Lecture #06: Features and Matching

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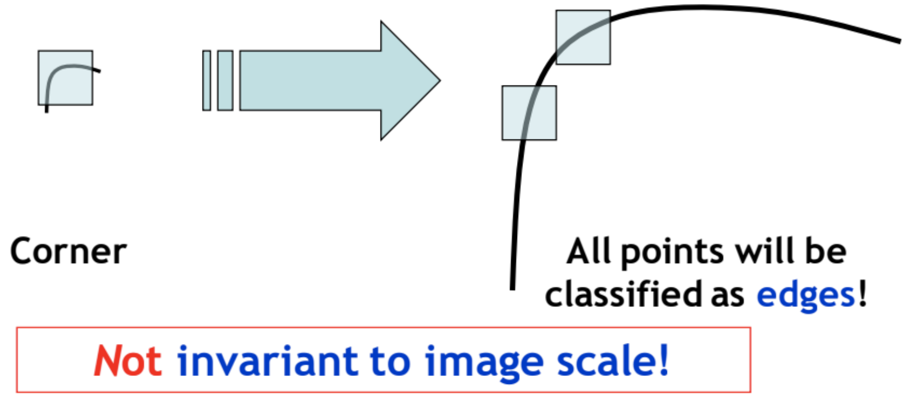
Contents

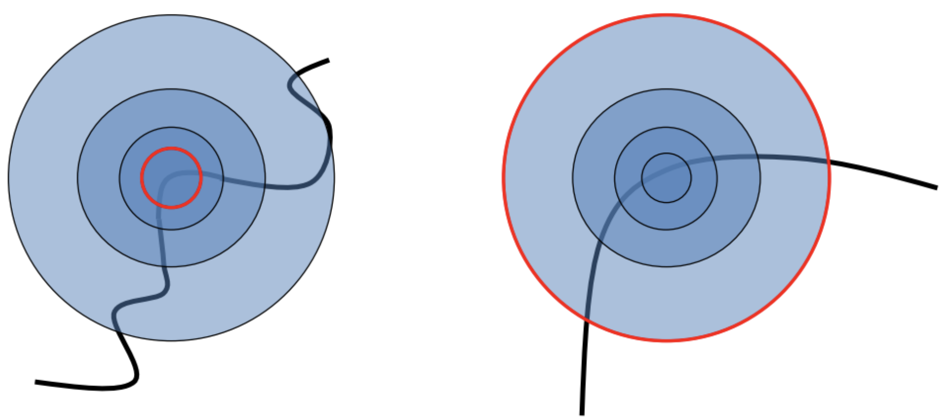
1 Scale invariant keypoint detection

1.1 Problem

The Harris Corner Detector is not scale invariant, meaning that identifying key points (e.g. corners) is not generalizable to the same image at different scales.

