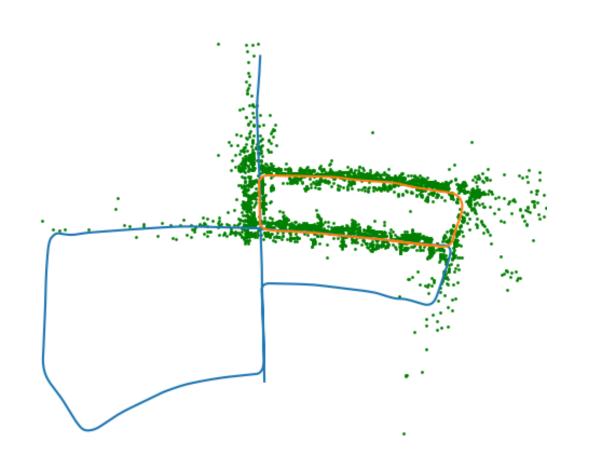
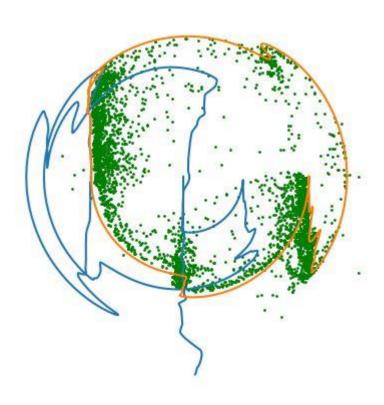
David Arnon

KITTI





Triangulation



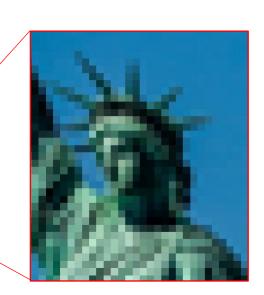




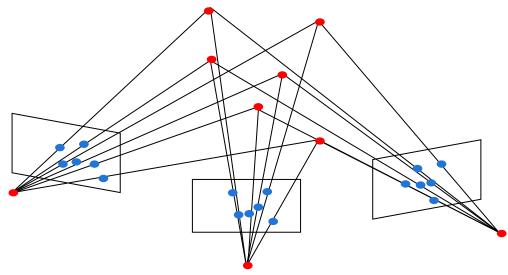


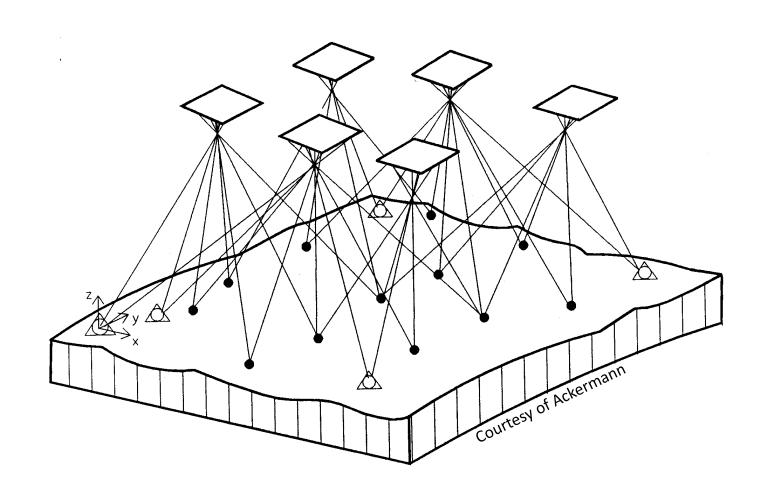


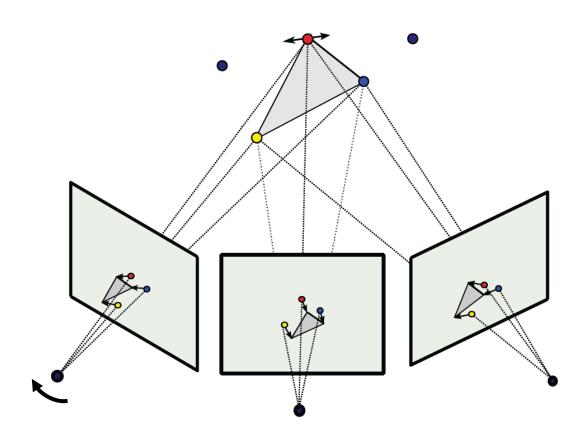




- Refines a visual reconstruction to produce jointly optimal 3D structure (world) and viewing parameters (cameras)
- 'bundle' refers to the bundle of light rays leaving each 3D feature and converging on each camera center.
- Developed in the field of photogrammetry in the 1950's

