Fusion of Median and Bilateral Filtering for Range Image Upsampling

Mentor TA – Kalyan Adithya

Project Repo URL – https://github.com/Digital-Image-Processing-IIITH/dip-project-paka

Team PAKA

Members –
Abdullah Mujtaba – 2019101093 (CSE)
Abhishek Chawla – 2019102020 (ECE)
Kevin Idiculla Vargis = 2019101092 (CSE)
Pragya Singhal – 2019112001 (ECD)

Introduction

- Depth sensing in dynamic real-world environment
- Active Depth Sensors
- Time-of-flight Systems
- Enhancing spatial resolution of depth images

Related Work

- Bilateral Filter
- Range Image Upsampling
  - Kopf et al. – Joint bilateral filter for range image upsampling.
  - Riemens et al. –Using the joint bilateral filter hierarchically
- Weighted Median Filter

Motivation

- Bilateral Filter

$$I_{\mathbf{x}}^{J} = \frac{\sum_{\mathbf{y}\in N(\mathbf{x})} f_S(\mathbf{x},\mathbf{y}) f_R(J_{\mathbf{x}}, J_{\mathbf{y}}) I_{\mathbf{y}}}{\sum_{\mathbf{y}\in N(\mathbf{x})} f_S(\mathbf{x},\mathbf{y}) f_R(J_{\mathbf{x}}, J_{\mathbf{y}})}.$$

- Weighted Median filter

$$\arg\min_{b} \sum_{\mathbf{y}\in N(\mathbf{x})} W(\mathbf{x},\mathbf{y}) |b - I_{\mathbf{y}}|,$$

Motivation

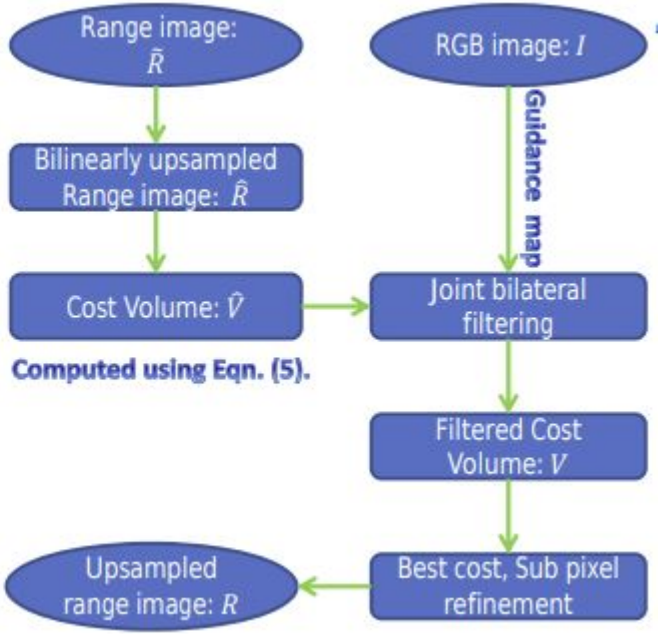
- Bilateral Weighted Median Filter

$$\arg\min_b \sum_{\mathbf{y}\in N(\mathbf{x})} f_S(\mathbf{x},\mathbf{y}) f_R(I_{\mathbf{x}}, I_{\mathbf{y}}) |b - I_{\mathbf{y}}|$$

- Joint Bilateral Weighted Median Filter

$$\arg\min_b \sum_{\mathbf{y}\in N(\mathbf{x})} f_S(\mathbf{x},\mathbf{y}) f_R(J_{\mathbf{x}}, J_{\mathbf{y}}) |b - I_{\mathbf{y}}|$$

