COMPSCI 527 Homework 6

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1 Introduction

3D object reconstruction from a set of 2D images is fundamentally an ill-conditioned problem, due to its inverse nature. We investigate the effects of noise and other parameters on the success of reconstructing the original 3D object from stereo images. To this effect, we use the 8-point algorithm with the Hartley preprocessing[1] (by using the canonical homogeneous coordinates). We quantify the accuracy of the reconstructed 3D object by measuring three types of errors: motion, structure, and reprojection error.

Our goal in this paper is to investigate the following questions:

- Which types of error fail first when enough noise is added for the shape to be unrecognizable?
- What happens when we change the image resolution but keep `sigma` fixed?

2 Progression of failure with increasing levels of noise

2.1 Introduction

The software provided creates a simulated world with a square object (with multiple colored squares on each side) and two cameras, adds Gaussian noise to the image coordinates, and runs the eight-point algorithm for 3-d reconstruction. Because reconstruction is a ill-conditioned/ill-posed problem (due to its inverse nature), small errors in the data will often result in large errors in the 3D reconstruction.

We investigate the effect of pseudo-random Gaussian noise on different types of errors, especially as the image become so distorted that the reconstructed shape becomes unrecognizable.

We have three broad categories of errors:

1. Motion error: the difference between true and computed motion, for both translation and rotation, measured in degrees
2. Structure error: the difference between true and computed structure, measured in RMS average percentage error of the overall size of the object
3. Reprojection error: the difference between the image of the original object and reprojected image of the reconstructed object, measured in RMS pixels per point

We pose the question: at the point where enough noise has been added so that the reconstructed object is unrecognizable, what types of errors fail first?

2.2 Methods

The experiment we ran was to run the following procedure, in which a subroutine was applied on a range of `sigmas` from `0:.25:5`, with n = 150 for each `sigma`; we recorded the average errors for each, as shown in Figures 1-3.

Procedure

1. Create a 3D world, with object (Gaussian noise `sigma` $= 0$), two cameras, and the resulting images
2. Compute the true transformation between the camera reference frames
3. Compute the true structure
4. Subroutine for each `sigma` in range `0:.25:4`
   - Add noise to the original image with `sigma`
   - Compute the resulting transformation figure
   - Measure and record motion, structure, and reprojection errors

After this, we also drew the reconstructed figures for choice `sigma` (Figures 4-9), to demonstrate the effects of noise on the resulting reconstruction and to find out when the reconstructed object became unrecognizable.

2.3 Data

Figures 1, 2, 3, and 4. Rotation, Translation, Structure, and Reprojection Error as a function of Sigma Value

