

Fast Weighted Median Filtering

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Introduction

What is Weighted Median Filtering?

Consider intensities in current window centered at some p as
 $\{ 10 ; 26 ; 122 ; 234 ; 256 ; \}$
with each intensity having weights as
 $\{ 0.15 ; 0.1 ; 0.2 ; 0.3 ; 0.25 ; \}$

So median is intensity at point p^* where

$$p^* = \min k \quad \text{s.t.} \quad \sum_{q=1}^k w_{pq} \geq \frac{1}{2} \sum_{q=1}^n w_{pq}.$$

In the above example median intensity will be 234 corresponding to weight 0.3

Intro

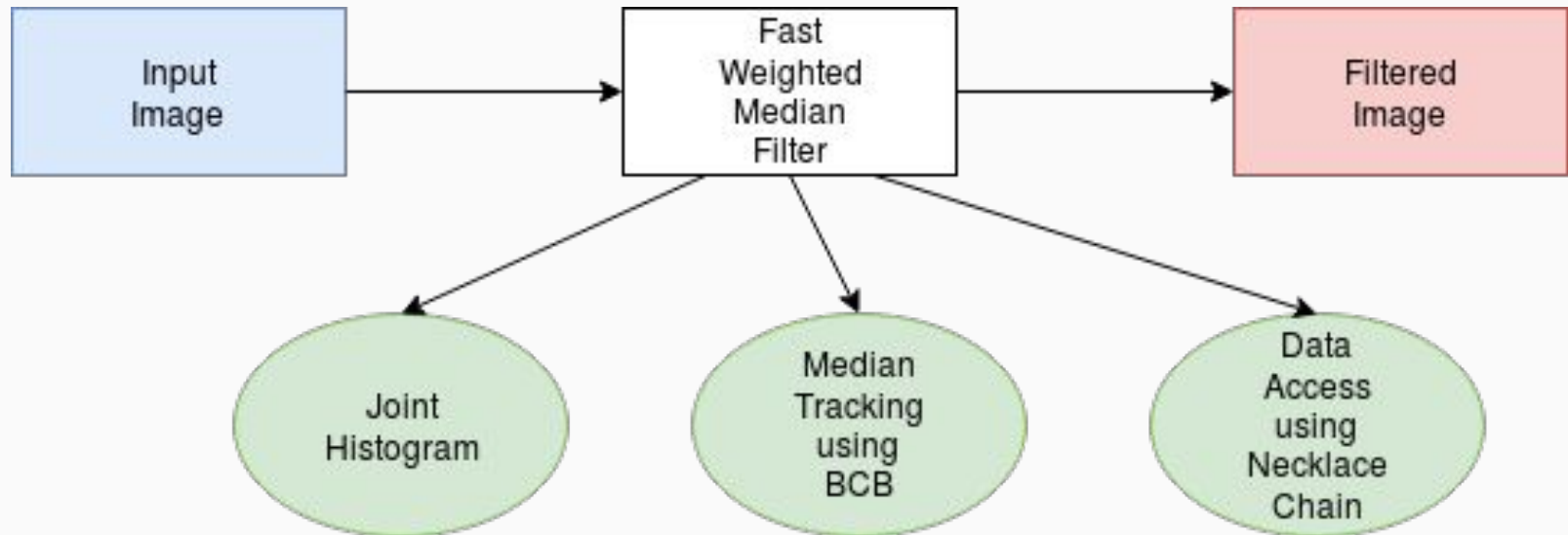
In our project we have re-implemented Weighted Median Filter for images in a much efficient way with reference to the research paper. In our project we have reduced time complexity of WMF from $O(r*r*\log r)$ to $O(r)$ which in most general cases 100+ times faster.

