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## 3D Sensing and Sensor Fusion

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Data-level fusion: Filtering and Guided Upsampling

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# Chapter 1

## Deliverable

The goal of this task is to implement different multilateral filters and upsampling algorithms using guided filtering and finally to compare upsampled depth images with corresponding ground truth images.

### 1.1 Subtask-1: Algorithms

Four different algorithms have been implemented and used for comparing 12 stereo pairs, taken from Middlebury Stereo 2005 and 2006 Datasets. The Algorithms are:

1. Bilateral(B) filter
2. Joint Bilateral(JB) filtering
3. Joint Bilateral Upsampling(JBU)
4. Iterative upsampling

Figure 1.1 represents the input high resolution image from Moebius dataset and its corresponding output after applying Bilateral filter, Joint Bilateral filter, Joint Bilateral Upsampling, Iterative Upsampling. For the upsampling algorithm I downsampled the depth image to 1/4th of its size.

### 1.2 Subtask-2: 3D Display

In this subtask, I've converted generated disparity map to 3D object with the help of Open3D(library for 3D data processing). The disparity map used for conversion was generated by iterative upsampling approach with window size 9 for "Aloe" images from

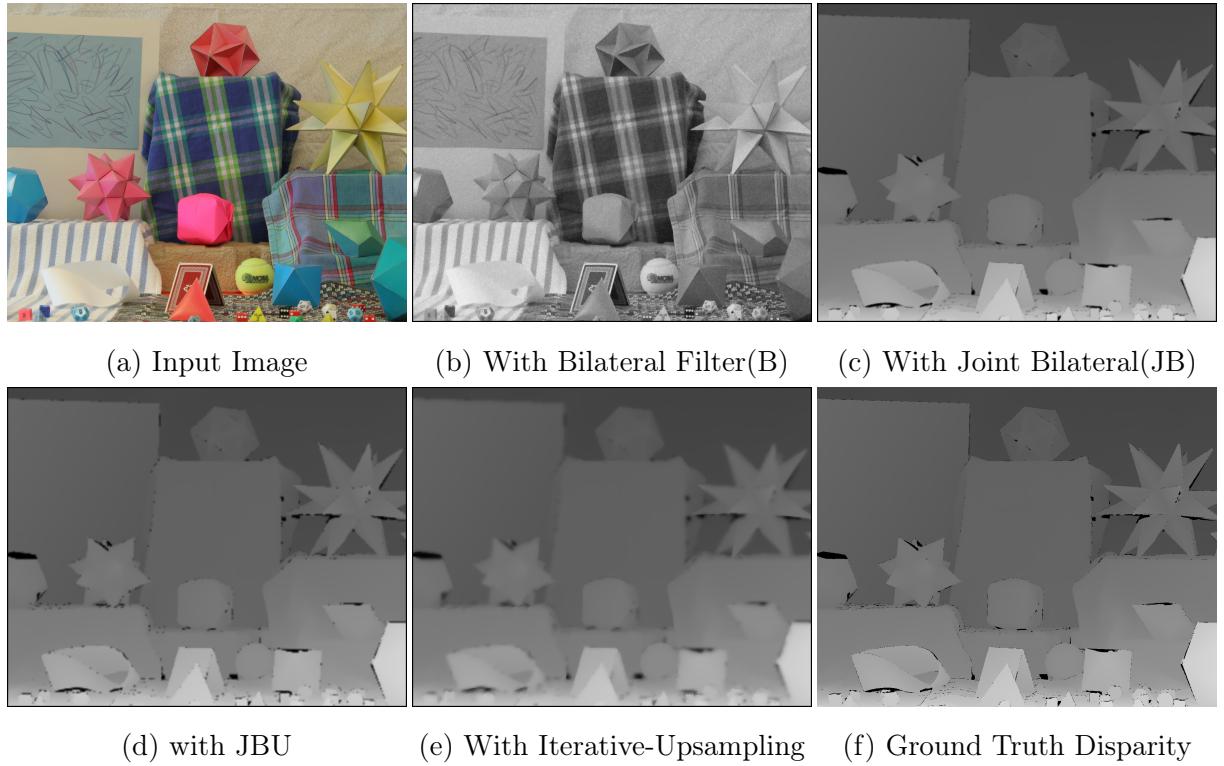


Figure 1.1: Result of different filter with window size 9.

middlebury 2006 data-set.

Figure 1.2 represents the generated point cloud from different viewpoint.

