor = np.array(descriptor, dtype=np.float32)


    norm = np.linalg.norm(descriptor)
    if norm > 0:
        descriptor /= norm


    descriptor = np.clip(descriptor, 0, 0.2)
```

```
        norm = np.linalg.norm(descriptor)
        if norm > 0:
            descriptor /= norm

        descriptors.append(descriptor)
        valid_keypoints.append((x_real, y_real, sigma, octave_i, dog_i, theta))

    return np.array(descriptors), valid_keypoints


def visualize_oriented_keypoints(image_path, oriented_keypoints,
max_display=500):

    img_color = cv2.imread(image_path)
    img_rgb = cv2.cvtColor(img_color, cv2.COLOR_BGR2RGB)

    plt.figure(figsize=(12, 12))
    plt.imshow(img_rgb)
    plt.title(f"Keypoints with Orientation (showing {min(len(oriented_keypoints),
max_display)} of {len(oriented_keypoints)})")
    plt.axis('off')

    display_kps = oriented_keypoints[:max_display]

    for kp in display_kps:
        x, y, sigma, octave, dog, theta = kp[:6]


        arrow_length = sigma * 15
        dx = arrow_length * np.cos(np.deg2rad(theta))
        dy = -arrow_length * np.sin(np.deg2rad(theta))

        circle = plt.Circle((x, y), sigma * 3, color='lime', fill=False,
linewidth=3, alpha=0.7)
        plt.gca().add_patch(circle)
```

```
        plt.arrow(x, y, dx, dy, color='red', width=2.5, head_width=8,
                  head_length=6, alpha=0.95, length_includes_head=True)

    plt.tight_layout()
    plt.show()



def compare_with_opencv(image_path):

    img_gray = cv2.imread(image_path, cv2.IMREAD_GRAYSCALE)
    sift = cv2.SIFT_create()
    opencv_kps, opencv_desc = sift.detectAndCompute(img_gray, None)

    print(f"\nOpenCV SIFT: {len(opencv_kps)} keypoints, Descriptor shape:
{opencv_desc.shape}")

    img_sift = cv2.drawKeypoints(img_gray, opencv_kps, None,

flags=cv2.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)
    img_sift_rgb = cv2.cvtColor(img_sift, cv2.COLOR_BGR2RGB)

    plt.figure(figsize=(12, 12))
    plt.imshow(img_sift_rgb)
    plt.title(f"OpenCV SIFT Keypoints (Total: {len(opencv_kps)})")
    plt.axis('off')
    plt.tight_layout()
    plt.show()

    return opencv_kps, opencv_desc


print("Step 1: Assigning orientations to keypoints...")
```

```
oriented_keypoints = assign_orientation_to_keypoints(octaves, dog_octaves,
keypoints)
print(f"Initial oriented keypoints: {len(oriented_keypoints)}")

print("\nStep 2: Applying non-maximum suppression...")
oriented_keypoints = non_maximum_suppression(oriented_keypoints, radius=2.0)
print(f"After NMS: {len(oriented_keypoints)}")

print("\nStep 3: Computing SIFT descriptors...")
descriptors, valid_keypoints = compute_sift_descriptors(octaves,
oriented_keypoints)
print(f"Valid descriptors: {descriptors.shape}")
print(f"Each descriptor is {descriptors.shape[1] if len(descriptors) > 0 else
0}-dimensional")

print("\nStep 4: Visualizing keypoints with orientations...")
visualize_oriented_keypoints('green.jpg', valid_keypoints)

print("\nStep 5: Comparing with OpenCV SIFT...")
opencv_kps, opencv_desc = compare_with_opencv('green.jpg')
```

Keypoints with Orientation (showing 500 of 4391)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