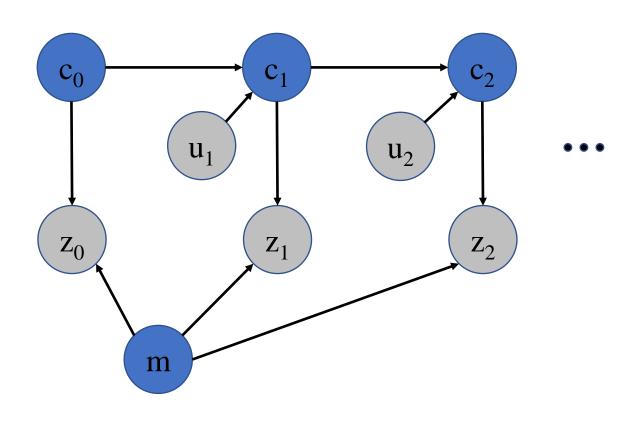






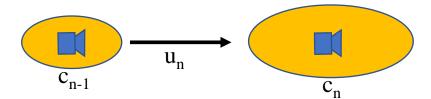
Slam

Graphical Model

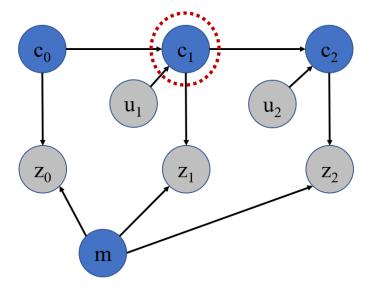


$$p(c_{0:2}, m \mid u_{1:2}, z_{0:2})$$

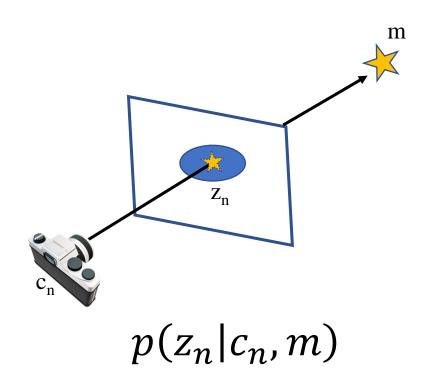
Motion Model

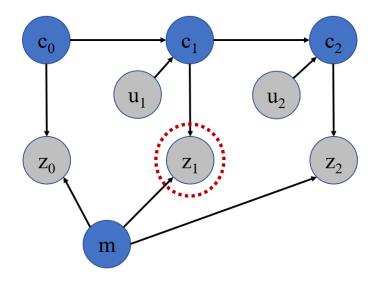


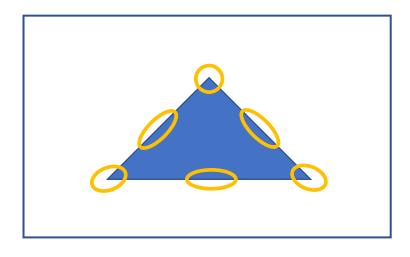
$$p(c_n|c_{n-1},u_n)$$



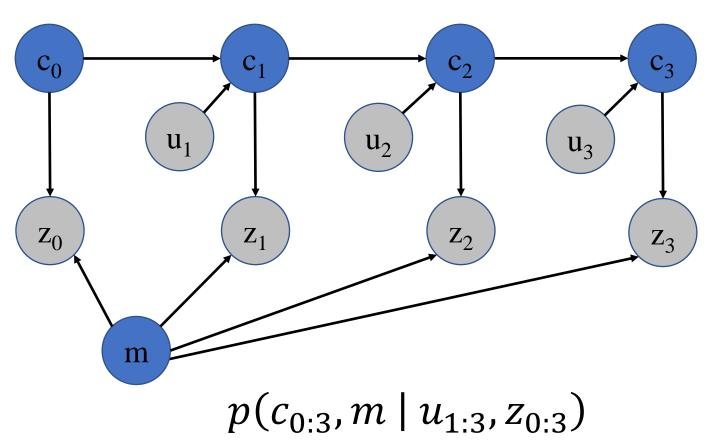
Measurement Model



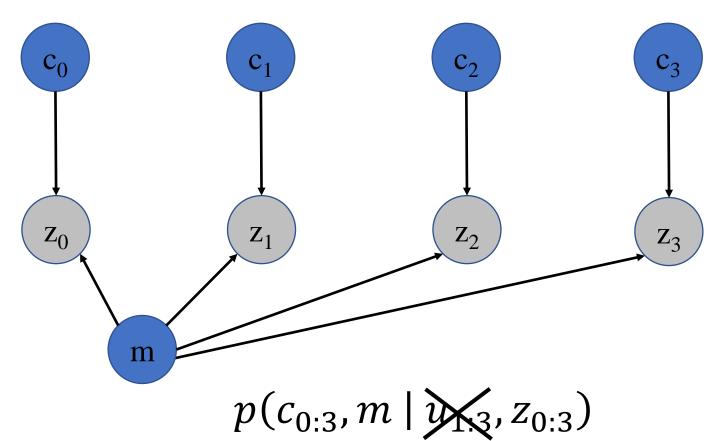




Graphical Model



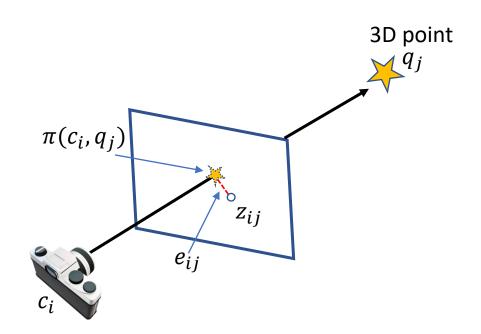
Graphical Model



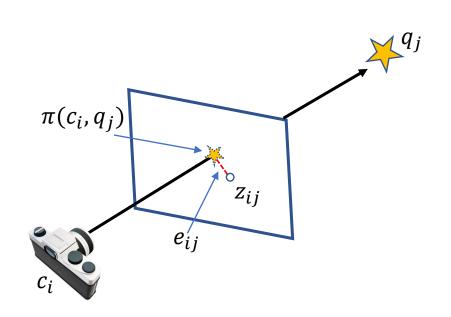
Probabilistic Formulation

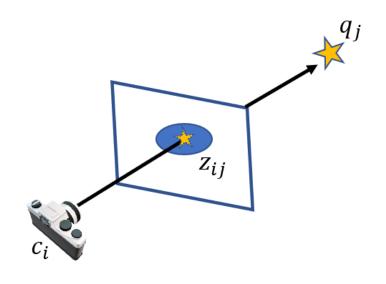