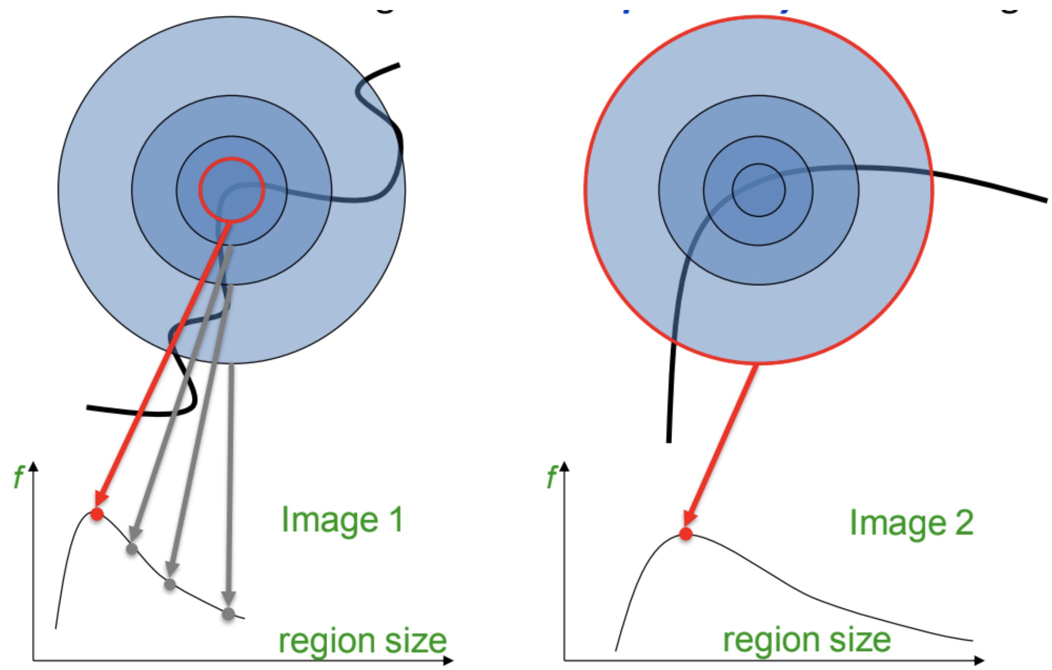


In reality, we would like to be able to match keypoints between images of different scale, so estimating the appropriate size of the neighborhood around the keypoint for each individual image independently is necessary.

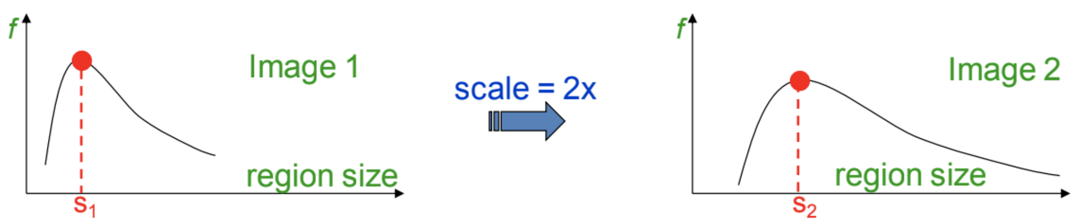


1.2 Solution

We can address the issue above by designing a function with respect to region size around the keypoint, which yields different outputs (responses) for different region size inputs. The maximum output, found by taking the local maximum of the function, is produced at the best region size.



This best region size is also co-variant with image scale.



1.3 Properties of a Good Function

It is important to design a function that is "scale invariant", meaning that the same outputs are produced for corresponding regions of images with different scales. For example, average intensity is a scale invariant function because even if the image is scaled to be larger, taking the intensity/brightness averages of corresponding regions between the two images will be the same. A good function should also have one stable sharp local maximum and respond well to contrast changes in the image.

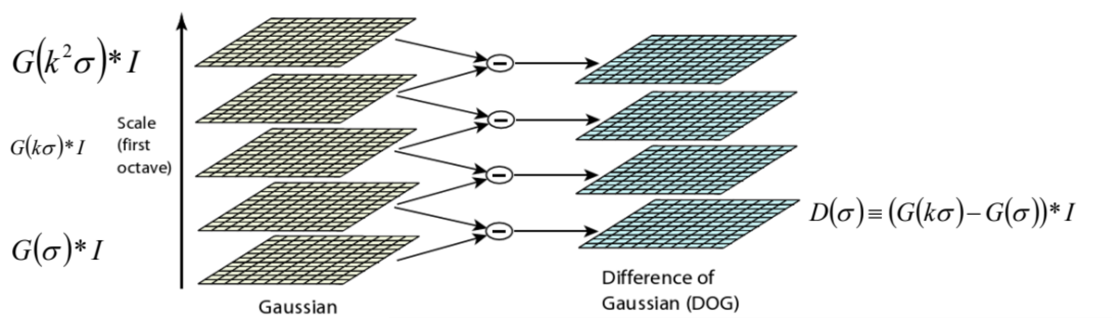
In this class, we use functions of the form f = kernel * image for determining scale. Here, we have two choices for a kernel: Laplacian of Gaussians and Difference of Gaussians.

