

http://users.ics.forth.gr/~lourakis/sba/PRCV_colloq.pdf
 lecture by Lourakis “Bundle adjustment gone public”

- Bundle Adjustment (BA) is a key ingredient of SaM, almost always used as its last step
 - It is an optimization problem over the 3D structure and viewing parameters (camera pose, intrinsic calibration, & radial distortion parameters), which are simultaneously refined for minimizing reprojection error
 - very large nonlinear least squares problem, typically solved with the Levenberg-Marquardt (LM) algorithm
 - Std LM involves the repetitive solution of linear systems, each with $O(N^3)$ time and $O(N^2)$ storage complexity, resp.
 - Example: for 54 cameras and 5207 3D points, $N = 15945$. $\implies N^3 = 1e12$
 - Sparse LM is a better solution.
 - Example:
 - M images
 - N features
 - \mathbf{x}_{i_j} = measured feature “ i ” on image “ j ”
 - \mathbf{a}_j = vector of parameters for camera “ j ”
 - \mathbf{b}_i = vectors of parameters for point “ i ”
 - $Q(\mathbf{a}_j, \mathbf{b}_i)$ = the predicted projection of point i on image j , \leq needs to be in camera ref frame
 - $d(., .)$ the Euclidean distance between image points
 - $v_{ij} = 1$ iff point i is visible in image j
 - minimize reprojection error over $\mathbf{a}_j, \mathbf{b}_i$: $\min_{\mathbf{a}_j, \mathbf{b}_i} (\sum_{i=1}^N (\sum_{j=1}^M (v_{ij} * d(Q(\mathbf{a}_j, \mathbf{b}_i), \mathbf{x}_{i_j}))^2))$
 - \implies total number of parameters is $M * (\text{camera parameters}) + N * (\text{point parameters})$
 - let \mathbf{P} = parameter vector of camera then point parameters = $[\mathbf{P}_C \ \mathbf{P}_P]$
 - let $\mathbf{X}_{\text{hat}} = [(\mathbf{x}_{\text{hat}}_{1_1})^T \ \mathbf{x}_{\text{hat}}_{1_2})^T \dots \mathbf{x}_{\text{hat}}_{1_M})^T \ \mathbf{x}_{\text{hat}}_{2_1})^T \dots \mathbf{x}_{\text{hat}}_{N_M})^T]$
 - where $\mathbf{x}_{\text{hat}}_{i_j} = Q(\mathbf{a}_j, \mathbf{b}_i)$ is the projection onto camera plane
 - let error $\mathbf{eps} = [(\mathbf{eps}_{1_1})^T \ \mathbf{eps}_{1_2})^T \dots \mathbf{eps}_{1_M})^T \ \mathbf{eps}_{2_1})^T \dots \mathbf{eps}_{N_M})^T]$
 - where $\mathbf{eps} = \mathbf{x}_{i_j} - \mathbf{x}_{\text{hat}}_{i_j}$

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Bundle Adjustment (BA) becomes

$\min (\text{summation}_{i=1_to_N}(\text{summation}_{j=1_to_M} (\text{eps}_{i_j})^2)))$ over P

Jacobian $J = d(X_hat) / d(P)$ which has a block structure because of P being [camera parameters point parameters]

$J = [A \mid B]$ where $A = d(X_hat) / d(a)$ and $B = d(X_hat) / d(b)$

The LM updating vector $\delta = [(\delta(a))^T \ (\delta(b))^T]^T$

The normal equations:

$$\begin{bmatrix} A^T A & A^T B \\ B^T A & B^T B \end{bmatrix} \begin{bmatrix} \delta(a) \\ \delta(b) \end{bmatrix} = \begin{bmatrix} A^T \text{eps} \\ B^T \text{eps} \end{bmatrix}$$

The lhs matrix above is sparse due to A and B being sparse:

$\partial \hat{x}_{ij} / \partial a_k = 0, \forall j \neq k$ and

$\partial \hat{x}_{ij} / \partial b_k = 0, \forall i \neq k$

(example cont.) M images = 3, N features = 4

$J = \frac{\partial \hat{X}}{\partial P}$ has a block structure $[A|B]$,

Let $A_{ij} = \frac{\partial \hat{x}_{ij}}{\partial a_j}$ and $B_{ij} = \frac{\partial \hat{x}_{ij}}{\partial b_i}$

- The Jacobian J in block form:

$$\frac{\partial \hat{X}}{\partial P} =$$

$$\begin{matrix} \mathbf{x}_{11} \\ \mathbf{x}_{12} \\ \mathbf{x}_{13} \\ \mathbf{x}_{21} \\ \mathbf{x}_{22} \\ \mathbf{x}_{23} \\ \mathbf{x}_{31} \\ \mathbf{x}_{32} \\ \mathbf{x}_{33} \\ \mathbf{x}_{41} \\ \mathbf{x}_{42} \\ \mathbf{x}_{43} \end{matrix}$$

$$\begin{pmatrix} \mathbf{a}_1^T & \mathbf{a}_2^T & \mathbf{a}_3^T & \mathbf{b}_1^T & \mathbf{b}_2^T & \mathbf{b}_3^T & \mathbf{b}_4^T \end{pmatrix}$$

$$\begin{pmatrix} \mathbf{A}_{11} & 0 & 0 & \mathbf{B}_{11} & 0 & 0 & 0 \\ 0 & \mathbf{A}_{12} & 0 & \mathbf{B}_{12} & 0 & 0 & 0 \\ 0 & 0 & \mathbf{A}_{13} & \mathbf{B}_{13} & 0 & 0 & 0 \\ \mathbf{A}_{21} & 0 & 0 & 0 & \mathbf{B}_{21} & 0 & 0 \\ 0 & \mathbf{A}_{22} & 0 & 0 & \mathbf{B}_{22} & 0 & 0 \\ 0 & 0 & \mathbf{A}_{23} & 0 & \mathbf{B}_{23} & 0 & 0 \\ \mathbf{A}_{31} & 0 & 0 & 0 & 0 & \mathbf{B}_{31} & 0 \\ 0 & \mathbf{A}_{32} & 0 & 0 & 0 & \mathbf{B}_{32} & 0 \\ 0 & 0 & \mathbf{A}_{33} & 0 & 0 & \mathbf{B}_{33} & 0 \\ \mathbf{A}_{41} & 0 & 0 & 0 & 0 & 0 & \mathbf{B}_{41} \\ 0 & \mathbf{A}_{42} & 0 & 0 & 0 & 0 & \mathbf{B}_{42} \\ 0 & 0 & \mathbf{A}_{43} & 0 & 0 & 0 & \mathbf{B}_{43} \end{pmatrix}$$

(1)