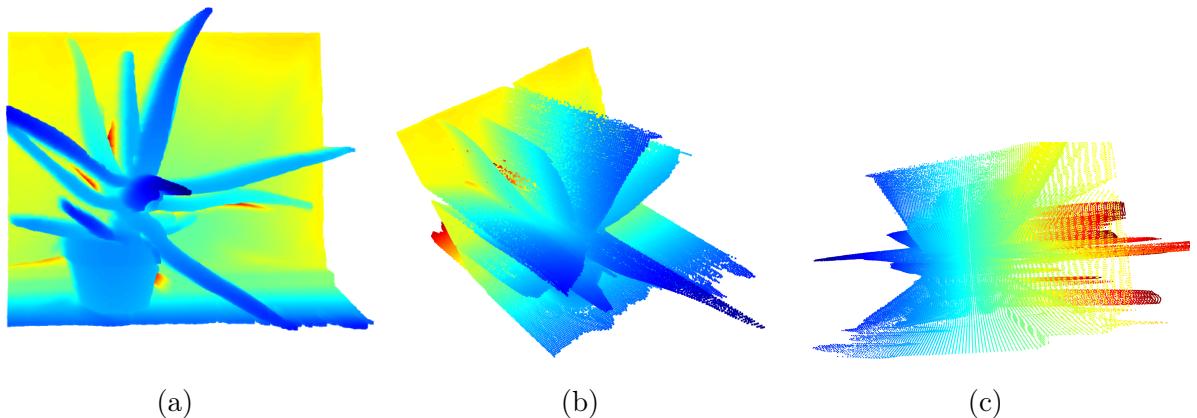


Figure 1.2: Point cloud from different viewpoint

Figure 1.3a illustrates the point cloud after assigning surface normal to each point. Finally, Figure 1.3b presents 3D triangulated surface.

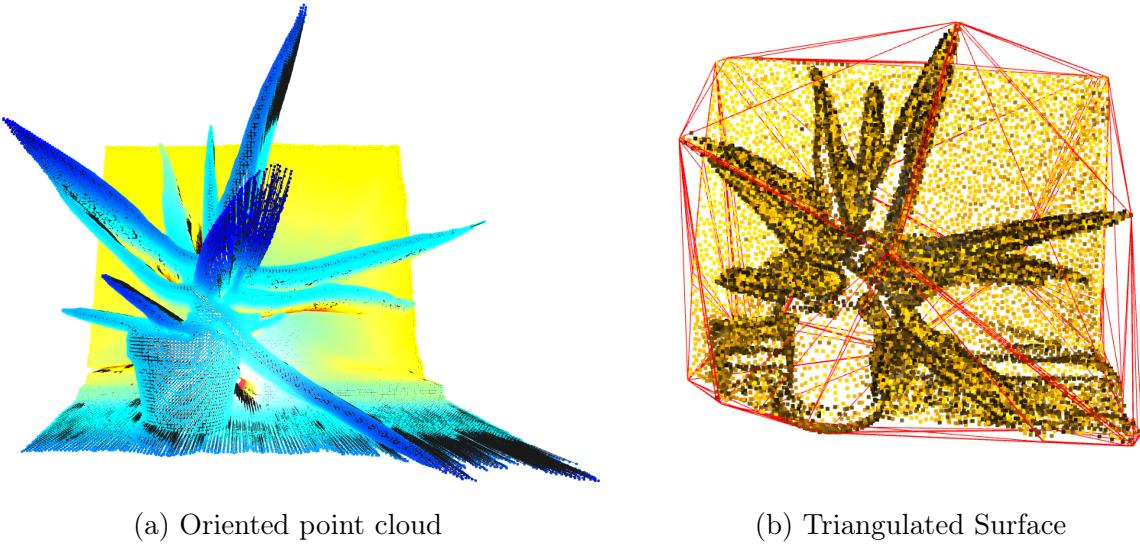


Figure 1.3: Point cloud after assigning surface normal and triangulation

### 1.3 Subtask-3: Evaluation

For evaluating the algorithms I've taken 12 pairs of stereo images and respective ground truth disparity maps from Middlebury 2005 and 2006 datasets.

