

Assignment 4 Report

Instructions on how to run code.

All the sections of this assignment run as per assignment specifications. Example runs:

Part 1:

```
./render <image_file> <disparity_file>
```

Part 2:

```
./segment <image_file> <seeds_file>
```

Part 3:

```
./stereo <image_file_1> <image_file_2> <gt_file>
```

Part 1.

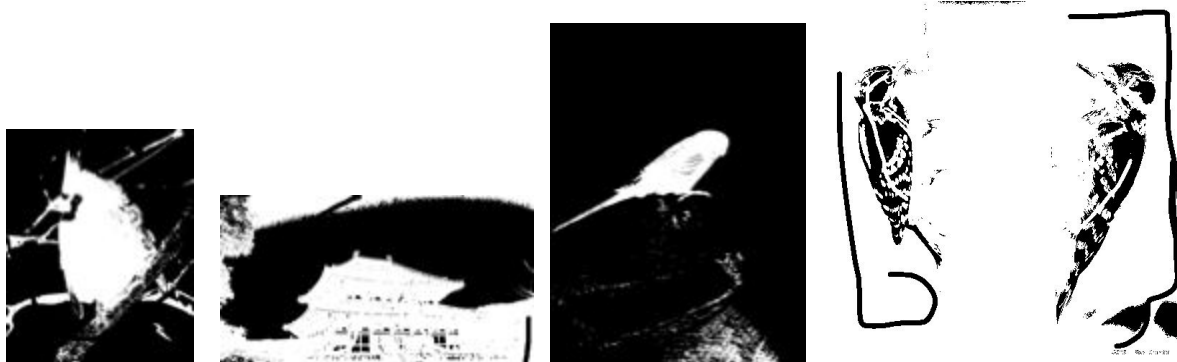
Stereograms derived from original image and disparity map.



Part 2. Semi-supervised segmentation

Part 2.1 Semi-supervised naive segmentation

Below are images from naive semi-supervised segmentation, with an optimized beta value (same for all images) after several trial and error attempts. The naive approach works relatively well for the cardinal, nara, and parakeet examples, but quite poorly for the woodpecker. It was able to work well for the former 3 examples because the color of the foreground and the color of the background were fairly consistent within each other, allowing the Gaussian probability density function to be effective. However, the woodpeckers (foreground) contain two disparate colors within the object and therefore would not be effective without some type of spatial coherency to distinguish the foreground from the background.



Part 2.2 Semi-supervised MRF segmentation

Having selected a beta value in Part 2.1, we found alpha through trial and error. We used 18 for beta which gave the best result in Part 2.2. Just to verify that the algorithm works, we used 200 for iteration and we changed it to the size of image (width + height) later. And we observed that increasing the value of α increases the smooth labeling across the image, but it also leads to a loss of object boundary features.

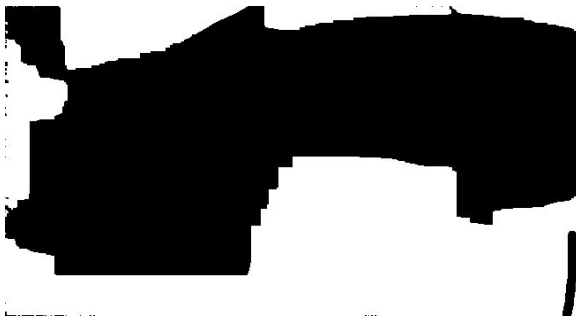
$\alpha=1$









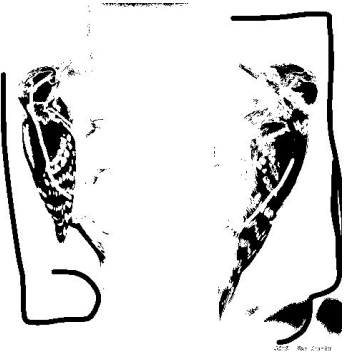
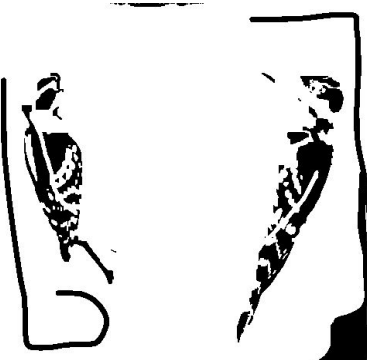
$\alpha=2$



