

Jesse Weisberg  
CSE 559a Computer Vision  
Furukawa

# Project 1: Feature Detection and Matching

## Feature Description

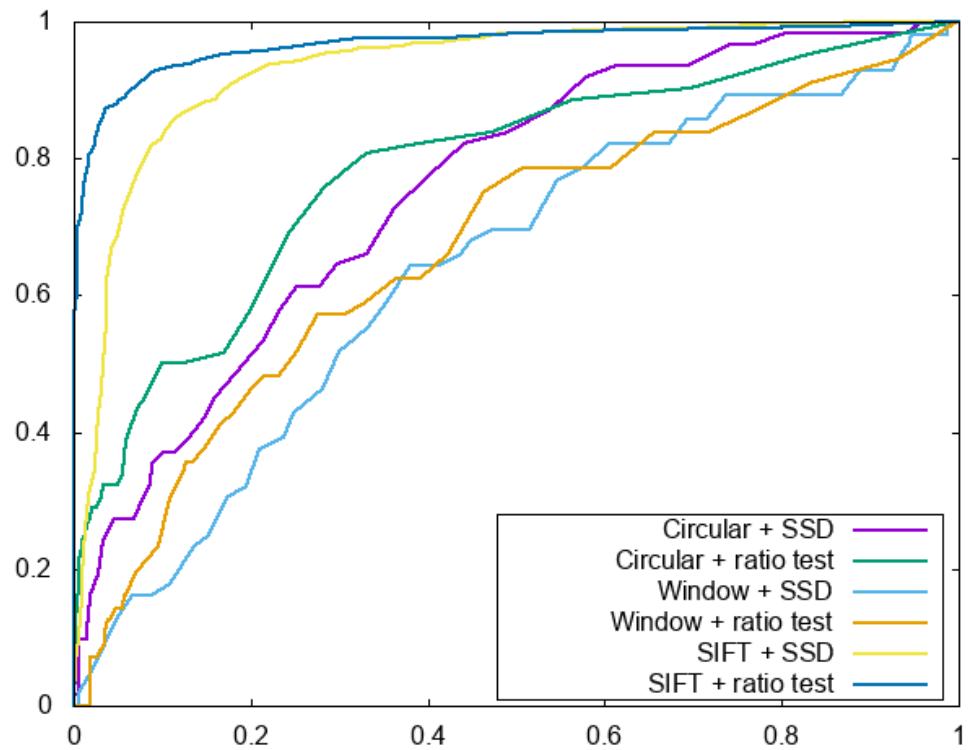
First, a simple 5x5 window was implemented storing 25 pixels centered about a feature and using them as feature descriptors. This window worked decently for bikes ( $AUC = \sim .63$ ) but was not robust enough to produce valid matches for the rest of benchmark sets (as a result, I would obtain  $AUC = \text{nan}$  when running the *benchmark* function).

The second descriptor implemented was a circular descriptor. After doing some research online, it seemed like I could accomplish rotation and illuminosity invariance with solid results using this method- so I decided to pursue it. Instead of using a square window, this descriptor uses a circular window and scans a circumference about the feature with a radius at three different intervals, each taking sample pixels at an angular step of 20 degrees. The descriptor scanning starts from the dominant orientation, which was calculated from the eigenvector corresponding to the larger eigenvalue of that feature (orientation was stored during the computation of harris values). Also, each sample pixel was rounded to the nearest integer pixel.

