COSC 342 Assignment 2 – Stereo Disparity Estimation

Report for Beckham Wilson ID #7564267

Introduction

The experiments conducted within this report explore the effects of maximum disparity and block size parameters used in block matching for stereo estimation and the effects of post-filtering. The first experiment investigates the relationship between the max disparity settings and distance to the scene. The second experiment investigates the relationship between the block size settings and surface type. In the third experiment, I explore post-filtering to improve the quality of disparity maps.

Image Dataset:

I will be using the SteroPairs dataset provided in Assignment 2 and Lab 7. For experiment one, I will use the hallway pair as a long-distance scene, and the bookshelf pair as a short-distance scene. In the second experiment, I will use the rock pair as a rough surface and the bell pair as a smooth surface. In the third experiment, I will use the bell pair and bookshelf pair.

Experiment Process:

Before this, I calibrated both cameras and exported the required parameters into calibration.json

For each image pair:

1. Perform stereo rectification to create a parallel pair
2. Resize image size to 30% since the further step is computation-intensive
3. Use either Block Matcher or Semi Global Matcher to compute disparity
4. Display disparity map

Note the disparity map displays closer objects as brighter/whiter and darker/black for further away objects.

Experiment 1: Distance and Max Disparity

Hypothesis/Question:

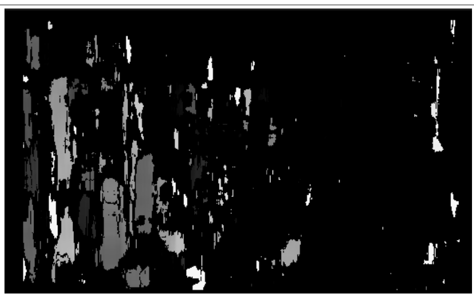
Does the quality of the disparity map depend on the distance to the scene and the choice of max disparity settings?

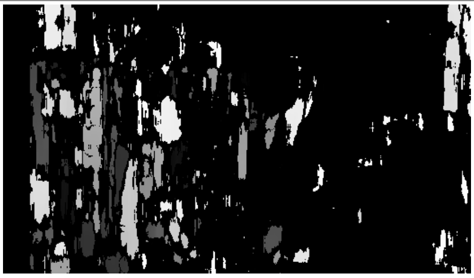
Experimental Design:

We will follow the outlined experiment process above but use the hallway pair as a long-distance scene and the bookshelf pair as a short-distance scene. The experiment will test different max disparity values with a constant block size and output the respective disparity maps for block matching and semi-global matching.

Results:

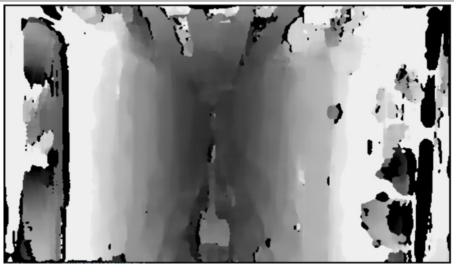
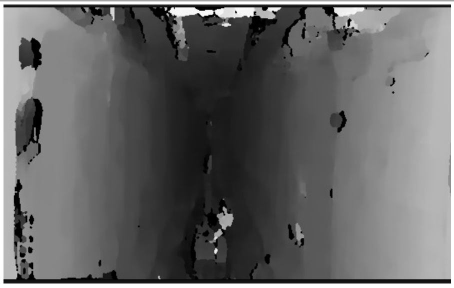
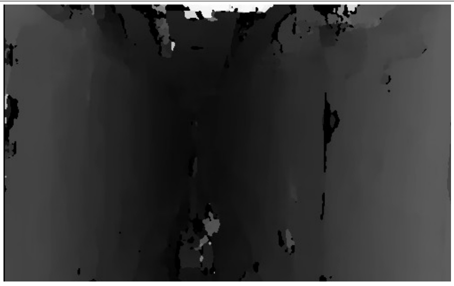
The table below shows the resulting disparity maps for the bookshelf pair (close).

