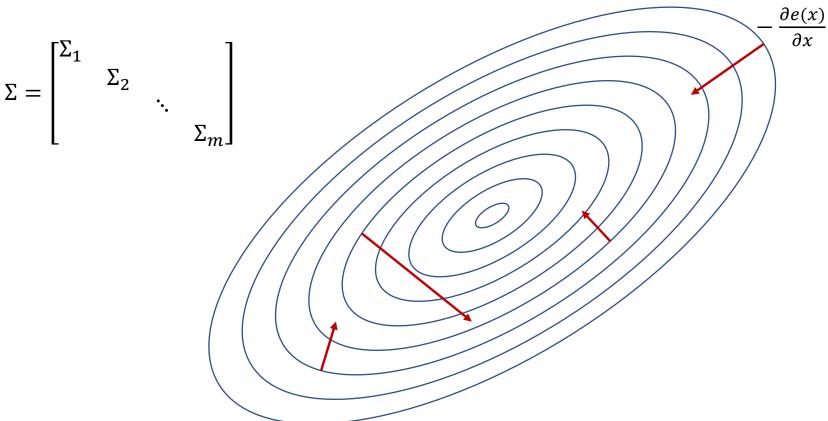
David Arnon

Gradient Decent

• Error function $e(x) = ||f(x) - z||_{\Sigma}^2$:



Linear Approximation

•
$$e(x) = \frac{1}{2}(f(x) - z)^T \Sigma^{-1}(f(x) - z)$$

•
$$\left(\frac{\partial e(x)}{\partial x}\right)^T = J(x)^T \Sigma^{-1} (f(x) - z) = J(x)^T \Sigma^{-1} \Delta z$$

•
$$e(x + \Delta x) \cong e(x) + \frac{\partial e(x)}{\partial x} \Delta x$$

•
$$e(x + \Delta x) \cong e(x) - \frac{1}{\lambda} \left\| \frac{\partial e(x)}{\partial x} \right\|_{2}^{2} < e(x)$$

•
$$\Delta x = -\frac{1}{\lambda} J(x)^T \Sigma^{-1} \Delta z$$

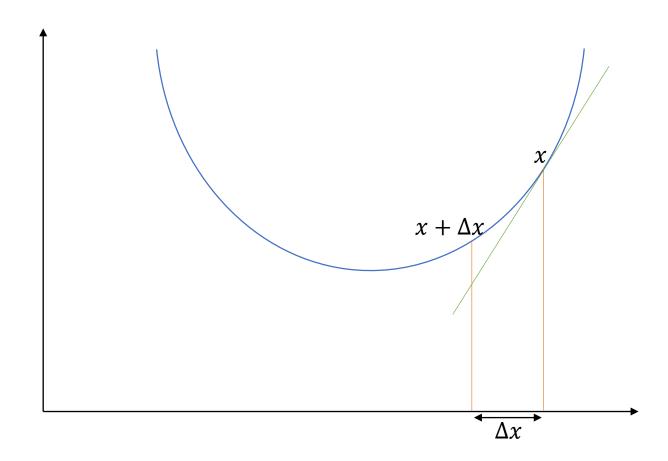
$$\Delta z \doteq f(x) - z$$

$$\Delta x = -\frac{1}{\lambda} \left(\frac{\partial e(x)}{\partial x} \right)^T$$

$$g \doteq J(x)^T \Sigma^{-1} \Delta z$$

$$\Delta x = -\frac{1}{\lambda}g$$

Bundle AdjustmentGradient Decent



Bundle AdjustmentGauss – Newton Algorithm

- Set starting point
- Linearize the measurement function
- Solve linear least squares problem
- Iterate

Quadratic Approximation!

Bundle AdjustmentQuadratic Approximation

- $argmin_{\Delta x} || f(x_i + \Delta x) z ||_{\Sigma}^2 \cong$
- $argmin_{\Delta x} || f(x_i) + J(x_i) \Delta x z ||_{\Sigma}^2 =$
- $argmin_{\Delta x} ||J(x_i)\Delta x + f(x_i) z||_{\Sigma}^2 =$
- $argmin_{\Delta x} ||J(x_i)\Delta x + \Delta z_i||_{\Sigma}^2 =$
- $argmin_{\Delta x} \| \Sigma^{-1/2} J(x_i) \Delta x + \Sigma^{-1/2} \Delta z_i \|_2^2$
- $J(x_i)^T \Sigma^{-1} J(x_i) \Delta x = -J(x_i)^T \Sigma^{-1} \Delta z_i$