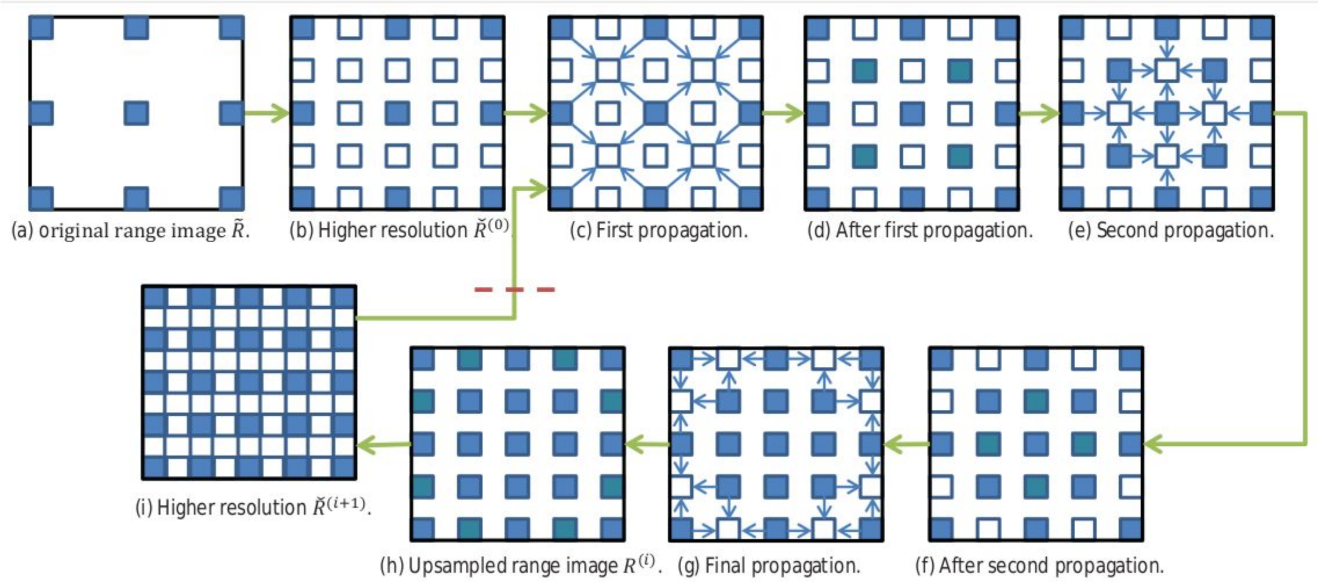
Approach


Range image: $\tilde{R}$
Bilinearly upsampled Range image: $\hat{R}$
Cost Volume: $\hat{V}$
Computed using Eqn. (5).
RGB image: I
Guidance map
Joint bilateral filtering
Filtered Cost Volume: V
Best cost, Sub pixel refinement
Upsampled range image: R

- Upsampling Using An Adaptive Cost Aggregation Framework

$$\hat{\mathcal{V}}_{\mathbf{x}}(d) = \min(\eta\mathcal{L}, |d - \hat{R}_{\mathbf{x}}|)$$

- Hierarchical Upsampling



- Final Computation

$$R_{\mathbf{x}}^{(0)} = \arg\min_{d \in \vec{d}_{\mathbf{x}}} \sum_{\mathbf{y} \in N(\mathbf{x})} \lambda(\mathbf{y}) f_S(\mathbf{x}, \mathbf{y})$$

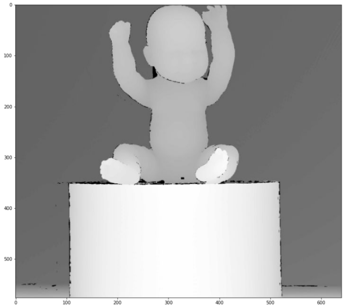
$$f_R(I_{\mathbf{x}}^{(0)}, I_{\mathbf{y}}^{(0)}) \min\left(\eta\mathcal{L}, |d - \check{R}_{\mathbf{y}}^{(0)}|\right),$$