• Reprojection error: $e_{ij} \doteq z_{ij} - \pi(c_i, q_j)$

$$e_{ij} \doteq z_{ij} - \pi(c_i, q_j)$$



Measurement Model



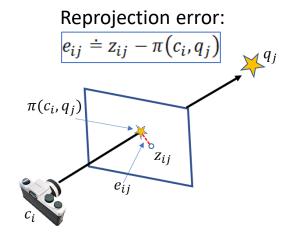


$$p(z_{ij}|c_i,q_j) \sim N(\pi(c_i,q_j),\Sigma)$$
$$z_{ij} = \pi(c_i,q_j) + w, \qquad w \sim N(0,\Sigma)$$

Bayes

- $p(z_{ij}|c_i,q_j)\sim N(\pi(c_i,q_j),\Sigma)$
- $p(c_i, q_j | z_{ij}) = \frac{1}{p(z_{ij})} p(z_{ij} | c_i, q_j) p(c_i, q_j)$
- $p(c_i, q_j | z_{ij}) \propto p(z_{ij} | c_i, q_j) p(c_i, q_j)$
- $p(c_i, q_j|z_{ij}) \propto p(z_{ij}|c_i, q_j)$
- $p(c_i, q_j | z_{ij}) \propto \exp\left(-\frac{1}{2} ||z_{ij} \pi(c_i, q_j)||_{\Sigma}^2\right)$
- $p(c_i, q_j | z_{ij}) \propto \exp\left(-\frac{1}{2} \|e_{ij}\|_{\Sigma}^2\right)$