•
$$J(x_i)^T \underbrace{\sum_{\Sigma=1}^{-1/2} J(x_i) \Delta x} = -J(x_i)^T \underbrace{\sum_{\Sigma=1}^{-1/2} \sum_{\Sigma=1}^{-1/2} \Delta z_i}$$

$$H\Delta x = -g$$

$$H \doteq J(x_i)^T \Sigma^{-1} J(x_i)$$
$$g \doteq J(x_i)^T \Sigma^{-1} \Delta z_i$$

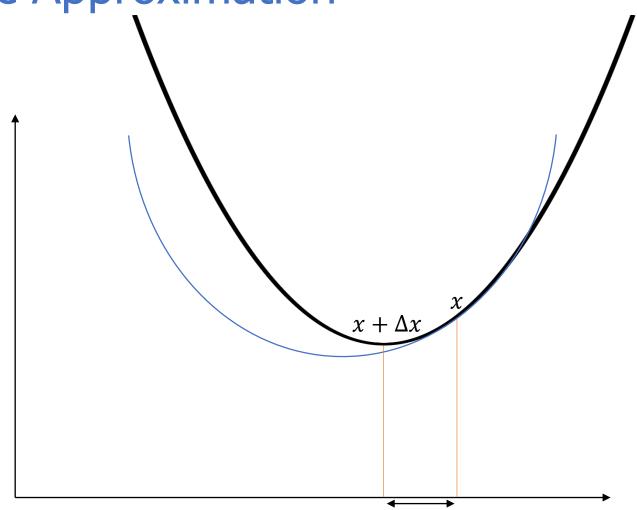
$$\Delta z_i \doteq f(x_i) - z$$

$$\Sigma = (\Sigma^{\frac{1}{2}})(\Sigma^{\frac{1}{2}})^{T}$$

$$\Sigma^{-1} = \Sigma^{-\frac{1}{2}T}\Sigma^{-\frac{1}{2}}$$

$$argmin_x ||Ax - b||_2^2 \implies A^T Ax = A^T b$$

Quadratic Approximation



Gauss - Newton

Converges in one iteration for quadratic functions

For general functions, the asymptotic convergence is quadratic



• Inverting *H* is expensive



Cholesky Decomposition

•
$$Hx = b$$

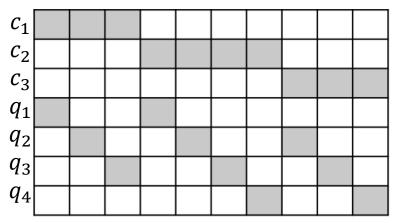
$$H = CC^T$$

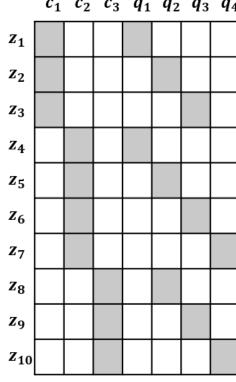
•
$$C \underbrace{C^T x}_{z} = b$$

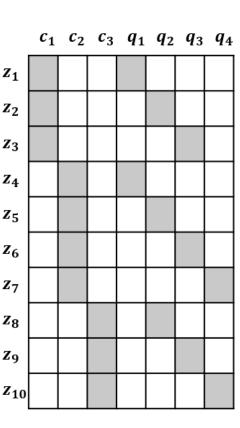
•
$$Cz = b$$

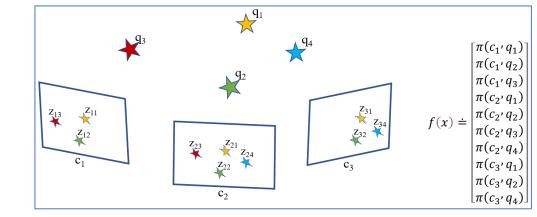
•
$$C^T x = z$$

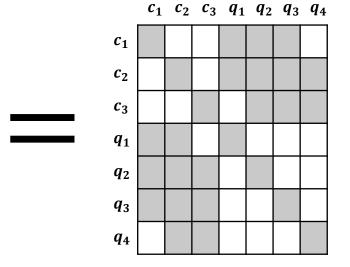
Sparsity











Bundle Adjustment Uncertainty

- H is the information matrix
 - Inverse of the covariance matrix of the estimated Δx
 - Approximation of the hessian second-order partial derivatives matrix

$$H^{-1} = \begin{bmatrix} \Sigma_1 & & & * \\ & \Sigma_2 & & \\ & & \ddots & \\ * & & & \Sigma_p \end{bmatrix}$$