$\alpha=4$



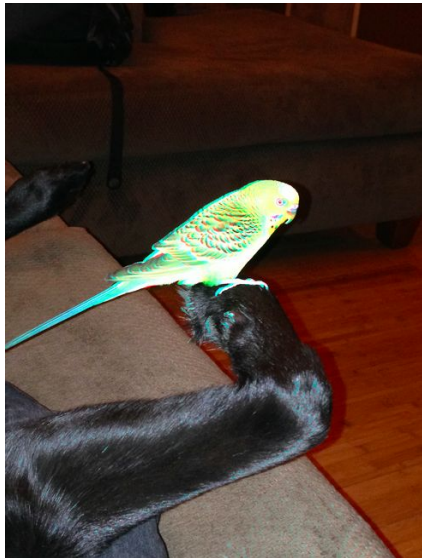
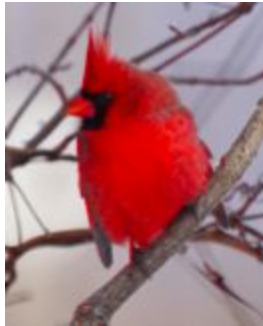
We observed that α was dependent on image. A image with sharp corner or more details,we should apply less smoothing to avoid losing information in the image. We also noticed that 25 iterations was enough to produce an approximation for segmentation.

Naive Segmentation	MRF	α
		1
		2
		1.5
		1

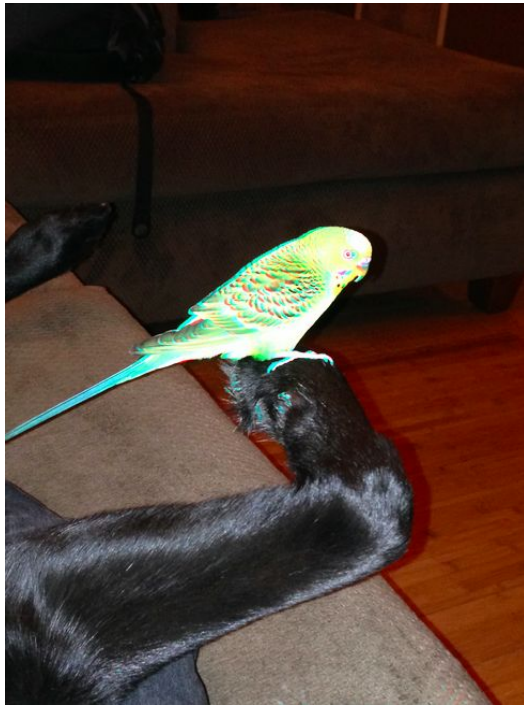
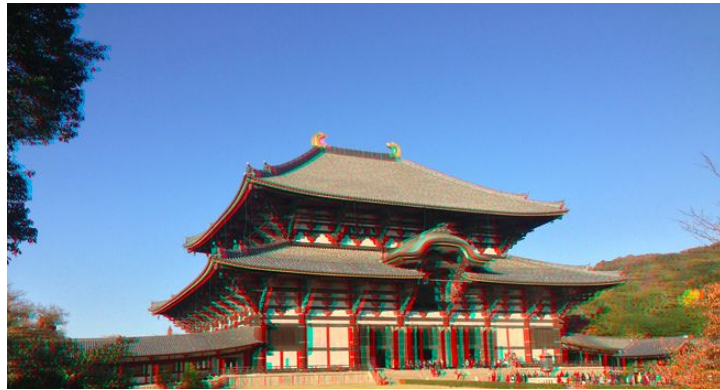
Part 2.3 Stereograms using Naive and MRF derived disparity maps

The stereograms below compare those derived from Naive and from MRF disparity maps. With the exception of the woodpeckers, the stereograms from MRF disparity maps show slightly better performance.

Part 2.3.1 Images derived from Naive segmentation



Part 2.3.2 Images derived from MRF segmentation



Part 3

To test how the algorithm performs we use only 15 iterations of BP to improve run time for testing. The following results are obtained using this number of iterations. We found that the MRF would converge in this time, and would then produce noisier results given more iterations. Naive stereo produces mean error of 123.56. With 15 iterations, an α of 200 gives the lowest mean error of 93.0762.