Max Disparity	Block Matching	Semi Global Matching
16		
32		

64		
96		
128		

The disparity maps for the close pair (bookshelf) display better disparity maps with higher max disparity. For the higher max disparity we see the near objects (bookbinding) appear brighter than the distant parts, and the map is smoother across the surface with minimal holes/artefacts. Whereas for the lower max disparity a lot of unusual noise and artefacts in the disparity map that don't align with the original scene.

The table below shows the resulting disparity maps for the hallway pair (long).

Max Disparity	Block Matching	Semi Global Matching
16		
32		
64		
96		

128		

The disparity maps for the long pair (hallway) seem to have better disparity maps with lower max disparity. For lower max disparity we see the near objects appear brighter than the distant parts, and the map is smooth across the surfaces with minimal holes/artefacts apart from when we reach a max disparity of 16 as the closer objects are missing some values. The higher max disparity failed to differentiate between near and far objects, creating a flat scene.

Discussion/Conclusions:

The results show that max disparity is inversely proportional to the distance to the scene. This matches up with the intuition as the distance from the camera (depth) is inversely proportional to the disparity. Hence on the close pair, we were close so the disparity for the corresponding point was higher so a higher max disparity was needed. Whereas for the long-distance pair, we were far so the corresponding point was at a lower disparity hence lower max disparity helps shorten our search window which avoids inaccurate matches.

Experiment 2: Surface type and Block size

Hypothesis/Question:

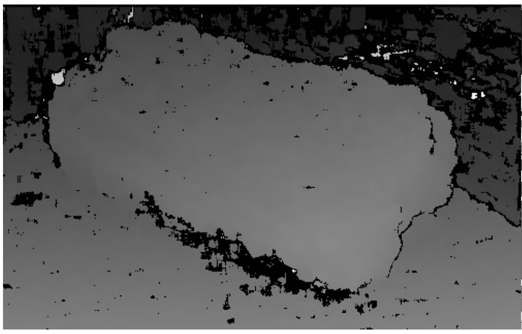
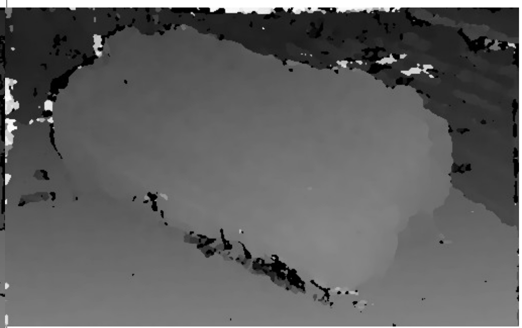
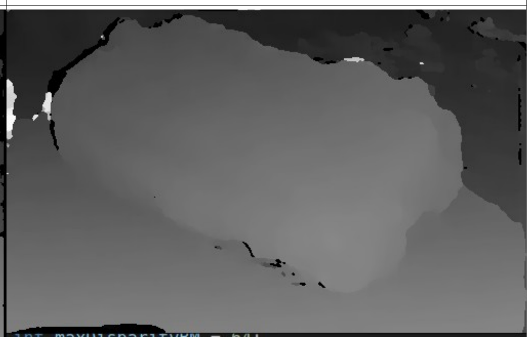
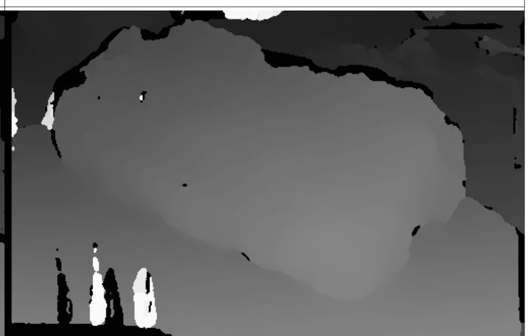
Does the quality of the disparity map depend on the surface texture and the choice of block size settings?