1.4 Laplacian of Gaussians Kernel

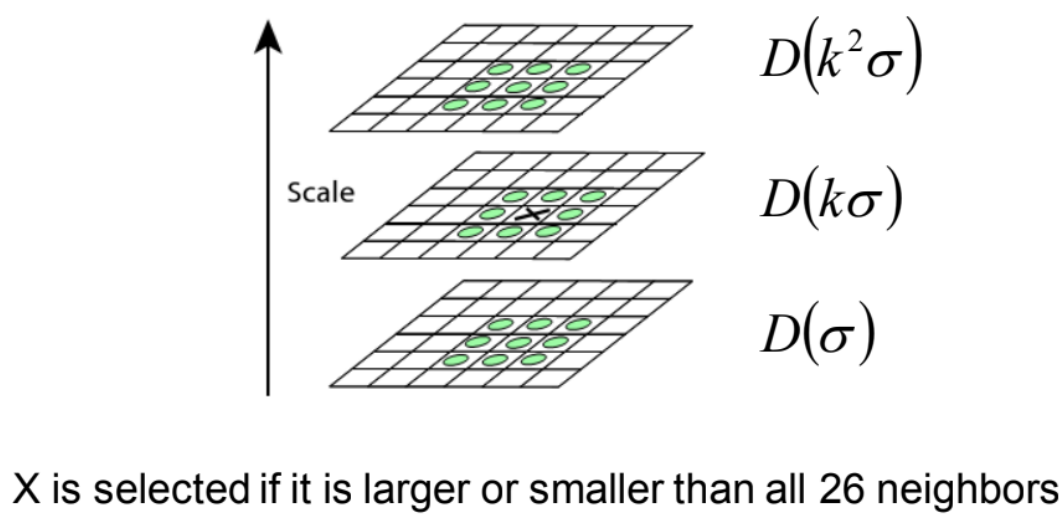
This kernel is defined by: $L = \sigma^2(G_{xx}(x, y, \sigma) + G_{yy}(x, y, \sigma))$. For this kernel, we can plug in different region size inputs into the Laplacian and then take the maximum of the f = Laplacian * image. In the Harris-Laplacian method, we run the Harris Corner Detection normally on a predefined scale to detect points first, then we plug in different neighborhood size inputs into the Laplacian, and take the maximum of f to detect the best scale. So, overall, we are extending Harris' measure of corner response over an image to be invariant with scale.

1.5 Difference of Gaussians Kernel

This kernel is defined by: $DoG = G(x, y, k\sigma) - G(x, y, \sigma)$. We can also use a Difference of Gaussians kernel, which accounts for both choosing the most optimal space and scale. We start by considering different Gaussian kernels at changing scales/sigma values, and then we compute the differences of consecutive Gaussians, which are each then convolved with the original image. Then, we then stack these output differences into a tensor.