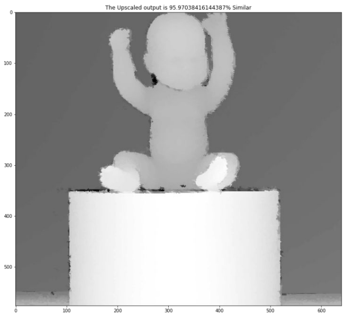
$$\lambda(\mathbf{y}) = \begin{cases} 1 & \text{if } \mathbf{y} \in \mathcal{B}, \\ 0 & \text{else.} \end{cases}$$

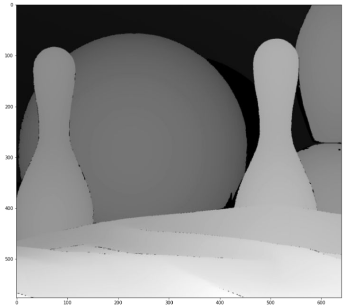
- Similarity Function

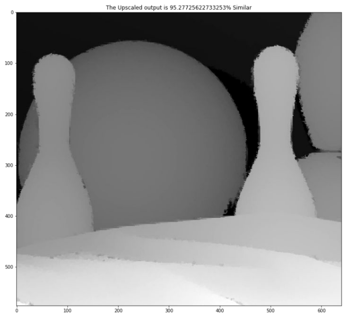
Experimentation

- Algorithm was tested on images from the Middlebury set with a similarity of 94.8% after two levels of upscaling (https://vision.middlebury.edu/stereo/data)