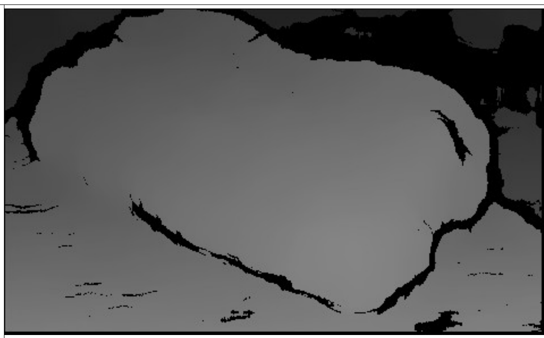
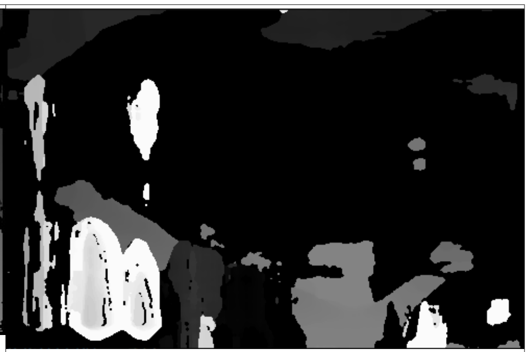
Experimental Design:

We will follow the outlined experiment process as above but use the rock pair as a rough texture scene, and the bell pair as a smooth texture scene. I will only vary the block size first while keeping the max disparity constant.

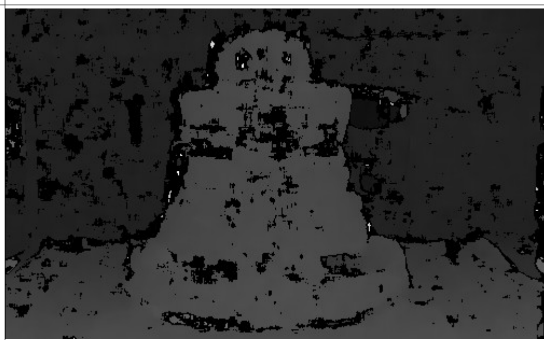
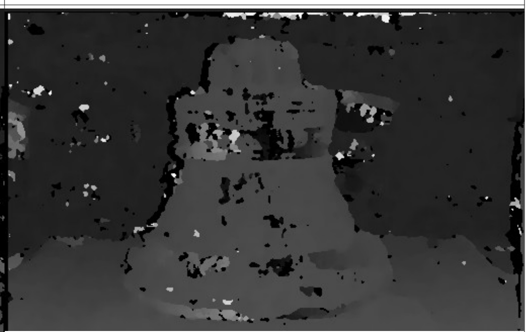
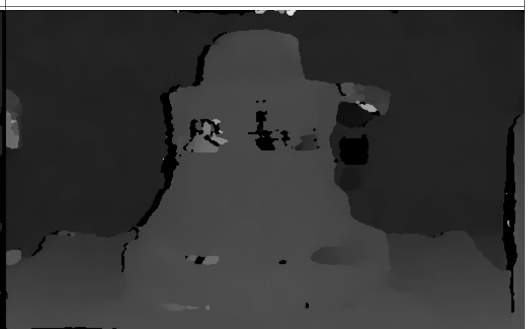
Results:

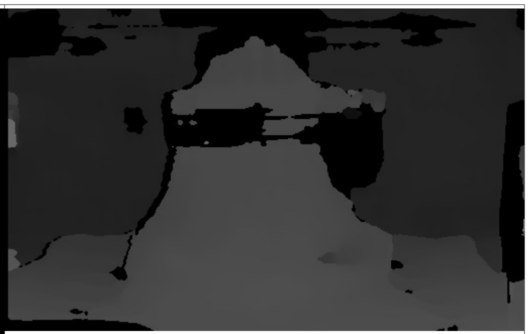
The table below shows the disparity maps for the rock pair (rough) using block-matching and semi-global matching for a given max disparity of 64 but a varying block size

Block Size	Block Matching	Semi Global Matching
11		
21		
31		

41		

The table below shows the disparity maps for bell pair (smooth) using block-matching and semi-global matching for a given max disparity of 64 but a varying block size.

