

# Computer Vision 1: Assignment 4

## (Due date: 10.01.2022)

Submission instructions:

- For each programming task, submit a `.py` source code file or a Jupyter/Colab notebook file. Do not include any images or data files you used.
- For each pen & paper task, submit a `.pdf` file. Type your solution in LaTeX, Word, or another text editor of your choice and convert it to PDF. Do not submit photographs or scans of handwritten solutions!
- In all submissions, include at the top names of all students in the group.
- Choose one person in your group that submits the solution for your entire group.

### Task 1: SIFT (pen & paper)

Consider Figure 1, which shows a normalized orientation histogram for a SIFT keypoint after weighting<sup>1</sup>.

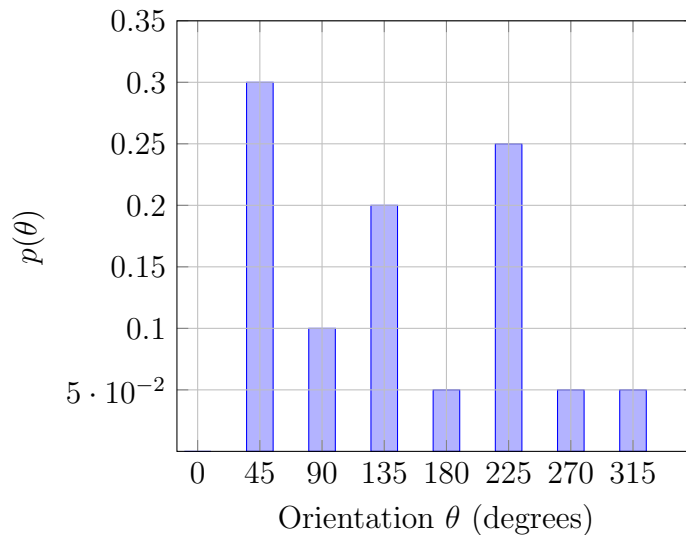


Figure 1: A normalized orientation histogram of a SIFT keypoint.

- What is the dominant local direction of the keypoint?
- How many new keypoints will be created, and why? What are their orientations?

### Task 2: Undersegmentation error (pen & paper)

We have developed a segmentation algorithm that has partitioned an image into segments  $S_i$ ,  $i = 1, \dots, n$  as described on the lecture slides. For the same image, we have a *ground truth segmentation*  $G_j$ ,  $j = 1, \dots, m$ , which specifies how the image ideally should be partitioned.

Intuitively, the *undersegmentation error* for an individual ground truth segment  $G_j$  measures the amount of “bleeding” that a segmentation exhibits beyond  $G_j$ . The undersegmentation

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<sup>1</sup>For simplicity, we consider an 8-bin orientation histogram. In the original SIFT algorithm, 36 bins are used.

error for a ground truth segment  $G_j$  is defined as

$$\text{UE}(G_j) = \frac{\left[ \sum_{\{S_i | S_i \cap G_j \neq \emptyset\}} \text{Area}(S_i) \right] - \text{Area}(G_j)}{\text{Area}(G_j)} \quad (1)$$

where the summation is over all segments  $S_i$  which have any overlap (non-empty intersection) with  $G_j$ , and the function Area returns the area, i.e., the number of pixels, of the corresponding segment.

Our image has 12 pixels in it, and our segmentation algorithm produces the segments  $S_i$  shown in Figure 2. Calculate the undersegmentation errors  $\text{UE}(G_1)$  and  $\text{UE}(G_2)$  of the ground truth segments  $G_1$  and  $G_2$  shown in Figure 3.

1	4	4	4
1	2	4	4
1	2	3	3

Figure 2: A segmentation  $S_i$ ,  $i = 1, 2, 3, 4$ , with  $i$  indicated on each pixel.

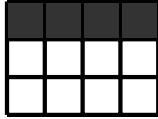


Figure 3: Two ground truth segments  $G_1$  (left) and  $G_2$  (right) highlighted in gray.

**Task 3:** Undersegmentation error (programming)

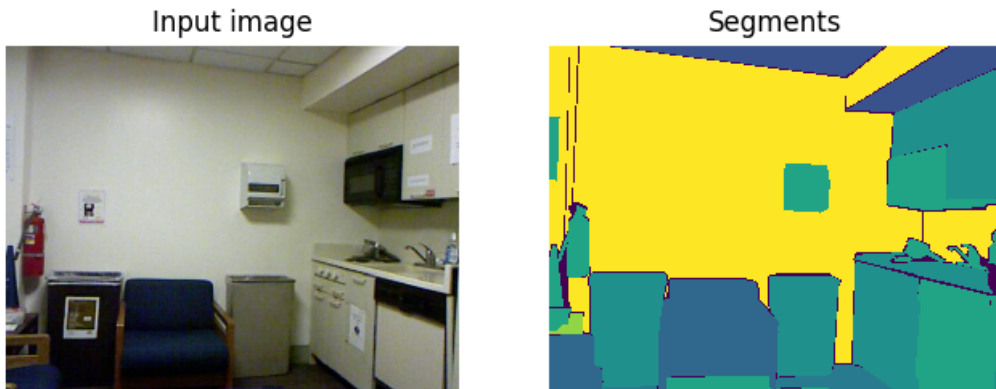


Figure 4: Input image (left), and a ground truth segmentation result (right), where the colors indicate the segments. Segments correspond to semantic classes such as “wall”. Source: NYUv2 dataset [https://cs.nyu.edu/~silberman/datasets/nyu\\_depth\\_v2.html](https://cs.nyu.edu/~silberman/datasets/nyu_depth_v2.html).

- Download the input image `0001_rgb.png` and the ground truth segmentation `0001_label.png` from Moodle. These images are shown in Figure 4.
- In the label image  $L$ , the pixel intensity value indicates which ground truth segment a pixel belongs to. For example, if  $L(x, y)$  has a value of  $i$ , the pixel  $(x, y)$  belongs to the  $i$ th segment.
- Use the implementation of the SLIC algorithm from `skimage.segmentation.slic` to segment the color image. Select reasonable values for the parameters  $n$  (number of segments) and  $c$  (compactness). Visualize the segmentation and revise the parameters if necessary. Leave the other parameters at their default values. **Note:** Because SLIC is not a *semantic segmentation* method, you should not expect its output to match that shown in Figure 4.
- Implement calculation of the undersegmentation error as defined in Eq. (1) for each ground truth segment in  $L$ . Compute and print out the undersegmentation error for every ground truth segment, and the average undersegmentation error over all ground truth segments.
- How does the average undersegmentation error change when you increase the desired number of superpixels  $n$ ? **Why? Answer in 1-2 sentences as a comment in your code.**

Hints:

- Use comparisons such as `L==i` to obtain binary masks areas of the label image  $L$  that belong to segment  $i$ .
- Use logical indexing with binary masks to extract corresponding areas of the segmentation result.
- Use `np.unique` and `np.count_nonzero` to find overlapping superpixels and to calculate their areas, respectively. You may also use `np.unique` to discover all labels that are present in  $L$ .
- Note that the label image has value 0 for pixels that are unlabeled (e.g., parts of boundaries). You can either ignore this or skip the label 0, as the undersegmentation error for this segment is not very meaningful.