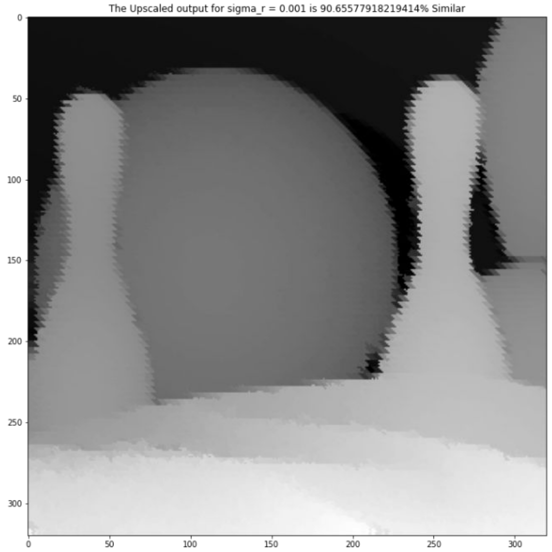


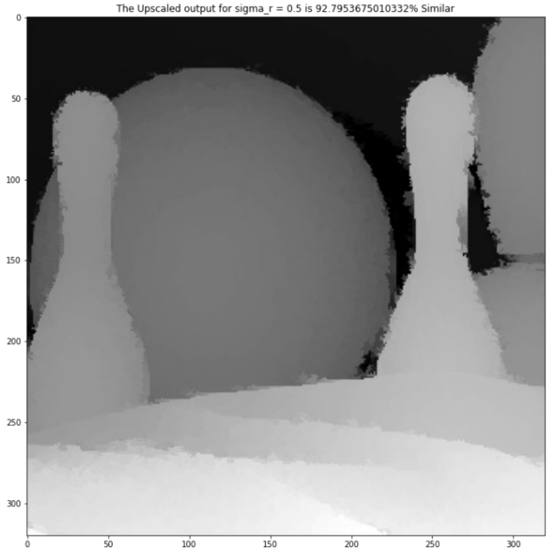


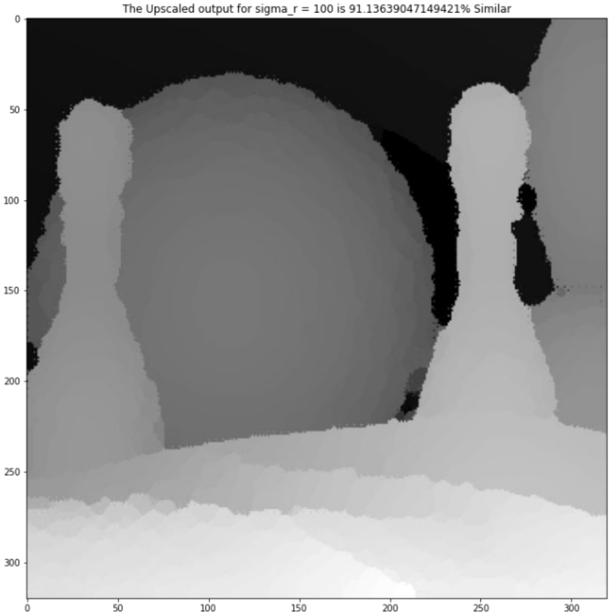




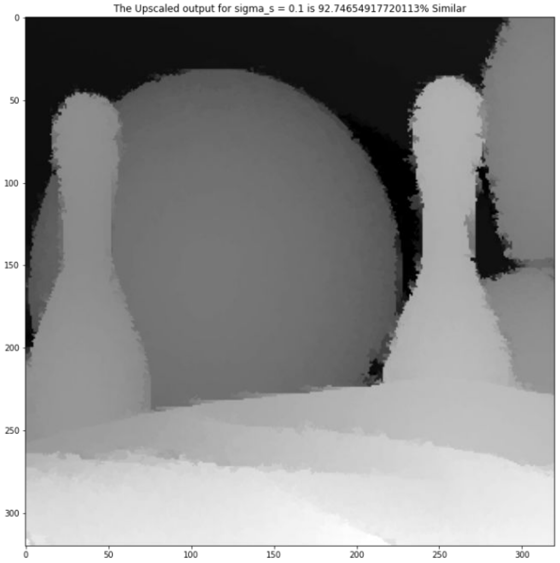
- Changing σ_R for constant $\sigma_S = 0.2$

