



Indian Institute of Science Education and Research
Bhopal
Computer Vision(DSE-312/EECS-320)
Assignment-2

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Time of submission:

Marks Obtained:

Please follow the instructions given in the assignment carefully.

Please provide your detailed answers and any explanations or diagrams directly below each question in the ‘Answers’ section.

1. Question 1

Answer:

Algorithm 1 SIFT (Scale-Invariant Feature Transform)

Require: Input image I , number of octaves n_o , images per octave n_i , initial σ , contrast threshold t_c , edge response threshold R_{th} , window size w .

Ensure: Keypoints and descriptors.

1: **procedure** SIFT(I)

2: Initialize n_o , n_i , σ , t_c , R_{th} , w .

3: Convert input image I to grayscale.

4: Initialize *Gaussian Pyramid* and *Difference of Gaussians (DoG) Pyramid*.

for $o = 1$ to n_o **do**

5:

 Generate $n_i + 3$ Gaussian-blurred images using

$$k = 2^{\frac{1}{n_i}}, \quad \sigma_i = \sigma \cdot k^i$$

6: Compute DoG images for each pair of consecutive Gaussian images:

$$\text{DoG} = G_{\sigma_{i+1}} - G_{\sigma_i}$$

7: Add Gaussian and DoG images to their respective pyramids.

8:

9: Initialize *keypoints* and *descriptors*. **for each** DoG octave in DoG Pyramid **do**

10:

 Identify candidate keypoints by finding local extrema in a 3D neighborhood.

for each candidate *keypoint* (x, y, s) **do**

11:

 Localize keypoints by solving:

$$\mathbf{J} = -\mathbf{H}^{-1}\mathbf{d}, \quad \mathbf{H} = \begin{bmatrix} \partial_x^2 & \partial_{xy}^2 & \partial_{xs}^2 \\ \partial_{xy}^2 & \partial_y^2 & \partial_{ys}^2 \\ \partial_{xs}^2 & \partial_{ys}^2 & \partial_s^2 \end{bmatrix}$$

12: Compute contrast $C = D(x, y, s) + 0.5 \cdot \mathbf{J}^T \cdot \mathbf{d}$. **if** $|C| < t_c$ or edge response exceeds R_{th} **then**

13:

 Discard keypoint. **else**

14:

 Compute descriptor using gradient magnitude and orientation within a neighborhood.

15: Normalize descriptor for scale invariance.

16: Add keypoint and descriptor to final list.

17:

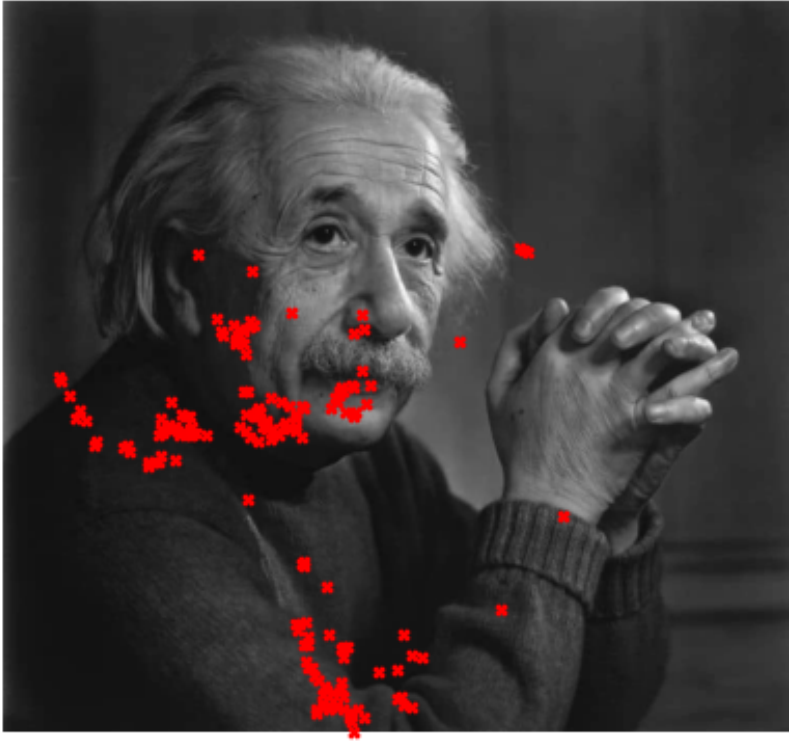
18:

19:

20: Visualize keypoints overlaid on the input image.

21: **return** Keypoints and Descriptors.