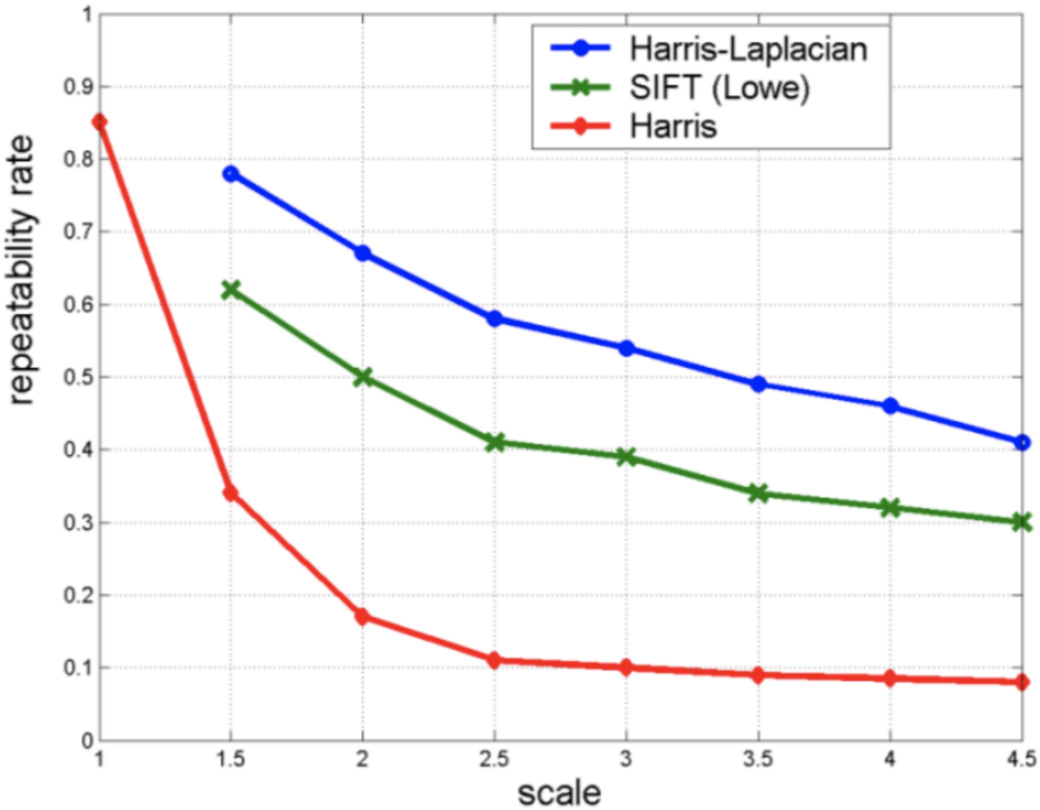


Now, the next step is space optimization, specifically by choosing pixel extrema in each scale in the tensor. This is done by comparing each pixel to other pixels in the same scale and in adjacent (above and below) scales in the tensor.



1.6 Detector Performance Evaluation

The evaluation metric for detector performance is repeatability (no. of correspondences / no. of possible correspondences), indicating how well the detector can find the same points when the images are resized. As a result, better detectors have higher repeatability scores across all scale variations of an image. As seen in the image, Harris-Laplacian and SIFT (Lowe) have higher repeatability scores than the original Harris algorithm, even though they are not perfect methods.



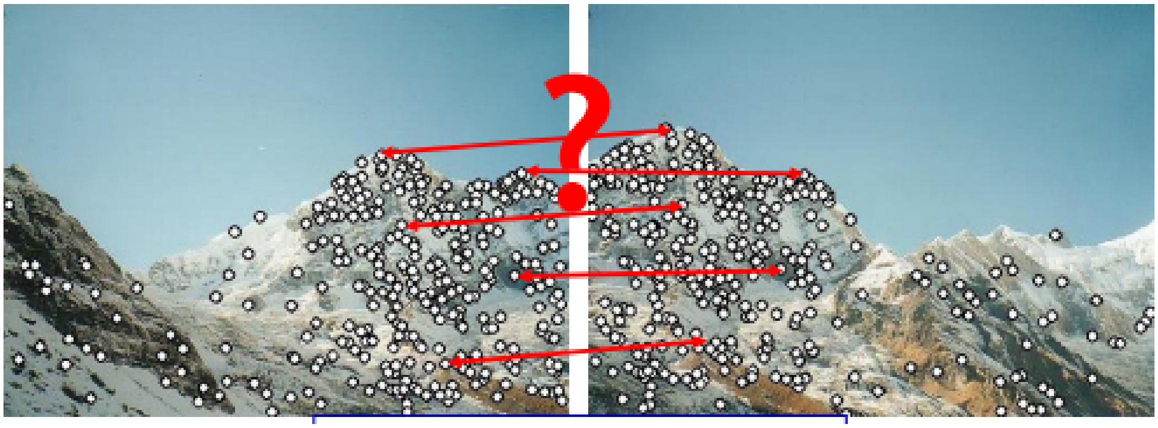
1.7 Takeaways and Applications

Overall, Scale invariant keypoint detection can be addressed by finding maxima of "good" functions in both scale and space over an image. There are many applications to Scale invariant keypoint detection, including searching for objects in different pictures and panorama stitching.

2 SIFT

2.1 Introduction and Motivation

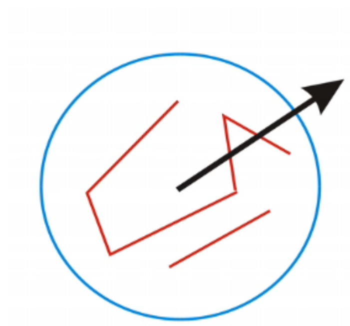
By now we have seen that it is possible to detect various numbers of key points in an image. The next important step is to be able to describe the key points for purposes such as matching. For example, in the below two photos:



We can see that we have many key points, but it is important to tell which points in one image correspond to points in another image in many real life applications.
To do so, we need to make sure that our point descriptor should be invariant and distinctive. We have mostly taken care of the distinctiveness in our key point selection, and will revisit its effectiveness in section 3.4. The features we extract must be invariant to translation, rotation, scale, etc.

