Project 2

Feature Detection and Matching

Due: Sunday Feb 17

Part 1. Feature Detection

- Use Harris corner detection
- For each image point
  - Use a window about the point
  - Compute the Harris matrix M
  - Use $R(H) = \det(M) - k(\text{trace } M)^2$ as the corner strength function
- Choose points where R is above a threshold and is a local maximum

Part 2. Feature Description

1. **Simple descriptor:** use a small square window about the feature point (say 5 X 5). This can be the baseline for matching. Feel free to try variants of this basic descriptor, too, like normalizing the gray tones.

2. **Advanced descriptor:** make your descriptor invariant to rotation, using the dominant orientation idea. You will find the dominant orientation in a window about an interest point and use it to rotate the window so that dominant orientation is up, as shown on Matt's slides.

Computing Dominant Orientation

- Find the gradient magnitude and direction of each pixel in a square window about the interest point

- Create a histogram of gradient directions, using the magnitudes as weights (instead of just adding 1 to bin counts)

- Find the direction θ with the highest bin value.

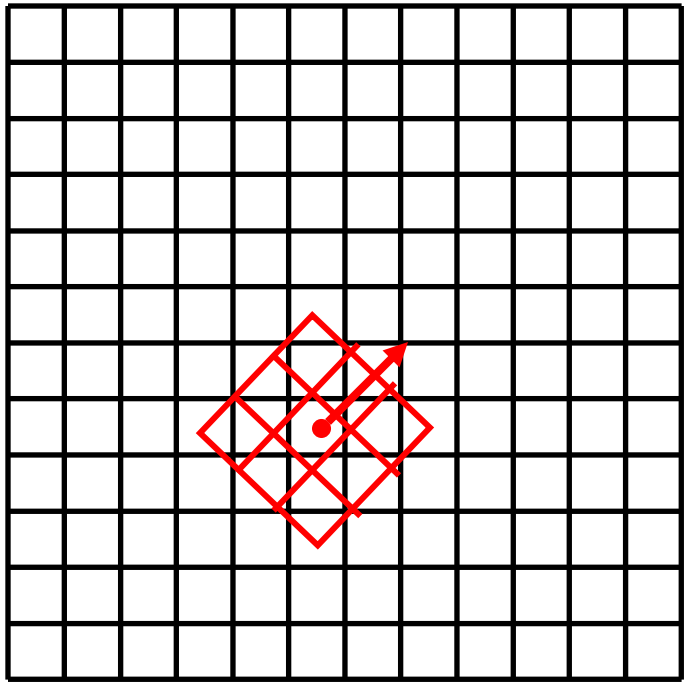
Computing the Rotated Window

- Now that you have θ, you can fill an empty descriptor with the values you sample from a counterclockwise rotation by θ.

- When you want the value for a pixel (x,y) in the descriptor, you have to sample it from the “rotated” window in the image. This requires a rotation followed by a translation.

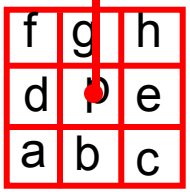
- Follow the directions in the project handout to compute the floating point coordinates, and use interopolation of the 4 closest pixel values to get the value for (x,y).

Interest point detected p (6,5)



(0,0)

Descriptor window



•When doing the rotation, assume the interest point is at (0,0)
•After rotation, translate the rotated points by the interest point location

a(-1,-1) -> rotate by 315 -> a'(-1.4,0) -> translate by (6,5) -> a''(4.6,5)
b(0,-1) -> rotate by 315 -> b'(-0.7, -0.7), translate by (6,5) -> b''(5.3, 4.3)
c(1,-1) -> rotate by 315 -> c'(-0, -1.4) translate by (6,5) -> c''(6,3.6)
d(-1,0) -> rotate by 315 -> d'(-0.7,0.7) translate by (6,5) -> d''(5.3, 5.7)
p(0,0) -> rotate by 315 -> p(0,0) translate by (6,5) -> p(6,5)
e(1,0) -> rotate by 315 -> e'(0.7,-0.7) translate by (6,5) -> e''(6.7,4.3)
f(-1,1) -> rotate by 315 -> f''(0, 1.4) translate by (6,5) -> f''(6,6.4)
g(0,1) -> rotate by 315 -> g'(0.7,0.7) translate by (6,5) -> g''(6.7,5.7)
h(1,1) -> rotate by 315 -> h'(1.4,0) translate by (6,5) -> h''(7.4,5)

Part 3. Feature Matching

- You will match your descriptors across a pair of images I1 and I2.
- For each feature detected in I1, find the best corresponding feature in I2 or null if there is no good match. The skeleton code provides the SSD to measure the goodness of a match.
- To decide if a match **exists**, threshold on (score of best feature match)/(score of second best feature match)
- Test on provided data sets. The fundamental matrix giving the exact transformation from one image to another is given. The function applyHomography is given in the C++ code.
- Compare your two feature descriptors and SIFT. Use testMatch for your own features and testSIFTMatch for SIFT features. EvaluateMatch does the evaluation.

Bikes

Leuven

Wall