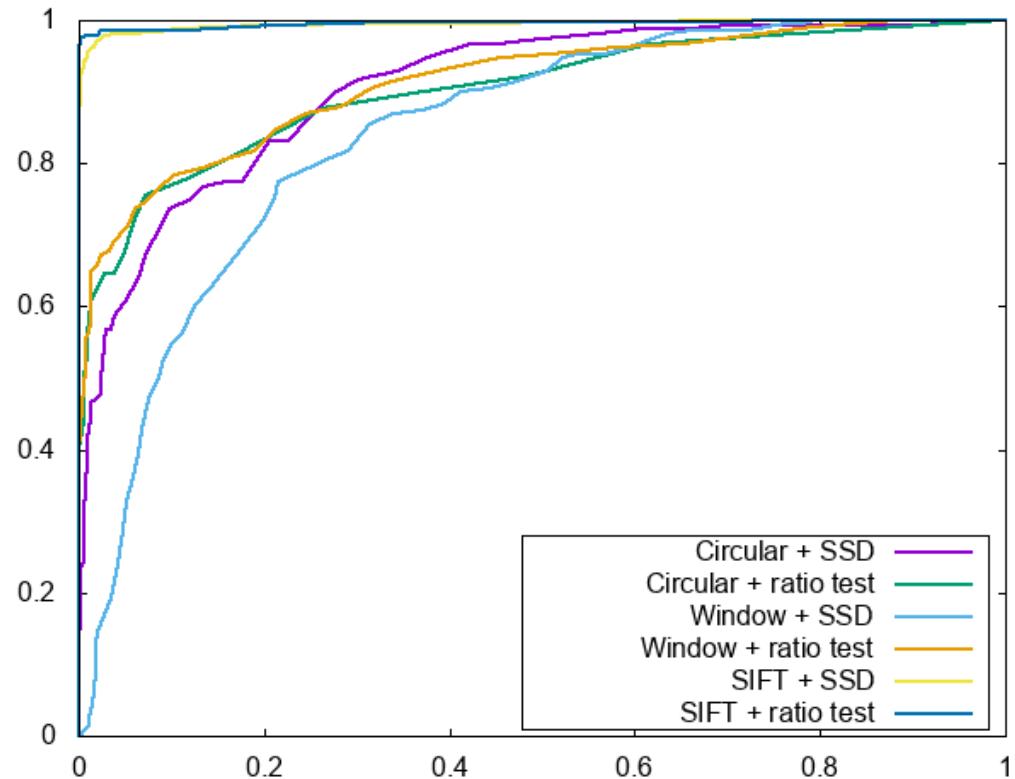
Through research online and experimenting myself, the best results for the four benchmark images were received with a radius of 6. One advantage of this sampling method is that the usage of dominant orientation makes the descriptors rotation invariant.

The descriptors are normalized and thus also illumination invariant. Normalization was performed for each descriptor by subtracting the mean and dividing by the standard deviation.