2.2 Rotation Invariance

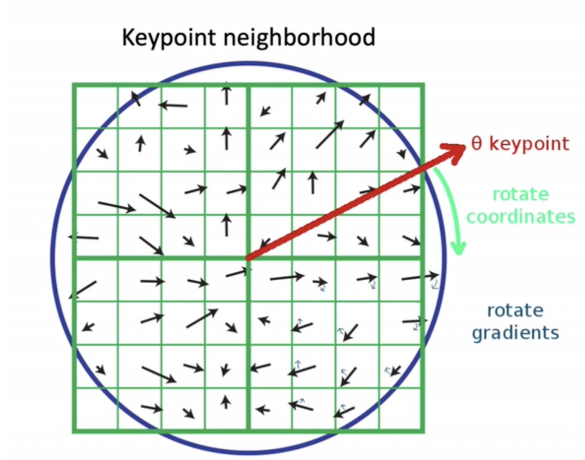
One of the more important properties of SIFT is that it is rotation invariant. Suppose that we take a patch of an image around a key point. At the start, we may not know its correct orienation. One option we have is to normalize patches by rotating them, trying out (potentially 360) rotations until we reach our best fit. The second option, which SIFT entails, consists of describing all features relative to a characteristic orientation.



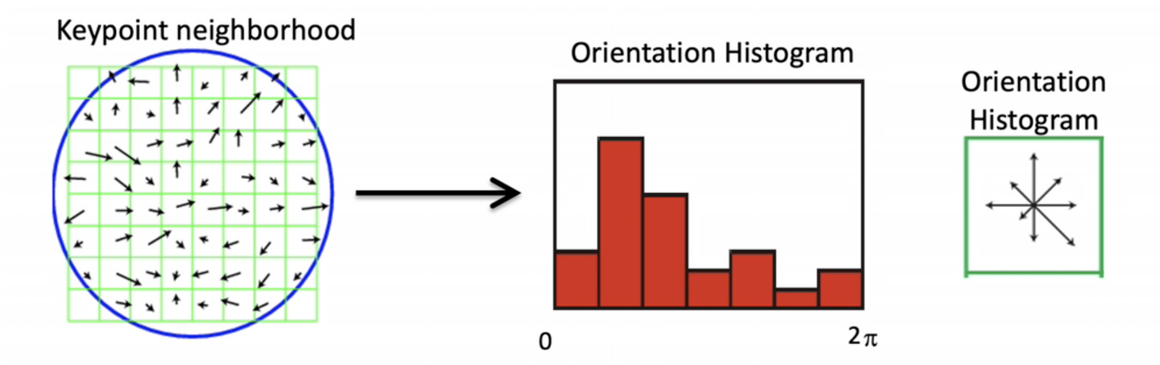
That is, first we determine a direction for the keypoint (often the most prominent gradient). Then, we describe all features relative to this orientation, usually with subtraction. Even if the image itself was rotated, all the features would remain the same relative to the key direction.

2.3 SIFT descriptor formation

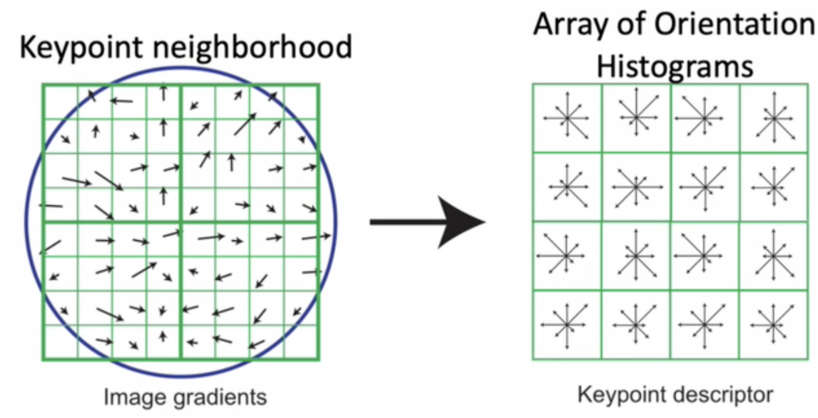
The above idea is the foundation for our SIFT descriptor. SIFT stands for Scale-Invariant Feature Transform and is a descriptor based on gradient information. Effectively, this method attempts to capture the texture around a key point neighborhood of pixels.



To achieve this, the image is first blurred and an image patch of $n \times n$ pixels is extracted centered around the key point. For optimum performance, most image patches are of size 8×8 pixels. Afterward, image gradients are taken for each pixel in the key point neighborhood. To become image invariant, each neighborhood pixel gradient direction and location is rotated by the negative angle of the key point orientation. This allows us to cancel out rotation and express the gradient locations relative to the key point orientation θ.