#### 1.3.1 Processing Time

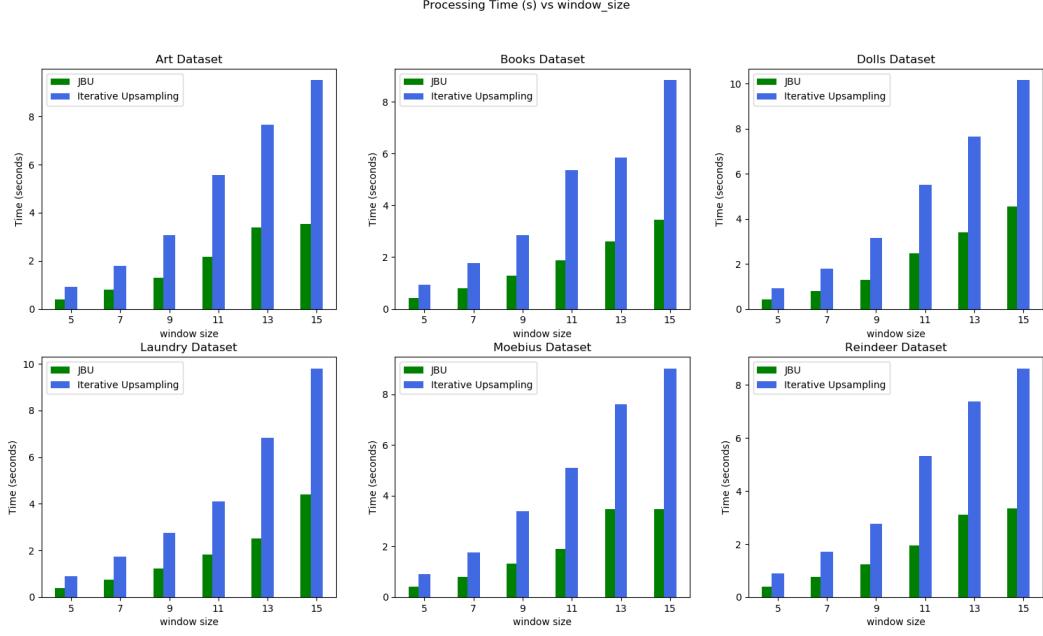
Figure 1.4 presents the processing time for different window size (5, 7, 9, 11, 13, 15) for the upsampling algorithms across all the datasets. In General, the iterative upsampling algorithm takes more time than the JBU for specific dataset and window size. For both JBU and iterative upsampling the processing time increases significantly with the increase of window size.

#### 1.3.2 Quality Comparison with Ground Truth Disparity

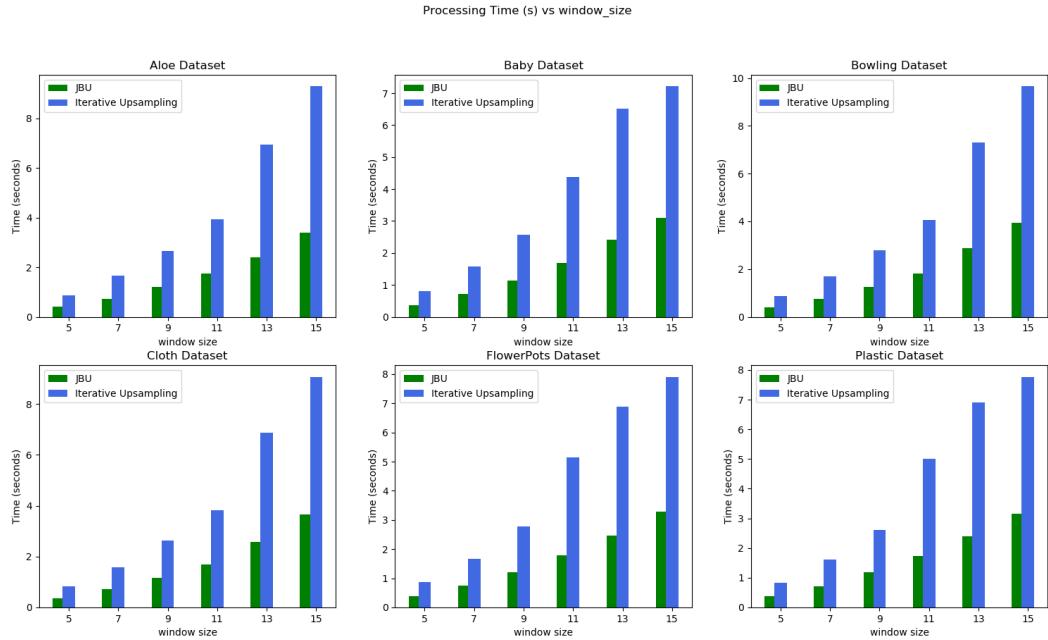
In this section, I've compared the quality of upsampled disparity maps by both JBU and Iterative upsampling, to ground truth disparity maps with three different matrices keeping fix sigmas (sigma spatial factor = 1.5, sigma range = 20).