This is the so-called *primary structure* of BA

- Approximate Hessian in block form:

$$\mathbf{J}^T \mathbf{J} =$$

$$\begin{matrix} \mathbf{a}_1^T & \mathbf{a}_2^T & \mathbf{a}_3^T & \mathbf{b}_1^T & \mathbf{b}_2^T & \mathbf{b}_3^T & \mathbf{b}_4^T \end{matrix}$$

$$\begin{pmatrix} \mathbf{U}_1 & 0 & 0 & \mathbf{W}_{11} & \mathbf{W}_{21} & \mathbf{W}_{31} & \mathbf{W}_{41} \\ 0 & \mathbf{U}_2 & 0 & \mathbf{W}_{12} & \mathbf{W}_{22} & \mathbf{W}_{32} & \mathbf{W}_{42} \\ 0 & 0 & \mathbf{U}_3 & \mathbf{W}_{13} & \mathbf{W}_{23} & \mathbf{W}_{33} & \mathbf{W}_{43} \\ \mathbf{W}_{11}^T & \mathbf{W}_{12}^T & \mathbf{W}_{13}^T & \mathbf{V}_1 & 0 & 0 & 0 \\ \mathbf{W}_{21}^T & \mathbf{W}_{22}^T & \mathbf{W}_{23}^T & 0 & \mathbf{V}_2 & 0 & 0 \\ \mathbf{W}_{31}^T & \mathbf{W}_{32}^T & \mathbf{W}_{33}^T & 0 & 0 & \mathbf{V}_3 & 0 \\ \mathbf{W}_{41}^T & \mathbf{W}_{42}^T & \mathbf{W}_{43}^T & 0 & 0 & 0 & \mathbf{V}_4 \end{pmatrix}$$

(2)

$$\equiv \begin{pmatrix} \mathbf{U} & \mathbf{W} \\ \mathbf{W}^T & \mathbf{V} \end{pmatrix},$$

$$\mathbf{U}_j \equiv \sum_{i=1}^4 \mathbf{A}_{ij}^T \mathbf{A}_{ij},$$

for 1 image, summing over all features

$$\mathbf{V}_i \equiv \sum_{j=1}^3 \mathbf{B}_{ij}^T \mathbf{B}_{ij},$$

for 1 feature, summing over all images

$$\mathbf{W}_{ij} = \mathbf{A}_{ij}^T \mathbf{B}_{ij}$$

(example cont.) M images = 3, N features = 4

Bundle Adjustment Revisited


Yu Chen¹, Yisong Chen¹, Guoping Wang¹

¹ Peking University, Department of Computer Science and Technology,
Graphics and Interactive Lab, Beijing, China

For convenience, we use (18) to show how to solve the bundle adjustment problem. set $\hat{u}_{ij} = \pi(C_j, X_i)$, and we order the parameter x into camera block c and structure block p :

$$x = [c, p] \quad (20)$$

it's easily to realize that:

$$J_{ij} = \frac{\partial r_{ij}}{\partial x_k} = \frac{\partial \hat{u}_{ij}}{\partial x_k}, \frac{\partial \hat{u}_{ij}}{\partial c_k} = 0, \forall j \neq k, \frac{\partial \hat{u}_{ij}}{\partial p_k} = 0, \forall i \neq k \quad (21)$$


Consider now, that we have $m = 3$ cameras and $n = 4$ 3D points. Set $A_{ij} = \frac{\partial \hat{u}_{ij}}{\partial c_j}$, $B_{ij} = \frac{\partial \hat{u}_{ij}}{\partial p_i}$, we can obtain the Jacobi:

**k dimension is
row number
w.r.t. the block
of i where i is
the feature
number**

$$J = \frac{\partial \hat{u}}{\partial x} = \begin{matrix} \begin{matrix} k = 1 \\ \\ \\ k = 4 \end{matrix} \left\{ \begin{array}{ccccccc} A_{11} & 0 & 0 & B_{11} & 0 & 0 & 0 \\ 0 & A_{12} & 0 & B_{12} & 0 & 0 & 0 \\ 0 & 0 & A_{13} & B_{13} & 0 & 0 & 0 \\ A_{21} & 0 & 0 & 0 & B_{21} & 0 & 0 \\ 0 & A_{22} & 0 & 0 & B_{22} & 0 & 0 \\ 0 & 0 & A_{23} & 0 & B_{23} & 0 & 0 \\ A_{31} & 0 & 0 & 0 & 0 & B_{31} & 0 \\ 0 & A_{32} & 0 & 0 & 0 & B_{32} & 0 \\ 0 & 0 & A_{33} & 0 & 0 & B_{33} & 0 \\ A_{41} & 0 & 0 & 0 & 0 & 0 & B_{41} \\ 0 & A_{42} & 0 & 0 & 0 & 0 & B_{42} \\ 0 & 0 & A_{43} & 0 & 0 & 0 & B_{43} \end{array} \right. \end{matrix} \quad (22)$$

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(example cont.) M images = 3, N features = 4

NOTE: $\text{eps}_a = A^T * \text{eps}$, $\text{eps}_b = B^T * \text{eps}$

- The augmented normal equations $(J^T J + \mu I) \delta_p = J^T \epsilon$ take the form

where $\mu > 0$

$$(3) \quad \begin{pmatrix} U^* & W \\ W^T & V^* \end{pmatrix} \begin{pmatrix} \delta_a \\ \delta_b \end{pmatrix} = \begin{pmatrix} \epsilon_a \\ \epsilon_b \end{pmatrix}$$

- Performing block Gaussian elimination in the lhs matrix, δ_a is determined with Cholesky from V^* 's Schur complement:

$$(4) \quad (U^* - W V^{*-1} W^T) \delta_a = \epsilon_a - W V^{*-1} \epsilon_b$$

Schur complement: multiply 1st matrix on res by

$$\begin{pmatrix} I & 0 \\ (((-V^*)^{-1})W^T & I \end{pmatrix}$$

resulting in:

$$\begin{pmatrix} (U^*) - W(((V^*)^{-1})W^T & W \\ 0 & (V^*) \end{pmatrix} * \begin{pmatrix} \delta_a \\ \delta_b \end{pmatrix} = \begin{pmatrix} \epsilon_a \\ \epsilon_b \end{pmatrix}$$

note (V^*) is invertible and only the block diagonals are populated, so each V_i is inverted.

separate δ_b : $0 * \delta_a + (V^*) * \delta_b = \text{eps}_b \Rightarrow \delta_b = \text{eps}_b * ((V^*)^{-1})$
solving for δ_a (typically M images \ll N features) after substitute δ_b :

$$((U^*) - W(((V^*)^{-1})W^T) * \delta_a + W * \delta_b = \text{eps}_a$$

$$((U^*) - W(((V^*)^{-1})W^T) * \delta_a = \text{eps}_a - W((V^*)^{-1})\text{eps}_b$$

NOTE: $(U^*) - W(((V^*)^{-1})W^T)$ is called the reduced camera matrix (because δ_a is camera parameters)

$$V^{*-1} = \begin{pmatrix} V_1^{*-1} & 0 & \dots \\ 0 & V_2^{*-1} & \dots \\ \vdots & \vdots & \ddots \end{pmatrix}$$

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RCM (reduced camera matrix) is sparse because not all features appear in all cameras.
this is known as **secondary structure**.