Once we have calculated the gradients within the selected neighborhood of pixels that were normalized relative to the domain orientation, we then stack the gradient numbers into a vector. Unfortunately, it is fragile to use precise gradients when defining our vector and we will require slight imprecision in the pixel configurations of the image. To achieve this while maintaining a relatively accurate descriptor, we introduce an array of histogram bins to categorize the gradient numbers into 8 distinct orientations. This array spans from angle 0 to 2π in increments of $\pi/4$ rad.



As you may expect, one histogram/vector may not contain enough information to properly convey the distinctiveness of all 64 squares. For this reason, we split the image further into a 4×4 histogram array, yielding $8 \times 4 \times 4 = 128$ numbers. This results in a length 128 vector which is invariant to rotation and scale. We can then compare vectors in two different images to find matching key points.

From here, we need to account for illumination changes in the image. It is highly likely that images are captured under varying lighting conditions, which necessitates a more robust method of representing the descriptor. It is important to note that since the descriptor is made of gradients, it is already invariant to direct changes in brightness. However, a higher contrast photo will increase the magnitude of the gradients linearly. To account for this scaling, we normalize the histogram array such that its magnitude is 1.0.

Additionally, we can further account for large image gradients that often arise from unreliable 3D illumination effects, such as glare. To reduce this effect, we can clamp the values of the histogram to be at most 0.2, and normalize the vector again. The result is a vector which is fairly invariant to illumination changes.

2.4 Sensitivity, Stability, and Distinctiveness

Why do we choose to use 8 orientations with a descriptor width of 4?

Empirically, researchers have seen that 8 orientations, coupled with a descriptor width of 4, provides the most accurate results.

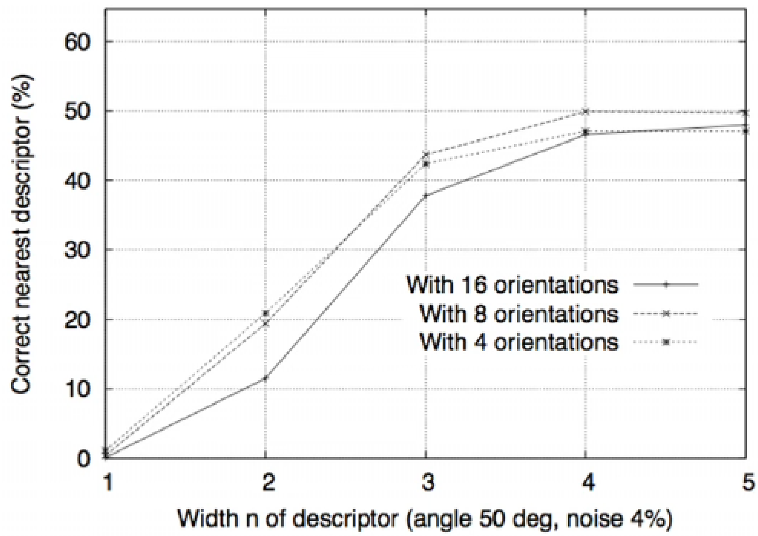
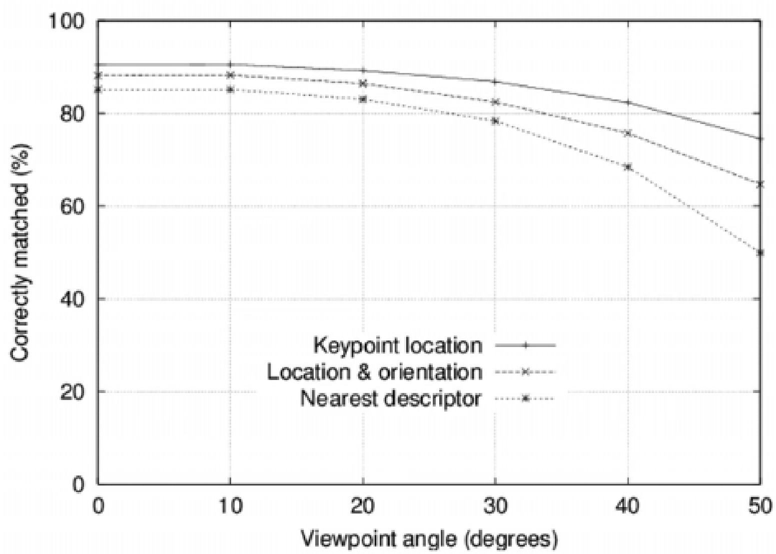