#### Sum of Squared Differences (SSD)

Figure 1.5 represents the results for SSD, where it can be seen that the error increases with the increase of window size. The JBU approach has relatively less error than Iterative Upsampling in all cases for this metric.



(a)



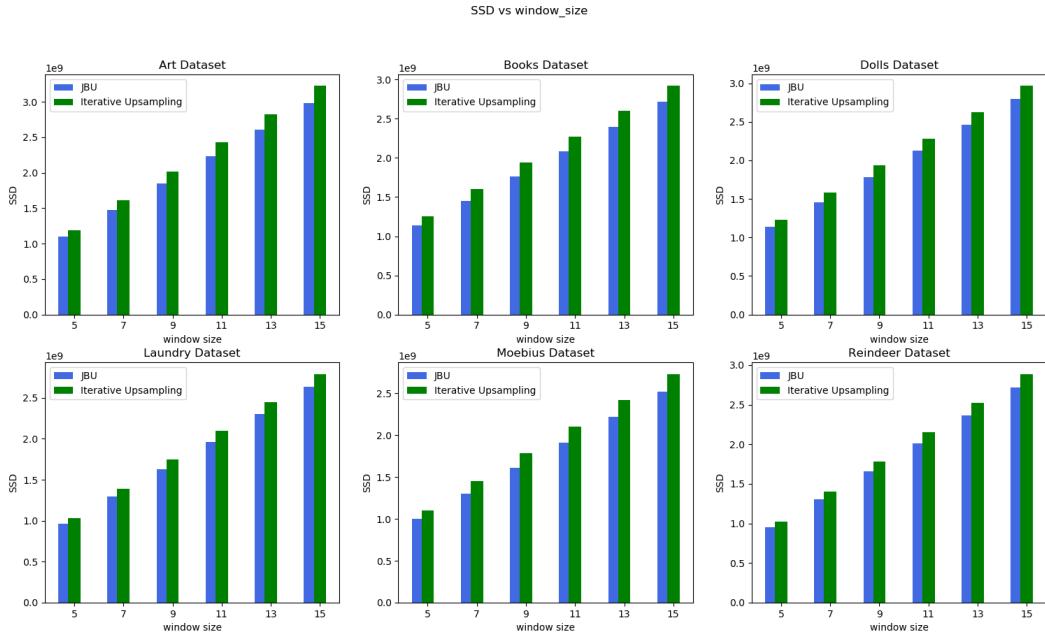
(b)

Figure 1.4: Processing time vs window size for different algorithms and all datasets

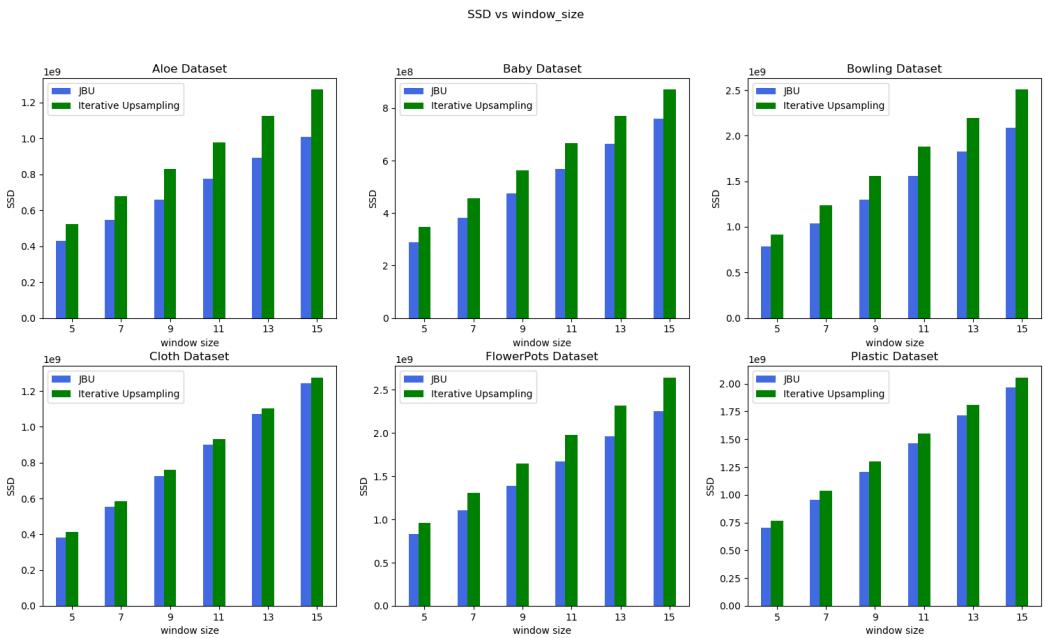
### Structural Similarity Index Measure (SSIM)

SSIM gives output as 1 if the images are perfectly matched. Figure 1.6 represents SSIM value for different window size for 1 pair from each dataset and for both of the upsampling algorithms.