Block Size	Block Matching	Semi Global Matching
11		
21		

31		
41		

The disparity maps for both surface/texture types seem to have similar quality disparity maps for all the block sizes apart from block size 11 due to noise and block size 41 for Semi Global Matching. Although the rock disparity map has much less noise on the rock compared to the noise on the bell at block size 11, as we increase the block size this difference is less noticeable. I noticed that these pairs showcase semi-global matching reduced missing/negative disparity (black) when depth changes around the rock and the bell. Also the higher the block size the more artefacts Semi Global Matching produces where the disparity map doesn't even resemble the scene at all.

Discussion/Conclusions:

Initially, I anticipated block size to play a significant role in determining disparity map quality, especially for surfaces with rough textures. My initial thought was that a smaller block size would allow for a more precise comparison of distinct features on these rough surfaces, leading to improved matching and a more accurate disparity map. As the results show there is still a noticeable improvement in quality in rough surface types over smooth surface types at lower block sizes.

Experiment 3: Post Filtering

Experiment Process:

Before this, I calibrated both cameras and exported the required parameters into calibration.json

For each image pair:

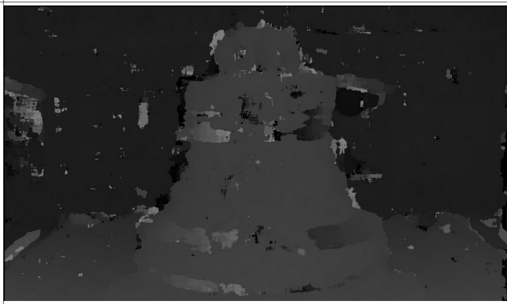
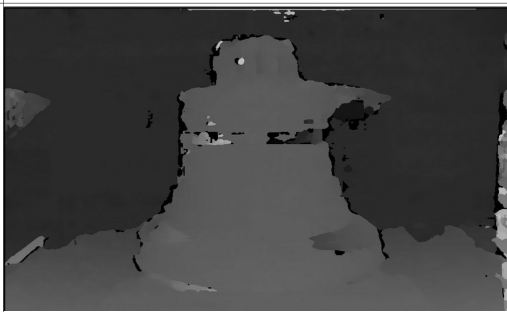
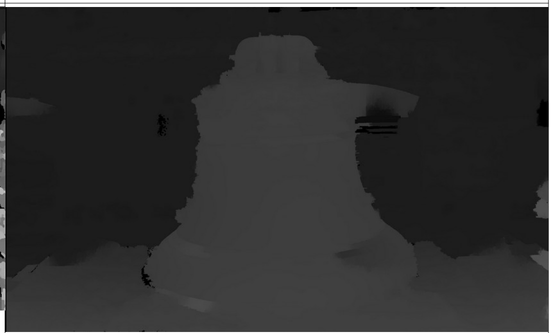
- Perform stereo rectification to create a parallel pair
- Resize image size to 50% (instead of 30% used earlier as we were losing a lot of detail) since the further step is computationally intensive
- Use both Block Matcher and Semi Global Matcher to compute disparity for left and right views
- Display both raw disparity maps for the left view
- Use WLSFilter to align original image edges to disparity map edges and use left and right disparity maps to refine the map
- Display filtered disparity map

Notes: I also set the P1, and P2 parameters for Semi Global Matching to the recommended values in the OpenCV docs, also mode is set to MODE_SGBM which converts the default 5 directional algorithm to 8 directions.

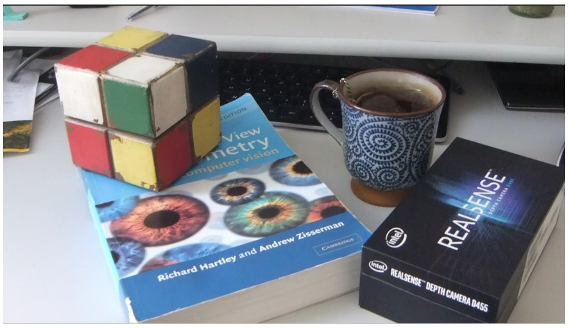
Stereo matching algorithms like Block Matching and Semi Global Matching struggle in smooth/texture-less areas, half-occlusions (regions visible in only one view but not the other view) and edges/object boundaries (sudden change in depth). These algorithms usually detect inaccurate disparity values and invalidate them with negative disparity values, therefore making the disparity map semi-sparse. Also, StereoSGBM uses P1 and P2 parameters to control the disparity smoothness by setting the penalty for small and large disparity changes.