Motivation

- Modern World of Digital Photography
- Transmission technology prone to noise
- Use in various computer vision problems like stereo matching, optical flow estimation, image denoising etc.
- Method used for making unweighted median filtering/mean filtering cannot be applied here

Approach Used

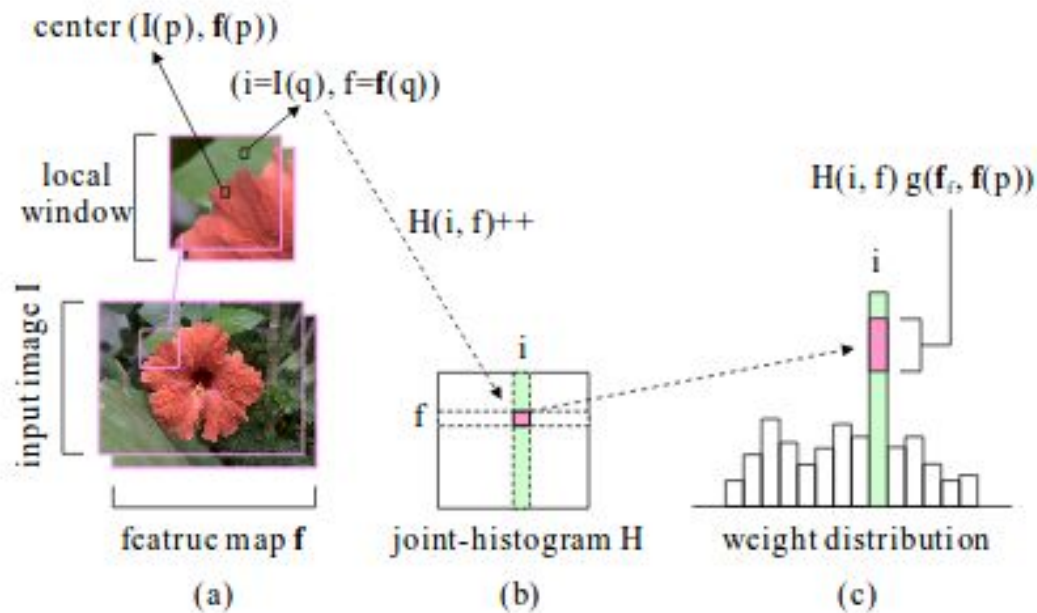
Overview



Joint Histogram

- Joint histogram is a two dimensional which stores the pixel count in its bins according to the corresponding features
- Each row of histogram corresponds to feature index and each column corresponds to intensity value of the pixel.

