Multiple View Geometry: Solution Sheet 9

Prof. Dr. Daniel Cremers, Nikolaus Demmel, Marvin Eisenberger
Computer Vision Group, TU Munich
http://vision.in.tum.de/teaching/ss2018/mvg2018

Exercise: June 27th, 2018

Part I: Theory

1. **Robust Least Squares**

   (a) What situations can you think of where a robust loss function might be needed?
   Missing (i.e. black or white) pixels in the image, dynamic changes of the scene, non-Lambertian surfaces like shiny or transparent objects, (local) changes in lighting conditions, ...

   (b) Write down the weight function for the Huber loss.

$$w_\delta(t) = \begin{cases} 1 & |t| \leq \delta \\ \frac{\delta}{|t|} & \text{else} \end{cases}$$

2. **Optimization Techniques**

   Write down the update step $\Delta\xi$ for each of the following minimization methods:

   (a) Gradient descent, normal least squares,

$$\Delta\xi = -\lambda J^\top \mathbf{r}$$

   (b) Gradient descent, weighted least squares,

$$\Delta\xi = -\lambda J^\top W \mathbf{r}$$

   (c) Gauss-Newton, normal least squares,

$$\Delta\xi = -(J^\top J)^{-1} J^\top \mathbf{r}$$

   (d) Gauss-Newton, weighted least squares,

$$\Delta\xi = -(J^\top W J)^{-1} J^\top W \mathbf{r}$$

   (e) Levenberg-Marquardt, normal least squares,

$$\Delta\xi = -(J^\top J + \lambda \text{diag}(J^\top J))^{-1} J^\top \mathbf{r}$$

   (f) Levenberg-Marquardt, weighted least squares.

$$\Delta\xi = -(J^\top W J + \lambda \text{diag}(J^\top W J))^{-1} J^\top W \mathbf{r}$$