Computer Vision II – Homework Assignment 2
Solution from Group 28

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Problem 1 – Markov random fields with Gaussian potentials

1-3. For solutions to programming exercises, please see the A2_problem1.py file.

3. This part has three questions:

   1) Comparison of the log-prior density values: According to the calculation result by $\mu = 0, \sigma = 1.1$.

      (1) the Log Prior of gt disparity map is -50685;

      (1) the Log Prior of noise disparity map is -2559991;

      (1) the Log Prior of constant disparity map is 0.

      Therefore we can derive the following relationship: $noise < gt < constant$

      Based on this relative relationship, we can conclude that the second disparity maps(noise) are unlikely to appear in the visual world due to the obvious difference in magnitude, while the first gt disparity maps are less favored but still show that the MRF model seems to be in a certain to some extent, it captures the properties of the visual world. The third map(constant) has a zero log prior density, which for a Gaussian probability distribution means that every pixel has the same property, which is also unlikely to occur in the visual world. [1]

   2) How does increasing σ of the Gaussian potentials affect the values of log-prior density: By adjusting different $\sigma = [1, 1.5, 2, 2.5, 3] (\mu = 0)$, we can draw a graph of the relationship: (fig.1)

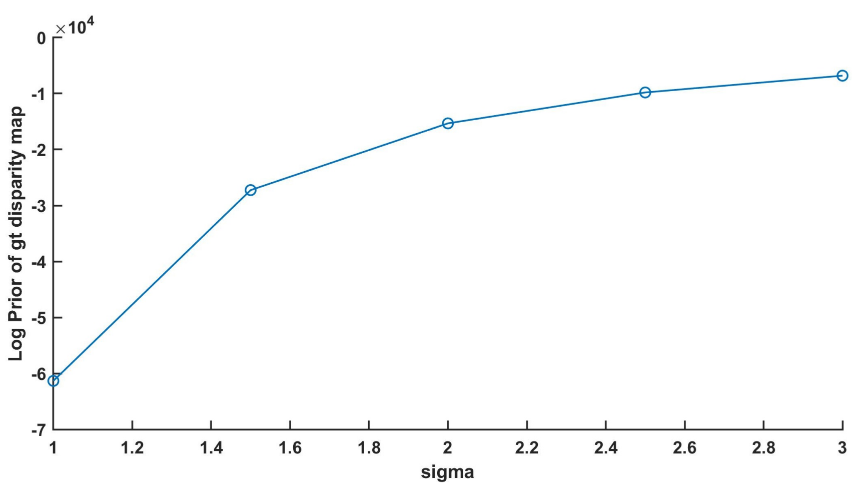

Figure 1: The affect of sigma on the values of log-prior of gt disparity map

According to the figure, increasing the σ of the Gaussian potential affects the value of the log prior density. To be precise, the larger σ is, the bigger the log prior is. This is because increasing σ makes the Gaussian potentials more diffuse, reducing their impact on the disparity map. As a result, the log prior density increases as σ increases

3) How does reducing the range of the noise map affect the values of the log-prior density: Similarly, we can plot relationship between the log prior density and the upper limit of the random noise: (fig.2)

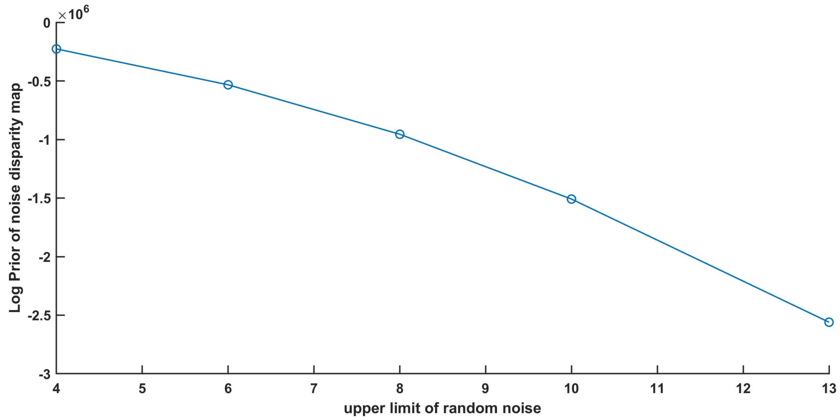

Figure 2: The affect of upper limit of the random noise

According to the figure, Reducing the variation range(upper limit) of the noise makes the log-prior bigger. This is because reducing the range of the noise map reduces the likelihood of large variances. As a result, the log-prior density increases as the range of the noise map decreases.

Problem 2 – Stereo with gradient-based optimization

1-6, 8. For solutions to programming exercises, please see the A2_problem2.py file.

7. This part has two questions:

1) Compare different initializations.
We visualized the ground truth disparity and estimated disparity map in the case of $\mu = 0, \sigma = 1.7, \alpha = 0.1, tol = 1$.(fig.3) It can be clearly seen from the maps that the first initialization(gt) gets the result closest to gt. And the second initialization(constant value) cannot reflect meaningful real-world characteristics. The estimated disparity map of the third initialization(random noise) embodies the outline of part of the foreground object. The above results are consistent with our conclusions about log priors in A1. That is, neither random noise nor constant values are suitable initial values.