Diagram



$$H(i, f) = \#\{q \in \mathcal{R}(p) | I(q) = I_i, f(q) = f_f\},$$

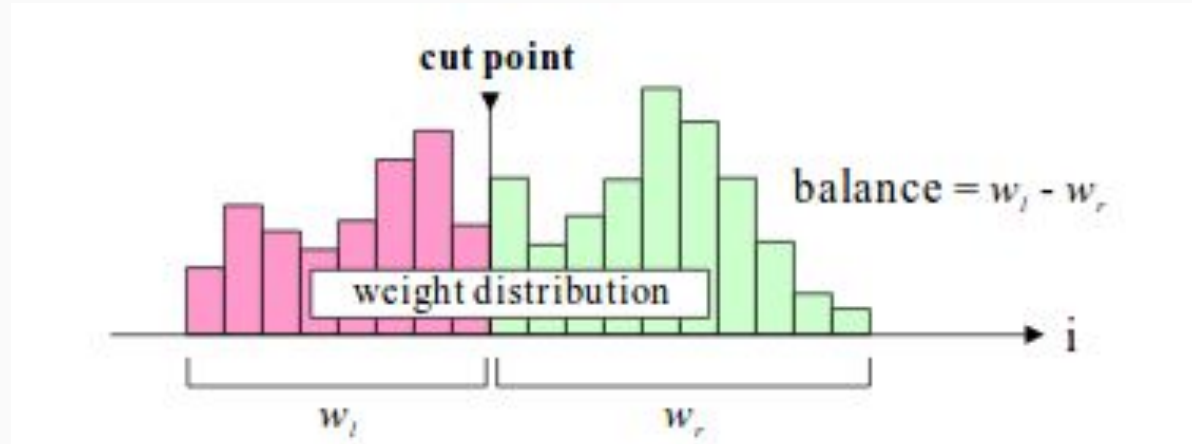
Algorithms

- Median Finding
- Shift and Update

Median Tracking

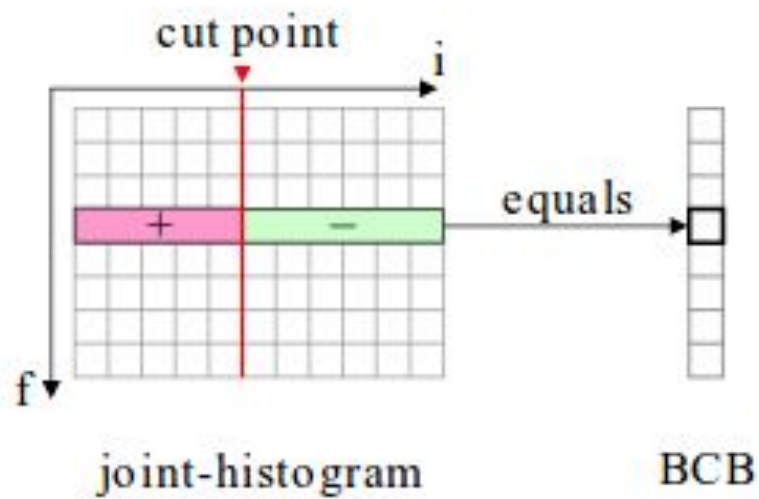
Median tracking basically exploits the property that almost all images have similar features in the adjacent median finding windows to iterate over joint-histogram in a much efficient way. Median tracking work on concept of Cut point and balance.

Cut Point and Balance



- Tracking Median
- Efficient calculation of Balance

Balance Counting Box



Balance Counting Box

Balance Counting Box stores difference of pixels on both side cut points

$$B(f) = \#\{q \in \mathcal{R}(p) | I(q) \leq c, \mathbf{f}(q) = \mathbf{f}_f\} \\ - \#\{r \in \mathcal{R}(p) | I(r) > c, \mathbf{f}(r) = \mathbf{f}_f\},$$

So balance can be calculate simply as

$$b = \sum_{f=0}^{N_f-1} B(f) g(\mathbf{f}_f, \mathbf{f}(p)).$$

Where g is weight map

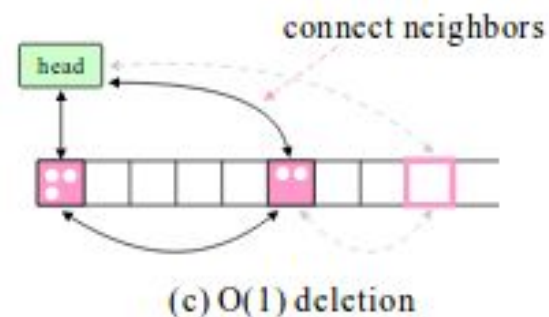
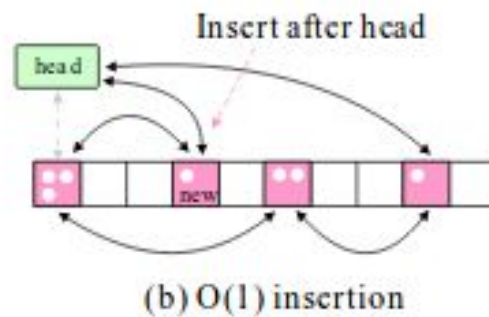
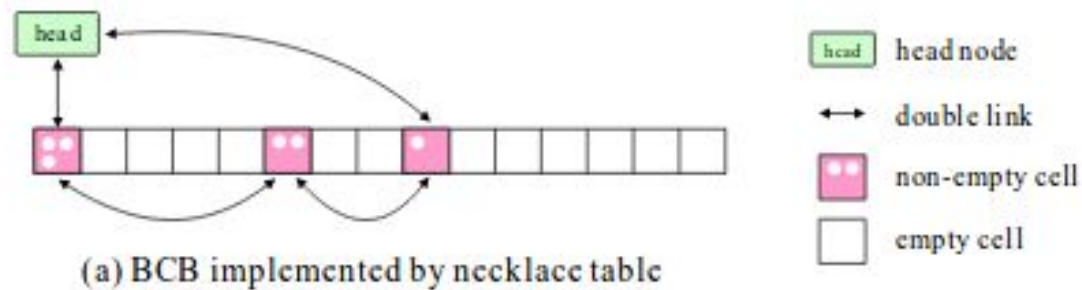
Necklace Table

Exploit the data sparsity in joint histogram and BCB and reduces the required space as well as time required to access a particular value.