22: **end procedure**

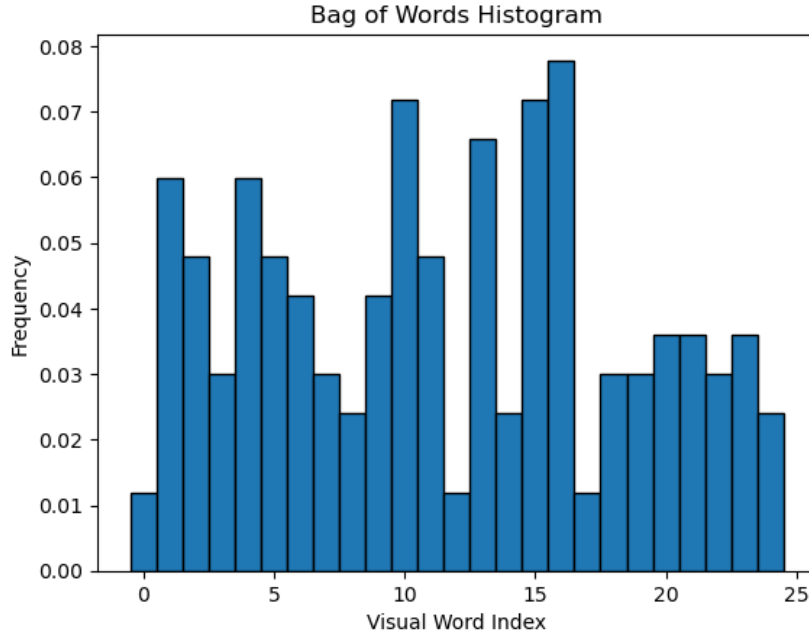


Algorithm 2 Bag of Visual Words Algorithm for an Image

Input: Image I , number of clusters k

Output: Normalized histogram H , cluster centers C

- 1 **Step 1: Extract SIFT Keypoints and Descriptors** Detect keypoints in the image I using SIFT. Compute descriptors for each keypoint, $D = \{d_1, d_2, \dots, d_n\}$
 - 2 **Step 2: Cluster Descriptors using K-Means** Apply K-Means clustering to D with k clusters. Obtain cluster centers $C = \{c_1, c_2, \dots, c_k\}$ and assign each descriptor d_i to its nearest cluster center
 - 3 **Step 3: Construct a Histogram** Initialize a histogram H with k bins: $H[j] = 0$ for $j = 1, 2, \dots, k$ **foreach** descriptor d_i **do**
 - 4 Determine the cluster index j for d_i . Increment $H[j] \leftarrow H[j] + 1$
 - 5 **end**
 - 6 Normalize H so that $\sum_{j=1}^k H[j] = 1$
 - 7 **Step 4: Visualize the Histogram** Plot H as a bar graph for visualization
 - 8 **return** H, C
-



Algorithm 3 Histogram of Oriented Gradients (HOG) Algorithm

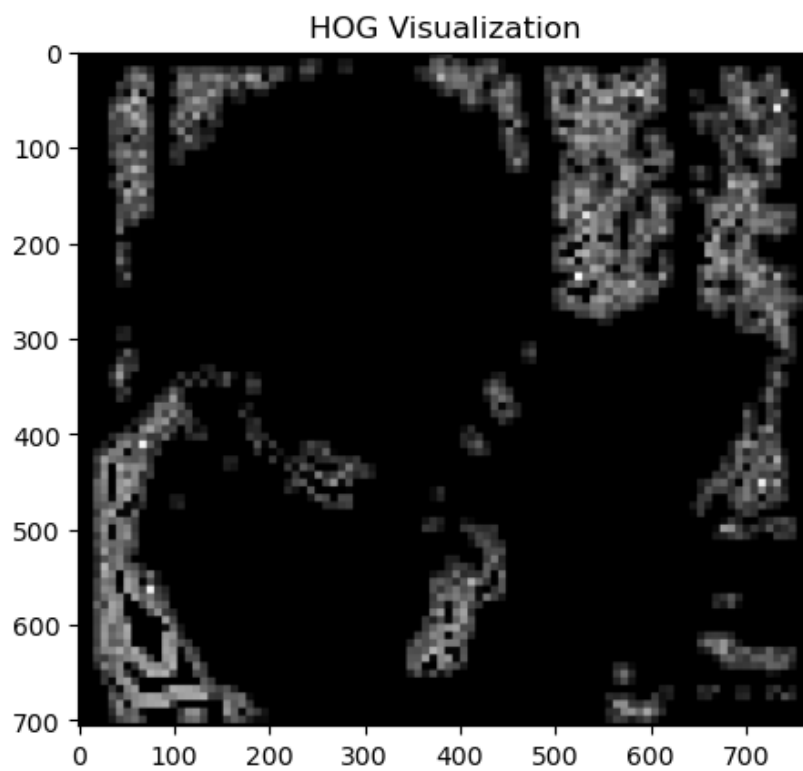
Input: Image I , Cell size (h_c, w_c) , Block size (h_b, w_b) , Number of bins n