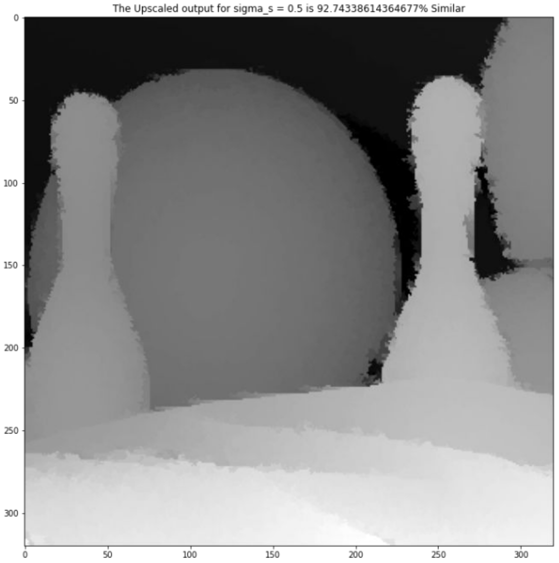


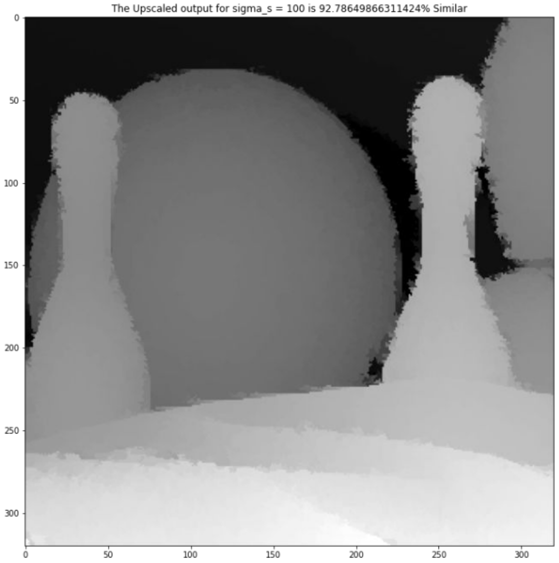




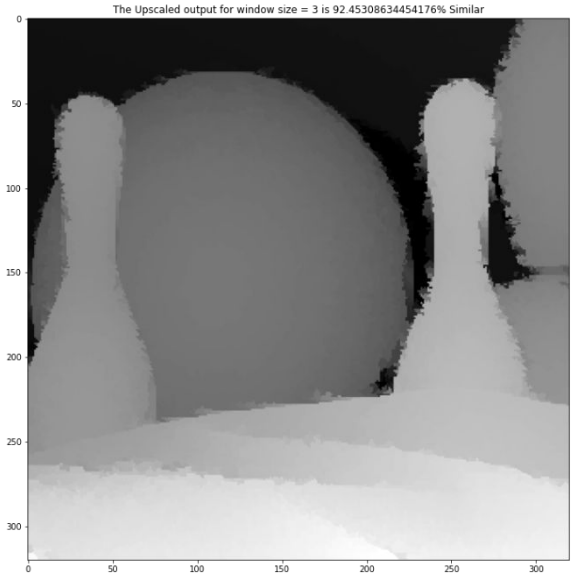
- Changing σ_S for constant $\sigma_R = 0.2$