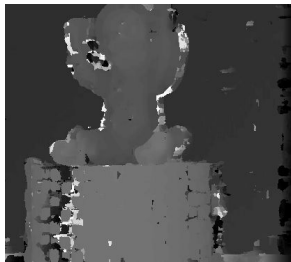
Interestingly, we find that a lower mean error does not necessarily correlate with a subjectively better match. With $\alpha=200$, the error is at it's lowest, but we can see looking at the disparity map that there is a large "artifact" of the smoothness running diagonally through the box. The background was also smoothed compared to the other tests, and this lead to a lower overall error, along with the solid white/black areas around the hands being minimized. We find that with $\alpha=50$ produces a result that is visually closest to the provided ground truth files.

We print out the best disparity for each pixel to choose a best value for max disparity. The range is from 0 to 45. So we use 100 for max disparity to guarantee that each pixel would be happy to find a best disparity for itself. Additionally, we kept the window size at 5x5 for all of these tests.

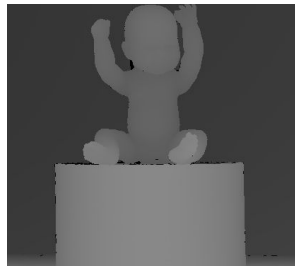
For the final result, we have 100 iterations, and we get the essentially the same result when we use 15 for iterations. So we can conclude that the algorithm converges early, but we get minor improvements by allowing it to run for a longer period of time.

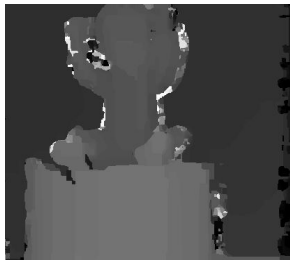



	$\alpha=25$	$\alpha=50$	$\alpha=100$	$\alpha=200$
Naive Error	123.56	123.56	123.56	123.56
MRF Error	101.43	100.283	102.821	93.0762

Naive stereo

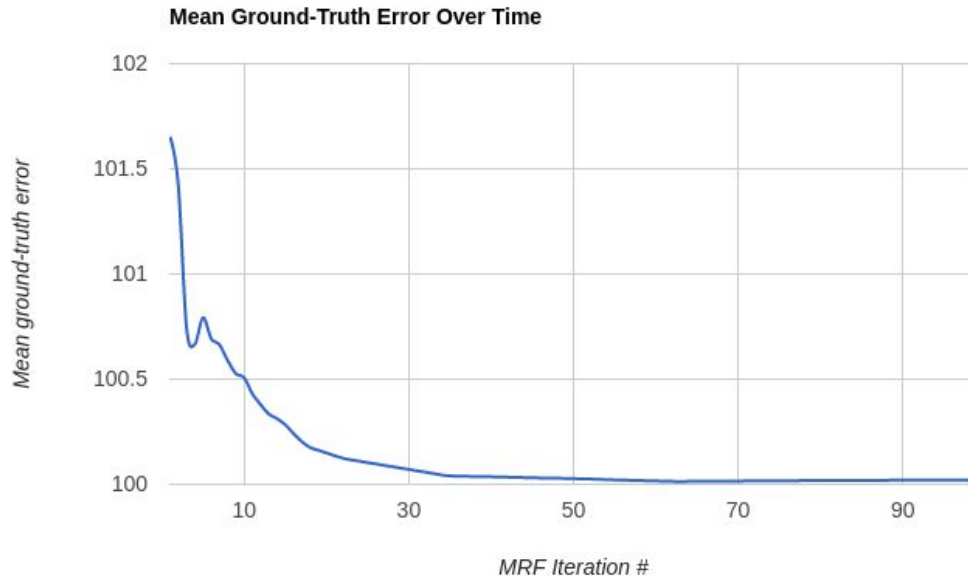


Ground Truth



MRF $\alpha = 25$	MRF $\alpha = 50$	MRF $\alpha = 100$	MRF $\alpha = 200$
			

MRF $\alpha = 50$, after 100 iterations: (mean error: 100.022)



Stereograms derived from best disparity map (above) and view1.png images:



Qualitatively, we have trouble seeing a 3d type effect with this example image. There is little difference viewing this image through the 3d glasses when compared side-by-side with the original, un-stereogrammed image. There are some “weird” areas, especially around the rightmost hand of the baby, that form a blurry blue/red region in the stereogram, but this doesn’t show up well when viewed through the glasses.



These stereograms look decent compared to the ones generated from the naive method. They do not, however, “pop” to the extent that the stereograms generated from ground truth do.