Features

- $O(1)$ data access
- $O(1)$ element insertion
- $O(1)$ element deletion
- $O(N)$ traversal

Insertion/Deletion



Results Obtained

Salt and Pepper denoising



JPEG artifacts removal



Original image showing the text "Lorem ipsum turpis vitae v" with visible JPEG artifacts, appearing as a noisy, pixelated pattern.



Image showing the text "Lorem ipsum turpis vitae v" after applying a Gaussian Filter with radius = 5. The image is slightly blurred, and the JPEG artifacts are reduced.

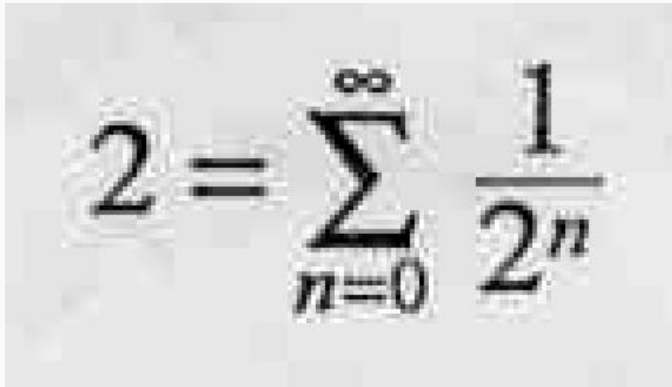
Gaussian Filter with radius = 5

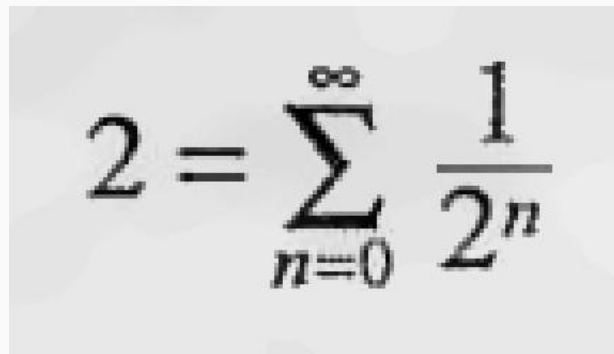


Image showing the text "Lorem ipsum turpis vitae v" after applying a Gaussian Filter with radius = 25. The image is significantly blurred, and the JPEG artifacts are almost completely removed.