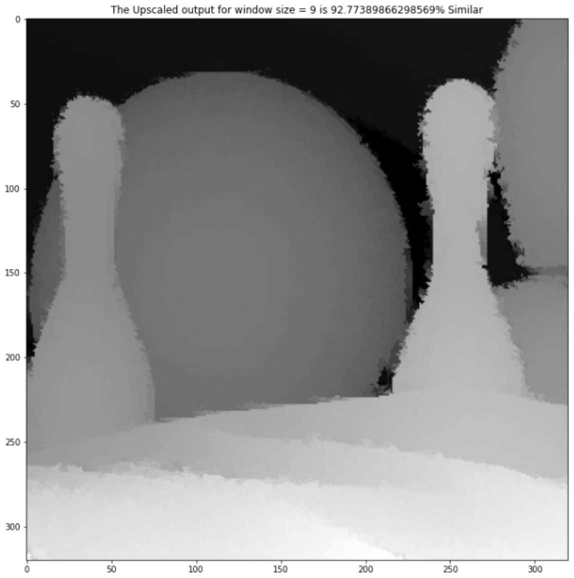


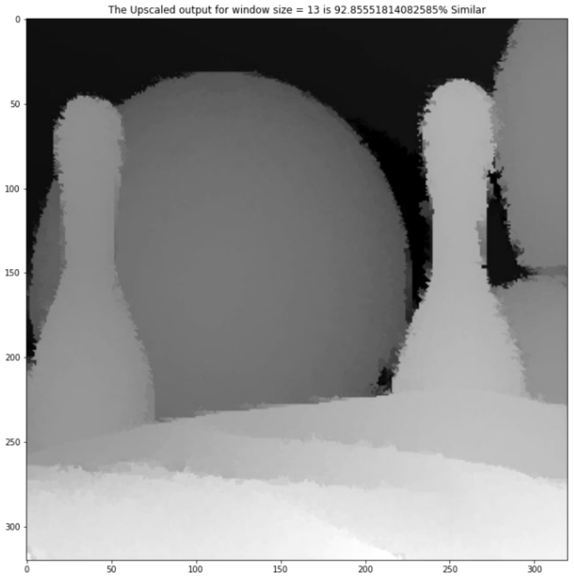




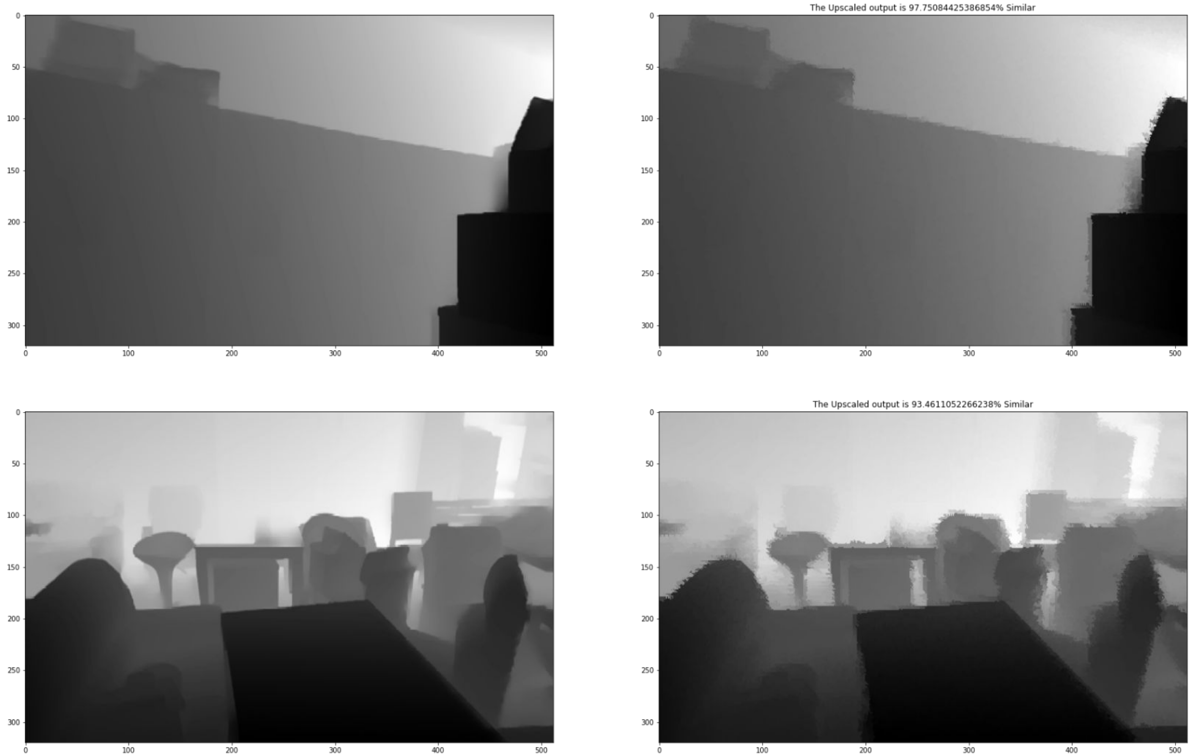
- Changing filter size for constant σ_S ,σ_R= 0.2