For very large datasets, RCM tends to be in one of two classes:

- (1) ◦ visual mapping: extended areas are traversed, limited image overlap (sparse RCM)
- (2) ◦ centered-object: a large number of overlapping images taken in a small area (dense RCM)

Solving for δ_a in the equation containing RCM. several ways:

- (1) Store as dense, decompose with **ordinary linear algebra** ◦ [M. Lourakis, A. Argyros: SBA: A Software Package For Generic Sparse Bundle Adjustment. ACM Trans. Math. Softw. 36(1): (2009) ◦ C. Engels, H. Stewenius, D. Nister: Bundle Adjustment Rules. Photogrammetric Computer Vision (PCV), 2006.
- (2) • Store as sparse, factorize with **sparse direct solvers** ◦ K. Konolige: Sparse Sparse Bundle Adjustment. BMVC 2010: 1-11
- (3) Store as sparse, use **conjugate gradient methods** memory efficient, iterative, preconditioners necessary! ◦ S. Agarwal, N. Snavely, S.M. Seitz, R. Szeliski: Bundle Adjustment in the Large. ECCV (2) 2010: 29-42 ◦ M. Byrod, K. Astrom: Conjugate Gradient Bundle Adjustment. ECCV (2) 2010: 114-127
- (4) • Avoid storing altogether ◦ C. Wu, S. Agarwal, B. Curless, S.M. Seitz: Multicore Bundle Adjustment. CVPR 2011: 30 57-3064 ◦ M. Lourakis: Sparse Non-linear Least Squares Optimization for Geometric Vision. ECCV (2) 2010: 43-56

Engels, Stewenius, Nister 2006, “Bundle Adjustment Rules”

m images (= video frames from same calibrated camera)

? features

each feature x has M dimensions

n iterations of bundle adjustment over the last m video frames

Engels “RCM” is formed from a jacobian which places point parameters before camera parameters, so is different than that in the Lourakis notes.

$$J_f = \begin{bmatrix} J_P & J_C \end{bmatrix}, \quad (15)$$

$$H = \begin{bmatrix} J_P^\top J_P & J_P^\top J_C \\ J_C^\top J_P & J_C^\top J_C \end{bmatrix}, \quad (16)$$

$$\begin{bmatrix} H_{PP} & H_{PC} \\ H_{PC}^\top & H_{CC} \end{bmatrix} \begin{bmatrix} dP \\ dC \end{bmatrix} = \begin{bmatrix} b_P \\ b_C \end{bmatrix}, \quad (17)$$

where we have defined $H_{PP} = J_P^\top J_P$, $H_{PC} = J_P^\top J_C$, $H_{CC} = J_C^\top J_C$, $b_P = -J_P^\top f$, $b_C = -J_C^\top f$ to simplify the notation, and dP and dC represent the update of the point parameters and the camera parameters, respectively. Note that the matrices H_{PP} and H_{CC} are block-diagonal, where the blocks correspond to

of as multiplying by

$$\begin{bmatrix} I & 0 \\ -H_{PC}^\top & I \end{bmatrix} \quad (20)$$

from the left on both sides, resulting in the smaller equation system (from the lower part)

$$\underbrace{(H_{CC} - H_{PC}^\top H_{PP}^{-1} H_{PC})}_A dC = \underbrace{b_C - H_{PC}^\top H_{PP}^{-1} b_P}_B \quad (21)$$

for the camera parameter update dC . For very large systems,

We use straightforward Cholesky factorization.

Engels, Stewenius, Nister 2006, "Bundle Adjustment Rules"

M images = 3, j
N features = 4, i

sparse blocks along diagonal: J_P_i is [3 X 3]

J_P is [2*n*m X 3*m]

J_P_i is [2*n*m X 3]

J_C is [2n*m X 9*n]

J_C_i is [2n*m X 9]

J is [2nm X (3m + 9n)]

J_C_i is [9 X 9]

their "RCM" is formed from a jacobian which places point parameters before camera parameters, so is different than that in the Lourakis notes.

Lourakis

Let $A_{ij} = \frac{\partial \hat{x}_{ij}}{\partial a_j}$ and $B_{ij} = \frac{\partial \hat{x}_{ij}}{\partial b_i}$
 $\begin{matrix} \boxed{2 \times 9} & \mathbf{C} & \boxed{2 \times 3} & \mathbf{P} \end{matrix}$

$$\mathbf{J} = \frac{\partial \hat{\mathbf{X}}}{\partial \mathbf{P}} = \left[\frac{\partial \hat{\mathbf{X}}}{\partial \mathbf{a}} \quad \frac{\partial \hat{\mathbf{X}}}{\partial \mathbf{b}} \right] = \begin{bmatrix} \mathbf{J}_C & \mathbf{J}_P \end{bmatrix}$$

• The Jacobian J in block form:

$$\frac{\partial \hat{\mathbf{X}}}{\partial \mathbf{P}} = \begin{matrix} \mathbf{x}_{11} \\ \mathbf{x}_{12} \\ \mathbf{x}_{13} \\ \mathbf{x}_{21} \\ \mathbf{x}_{22} \\ \mathbf{x}_{23} \\ \mathbf{x}_{31} \\ \mathbf{x}_{32} \\ \mathbf{x}_{33} \\ \mathbf{x}_{41} \\ \mathbf{x}_{42} \\ \mathbf{x}_{43} \end{matrix} \begin{pmatrix} \mathbf{a}_1^T & \mathbf{a}_2^T & \mathbf{a}_3^T & \mathbf{b}_1^T & \mathbf{b}_2^T & \mathbf{b}_3^T & \mathbf{b}_4^T \\ \mathbf{A}_{11} & 0 & 0 & \mathbf{B}_{11} & 0 & 0 & 0 \\ 0 & \mathbf{A}_{12} & 0 & \mathbf{B}_{12} & 0 & 0 & 0 \\ 0 & 0 & \mathbf{A}_{13} & \mathbf{B}_{13} & 0 & 0 & 0 \\ \mathbf{A}_{21} & 0 & 0 & 0 & \mathbf{B}_{21} & 0 & 0 \\ 0 & \mathbf{A}_{22} & 0 & 0 & \mathbf{B}_{22} & 0 & 0 \\ 0 & 0 & \mathbf{A}_{23} & 0 & \mathbf{B}_{23} & 0 & 0 \\ \mathbf{A}_{31} & 0 & 0 & 0 & 0 & \mathbf{B}_{31} & 0 \\ 0 & \mathbf{A}_{32} & 0 & 0 & 0 & \mathbf{B}_{32} & 0 \\ 0 & 0 & \mathbf{A}_{33} & 0 & 0 & \mathbf{B}_{33} & 0 \\ \mathbf{A}_{41} & 0 & 0 & 0 & 0 & 0 & \mathbf{B}_{41} \\ 0 & \mathbf{A}_{42} & 0 & 0 & 0 & 0 & \mathbf{B}_{42} \\ 0 & 0 & \mathbf{A}_{43} & 0 & 0 & 0 & \mathbf{B}_{43} \end{pmatrix}$$

(1)

Engels

Let $A_{ij} = \frac{\partial \hat{x}_{ij}}{\partial a_j}$ and $B_{ij} = \frac{\partial \hat{x}_{ij}}{\partial b_i}$
 $\begin{matrix} \boxed{2 \times 9} & \mathbf{C} & \boxed{2 \times 3} & \mathbf{P} \end{matrix}$

$$\mathbf{J}_f = \begin{bmatrix} \mathbf{J}_P & \mathbf{J}_C \end{bmatrix},$$

• The Jacobian J in block form:

$$\frac{\partial \hat{\mathbf{X}}}{\partial \mathbf{P}} = \begin{matrix} \mathbf{x}_{11} \\ \mathbf{x}_{12} \\ \mathbf{x}_{13} \\ \mathbf{x}_{21} \\ \mathbf{x}_{22} \\ \mathbf{x}_{23} \\ \mathbf{x}_{31} \\ \mathbf{x}_{32} \\ \mathbf{x}_{33} \\ \mathbf{x}_{41} \\ \mathbf{x}_{42} \\ \mathbf{x}_{43} \end{matrix} \begin{pmatrix} \mathbf{b}_1^T & \mathbf{b}_2^T & \mathbf{b}_3^T & \mathbf{b}_4^T & \mathbf{a}_1^T & \mathbf{a}_2^T & \mathbf{a}_3^T \\ \mathbf{B}_{11} & 0 & 0 & 0 & \mathbf{A}_{11} & 0 & 0 \\ \mathbf{B}_{12} & 0 & 0 & 0 & 0 & \mathbf{A}_{12} & 0 \\ \mathbf{B}_{13} & 0 & 0 & 0 & 0 & 0 & \mathbf{A}_{13} \\ 0 & \mathbf{B}_{21} & 0 & 0 & \mathbf{A}_{21} & 0 & 0 \\ 0 & \mathbf{B}_{22} & 0 & 0 & 0 & \mathbf{A}_{22} & 0 \\ 0 & \mathbf{B}_{23} & 0 & 0 & 0 & 0 & \mathbf{A}_{23} \\ 0 & 0 & \mathbf{B}_{31} & 0 & \mathbf{A}_{31} & 0 & 0 \\ 0 & 0 & \mathbf{B}_{32} & 0 & 0 & \mathbf{A}_{32} & 0 \\ 0 & 0 & \mathbf{B}_{33} & 0 & 0 & 0 & \mathbf{A}_{33} \\ 0 & 0 & 0 & \mathbf{B}_{41} & \mathbf{A}_{41} & 0 & 0 \\ 0 & 0 & 0 & \mathbf{B}_{42} & 0 & \mathbf{A}_{42} & 0 \\ 0 & 0 & 0 & \mathbf{B}_{43} & 0 & 0 & \mathbf{A}_{43} \end{pmatrix}$$

(1)

Engels, Stewenius, Nister 2006, "Bundle Adjustment Rules"

M images = 3, j

N features = 4, i

their "RCM" is formed from a jacobian which places point parameters before camera parameters, so is different than that in the Lourakis notes.

J is [2nm X (3n + 9m)]

J^T * J is [(3n+9m) X (3n+9m)]

Lourakis

Let $A_{ij} = \frac{\partial \hat{x}_{ij}}{\partial \mathbf{a}_j}$ and $B_{ij} = \frac{\partial \hat{x}_{ij}}{\partial \mathbf{b}_i}$
C P

$$\mathbf{J} = \frac{\partial \hat{\mathbf{X}}}{\partial \mathbf{P}} = \begin{bmatrix} \frac{\partial \hat{\mathbf{X}}}{\partial \mathbf{a}} & \frac{\partial \hat{\mathbf{X}}}{\partial \mathbf{b}} \end{bmatrix} = \begin{bmatrix} J_C & J_P \end{bmatrix}$$

$$\mathbf{J}^T \mathbf{J} =$$

J^T * J is [(3*n + 9*m)] X (3*n + 9*m)]

$$\begin{matrix} & \mathbf{a}_1^T & \mathbf{a}_2^T & \mathbf{a}_3^T & \mathbf{b}_1^T & \mathbf{b}_2^T & \mathbf{b}_3^T & \mathbf{b}_4^T \\ \mathbf{a}_1 & \mathbf{U}_1 & 0 & 0 & \mathbf{W}_{11} & \mathbf{W}_{21} & \mathbf{W}_{31} & \mathbf{W}_{41} \\ \mathbf{a}_2 & 0 & \mathbf{U}_2 & 0 & \mathbf{W}_{12} & \mathbf{W}_{22} & \mathbf{W}_{32} & \mathbf{W}_{42} \\ \mathbf{a}_3 & 0 & 0 & \mathbf{U}_3 & \mathbf{W}_{13} & \mathbf{W}_{23} & \mathbf{W}_{33} & \mathbf{W}_{43} \\ \mathbf{b}_1 & \mathbf{W}_{11}^T & \mathbf{W}_{12}^T & \mathbf{W}_{13}^T & \mathbf{V}_1 & 0 & 0 & 0 \\ \mathbf{b}_2 & \mathbf{W}_{21}^T & \mathbf{W}_{22}^T & \mathbf{W}_{23}^T & 0 & \mathbf{V}_2 & 0 & 0 \\ \mathbf{b}_3 & \mathbf{W}_{31}^T & \mathbf{W}_{32}^T & \mathbf{W}_{33}^T & 0 & 0 & \mathbf{V}_3 & 0 \\ \mathbf{b}_4 & \mathbf{W}_{41}^T & \mathbf{W}_{42}^T & \mathbf{W}_{43}^T & 0 & 0 & 0 & \mathbf{V}_4 \end{matrix}$$

where

$$\mathbf{U}_j \equiv \sum_{i=1}^4 \mathbf{A}_{ij}^T \mathbf{A}_{ij},$$

$$\mathbf{V}_i \equiv \sum_{j=1}^3 \mathbf{B}_{ij}^T \mathbf{B}_{ij},$$

$$\mathbf{W}_{ij} = \mathbf{A}_{ij}^T \mathbf{B}_{ij}$$

for 1 image, sum over features

9X9

for 1 feature, sum over images

3X3

9X3

$$\equiv \sum_{j=1}^3 \left(\frac{\partial \hat{x}_{ij}}{\partial \mathbf{b}_i} \right)^T \frac{\partial \hat{x}_{ij}}{\partial \mathbf{b}_i}$$

Engels

Let $A_{ij} = \frac{\partial \hat{x}_{ij}}{\partial \mathbf{a}_j}$ and $B_{ij} = \frac{\partial \hat{x}_{ij}}{\partial \mathbf{b}_i}$
C P

$$\mathbf{J} = \frac{\partial \hat{\mathbf{X}}}{\partial \mathbf{P}} = \begin{bmatrix} \frac{\partial \hat{\mathbf{X}}}{\partial \mathbf{b}} & \frac{\partial \hat{\mathbf{X}}}{\partial \mathbf{a}} \end{bmatrix} = \begin{bmatrix} J_P & J_C \end{bmatrix},$$

$$\mathbf{J}^T \mathbf{J} =$$

J^T * J is [(3*n + 9*m)] X (3*n + 9*m)]

$$\begin{matrix} & \mathbf{b}_1^T & \mathbf{b}_2^T & \mathbf{b}_3^T & \mathbf{b}_4^T & \mathbf{a}_1^T & \mathbf{a}_2^T & \mathbf{a}_3^T \\ \mathbf{b}_1 & \mathbf{V}_1 & 0 & 0 & 0 & \mathbf{W}_{11}^T & \mathbf{W}_{12}^T & \mathbf{W}_{13}^T \\ \mathbf{b}_2 & 0 & \mathbf{V}_2 & 0 & 0 & \mathbf{W}_{21}^T & \mathbf{W}_{22}^T & \mathbf{W}_{23}^T \\ \mathbf{b}_3 & 0 & 0 & \mathbf{V}_3 & 0 & \mathbf{W}_{31}^T & \mathbf{W}_{32}^T & \mathbf{W}_{33}^T \\ \mathbf{b}_4 & 0 & 0 & 0 & \mathbf{V}_4 & \mathbf{W}_{41}^T & \mathbf{W}_{42}^T & \mathbf{W}_{43}^T \\ \mathbf{a}_1 & \mathbf{W}_{11} & \mathbf{W}_{21} & \mathbf{W}_{31} & \mathbf{W}_{41} & \mathbf{U}_1 & 0 & 0 \\ \mathbf{a}_2 & \mathbf{W}_{12} & \mathbf{W}_{22} & \mathbf{W}_{32} & \mathbf{W}_{42} & 0 & \mathbf{U}_2 & 0 \\ \mathbf{a}_3 & \mathbf{W}_{13} & \mathbf{W}_{23} & \mathbf{W}_{33} & \mathbf{W}_{43} & 0 & 0 & \mathbf{U}_3 \end{matrix}$$