It can be noted that JBU has slightly better matches than Iterative upsampling and with



(a)



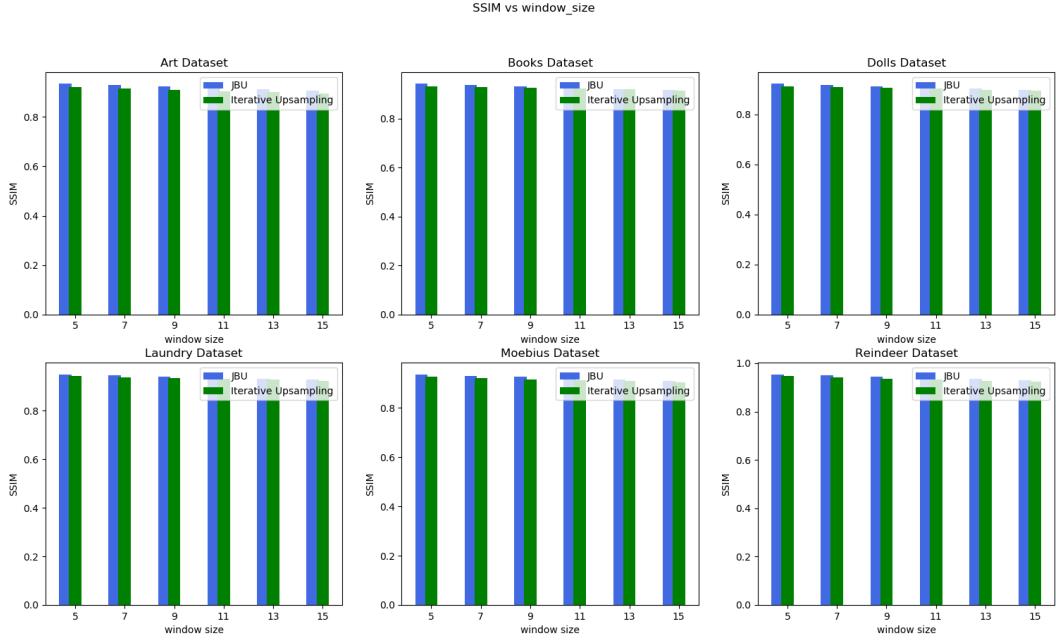
(b)

Figure 1.5: SSD vs window size for different algorithms and all datasets.

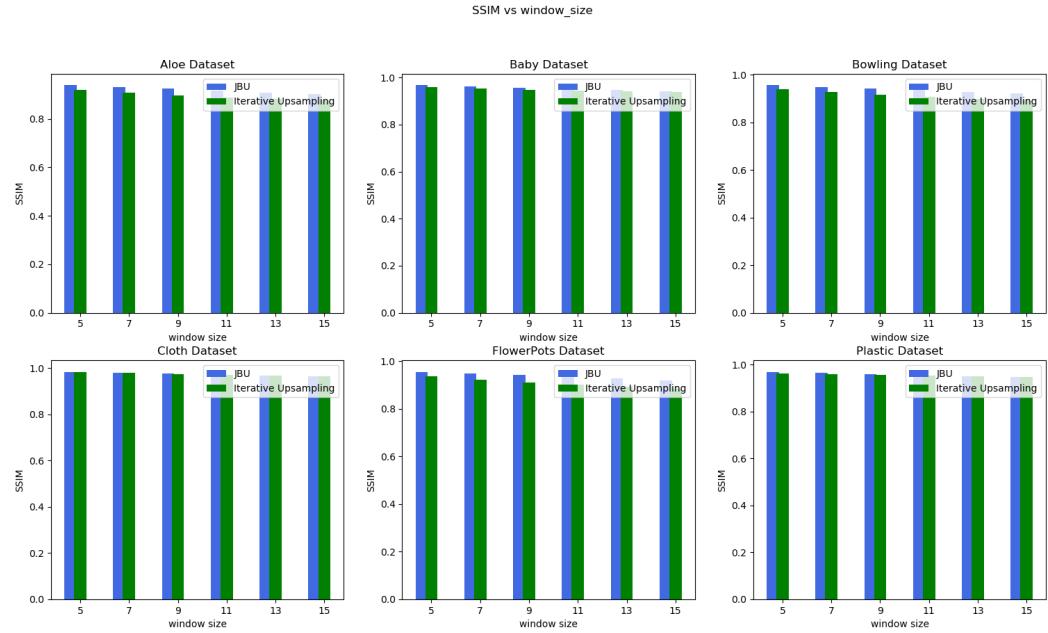
different window size it's almost constant.