$$N_{\mu,\Sigma}(z) \propto exp\left(-\frac{1}{2}||z-\mu||_{\Sigma}^{2}\right)$$



- $argmax_{C,Q}[p(C,Q|Z)]$
- $argmax_{C,Q}[p(Z|C,Q)]$
- $argmax_{C,Q} \left[\prod_{c_i} \prod_{j \in M_i} p(z_{ij} | c_i, q_j) \right]$
- $argmax_{C,Q} \left[\prod_{c_i} \prod_{j \in M_i} \exp\left(-\frac{1}{2} \|e_{ij}\|_{\Sigma}^2\right) \right]$
- $argmax_{C,Q} \left[\sum_{c_i} \sum_{j \in M_i} -\frac{1}{2} \left\| e_{ij} \right\|_{\Sigma}^2 \right]$
- $argmin_{C,Q} \left[\sum_{c_i} \sum_{j \in M_i} \left\| e_{ij} \right\|_{\Sigma}^2 \right]$
- $argmin_{C,Q} \left[\sum_{c_i} \sum_{j \in M_i} \left\| \sum^{-1/2} e_{ij} \right\|^2 \right]$

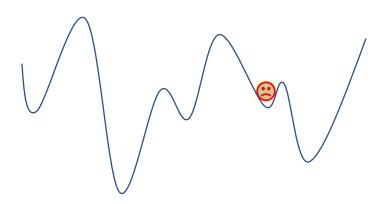
$$e_{ij} \doteq z_{ij} - \pi(c_i, q_j)$$

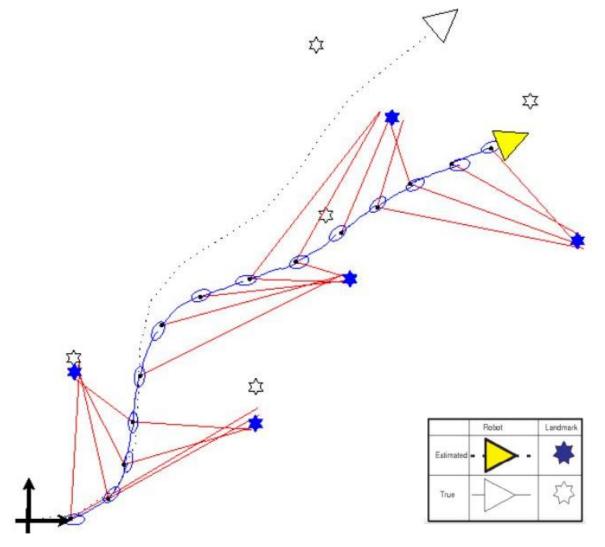
$$\Sigma^{1/2} = \operatorname{chol}(\Sigma)$$

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

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

- Maximum likelihood for normally distributed measurements
- Sensitive to outliers
 - The Gaussian has extremely small tail compared to most real measurement error distribution
- Non-linear least squares problem
- Solved using an iterative process
- General problem is non-convex, can settle in a local minima
- Requires a reasonable starting point

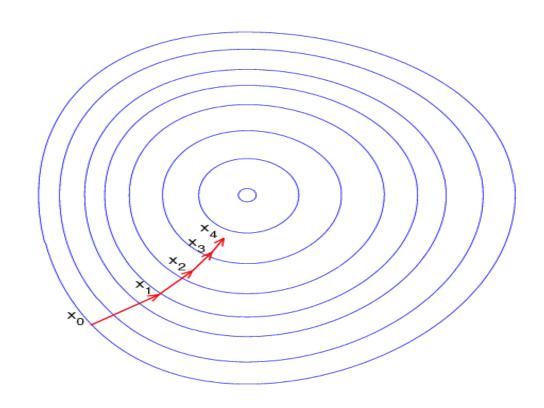




Courtesy of Durrant-Whyte, Baily; Slam: The essential algorithm

• Define a measurement function f that given the problem parameters calculates the expected measurements

- In optimal conditions f(x) = z
- Minimize $||f(x) z||_{\Sigma}^2$
- Iterative solution