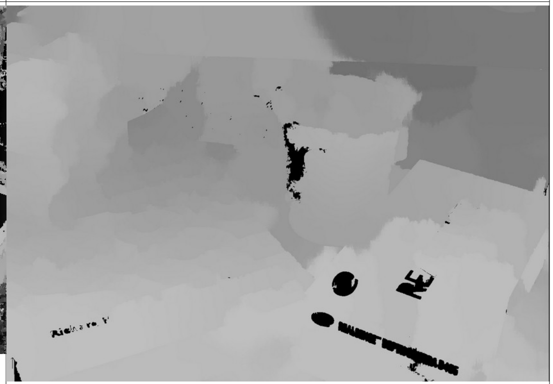
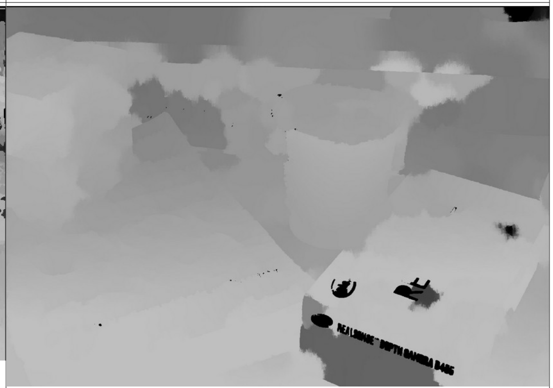
Although I will be exploring the WLSFilter method shown in the OpenCV contrib docs titled Disparity map post filtering [1] [2]. This method uses a smoothing technique while aligning disparity map edges with those of the source image and propagates the disparity values from high to low confidence regions using left and right disparity maps to fill half occlusions and smooth/texture-less areas. The main reason I was intrigued was the WLSFilter disparity map aligns better with 3D structure while outputting a full-size disparity map whereas earlier we only showed the downscaled disparity map.

The tables below are the unfiltered and filtered disparity maps for the bell pair using both block matching and semi-global block matching.

	Raw Disparity Map	WLSFiltered Disparity Map
Block Matching		
Semi Global Block Matching		

The tables below are the unfiltered and filtered disparity maps for the desktop pair using both block matching and semi-global block matching.



	Raw Disparity Map	WLSFiltered Disparity Map
Block Matching		
Semi Global Block Matching		

The raw/unfiltered disparity map is noisy, with sudden depth changes causing missing values and missing values across smooth surfaces. WLSFilter fills in almost all the missing values and smooths out a lot of the surfaces while maintaining sharp edges. The filtered disparity map aligns much better with the original 3D scene.

Final Remarks

In conclusion, we found a relationship between the optimal max disparity settings and distance to the scene, since disparity and distance to the scene are inversely proportional. However, we found a smaller block size works better for rough surface types over smooth surface types. Also, we explored the WLSFilter which is a smoothing filter in an edge-aware fashion which significantly improved the quality of the disparity maps.

If I were to repeat these experiments in the future I would only resize the images to 50% rather than 30% as I think we lost a lot of details of the original scene. This was clear during experiment 3 post-filtering with the bell image pair. For experiment 1 when I calculated the 8-bit disparity values by using the max disparity parameter I should have used the actual max disparity in the image because the max disparity images got quite dark because of this. For experiment 2, I think it's possible to find a stronger relationship between the rough and smooth surface that is less dependent on block size if we didn't resize the image to 30%. Also if I had more time I would find a better method/implementation of the cv::ximgproc::getDisparityVis method. When displaying the filtered maps I had to tune the disparity scaling on a case-by-case basis.

References

[1] Disparity map post-filtering, OpenCV docs:
https://docs.opencv.org/3.4/d3/d14/tutorial_ximgproc_disparity_filtering.html

[2] disparity_filtering.cpp, OpenCV[contrib] source code example:

https://github.com/opencv/opencv_contrib/blob/master/modules/ximgproc/samples/disparity_filtering.cpp