### Normalized Cross Corelation (NCC)

Similarly, figure 1.7 illustrates the normalized cross correlation results.



(a)



(b)

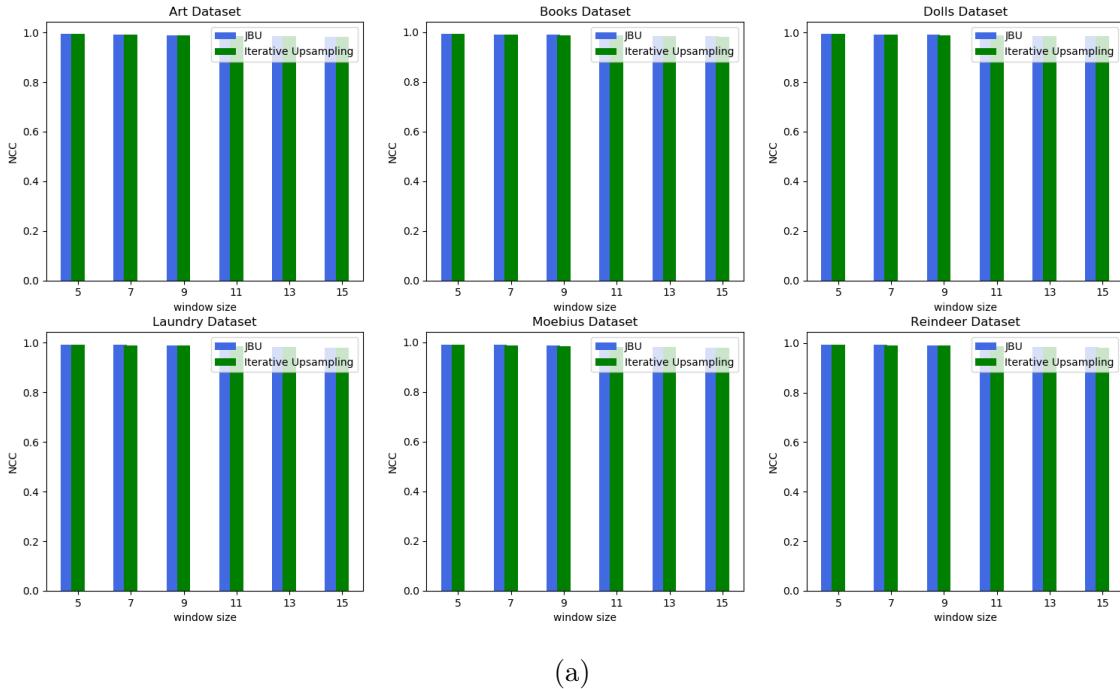
Figure 1.6: SSIM vs window size for different algorithms and all datasets.

### 1.3.3 Difference Image

Figure 1.8 represents the difference image between upsampled disparity with ground truth disparity for both of the upsampling algorithms. In the difference image the blue area represents the missing part of right image with respect to the left image.