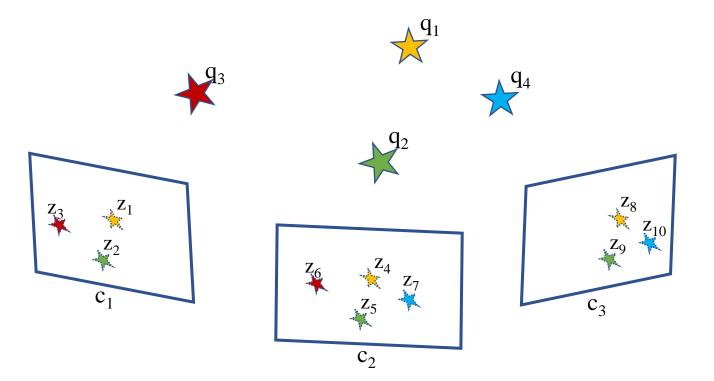
Representation

- Two system variables
 - Camera $c_i = [\psi \quad \theta \quad \phi \quad x \quad y \quad z]^T$
 - 3D position and Euler angles
 - Can produce camera matrix $K[R_i|t_i]$
 - $R_i = R(\psi, \theta, \phi) = R_z(\psi)R_v(\theta)R_x(\phi)$
 - $t_i = [x \quad y \quad z]^T$
 - Landmark $q_i = [x \ y \ z]^T$
 - 3D position
- Projection: $\lambda \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = K[R_i|t_i] \begin{bmatrix} q_j \\ 1 \end{bmatrix} \longrightarrow \begin{bmatrix} u \\ v \end{bmatrix} = \pi(c_i, q_j)$

Representation

$$z = \begin{bmatrix} z_1 & z_2 & z_3 & z_4 & z_5 & z_6 & z_7 & z_8 & z_9 & z_{10} \end{bmatrix}^T$$

$$x = \begin{bmatrix} c_1 & c_2 & c_3 & q_1 & q_2 & q_3 & q_4 \end{bmatrix}^T$$



$$f(x) \doteq \begin{bmatrix} \pi(c_{1}, q_{1}) \\ \pi(c_{1}, q_{2}) \\ \pi(c_{1}, q_{3}) \\ \pi(c_{2}, q_{1}) \\ \pi(c_{2}, q_{2}) \\ \pi(c_{2}, q_{3}) \\ \pi(c_{2}, q_{4}) \\ \pi(c_{3}, q_{2}) \\ \pi(c_{3}, q_{3}) \\ \pi(c_{3}, q_{4}) \end{bmatrix}$$

Jacobian

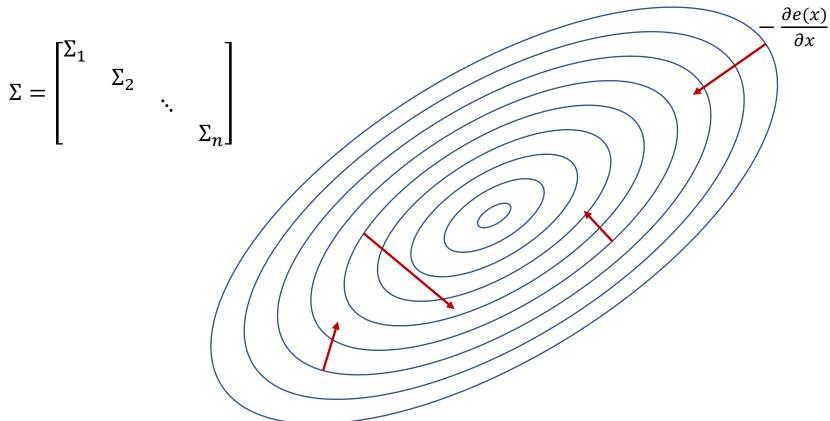
• $f(x + \Delta x) \cong f(x) + J(x)\Delta x$

$$\begin{bmatrix} f_{1}(x) \\ f_{2}(x) \\ \vdots \\ f_{m}(x) \end{bmatrix} + \begin{bmatrix} \frac{\partial f_{1}(x)}{\partial x_{1}} & \frac{\partial f_{1}(x)}{\partial x_{2}} & \cdots & \frac{\partial f_{1}(x)}{\partial x_{p}} \\ \frac{\partial f_{2}(x)}{\partial x_{1}} & \frac{\partial f_{2}(x)}{\partial x_{2}} & \cdots & \frac{\partial f_{2}(x)}{\partial x_{p}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f_{m}(x)}{\partial x_{1}} & \frac{\partial f_{m}(x)}{\partial x_{2}} & \cdots & \frac{\partial f_{m}(x)}{\partial x_{p}} \end{bmatrix} \begin{bmatrix} \Delta x_{1} \\ \Delta x_{2} \\ \vdots \\ \Delta x_{p} \end{bmatrix}$$

$$f(x) \qquad J_{f}(x) \qquad \Delta x$$

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