2) How does alpha qualitatively affect the results?
Different convergence results will appear when the values of tolerance and alpha are different. We can quantify this difference by computing the standard deviation of the difference between estimates and gt at different alpha values. It can be concluded from the figure(fig.4) that the alpha value does affect the estimation results. But the positive and negative correlation of its impact is uncertain. In the case of this test, the increase of the alpha value will cause the estimation result of the initial situation to be gt to become worse. Relatively, the increase of the alpha value will lead to a better estimation result of the initial value of random noise, while the initial value of constant The estimated result does not change with the alpha value.

References

[1] Li Zhang and Steven M Seitz. "Parameter estimation for MRF stereo". In: *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05)*. Vol. 2. IEEE. 2005, pp. 288–295.

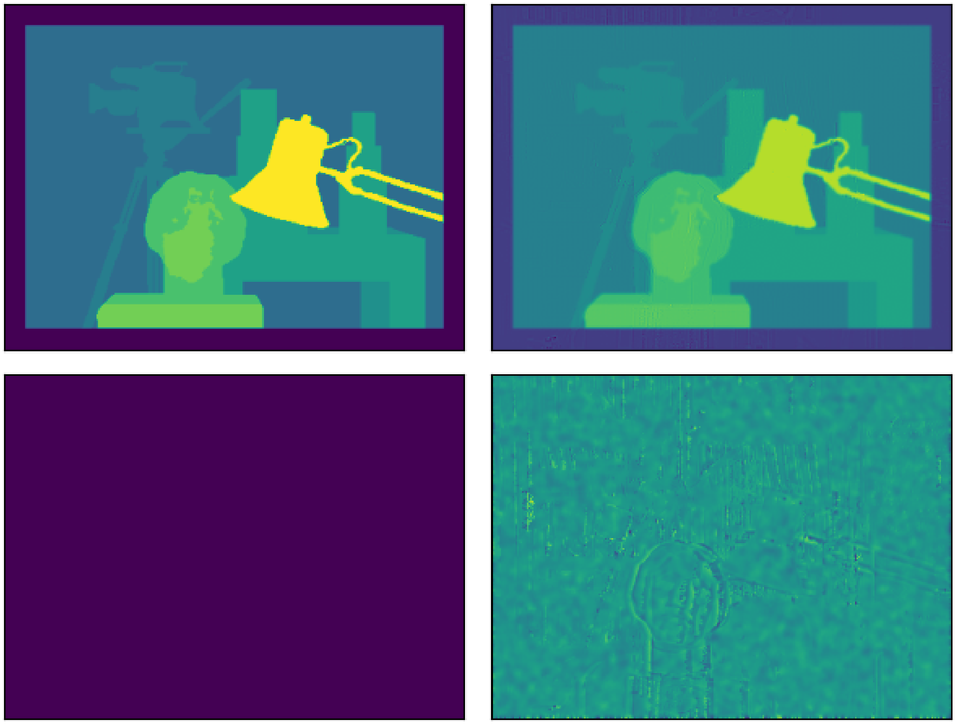

Figure 3: ground truth and estimated disparity map. (upper left: ground truth, upper right: initialization with gt, lower left: initialization with constant, lower right: initialization with random)

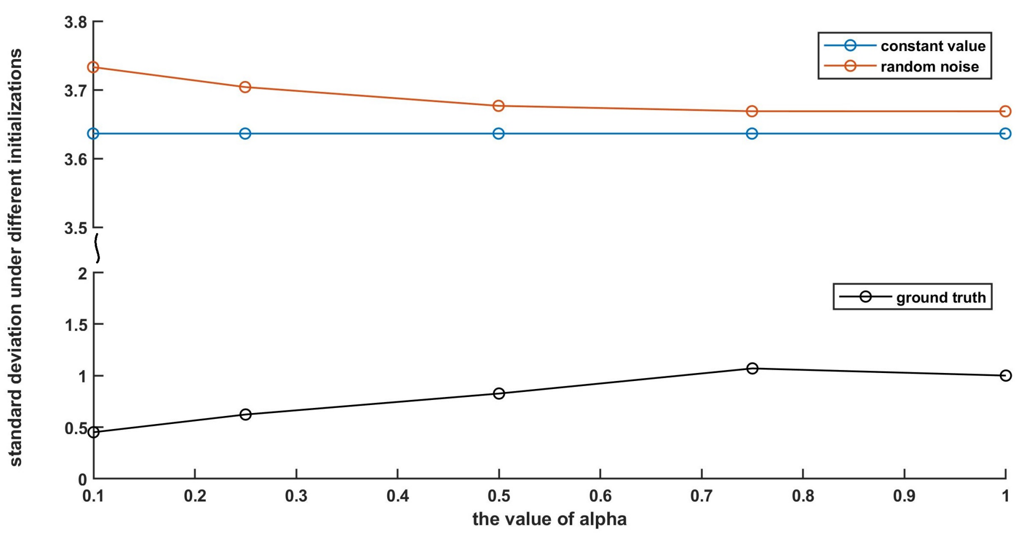

Figure 4: The standard deviation under different initializations