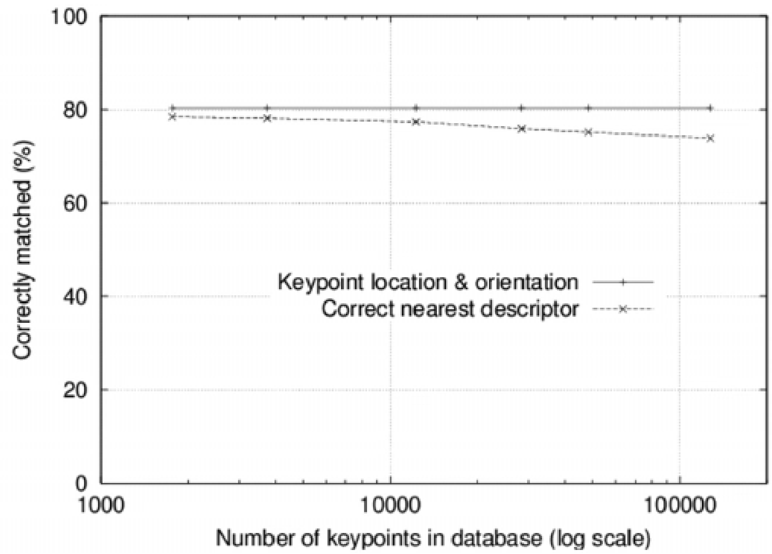
Figure 8: This graph shows the percent of keypoints giving the correct match to a database of 40,000 keypoints as a function of width of the $n \times n$ keypoint descriptor and the number of orientations in each histogram. The graph is computed for images with affine viewpoint change of 50 degrees and addition of 4% noise.

So how well does SIFT work? Empirically, researchers have shown that SIFT is quite robust to noise, and frequently correctly identifies the nearest descriptor, meaning that its features for each keypoint are mostly unique and descriptive.



(Above): We can see rather strong performance, even up to a viewpoint angle of 50 degrees. In addition to 2% image noise, we can see that SIFT is robust to affine changes.

(Below): Even with over 100k keypoints, SIFT is distinctive enough to identify the exact nearest descriptor about three-quarters of the time.



2.5 Applications

SIFT's local invariance ability allow its use to span across numerous real world applications, including but not limited to: Recognition, Wide baseline stereo, Panorama stitching, Mobile robot navigation, Motion tracking, and 3D reconstruction.

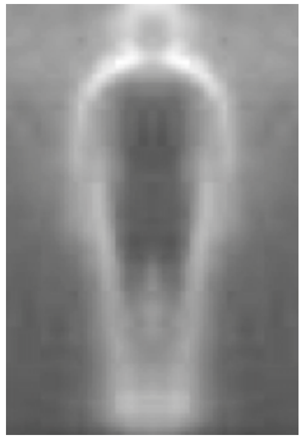
3 HoG

3.1 Histogram of Oriented Gradients Overview

Histogram of Oriented Gradients (HoG) is a type of feature descriptor. It is similar to DoG, but HoG can cover all of an image.

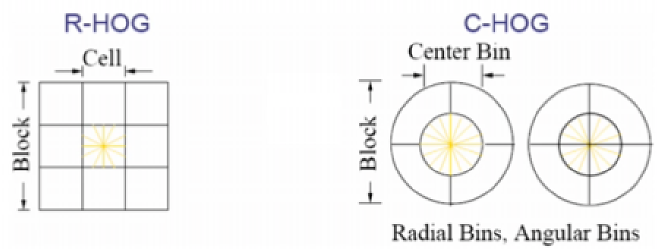
3.2 Method

: HoG works by exploiting the fact that local objects (specifically their shape and appearance are recognizable by their local intensity gradients (typically).



Example of a HoG compilation of images of pedestrians.

To use HoG, divide the image into uniform cells, which can be circular (C-HoG) or rectangular (R-HoG). Then, calculate a histogram of weighted gradient directions of each pixel for each cell. Finally, normalize these histograms at the cell level and also at a larger block of cells level.



This diagram shows a visualization of how normalization of cells is conducted for HoG.

3.3 Differences with SIFT

: HoG: normalized to neighborhood bins and (often) used for image regions that are bigger than just a feature.

SIFT: normalized to dominant gradient and used for key point detection.