Gaussian Filter with radius = 25

JPEG artifacts removal

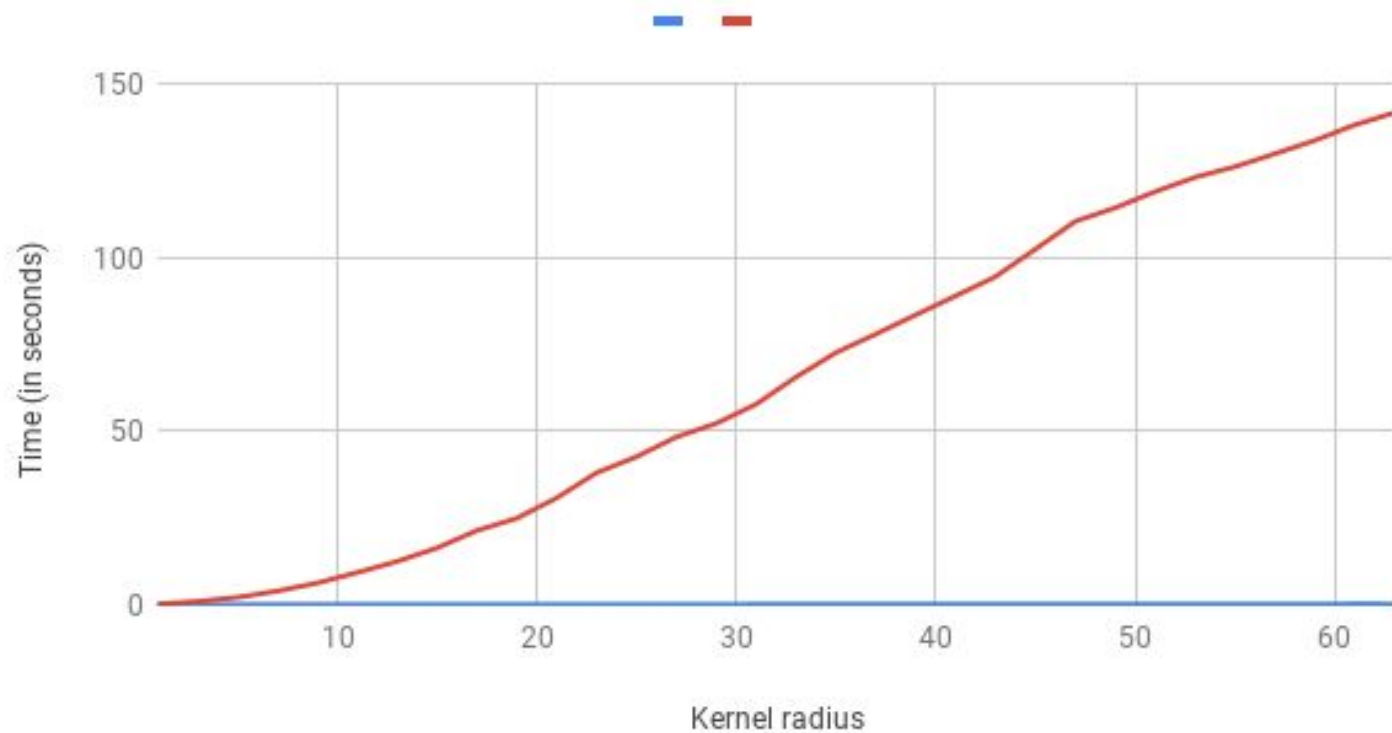

$$2 = \sum_{n=0}^{\infty} \frac{1}{2^n}$$


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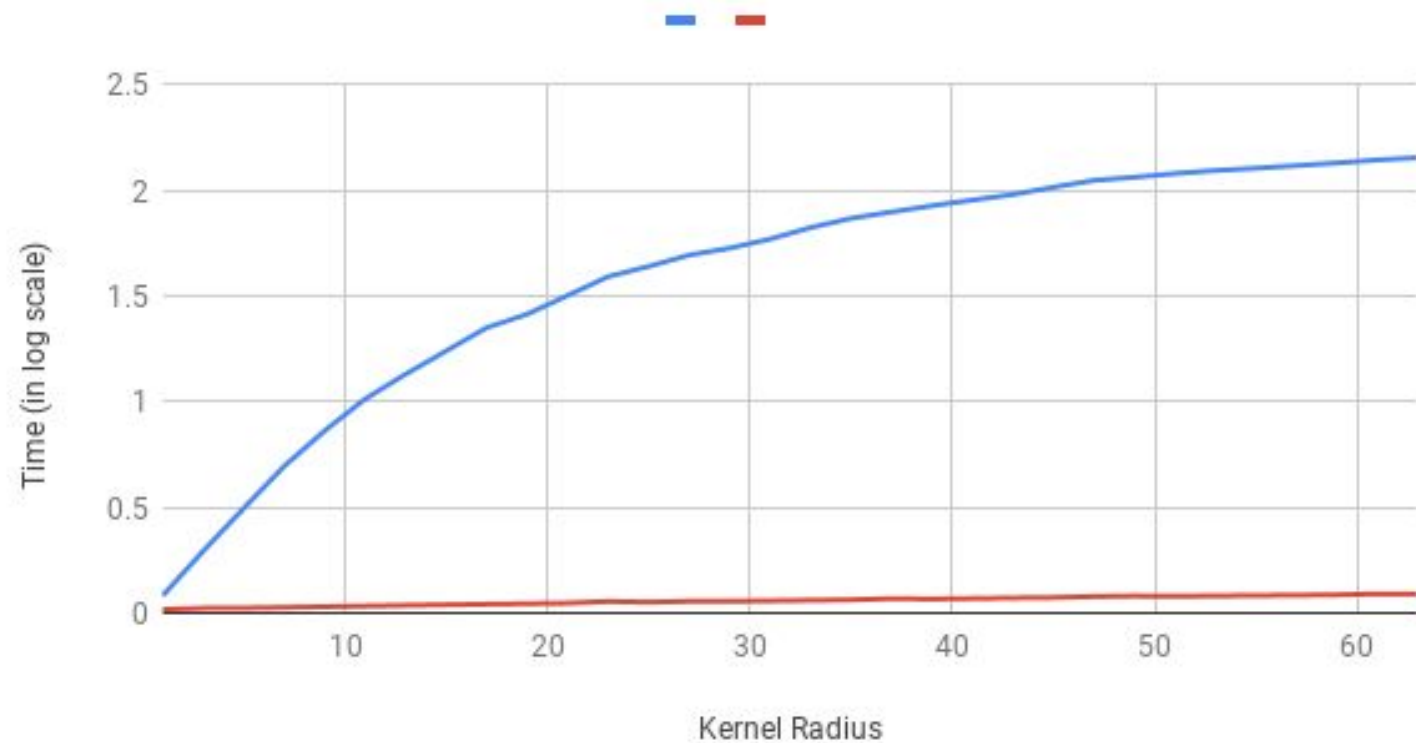
Gaussian Filter with radius = 25