- Can be used to estimate the uncertainty of the result
 - Marginal covariances
- Conditioning $p(x_j|x_i)$ It is possible to estimate the relative uncertainty between x_j and x_i
 - erase row and column i
 - invert and use diagonal block j

Gauss-Newton Example

David Arnon

Example

•
$$z = \begin{pmatrix} z_1 \\ z_2 \end{pmatrix} = \begin{pmatrix} 1 \\ 2 \end{pmatrix}$$
, $\Sigma = \begin{bmatrix} \frac{1}{2} \\ \frac{1}{4} \end{bmatrix}$ \Rightarrow $\Sigma^{-1} = \begin{bmatrix} 2 \\ 4 \end{bmatrix}$

•
$$f\begin{pmatrix} x_0 \\ x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} x_1 - x_0 \\ x_2 - x_1 \end{pmatrix} \stackrel{!}{=} \begin{pmatrix} z_1 \\ z_2 \end{pmatrix}$$

•
$$J = \begin{bmatrix} -1 & 1 & 0 \\ 0 & -1 & 1 \end{bmatrix}$$

Example

•
$$-g = -\begin{bmatrix} -1 & 0 \\ 1 & -1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 2 \\ 4 \end{bmatrix} (\begin{bmatrix} 0 \\ 0 \end{bmatrix} - \begin{bmatrix} 1 \\ 2 \end{bmatrix}) = \begin{bmatrix} -2 \\ -6 \\ 8 \end{bmatrix}$$

Take 2

•
$$z = \begin{pmatrix} z_0 \\ z_1 \\ z_2 \end{pmatrix} = \begin{pmatrix} 0 \\ 1 \\ 2 \end{pmatrix}$$
, $\Sigma = \begin{bmatrix} 1 \\ 1/2 \\ 1/4 \end{bmatrix}$ \Rightarrow $\Sigma^{-1} = \begin{bmatrix} 1 \\ 2 \\ 4 \end{bmatrix}$

•
$$f\begin{pmatrix} x_0 \\ x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} x_0 \\ x_1 - x_0 \\ x_2 - x_1 \end{pmatrix} \stackrel{!}{=} \begin{pmatrix} z_0 \\ z_1 \\ z_2 \end{pmatrix}$$

•
$$J = \begin{bmatrix} 1 & 0 & 0 \\ -1 & 1 & 0 \\ 0 & -1 & 1 \end{bmatrix}$$

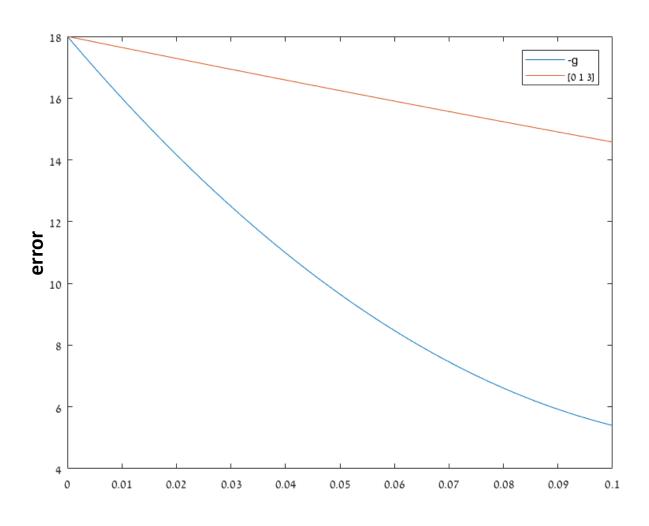
Take 2

•
$$-g = -\begin{bmatrix} 1 & -1 & 0 \\ 0 & 1 & -1 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 2 \\ 4 \end{bmatrix} \begin{pmatrix} \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} - \begin{bmatrix} 0 \\ 1 \\ 2 \end{bmatrix} \end{pmatrix} = \begin{bmatrix} -2 \\ -6 \\ 8 \end{bmatrix}$$

•
$$H = \begin{bmatrix} 1 & -1 & 0 \\ 0 & 1 & -1 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 2 \\ 4 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ -1 & 1 & 0 \\ 0 & -1 & 1 \end{bmatrix} = \begin{bmatrix} 3 & -2 & 0 \\ -2 & 6 & -4 \\ 0 & -4 & 4 \end{bmatrix}$$

•
$$\Delta x = -H^{-1}g = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1\frac{1}{2} & 1\frac{1}{2} \\ 1 & 1\frac{1}{2} & 1\frac{3}{4} \end{bmatrix} \begin{bmatrix} -2 \\ -6 \\ 8 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \\ 3 \end{bmatrix}$$

Gauss-NewtonExample



Gauss-NewtonExample

