



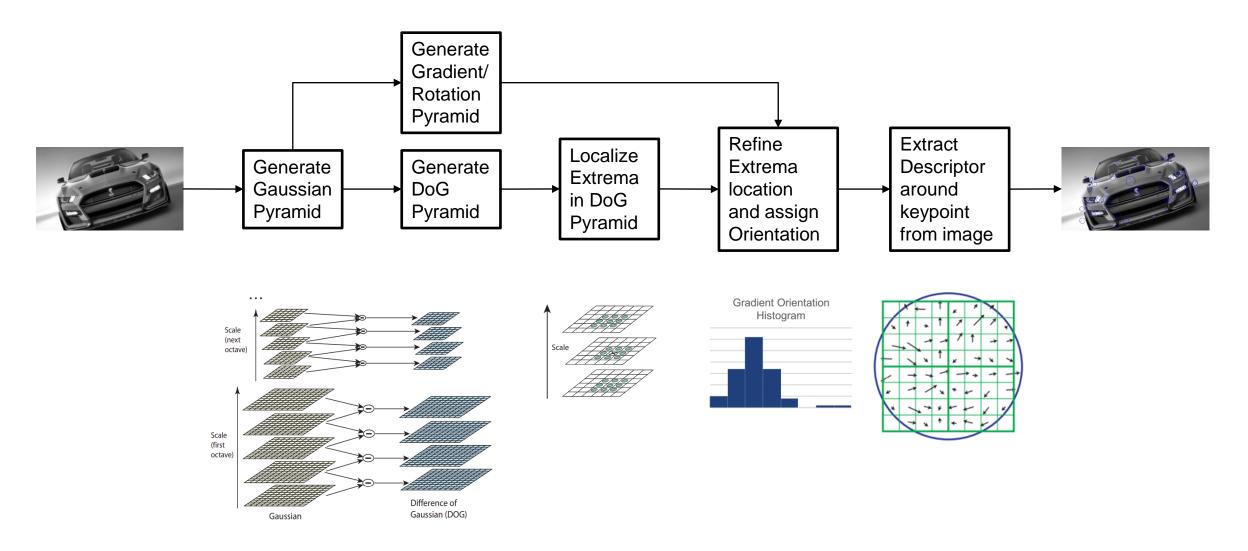
A SIFT Descriptor for Feature Matching

Advanced Systems Lab

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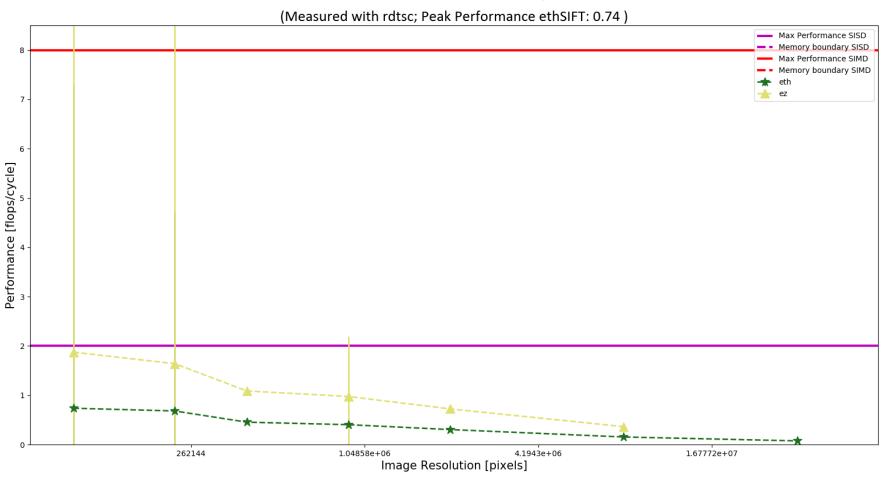
Rough Visualization of our Algorithm





Performance Plot of straightforward Code

Performance ExtractDescriptor



Plan on how to move forward

For each of these building blocks of our algorithm

- Apply C optimization techniques
- Try to use AVX2 techniques whenever possible
- Do all time measurements on the same Intel Machine
- Generate Performance Plots
- Write detailed Report



Preliminary Work Split

- Nicolas:
 - Descriptor Extraction
 - Keypoint Detection

- Costanza
 - DoG Pyramid
 - Rotation/Gradient Pyramid

- Jan
 - Convolution
 - Extrema Refinement

- Zsombor
 - Gaussian Pyramid and Kernel Generation
 - Histograms



Questions

- Flop counts for std-c methods (exp, floor, ceil, sqrt, pow, sin, cos, min, max)
- Flop counts for loop depending on keypoint scale
- Flop counts for mem alloc and mem copy
- Is it necessary to count flops for reference library (ezSift)?
- How to treat casting to floats?