### Graf ROC Graphs

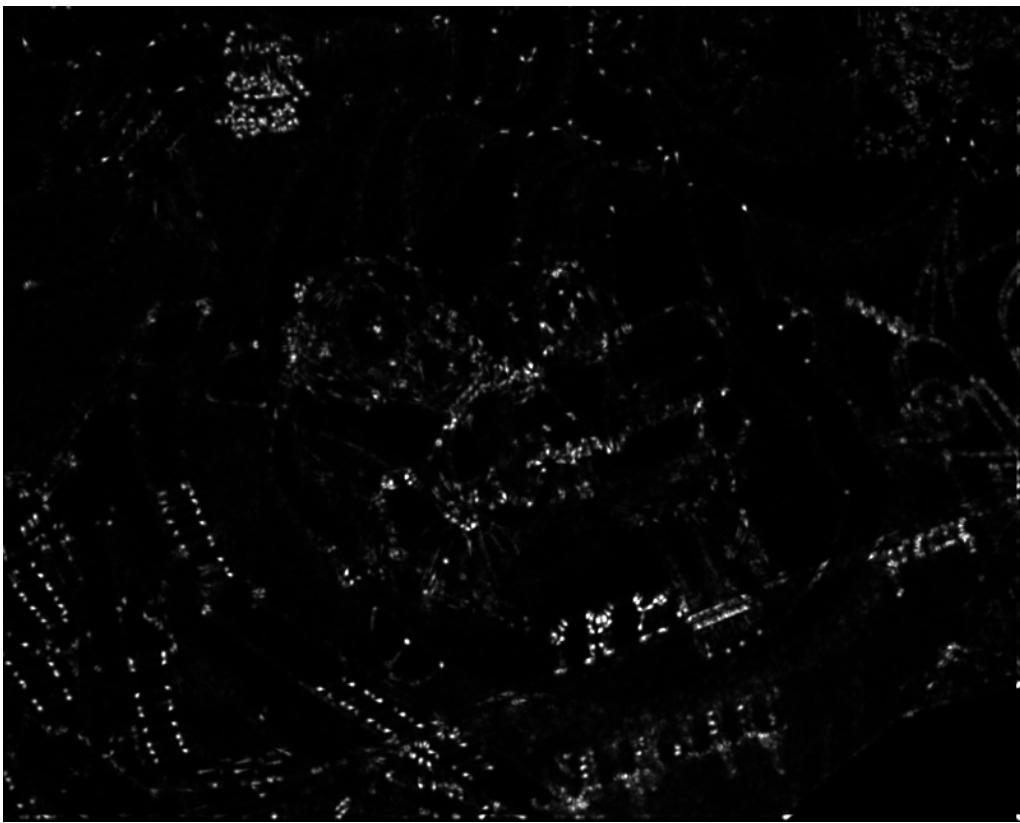


### Yosemite ROC Graphs

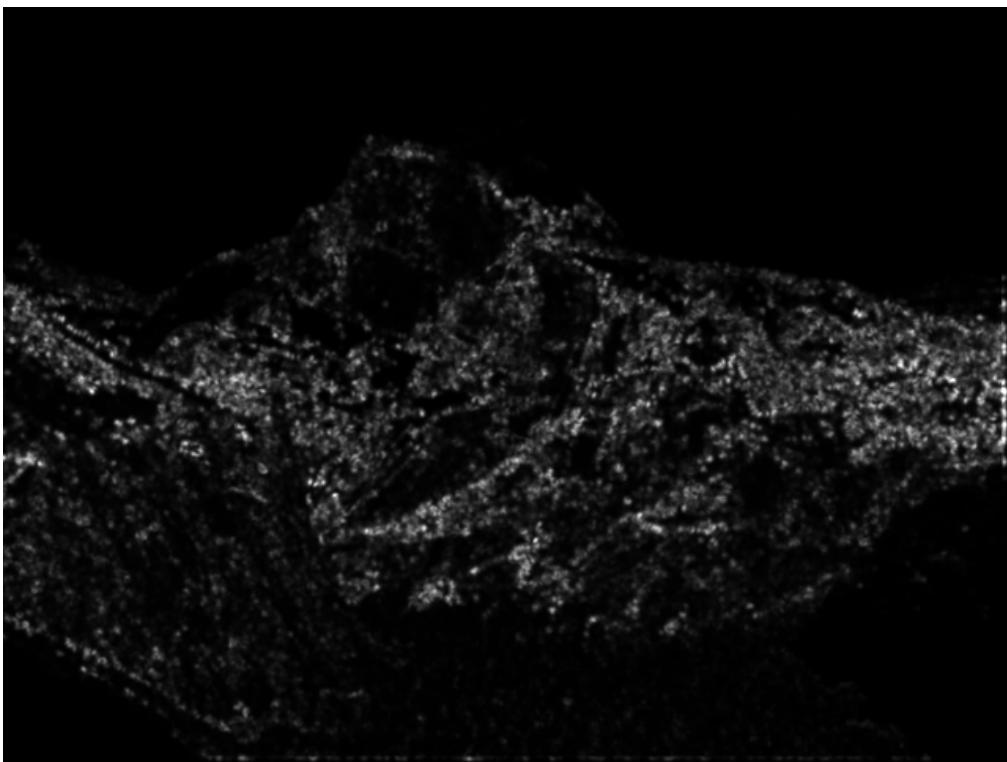


**Example Harris Images:**

**Graf img2.ppm using circular + ratio**



**Yosemite Yosemite2.jpg using circular + ratio**



## Average Benchmark AUC

AUC				
	Window + SSD	Window + ratio	Circular + SSD	Circular + ratio
<b>bikes</b>	0.487397	0.646534	0.744304	0.823196
<b>graf</b>	0.491549	0.612812	0.678230	0.687592
<b>leuven</b>	0.328773	0.486025	0.798289	0.869799
<b>wall</b>	0.498516	0.605915	0.773061	0.761069

## Strengths & Weaknesses

### Strengths

The algorithm is translation invariant (due to the nature of harris corner detection), illumination invariant, and rotation invariant (as described in “Feature Description” above).

### Weaknesses

One weakness is that the sampling radius and step size are not optimized for each photo. I am also not extremely confident in my computation of local maxima, as there are still features that are close together.

## My Own Images



*matched with window descriptor*



*matched with circular descriptor*

Here you can see the effectiveness of the implemented rotation invariance, which works relatively well in this example granted the number of matches achieved.



*matched with window descriptor*



*matched with circular descriptor*

Here is another photo, which shows that the circular feature descriptor is slightly illuminosity invariant. It is not as effective as I had hoped, but you can also see how clustering has adversely affected my results.