Experiments

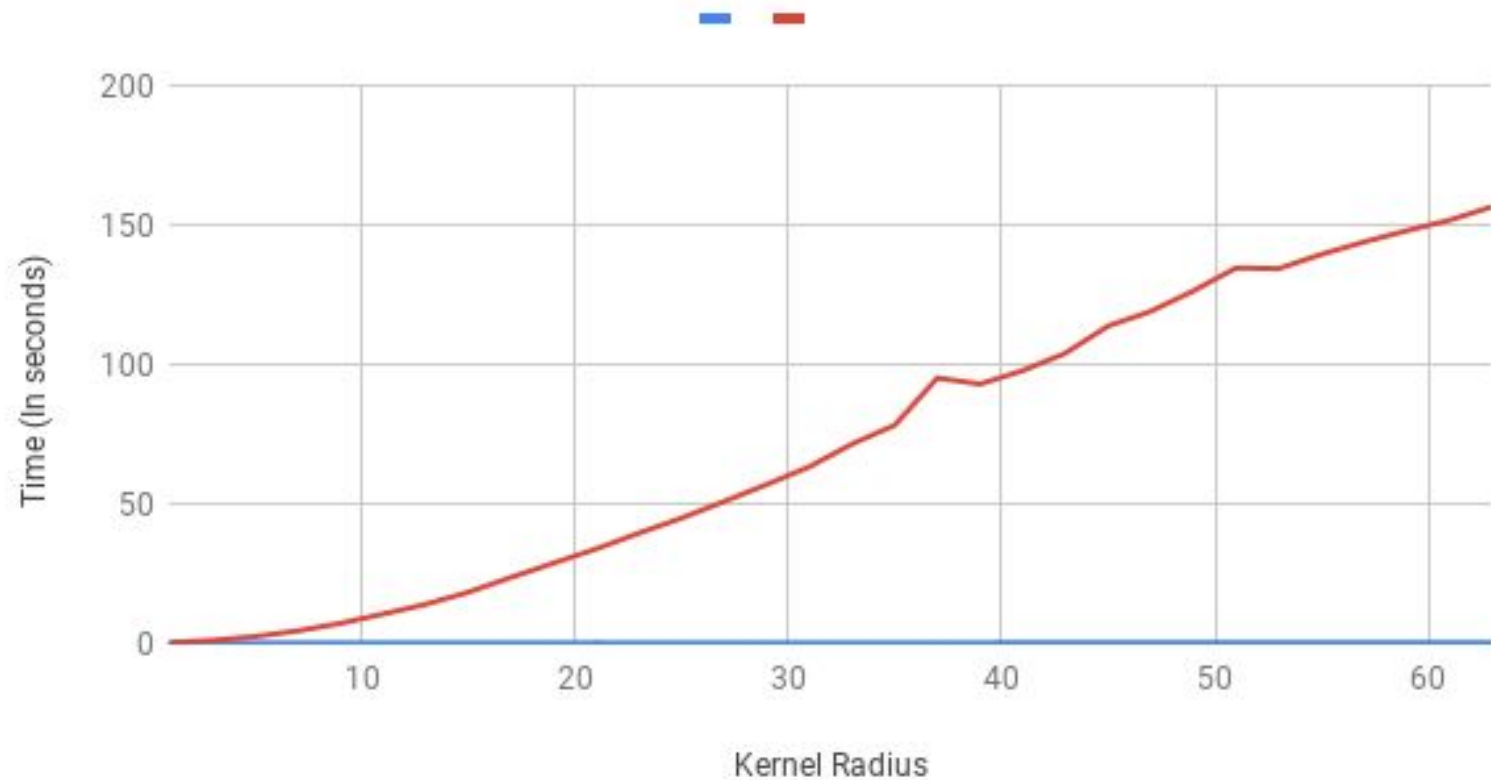
Varying Kernel Radius



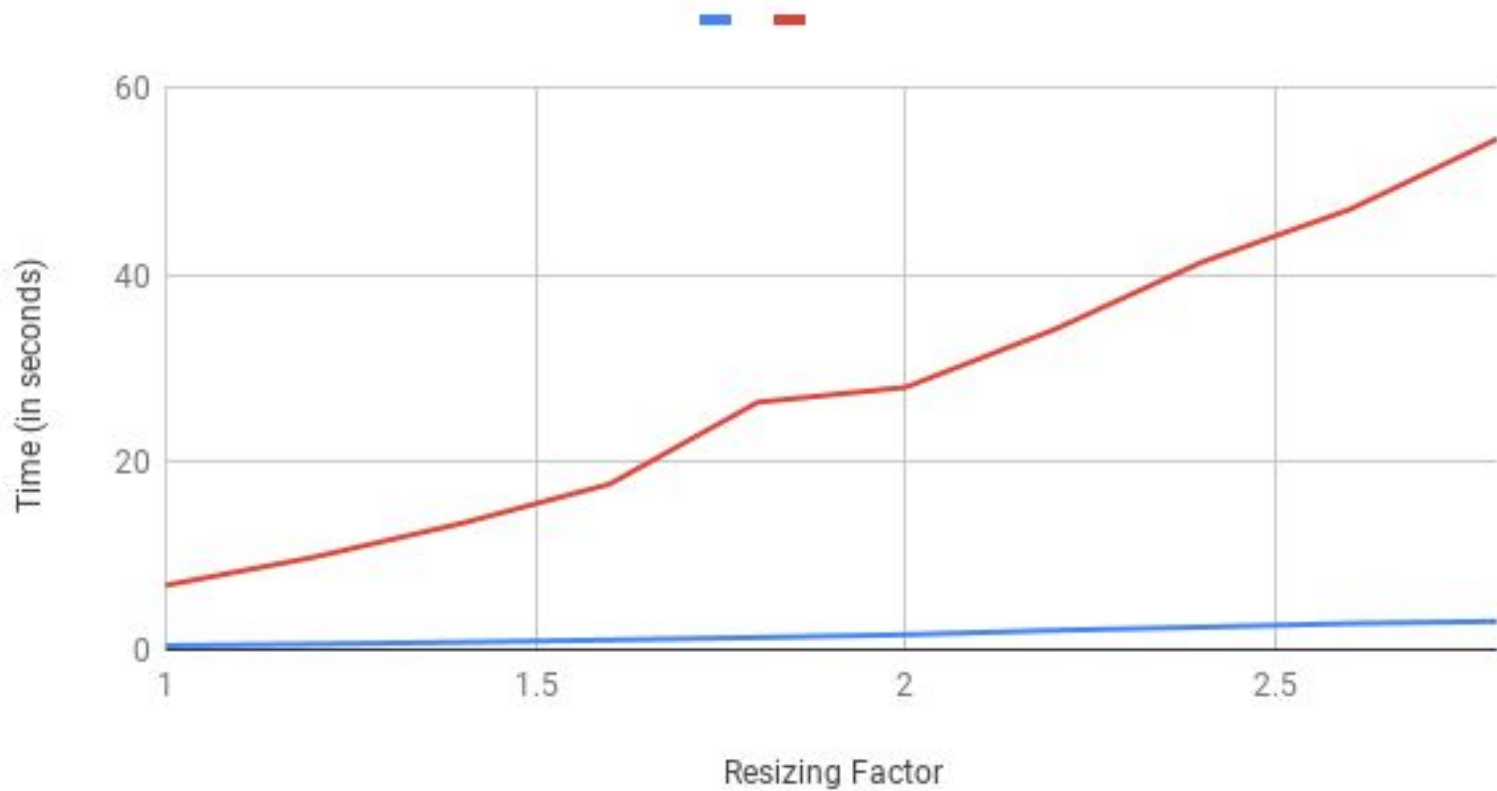