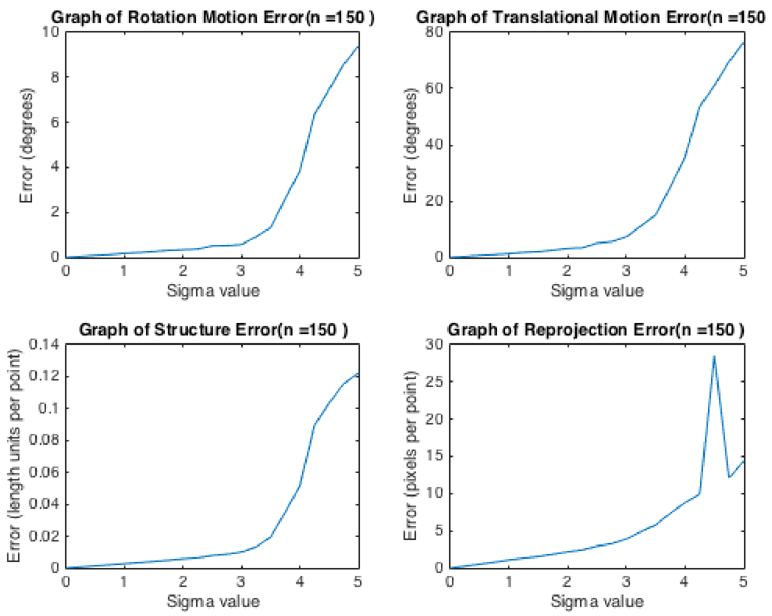


Figure 4. Reconstructed objects for `sigma`=0

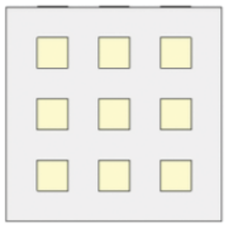


Figure 5. Reconstructed objects for `sigma`=1

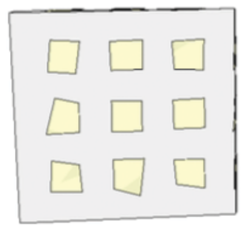


Figure 6. Reconstructed objects for `sigma`=2

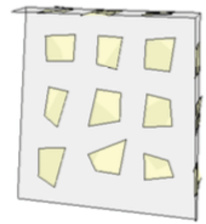


Figure 7. Reconstructed objects for `sigma`=3

Figure 8. Reconstructed objects for `sigma`=4

Figure 9. Reconstructed objects for `sigma`=5

TODO: graph reprojection error

2.4 Conclusions

Clearly, there is a severe drop in quality of the reconstructed object after `sigma` reaches around 3.25, and the reconstructed object for `sigma`=4 (Figure 8) is completely unrecognizable.

As we can see from the error plots, there is an inflection point around 3.25 where motion error (especially translation error) begins to climb drastically. This is followed immediately by structure error, which also has a similar inflection point. Finally, there is a slight inflection point in reprojection error, which is relatively delayed compared to the other errors (around `sigma`=4.25).

Why is the graph approximately linear before the inflection point? As we increase `sigma`, the Gaussian noise-generating function gets linearly scaled, making the slight errors increase linearly (on average).

Why is there an inflection point around `sigma`=3.25? That is the point where there is enough error for catastrophic failure in the reconstructed object such that it becomes unrecognizable. Again, this point exists because 3D reconstruction is an ill-posed problem, where minor errors in input result in massive failures in output. This inflection point is exactly that amount of errors. As obvious in figure 8 and 9 (which correspond to points after this inflection point), the object is completely unrecognizable.

After a certain point, however, the image has enough noise so that it is essentially a random image (one with random values for pixels), uncorrelated with the original object. This is essentially the maximum amount of average error attainable, and is the reason why the error rate tapers off (at around 10 degrees for rotation error, 80 degrees for translation error, and 0.12 unit lengths per point for structural error, according to figures 1-3). TODO: explain this with data

TODO: why reprojection is only non-sigmoid

TODO: reprojection error changes (0 – ¿ straight line – ¿ random points)

The reprojection error plots for different `sigma` are also insightful in showing the progression of reprojection error as the reconstructed image experiences failure. When sigma is 0, the plot includes all points that are essentially 0– indicating an almost perfect reconstruction of the reprojected image. However, as sigma gets larger but below the inflection point talked about above, the errors all lie on a straight line– since the size of the displacements depend roughly *only on distance from the camera* (because of the nature of projecting a 3D object down onto 2D, where farther points seem smaller). Finally, when the sigma reaches the point where catastrophic failure occurs, the displacements become a random cluster around the origin (the reprojected image now no longer has much correlation to the original object). TODO: reference figures

