

# BP Denoising

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## 1 Robust Measurement Factor

The state of pixel  $x$  is  $y$ :  $x = (y)$ , where  $x$  is the pixel ID and  $y$  is the pixel value. The precision  $\Lambda$  and measurement  $z$  are scalars. The measurement function is:

$$h(x) = y \quad (1)$$

And the Jacobian:

$$J = \frac{\partial h(x)}{\partial x} = \frac{\partial y}{\partial y} = 1 \quad (2)$$

When linearising:

$$\eta = J^T \Lambda (Jx_0 + z - h(x_0)) = J^T \Lambda (y_0 + z - y_0) = J^T \Lambda z \quad (3)$$

$$\Lambda' = J^T \Lambda J \quad (4)$$

Notice that neither of these terms depend on the state, so they always have the same linearisation form.

When choosing the  $N_\sigma$  threshold for Huber, we can first analyse the Mahalanobis distance:

$$M_s = \sqrt{(z - h(x))^T \Lambda (z - h(x))} = |z - y| \sqrt{\Lambda} = |z - y| \frac{1}{\sigma} \quad (5)$$

So, for example, I can choose  $N_\sigma = 1\sqrt{\Lambda}$ . In my opinion it is a good idea to define this as a function of  $\Lambda$  because the scalar next to it will then represent a distance in pixel space.

When uncertainty is high,  $\sigma$  is large, meaning that  $\frac{1}{\sigma}$  is small. In this setup, this results in having a stricter threshold  $N_\sigma$  for higher uncertainties. However we should probably also have an upper bound for  $N_\sigma$  in case uncertainty is too low, so perhaps something like  $N_\sigma = \min(\alpha\sqrt{\Lambda}, \epsilon)$  could work well in practice.

My main concern with not having a dependence on  $\sqrt{\Lambda}$  is that if uncertainty is set very high, large errors may be below the threshold and not treated using the L1 term.

## 2 Robust Smoothness Factor

This is a function of two pixels,  $(x_1, x_2)^T$ , whose states are  $(y_1, y_2)^T$ . The precision  $\Lambda$  is a scalar and the measurement  $z = 0$ . The measurement function is:

$$h(x_1, x_2) = y_2 - y_1 \quad (6)$$

And the Jacobian:

$$J = \left( \frac{\partial h(x_1, x_2)}{\partial x_1}, \frac{\partial h(x_1, x_2)}{\partial x_2} \right) = \left( \frac{\partial(y_2 - y_1)}{\partial y_1}, \frac{\partial(y_2 - y_1)}{\partial y_2} \right) = (-1, 1) \quad (7)$$

When linearising:

$$\eta = J^T \Lambda (J(x_1, x_2) + z - h(x_1, x_2)) = J^T \Lambda ((-1, 1)(y_1, y_2)^T + 0 - (y_2 - y_1)) = J^T \Lambda 0 = (0, 0)^T \quad (8)$$

$$\Lambda' = J^T \Lambda J \quad (9)$$

Where  $\Lambda'$  is a 2 x 2 matrix. These quantities also do not depend on the current state values so this linearisation always has the same form. The Mahalanobis distance:

$$M_s = \sqrt{(z - h(x_1, x_2))^T \Lambda (z - h(x_1, x_2))} = |y_1 - y_2| \sqrt{\Lambda} \quad (10)$$

For this I also choose  $N_\sigma = 1\sqrt{\Lambda}$  as explained above.