Engels, Stewenius, Nister 2006, "Bundle Adjustment Rules"

$$\text{Note that } \mathbf{V}^{*-1} = \begin{pmatrix} \mathbf{V}_1^{*-1} & 0 & \cdots \\ 0 & \mathbf{V}_2^{*-1} & \cdots \\ \vdots & \vdots & \ddots \end{pmatrix}$$

δ_b is dP is $[3*n_features \times 1]$
 ϵ_b is b_P is $[3*n_features \times 1]$
 δ_a is dC is $[9*m_images \times 1]$
 ϵ_a is b_C is $[9*m_images \times 1]$

\mathbf{V}^* is $[3*n \times 3*n]$

\mathbf{W} is $[9*m \times 3*n]$

\mathbf{U}^* is $[9*m \times 9*m]$

Lourakis

The augmented normal equations $(\mathbf{J}^T \mathbf{J} + \mu \mathbf{I}) \delta_P = \mathbf{J}^T \epsilon$ take the form

$$(3) \quad \begin{pmatrix} \mathbf{U}^* & \mathbf{W} \\ \mathbf{W}^T & \mathbf{V}^* \end{pmatrix} \begin{pmatrix} \delta_a \\ \delta_b \end{pmatrix} = \begin{pmatrix} \epsilon_a \\ \epsilon_b \end{pmatrix}$$

$$\begin{bmatrix} \mathbf{U} - \mathbf{W} \mathbf{V}^{*-1} \mathbf{W}^T & 0 \end{bmatrix} \begin{bmatrix} \delta_a \\ \delta_b \end{bmatrix} = \begin{bmatrix} \mathbf{I} & -\mathbf{W} \mathbf{V}^{*-1} \end{bmatrix} \begin{bmatrix} \epsilon_a \\ \epsilon_b \end{bmatrix}$$

(solve delta a first because typically $m_images \ll n_features$)

determine δ_a with Cholesky (or other method)

$$(\mathbf{U}^* - \mathbf{W} \mathbf{V}^{*-1} \mathbf{W}^T) \delta_a = \epsilon_a - \mathbf{W} \mathbf{V}^{*-1} \epsilon_b$$

δ_b can be computed by back substitution into

$$\mathbf{V}^* \delta_b = \epsilon_b - \mathbf{W}^T \delta_a$$

$$\delta_b = \mathbf{V}^{*-1} \epsilon_b - \mathbf{V}^{*-1} \mathbf{W}^T \delta_a$$

Engels

$$\begin{pmatrix} \mathbf{V}^* & \mathbf{W}^T \\ \mathbf{W} & \mathbf{U}^* \end{pmatrix} \begin{pmatrix} \delta_b \\ \delta_a \end{pmatrix} = \begin{pmatrix} \epsilon_b \\ \epsilon_a \end{pmatrix}$$

$$\begin{bmatrix} H_{PP} & H_{PC} \\ H_{PC}^T & H_{CC} \end{bmatrix} \begin{bmatrix} dP \\ dC \end{bmatrix} = \begin{bmatrix} b_P \\ b_C \end{bmatrix}, \quad \begin{aligned} H_{PP} &= J_P^T J_P \\ H_{PC} &= J_P^T J_C, \\ H_{CC} &= J_C^T J_C, \\ b_P &= -J_P^T f, \\ b_C &= -J_C^T f \end{aligned}$$

$$\underbrace{(\mathbf{U}^* - \mathbf{W} \mathbf{V}^{*-1} \mathbf{W}^T)}_A \delta_a = \epsilon_a - \underbrace{\mathbf{W} \mathbf{V}^{*-1} \epsilon_b}_B$$

$$\underbrace{(H_{CC} - H_{PC}^T H_{PP}^{-1} H_{PC})}_A dC = \underbrace{b_C - H_{PC}^T H_{PP}^{-1} b_P}_B$$

δ_b can be computed by back substitution into

$$\mathbf{V}^* \delta_b = \epsilon_b - \mathbf{W}^T \delta_a$$

$$\begin{aligned} H_{PP} dP &= b_P - H_{PC} dC \\ dP &= H_{PP}^{-1} b_P - H_{PP}^{-1} H_{PC} dC. \end{aligned}$$

Qu

(3.61)

$$\begin{pmatrix} \mathbf{B} & \mathbf{E} \\ \mathbf{E}^T & \mathbf{C} \end{pmatrix} \begin{pmatrix} p_c \\ p_p \end{pmatrix} = - \begin{pmatrix} g_c \\ g_p \end{pmatrix}$$

see eqn (3.70) too

$$-g^k = -\mathbf{J}^{kT} \mathbf{F}^k$$

where k is a feature block summed over all images?

$$(\mathbf{B} - \mathbf{E} \mathbf{C}^{-1} \mathbf{E}^T) p_c = -g_c + \mathbf{E} \mathbf{C}^{-1} g_p$$

$$p_p = \mathbf{C}^{-1} (-g_p - \mathbf{E}^T p_c)$$

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M images = 3, j
N features = 4, i

$$\begin{aligned} H_{PP} &= J_P^\top J_P && \equiv && \mathbf{V}^* \\ H_{PC} &= J_P^\top J_C, && \equiv && \mathbf{W}^T \\ H_{CC} &= J_C^\top J_C, && \equiv && \mathbf{U}^* \\ b_P &= -J_P^\top f, && \equiv && \epsilon_b \\ b_C &= -J_C^\top f && \equiv && \epsilon_a \end{aligned}$$

$$\underbrace{(\mathbf{U}^* - \mathbf{W} \mathbf{V}^{*-1} \mathbf{W}^T)}_A \delta_a = \epsilon_a - \underbrace{\mathbf{W} \mathbf{V}^{*-1}}_B \epsilon_b$$

$$\underbrace{(H_{CC} - H_{PC}^\top H_{PP}^{-1} H_{PC})}_A dC = \underbrace{b_C - H_{PC}^\top H_{PP}^{-1} b_P}_B$$

$$\begin{aligned} dP &= H_{PP}^{-1} b_P - H_{PP}^{-1} H_{PC} dC. \\ &= \text{tP} - \text{tPC}^\top \text{t}^* dC \\ &\quad [3n \times 1] \quad [3n \times 9m] \quad [9m \times 1] \end{aligned}$$

$$\mathbf{A}_{ij} = \frac{\partial \hat{x}_{ij}}{\partial \mathbf{a}_j} \text{ and } \mathbf{B}_{ij} = \frac{\partial \hat{x}_{ij}}{\partial \mathbf{b}_i}$$