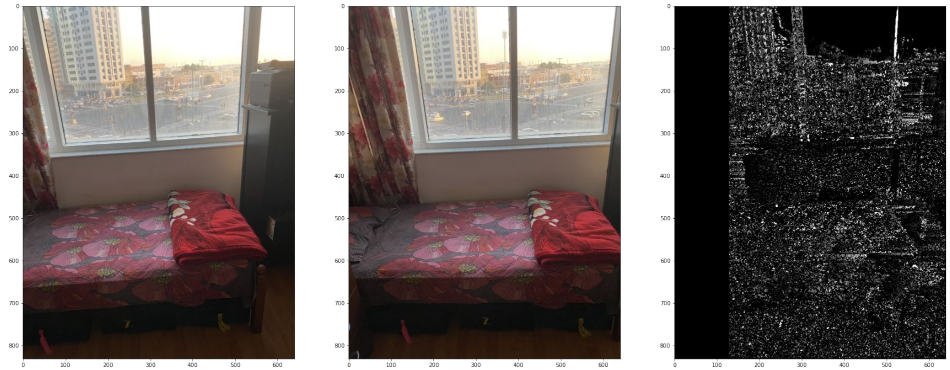


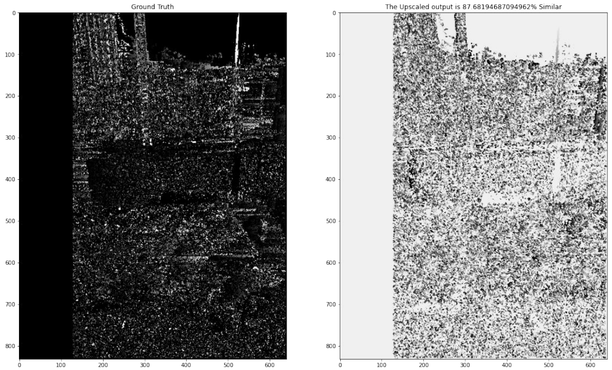


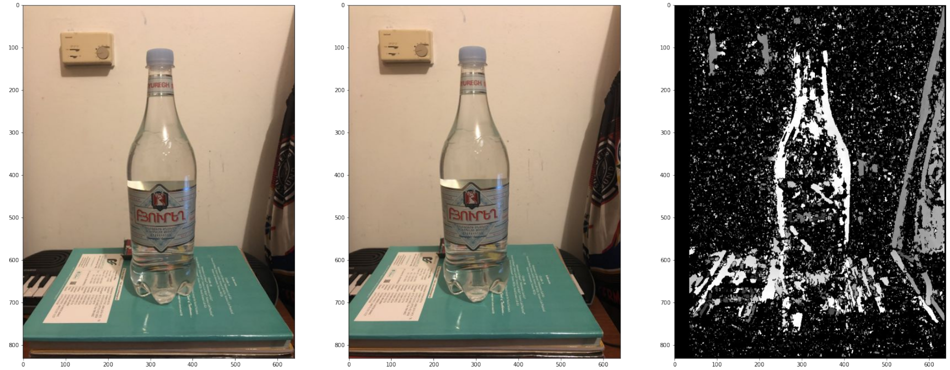
- The DIML RGB+D Dataset gives 94.02% similarity (https://dimlrgbd.github.io/)

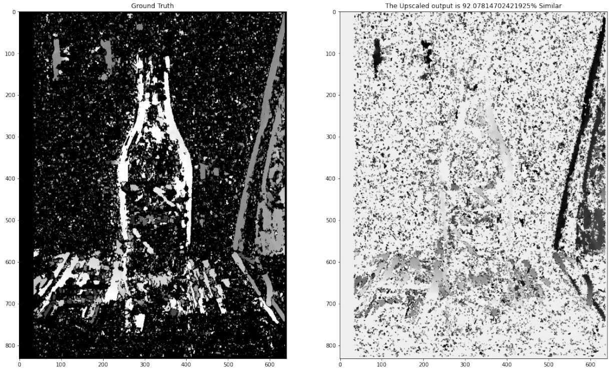


▪ Our attempt at making depth images









Inferences

- The ideal σ_S and σ_R were found to be 0.2 for our datasets.
- For these values, the accuracy of upscaling increased along with the computation times for larger filter sizes
- Using a different dataset gave us similar average accuracy values.

Conclusion

- The algorithm was able to upscale low resolution range images 2-3 levels(4x - 8x upscaling), while giving 90%+ similarity to the ground truth image.

Contributions:

- **Kevin Vargis -** Coded setup and helper functions for preparing image, Implemented GUI, helped with Experimentation
- **Abdullah Mujtaba -** Implemented first level of hierarchical depth propagation, wrote the documentation and Debugging
- **Abhishek Chawla -** Completed Hierarchical Depth Propagation, Experimentation and Testing
- **Pragya Singhal -** Added Error function, Implemented function for scaling the images properly, Made the Presentation