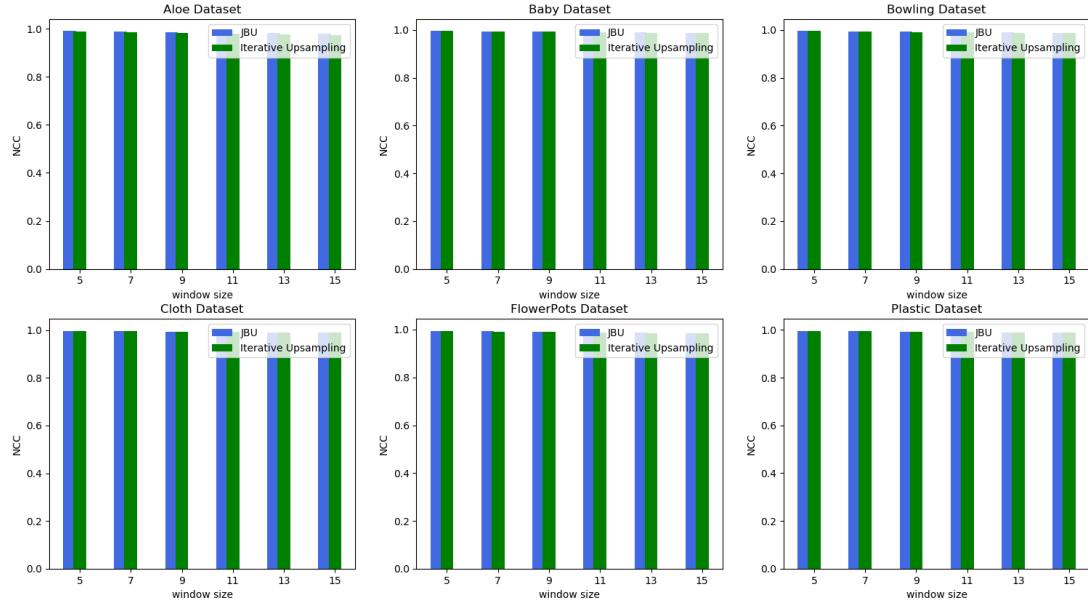
Figure 1.9 shows with increasing window size the difference between upsampled depth

NCC vs window\_size



(a)

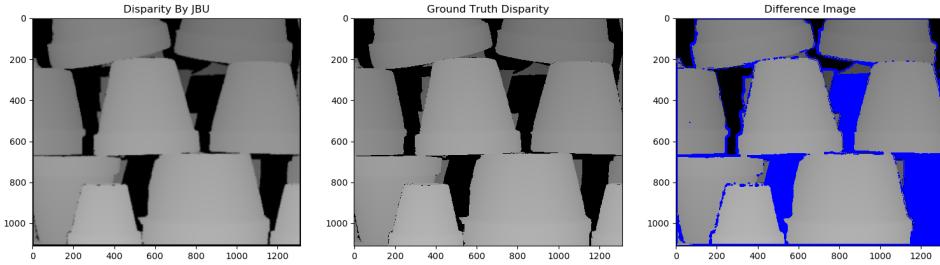
NCC vs window\_size



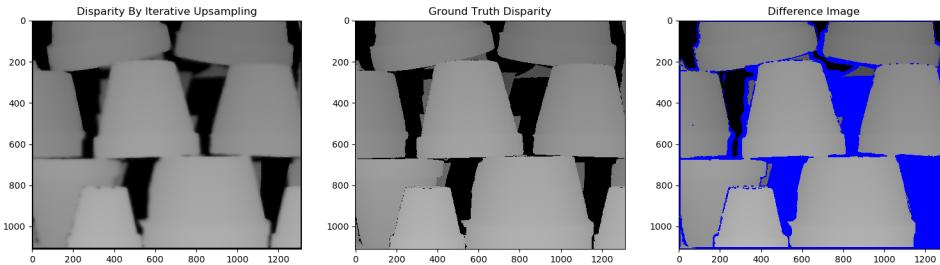
(b)

Figure 1.7: NCC vs window size for different algorithms and all datasets.

image and the ground truth depth image is decreasing.

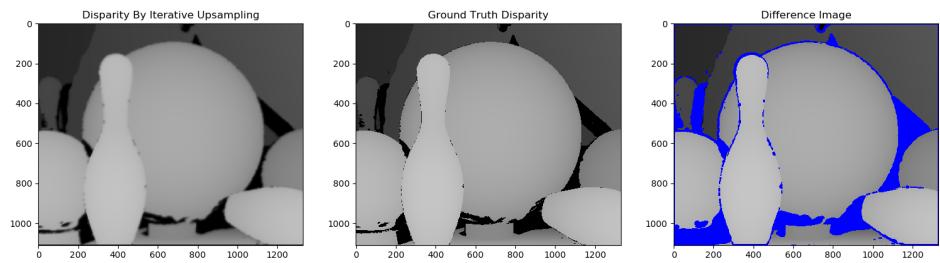


(a) For JBU

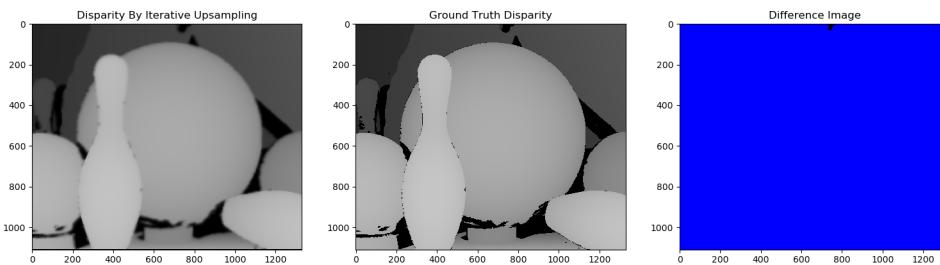


(b) For Iterative Upsampling

Figure 1.8: Difference image between upsampled and ground truth disparity.