$\boxed{2 \times 9}$ \mathbf{C} $\boxed{2 \times 3}$ \mathbf{P}

Note that $\mathbf{V}^{*-1} = \begin{pmatrix} \mathbf{V}_1^{*-1} & 0 & \dots \\ 0 & \mathbf{V}_2^{*-1} & \dots \\ \vdots & \vdots & \ddots \end{pmatrix}$

$$\mathbf{J}^\top \mathbf{J} = \begin{matrix} & \mathbf{b}_1^\top & \mathbf{b}_2^\top & \mathbf{b}_3^\top & \mathbf{b}_4^\top & \mathbf{a}_1^\top & \mathbf{a}_2^\top & \mathbf{a}_3^\top \\ \begin{matrix} \mathbf{b}_1 \\ \mathbf{b}_2 \\ \mathbf{b}_3 \\ \mathbf{b}_4 \\ \mathbf{a}_1 \\ \mathbf{a}_2 \\ \mathbf{a}_3 \end{matrix} & \begin{pmatrix} \mathbf{V}_1 & 0 & 0 & 0 & \mathbf{W}_{11}^\top & \mathbf{W}_{12}^\top & \mathbf{W}_{13}^\top \\ 0 & \mathbf{V}_2 & 0 & 0 & \mathbf{W}_{21}^\top & \mathbf{W}_{22}^\top & \mathbf{W}_{23}^\top \\ 0 & 0 & \mathbf{V}_3 & 0 & \mathbf{W}_{31}^\top & \mathbf{W}_{32}^\top & \mathbf{W}_{33}^\top \\ 0 & 0 & 0 & \mathbf{V}_4 & \mathbf{W}_{41}^\top & \mathbf{W}_{42}^\top & \mathbf{W}_{43}^\top \\ \mathbf{W}_{11} & \mathbf{W}_{21} & \mathbf{W}_{31} & \mathbf{W}_{41} & \mathbf{U}_1 & 0 & 0 \\ \mathbf{W}_{12} & \mathbf{W}_{22} & \mathbf{W}_{32} & \mathbf{W}_{42} & 0 & \mathbf{U}_2 & 0 \\ \mathbf{W}_{13} & \mathbf{W}_{23} & \mathbf{W}_{33} & \mathbf{W}_{43} & 0 & 0 & \mathbf{U}_3 \end{pmatrix} \end{matrix}$$

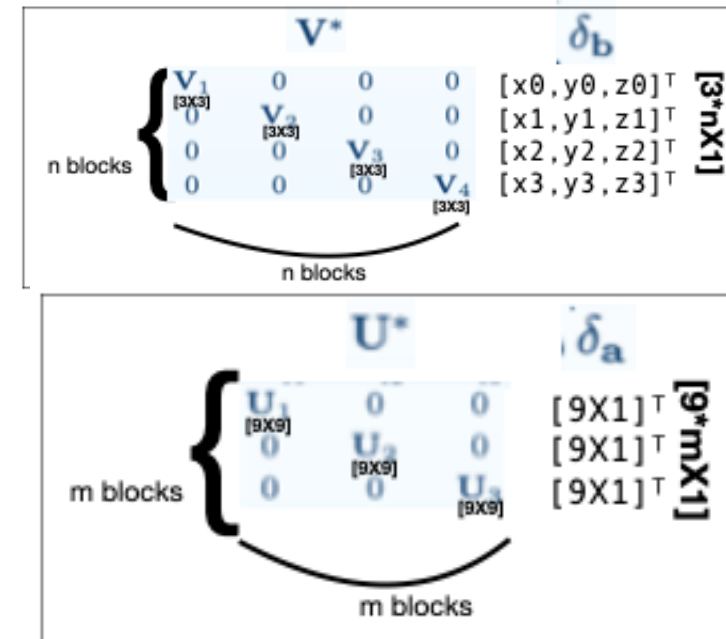
$$\begin{aligned} \mathbf{U}_j &\equiv \sum_{i=1}^4 \mathbf{A}_{ij}^\top \mathbf{A}_{ij}, && [9 \times 9], \text{ for 1 image, sum over features} \\ \mathbf{V}_i &\equiv \sum_{j=1}^3 \mathbf{B}_{ij}^\top \mathbf{B}_{ij}, && [3 \times 3], \text{ for 1 feature, sum over images} \\ \mathbf{W}_{ij} &= \mathbf{A}_{ij}^\top \mathbf{B}_{ij} && [9 \times 3] \end{aligned}$$

\mathbf{V}^* is $[3^n \times 3^n]$

\mathbf{W} is $[9^m \times 3^n]$

\mathbf{U}^* is $[9^m \times 9^m]$

$$\begin{pmatrix} \mathbf{V}^* & \mathbf{W}^T \\ \mathbf{W} & \mathbf{U}^* \end{pmatrix} \begin{pmatrix} \delta_b \\ \delta_a \end{pmatrix} = \begin{pmatrix} \epsilon_b \\ \epsilon_a \end{pmatrix}$$



Engels, et al 2006

M images = 3, j
N features = 4, i

$$\begin{aligned} H_{PP} &= J_P^T J_P && \equiv \mathbf{V}^* \\ H_{PC} &= J_P^T J_C, && \equiv \mathbf{W}^T \\ H_{CC} &= J_C^T J_C, && \equiv \mathbf{U}^* \\ b_P &= -J_P^T f, && \equiv \epsilon_b \\ b_C &= -J_C^T f && \equiv \epsilon_a \end{aligned}$$

$$\mathbf{A}_{ij} = \frac{\partial \hat{x}_{ij}}{\partial \mathbf{a}_j} \text{ and } \mathbf{B}_{ij} = \frac{\partial \hat{x}_{ij}}{\partial \mathbf{b}_i}$$

2X9 **C** 2X3 **P**

Note that $\mathbf{V}^{*-1} = \begin{pmatrix} \mathbf{V}_1^{*-1} & 0 & \dots \\ 0 & \mathbf{V}_2^{*-1} & \dots \\ \vdots & \vdots & \ddots \end{pmatrix}$

$$\begin{aligned} \mathbf{U}_j &\equiv \sum_{i=1}^4 \mathbf{A}_{ij}^T \mathbf{A}_{ij}, && \text{[9X9], for 1 image, sum over features} \\ \mathbf{V}_i &\equiv \sum_{j=1}^3 \mathbf{B}_{ij}^T \mathbf{B}_{ij}, && \text{[3X3], for 1 feature, sum over images} \\ \mathbf{W}_{ij} &= \mathbf{A}_{ij}^T \mathbf{B}_{ij} && \text{[9X3]} \end{aligned}$$

V* is [3*n X 3*n]

W is [9*m X 3*n]

U* is [9*m X 9*m]

$$\begin{pmatrix} \mathbf{V}^* & \mathbf{W}^T \\ \mathbf{W} & \mathbf{U}^* \end{pmatrix} \begin{pmatrix} \delta_b \\ \delta_a \end{pmatrix} = \begin{pmatrix} \epsilon_b \\ \epsilon_a \end{pmatrix}$$

```
* calculate bC = -JC^T*F [9m X 1]
JC^T[9m X 2mn]
A11T 0 0 | A21T 0 0 | A31T 0 0 | A41T 0 0 * F [2mn X 1]]
0 A12T 0 | 0 A22T 0 | 0 A32T 0 | 0 A42T 0 F11
0 0 A13T | 0 0 A23T | 0 0 A33T | 0 0 A43T F12
[9m X 2m] [9m X 2m] [9m X 2m] [9m X 2m] F13
F21
F22
F23
[2m X 1]
F31
F32
F33
[2m X 1]
F41
F42
F43
[2m X 1]

bC [9m X 1]
-A11T*F11-A21T*F21-A31T*F31-A41T*F41
-A12T*F12-A22T*F22-A32T*F32-A42T*F42
-A13T*F13-A23T*F23-A33T*F33-A43T*F43
each block is [9X1]

i=1:nFeatures
j = 1:mImages
AIJ, FIJ

[i=1:n,j=1] row=j, col=1 : Σ_i(-AIJT*FIJ)
[i=1:n,j=2] row=j, col=1 : Σ_i(-AIJT*FIJ)
[i=1:n,j=3] row=j, col=1 : Σ_i(-AIJT*FIJ)
```

