

Feature Matching

Course 3, Module 2, Lesson 3 – Part 1

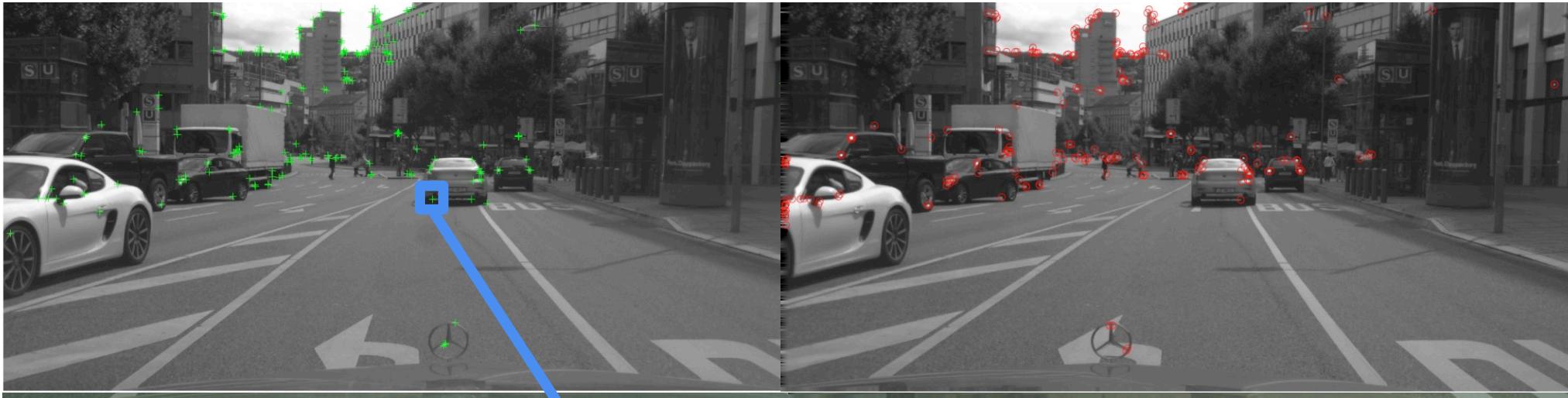


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Learning Objectives

- Learn how to match features based on a predefined distance function
- Learn how to perform **brute force** matching
- List faster alternatives to brute force matching, when the number of features to be matched is high

Image Features: A General Process



Images from CITYSCAPES dataset: <https://www.cityscapes-dataset.com/>

$$\{f_1, \dots, f_N\}$$

Feature Matching

- **Feature Matching:** Given a **feature and its descriptor**

in image 1, find the best match in image 2



Image 1



Image 2

?

Brute Force Feature Matching

- Define a **distance function** $d(f_i, f_j)$ that compares the two descriptors
- For every feature f_i in Image 1:
 - Compute $d(f_i, f_j)$ with all features f_j in image 2
 - Find the **closest** match f_c , the match that has the minimum distance

Distance Function

- Sum of Squared Differences (SSD):

$$d(f_i, f_j) = \sum_{k=1}^D (f_{i,k} - f_{j,k})^2$$

- Other distance functions:

- Sum of absolute differences (SAD):

$$d(f_i, f_j) = \sum_{k=1}^D |f_{i,k} - f_{j,k}|$$

- Hamming Distance:

Binary features

$$d(f_i, f_j) = \sum_{k=1}^D XOR(f_{i,k}, f_{j,k})$$

Brute Force Feature Matching

$$f_1 = [10, 34, 23, 55]$$



$$f_2 = [10, 37, 23, 55]$$



$$SSD(f_1, f_2) = 9$$

$$SSD(f_1, f_3) = 652$$

$$f_3 = [9, 35, 12, 32]$$

Brute Force Feature Matching

$$f_1 = [10, 34, 23, 55]$$



$$f_2 = [10, 13, 23, 55]$$



$$\delta = 20$$

$$SSD(f_1, f_2) = 441$$

$$SSD(f_1, f_3) = 652$$

$$f_3 = [9, 35, 12, 32]$$

Brute Force Feature Matching

- Define a distance function $d(f_i, f_j)$ that compares the two descriptors
- Define **distance threshold δ**
- For every feature f_i in Image 1:
 - Compute $d(f_i, f_j)$ with all features f_j in image 2
 - Find the **closest** match f_c , the match that has the minimum distance
 - Keep this match only if $d(f_i, f_j)$ is below threshold δ

Feature Matching

- **Brute force** feature matching might not be fast enough for extremely large amounts of features
- Use a multidimensional search tree, usually a k-d tree to speed the search by constraining it spatially
- Both of these matchers are implemented in OpenCV as:
 - `cv2.BFMatcher()`: Brute force matcher
 - `cv2.FlannBasedMatcher()`: K-D tree based approximate nearest neighbor matcher
 - Link : https://docs.opencv.org/3.4.3/dc/dc3/tutorial_py_matcher.html