Appendix



1. Scale-space Extrema Detection

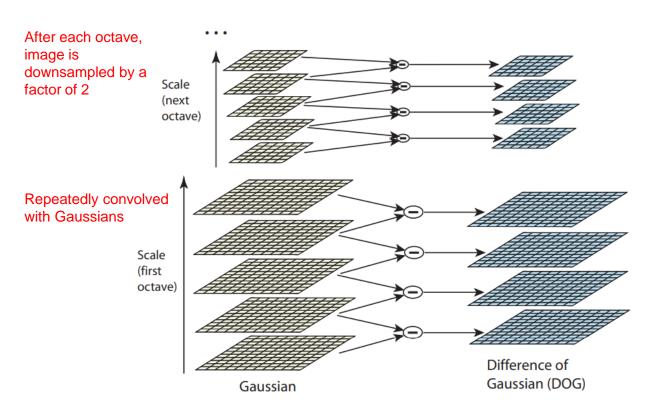
$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Layers in Gaussian Pyramid

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y)$$

Layers in Difference of Gaussians

$$D(x, y, \sigma) = L(x, y, k\sigma) - L(x, y, \sigma)$$
Constant multiplicative factor k

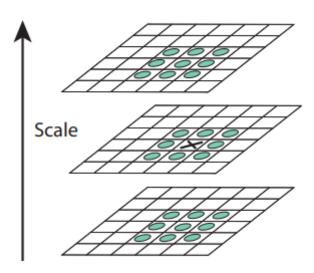




1. Scale-space Extrema Detection

Find local extrema in DoG pyramid by comparing a pixel to its 8 neighbour pixels in the same scale, as well as to the 9 pixels in each of the adjacent scales.

It is only selected if it is either larger or smaller than all of these other pixel values.





2. Keypoint Localization

Refinement of potential keypoint candidates:

• Determine interpolated location of extrema, using Taylor Expansion of scale-space function $D(x, y, \sigma)$

$$x = (x, y, \sigma)^{T} \qquad D(x) = D + \frac{\partial D^{T}}{\partial x} x + \frac{1}{2} x^{T} \frac{\partial^{2} D}{\partial x^{2}} x \qquad \hat{x} = -\frac{\partial^{2} D^{-1}}{\partial x} \frac{\partial D}{\partial x}$$

- Where \hat{x} is the derived location of the extremum. Remove a keypoint if $|D(\hat{x})| < "threshold"$
- For stability, edge responses get eliminated. This is done by first computing the Hessian H:

$$H = \begin{bmatrix} D_{xx} & D_{xy} \\ D_{xy} & D_{yy} \end{bmatrix}$$

And use the Hessian to check if ratio of principal curvatures is below some curvature threshold r

$$\frac{Tr(H)^2}{Det(H)} < \frac{(r+1)^2}{r}$$



3. Orientation Assignment

Next, Orientation is assigned to each keypoint to achieve invariance to image rotation.

• Calculation of gradient magnitude m(x,y), and orientation $\Theta(x,y)$, using pixel differences:

$$m(x,y) = \sqrt{(L(x+1,y) - L(x-1,y))^2 + (L(x,y+1) - L(x,y-1))^2}$$

$$\Theta(x,y) = \tan^{-1} \frac{L(x,y+1) - L(x,y-1)}{L(x+1,y) - L(x-1,y)}$$

- An orientation histogram is formed from gradient orientations of sample points within a region around the keypoint. It has 36 bins covering the 360° range of orientations.
- Each sample added to histogram is weighted by its gradient magnitude.
- Peaks in the orientation histogram correspond to dominant directions of local gradients.

4. Extraction of Keypoint Descriptor

Last step is to create a descriptor for the local image region:

- We consider a 16x16 pixel patch around the keypoint
- The patch is subdivided in 16 blocks of size 4x4, for each of these blocks an 8 bin orientation histogram is created
- This gives us a total of 128 bin values. These values are represented as a vector to form the keypoint descriptor

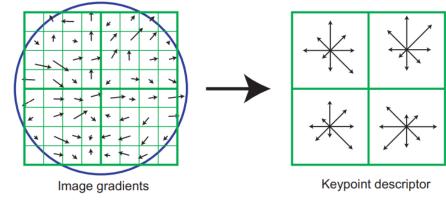
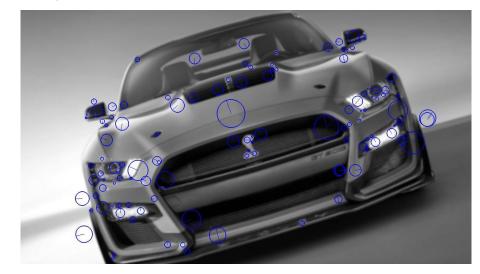


Figure: Shows a 2x2 descriptor array computed from an 8x8 set of samples





References

- Distinctive Image Features from Scale-Invariant Keypoints [Lowe, 2004]
- Guohui Wang, ezSIFT: an easy-to-use standalone SIFT library, 2013