Engels, et al 2006

M images = 3, j
N features = 4, i

$$\begin{aligned} H_{PP} &= J_P^T J_P && \equiv \mathbf{V}^* \\ H_{PC} &= J_P^T J_C, && \equiv \mathbf{W}^T \\ H_{CC} &= J_C^T J_C, && \equiv \mathbf{U}^* \\ b_P &= -J_P^T f, && \equiv \epsilon_b \\ b_C &= -J_C^T f && \equiv \epsilon_a \end{aligned}$$

$$\mathbf{A}_{ij} = \frac{\partial \hat{x}_{ij}}{\partial \mathbf{a}_j} \text{ and } \mathbf{B}_{ij} = \frac{\partial \hat{x}_{ij}}{\partial \mathbf{b}_i}$$

2X9 **C** 2X3 **P**

Note that $\mathbf{V}^{*-1} = \begin{pmatrix} \mathbf{V}_1^{*-1} & 0 & \dots \\ 0 & \mathbf{V}_2^{*-1} & \dots \\ \vdots & \vdots & \ddots \end{pmatrix}$

$$\begin{aligned} \mathbf{U}_j &\equiv \sum_{i=1}^4 \mathbf{A}_{ij}^T \mathbf{A}_{ij}, && \text{[9X9], for 1 image, sum over features} \\ \mathbf{V}_i &\equiv \sum_{j=1}^3 \mathbf{B}_{ij}^T \mathbf{B}_{ij}, && \text{[3X3], for 1 feature, sum over images} \\ \mathbf{W}_{ij} &= \mathbf{A}_{ij}^T \mathbf{B}_{ij} && \text{[9X3]} \end{aligned}$$

```
*calculate bP = -JP^T*F [3n X 1]
JP^T [3n X 2mn]
B11^T B12^T B13^T | 0 0 0 | 0 0 0 | 0 0 0 * F [2mn X 1]
0 0 0 | B21^T B22^T B23^T | 0 0 0 | 0 0 0 F11
0 0 0 | 0 0 0 | B31^T B32^T B33^T | 0 0 0 F12
0 0 0 | 0 0 0 | 0 0 0 | B41^T B42^T B43^T F13
[3n X 2m] [3n X 2m] [3n X 2m] [3n X 2m] [2m X 1]
F21
F22
F23
[2m X 1]
F31
F32
F33
[2m X 1]
F41
F42
F43
[2m X 1]

-JP^T*F [3n X 1]
-B11T*F11 - B12T*F12 - B13T*F13
-B21T*F21 - B22T*F22 - B23T*F23
-B31T*F31 - B32T*F32 - B33T*F33
-B41T*F41 - B42T*F42 - B43T*F43
each block is [3X1]

i=1:nFeatures
j = 1:mImages
BIJ, FIJ

[i=1,j=1:m] row=i, col=1 : Σ_j (-BIJT*FIJ)
[i=2,j=1:m] row=i, col=1 : Σ_j (-BIJT*FIJ)
[i=3,j=1:m] row=i, col=1 : Σ_j (-BIJT*FIJ)
[i=4,j=1:m] row=i, col=1 : Σ_j (-BIJT*FIJ)
```

V* is [3*n X 3*n]

W is [9*m X 3*n]

U* is [9*m X 9*m]

$$\begin{pmatrix} \mathbf{V}^* & \mathbf{W}^T \\ \mathbf{W} & \mathbf{U}^* \end{pmatrix} \begin{pmatrix} \delta_b \\ \delta_a \end{pmatrix} = \begin{pmatrix} \epsilon_b \\ \epsilon_a \end{pmatrix}$$

Engels, et al 2006

M images = 3, j
N features = 4, i

$$\begin{aligned} H_{PP} &= J_P^T J_P && \equiv && \mathbf{V}^* \\ H_{PC} &= J_P^T J_C, && \equiv && \mathbf{W}^T \\ H_{CC} &= J_C^T J_C, && \equiv && \mathbf{U}^* \\ b_P &= -J_P^T f, && \equiv && \epsilon_b \\ b_C &= -J_C^T f && \equiv && \epsilon_a \end{aligned}$$

$$\underbrace{(\mathbf{U}^* - \mathbf{W} \mathbf{V}^{*-1} \mathbf{W}^T)}_A \delta_a = \epsilon_a - \underbrace{\mathbf{W} \mathbf{V}^{*-1} \epsilon_b}_B$$

$$\underbrace{(H_{CC} - H_{PC}^T H_{PP}^{-1} H_{PC})}_{A} dC = \underbrace{b_C - H_{PC}^T H_{PP}^{-1} b_P}_{B}$$

$$\mathbf{A}_{ij} = \frac{\partial \hat{x}_{ij}}{\partial \mathbf{a}_j} \text{ and } \mathbf{B}_{ij} = \frac{\partial \hat{x}_{ij}}{\partial \mathbf{b}_i}$$

$\boxed{2 \times 9}$ \mathbf{C} $\boxed{2 \times 3}$ \mathbf{P}

Note that $\mathbf{V}^{*-1} = \begin{pmatrix} \mathbf{V}_1^{*-1} & 0 & \dots \\ 0 & \mathbf{V}_2^{*-1} & \dots \\ \vdots & \vdots & \ddots \end{pmatrix}$

$$\mathbf{J}^T \mathbf{J} = \begin{matrix} & \mathbf{b}_1^T & \mathbf{b}_2^T & \mathbf{b}_3^T & \mathbf{b}_4^T & \mathbf{a}_1^T & \mathbf{a}_2^T & \mathbf{a}_3^T \\ \begin{matrix} \mathbf{b}_1 \\ \mathbf{b}_2 \\ \mathbf{b}_3 \\ \mathbf{b}_4 \\ \mathbf{a}_1 \\ \mathbf{a}_2 \\ \mathbf{a}_3 \end{matrix} & \begin{pmatrix} \mathbf{V}_1 & 0 & 0 & 0 & \mathbf{W}_{11}^T & \mathbf{W}_{12}^T & \mathbf{W}_{13}^T \\ 0 & \mathbf{V}_2 & 0 & 0 & \mathbf{W}_{21}^T & \mathbf{W}_{22}^T & \mathbf{W}_{23}^T \\ 0 & 0 & \mathbf{V}_3 & 0 & \mathbf{W}_{31}^T & \mathbf{W}_{32}^T & \mathbf{W}_{33}^T \\ 0 & 0 & 0 & \mathbf{V}_4 & \mathbf{W}_{41}^T & \mathbf{W}_{42}^T & \mathbf{W}_{43}^T \\ \mathbf{W}_{11} & \mathbf{W}_{21} & \mathbf{W}_{31} & \mathbf{W}_{41} & \mathbf{U}_1 & 0 & 0 \\ \mathbf{W}_{12} & \mathbf{W}_{22} & \mathbf{W}_{32} & \mathbf{W}_{42} & 0 & \mathbf{U}_2 & 0 \\ \mathbf{W}_{13} & \mathbf{W}_{23} & \mathbf{W}_{33} & \mathbf{W}_{43} & 0 & 0 & \mathbf{U}_3 \end{pmatrix} \end{matrix}$$

$$\begin{aligned} \mathbf{U}_j &\equiv \sum_{i=1}^4 \mathbf{A}_{ij}^T \mathbf{A}_{ij}, && \text{[9X9], for 1 image, sum over features} \\ \mathbf{V}_i &\equiv \sum_{j=1}^3 \mathbf{B}_{ij}^T \mathbf{B}_{ij}, && \text{[3X3], for 1 feature, sum over images} \\ \mathbf{W}_{ij} &= \mathbf{A}_{ij}^T \mathbf{B}_{ij} && \text{[9X3]} \end{aligned}$$