3 Effects of modifying image resolution

3.1 Introduction

3.2 Data

Figure 10. Error Plots for Resolution of 960x540

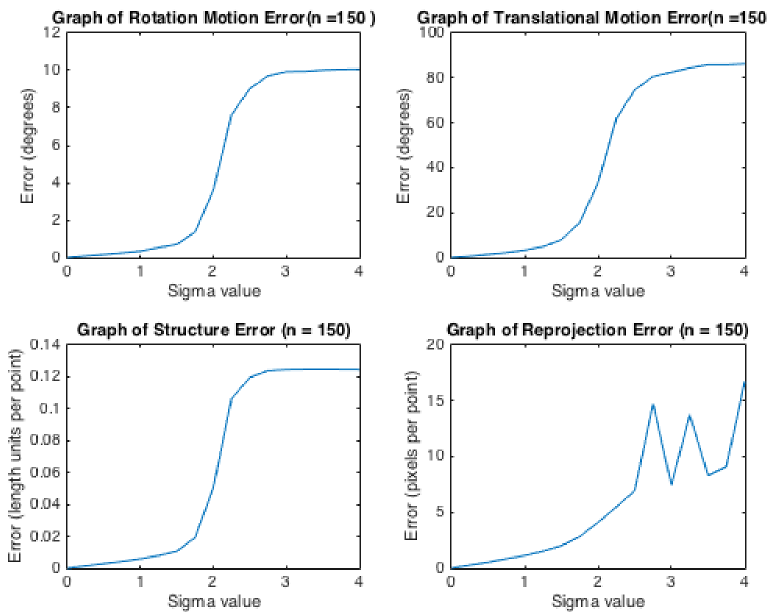


Figure 11. Error Plots for Resolution of 1920x1080

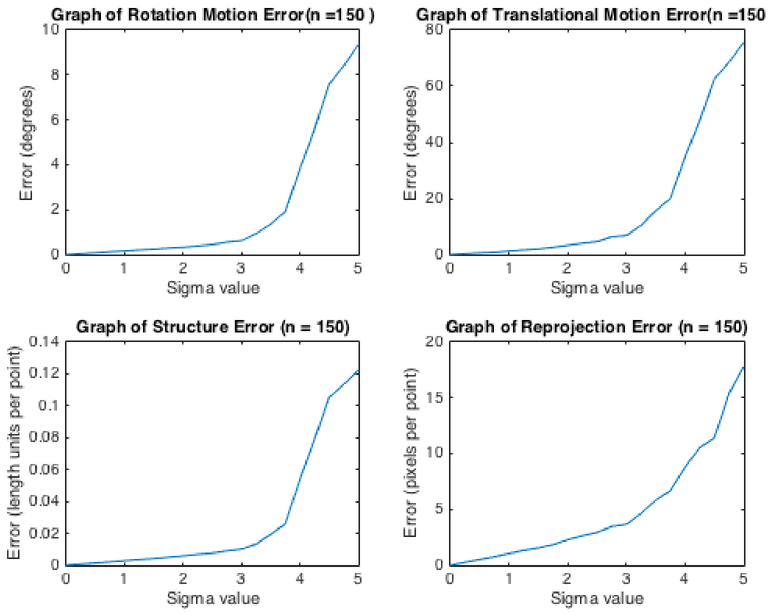
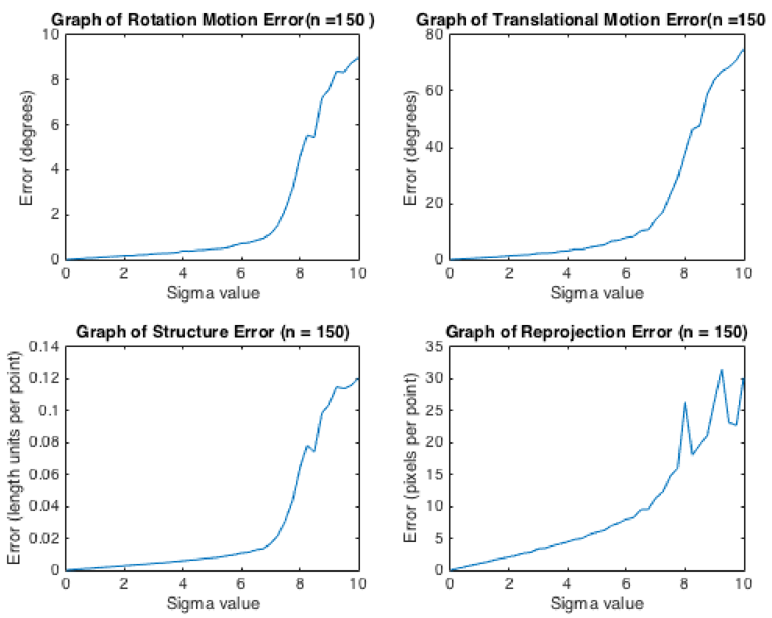


Figure 12. Error Plots for Resolution of 3840x2160



3.3 Conclusions

TODO: higher res –¿ lower error (because in pixels)

TODO: what relationship is (O(n)), direct scaling

TODO: explain why (Gaussian sigma affects both dimensions)

4 Conclusion

References

[1] Hartley, Richard. "In defense of the eight-point algorithm." Pattern Analysis and Machine Intelligence, IEEE Transactions on 19, no. 6 (1997): 580-593.

[2] Chojnacki, Wojciech, and Michael J. Brooks. "On the consistency of the normalized eight-point algorithm." Journal of Mathematical Imaging and Vision 28, no. 1 (2007): 19-27.