(a) with window size 7



(b) with window size 9

Figure 1.9: Difference image between upsampled and ground truth disparity for different window size.

### 1.3.4 Sigma Optimization for JBU

#### Sigma Spatial Optimization:

Sigma Spatial is calculated as:

$\text{Sigma Spatial} = \text{Sigma Spatial Factor} * \text{Half window size} / 2.5$ . So here I'm optimising sigma spatial factor. For the optimization I fixed the window size and Sigma Range and computed JBU depth image for 3 different dataset for a list of chosen value as sigma spatial factor ([0.1, 0.3, 0.5, 0.7, 0.9, 1.1, 1.3, 1.5, 1.7, 1.9, 2.1, 2.3, 2.5]). And the compared the generated depth image with ground truth using 3 metric. The result is shown in 1.10. It can be seen that with increasing values error is also increasing. Because with increasing

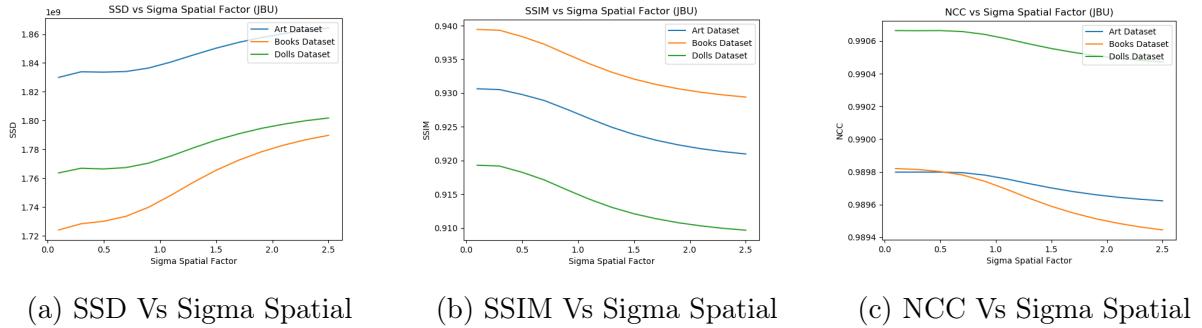


Figure 1.10: Sigma Spatial Factor optimization

sigma spatial it removes outlier and do more blurring of the image. So it should be low. From the plot it can be analysed that 0.5 could be a good value for Sigma Spatial Factor.

### Sigma Range Optimization:

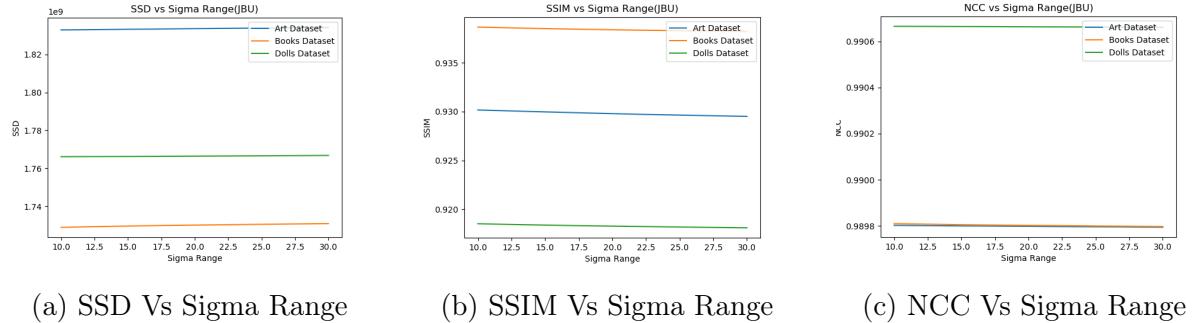


Figure 1.11: Sigma Range optimization

For optimizing sigma range I followed the same procedure. This time I fixed the window size to 9 and sigma spatial to 0.5. And the chosen values of sigma range was [10, 12, 15, 17, 20, 22, 25, 27, 30]. The effect of changing sigma range to bigger values is very less in this case. Because sigma range helps in preserving edges and edges of the image has less effect on comparison of the whole image with ground truth. So sigma range should be something in the middle .