Output: HOG descriptor H

```

9 Step 1: Preprocess Image if  $I$  is a color image then
10 |   Convert  $I$  to grayscale by averaging RGB channels
11 end
12 Resize  $I$  so that its dimensions are divisible by the cell size  $(h_c, w_c)$ 
13 Step 2: Compute Gradients Use Sobel filters to compute gradients  $\nabla_x$  and  $\nabla_y$ 
    Calculate magnitude  $M = \sqrt{\nabla_x^2 + \nabla_y^2}$  and angle  $\theta = \arctan 2(\nabla_y, \nabla_x)$ 
14 Step 3: Compute Cell Histograms Initialize histogram  $H_c$  for each cell foreach
    cell  $(i, j)$  of size  $(h_c, w_c)$  do
15 |   Extract gradients within the cell Quantize angles  $\theta$  into  $n$  bins (e.g.,  $0^\circ$  to  $360^\circ$ 
    divided equally) Populate the histogram using gradient magnitudes  $M$  as weights
16 end
17 Step 4: Normalize Block Histograms Group neighboring cells into overlapping
    blocks of size  $(h_b, w_b)$  foreach block  $(i, j)$  do
18 |   Concatenate histograms of cells in the block Normalize the block histogram using
     $L_2$  normalization
19 end
20 Step 5: Construct Final Descriptor Flatten all normalized block histograms into
    a single vector  $H$ 
21 return  $H$ 

```



2. Question 2

Answer: Optical Flow Computation using Lucas-Kanade Method

Algorithm 4 Optical Flow Computation using Lucas-Kanade Method

```
1: Input: Video frames  $\{I_t\}$ , background model, window size  $w$ , number of background frames
2: Output: Optical flow vectors  $(u, v)$  representing horizontal and vertical velocities
3: procedure INITIALIZE BACKGROUND
4:   Read first  $n$  frames from the video
5:   Convert frames to grayscale
6:   Compute the median of the frames to initialize background model
7: end procedure
8: procedure GRADIENT COMPUTATION
9:   For each pixel in the previous and current frame:
10:    Calculate  $I_x$  (gradient in x-direction),  $I_y$  (gradient in y-direction), and  $I_t$  (time gradient) for each pixel  $(i, j)$  in the frame do
11:
12:      $I_x[i, j] = \frac{I[i, j+1] - I[i, j-1]}{2}$  ▷ Gradient in x-direction
13:      $I_y[i, j] = \frac{I[i+1, j] - I[i-1, j]}{2}$  ▷ Gradient in y-direction
14:      $I_t[i, j] = I_{current}[i, j] - I_{previous}[i, j]$  ▷ Time gradient
15:   end procedure
16: procedure LUCAS-KANADE OPTICAL FLOW
17:   For each pixel  $(i, j)$  in the frame, apply the following steps:
18:   Construct  $A$  and  $b$  matrices for the optical flow equation:
```

$$A = \begin{pmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{pmatrix}, \quad b = \begin{pmatrix} -I_x I_t \\ -I_y I_t \end{pmatrix}$$

```
19:   Solve the optical flow equation  $A \cdot v = b$  to get velocity components:
```

$$v = \begin{pmatrix} u \\ v \end{pmatrix} = A^{-1} \cdot b$$

```
20:   If  $A$  is invertible (i.e.,  $\det(A) \neq 0$ ), compute the horizontal ( $u$ ) and vertical ( $v$ ) velocities for the pixel
21:   If  $A$  is not invertible, set  $u[i, j] = 0$  and  $v[i, j] = 0$  (handle singular matrix case)
22: end procedure
23: procedure FOREGROUND DETECTION
24:   Compute foreground mask by subtracting the background from the current frame:
```

$$\text{fg_mask} = |I_{background} - I_{current}|$$

```
25:   Threshold the foreground mask to highlight moving objects
26:   Create an overlay where the foreground pixels are highlighted (e.g., green color)
27: end procedure
28: procedure OVERLAY AND VISUALIZE
29:   Combine the original frame with the foreground mask overlay
30:   Draw optical flow vectors (arrows) representing the direction and speed of movement
31: end procedure
32: procedure PROCESS VIDEO
33:   Initialize background using Initialize Background() for each frame in the video do
34:
35:    Convert current frame to grayscale
36:    Perform gradient computation using Gradient Computation()
37:    Compute optical flow using Lucas-Kanade Optical Flow()
38:    Detect foreground using Foreground Detection()
```

Final Output The output video includes:

- A foreground mask highlighting the moving objects with a green overlay