Comparison in log scale



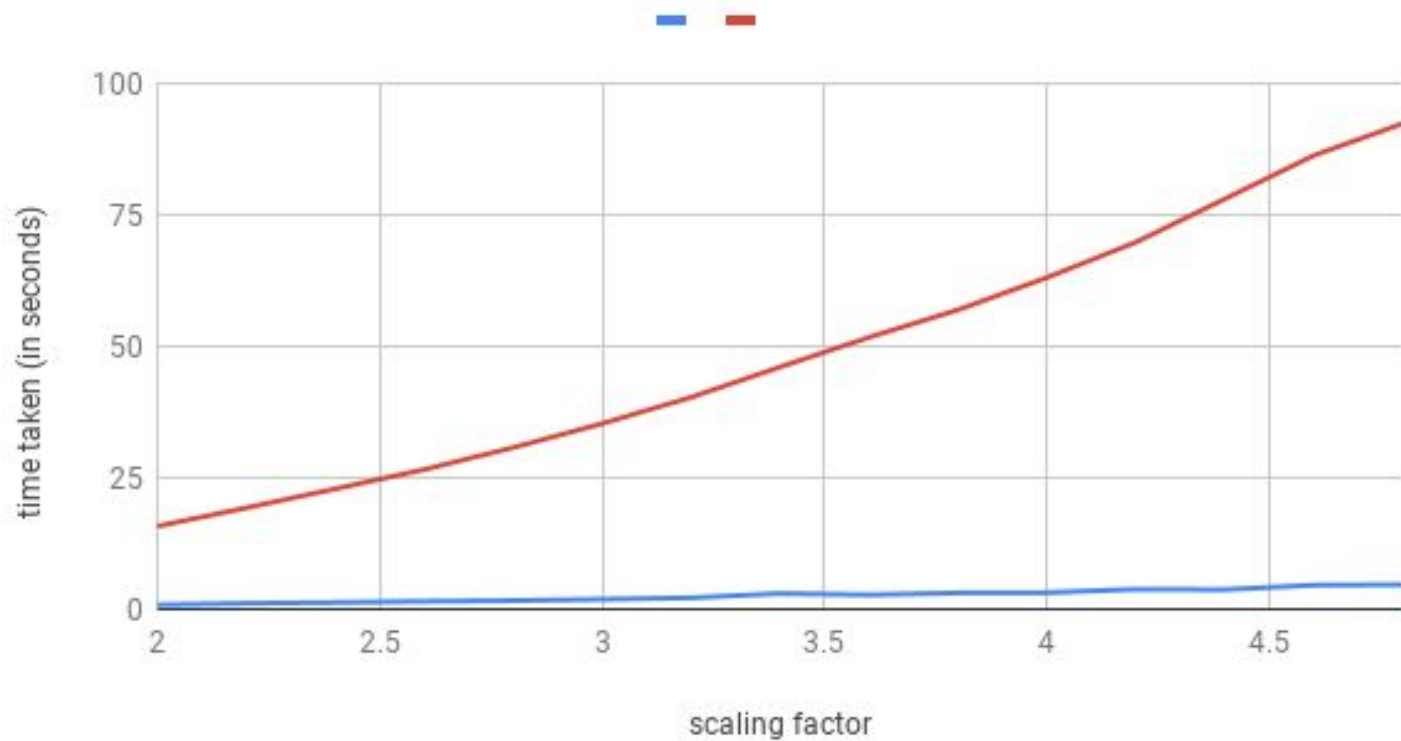
Varying Kernel radius (Guassian weighting)



Varying Image Size



Varying Image size(Gaussian Kernel)



Thanks :)