\mathbf{V}^* is [3*n X 3*n]

\mathbf{W} is [9*m X 3*n]

\mathbf{U}^* is [9*m X 9*m]

$$\begin{pmatrix} \mathbf{V}^* & \mathbf{W}^T \\ \mathbf{W} & \mathbf{U}^* \end{pmatrix} \begin{pmatrix} \delta_b \\ \delta_a \end{pmatrix} = \begin{pmatrix} \epsilon_b \\ \epsilon_a \end{pmatrix}$$

*calculate $\mathbf{tP} = \mathbf{HPP}^{-1} * \mathbf{bP} = \mathbf{V}^{-1} * \mathbf{bP}$ [3n X 1]

$\mathbf{HPP}^{-1} = \mathbf{V}^{-1}$ [3nX3n] | $\mathbf{bP} = -\mathbf{JP}^T * \mathbf{F}$ [3n X 1]
 $\mathbf{V}_1^{-1} \begin{matrix} 0 & 0 & 0 \end{matrix}$ | $\begin{matrix} -\mathbf{B}_{11}^T * \mathbf{F}_{11} - \mathbf{B}_{12}^T * \mathbf{F}_{12} - \mathbf{B}_{13}^T * \mathbf{F}_{13} \\ -\mathbf{B}_{21}^T * \mathbf{F}_{21} - \mathbf{B}_{22}^T * \mathbf{F}_{22} - \mathbf{B}_{23}^T * \mathbf{F}_{23} \\ -\mathbf{B}_{31}^T * \mathbf{F}_{31} - \mathbf{B}_{32}^T * \mathbf{F}_{32} - \mathbf{B}_{33}^T * \mathbf{F}_{33} \\ -\mathbf{B}_{41}^T * \mathbf{F}_{41} - \mathbf{B}_{42}^T * \mathbf{F}_{42} - \mathbf{B}_{43}^T * \mathbf{F}_{43} \end{matrix}$
 where each block is [3X3] | each row is [3X2]*[2X1]=[3X1]

$\mathbf{tP} = \mathbf{V}^{-1} * \mathbf{bP}$ [3nX1n]
 $\mathbf{V}_1^{-1} * (-\mathbf{B}_{11}^T * \mathbf{F}_{11} - \mathbf{B}_{12}^T * \mathbf{F}_{12} - \mathbf{B}_{13}^T * \mathbf{F}_{13})$ 0 0
 0 $\mathbf{V}_2^{-1} * (-\mathbf{B}_{21}^T * \mathbf{F}_{21} - \mathbf{B}_{22}^T * \mathbf{F}_{22} - \mathbf{B}_{23}^T * \mathbf{F}_{23})$ 0 0
 0 0 $\mathbf{V}_3^{-1} * (-\mathbf{B}_{31}^T * \mathbf{F}_{31} - \mathbf{B}_{32}^T * \mathbf{F}_{32} - \mathbf{B}_{33}^T * \mathbf{F}_{33})$ 0 0
 0 0 0 $\mathbf{V}_4^{-1} * (-\mathbf{B}_{41}^T * \mathbf{F}_{41} - \mathbf{B}_{42}^T * \mathbf{F}_{42} - \mathbf{B}_{43}^T * \mathbf{F}_{43})$
 each block is [3X1]

i=1:nFeatures
j = 1:mImages
invVI, BIJ

[row I, col I] = invVI*(\sum_j (-BIJT*F1j))

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M images = 3, j
N features = 4, i

$$\begin{aligned} H_{PP} &= J_P^\top J_P && \equiv && \mathbf{V}^* \\ H_{PC} &= J_P^\top J_C, && \equiv && \mathbf{W}^T \\ H_{CC} &= J_C^\top J_C, && \equiv && \mathbf{U}^* \\ b_P &= -J_P^\top f, && \equiv && \epsilon_b \\ b_C &= -J_C^\top f && \equiv && \epsilon_a \end{aligned}$$

$$\underbrace{(\mathbf{U}^* - \mathbf{W} \mathbf{V}^{*-1} \mathbf{W}^T)}_A \delta_a = \epsilon_a - \mathbf{W} \mathbf{V}^{*-1} \epsilon_b$$

$$\underbrace{(H_{CC} - H_{PC}^\top H_{PP}^{-1} H_{PC})}_{B} dC = b_C - H_{PC}^\top H_{PP}^{-1} b_P$$

$$\mathbf{A}_{ij} = \frac{\partial \hat{x}_{ij}}{\partial \mathbf{a}_j} \text{ and } \mathbf{B}_{ij} = \frac{\partial \hat{x}_{ij}}{\partial \mathbf{b}_i}$$

2X9 **C** **2X3** **P**

Note that $\mathbf{V}^{*-1} = \begin{pmatrix} \mathbf{V}_1^{*-1} & 0 & \dots \\ 0 & \mathbf{V}_2^{*-1} & \dots \\ \vdots & \vdots & \ddots \end{pmatrix}$

$$\mathbf{J}^T \mathbf{J} = \begin{matrix} & \mathbf{b}_1^T & \mathbf{b}_2^T & \mathbf{b}_3^T & \mathbf{b}_4^T & \mathbf{a}_1^T & \mathbf{a}_2^T & \mathbf{a}_3^T \\ \begin{matrix} \mathbf{b}_1 \\ \mathbf{b}_2 \\ \mathbf{b}_3 \\ \mathbf{b}_4 \\ \mathbf{a}_1 \\ \mathbf{a}_2 \\ \mathbf{a}_3 \end{matrix} & \begin{pmatrix} \mathbf{V}_1 & 0 & 0 & 0 & \mathbf{W}_{11}^T & \mathbf{W}_{12}^T & \mathbf{W}_{13}^T \\ 0 & \mathbf{V}_2 & 0 & 0 & \mathbf{W}_{21}^T & \mathbf{W}_{22}^T & \mathbf{W}_{23}^T \\ 0 & 0 & \mathbf{V}_3 & 0 & \mathbf{W}_{31}^T & \mathbf{W}_{32}^T & \mathbf{W}_{33}^T \\ 0 & 0 & 0 & \mathbf{V}_4 & \mathbf{W}_{41}^T & \mathbf{W}_{42}^T & \mathbf{W}_{43}^T \\ \mathbf{W}_{11} & \mathbf{W}_{21} & \mathbf{W}_{31} & \mathbf{W}_{41} & \mathbf{U}_1 & 0 & 0 \\ \mathbf{W}_{12} & \mathbf{W}_{22} & \mathbf{W}_{32} & \mathbf{W}_{42} & 0 & \mathbf{U}_2 & 0 \\ \mathbf{W}_{13} & \mathbf{W}_{23} & \mathbf{W}_{33} & \mathbf{W}_{43} & 0 & 0 & \mathbf{U}_3 \end{pmatrix} \end{matrix}$$

$$\mathbf{U}_j \equiv \sum_{i=1}^4 \mathbf{A}_{ij}^T \mathbf{A}_{ij}, \quad \text{[9X9], for 1 image, sum over features}$$

$$\mathbf{V}_i \equiv \sum_{j=1}^3 \mathbf{B}_{ij}^T \mathbf{B}_{ij}, \quad \text{[3X3], for 1 feature, sum over images}$$

$$\mathbf{W}_{ij} = \mathbf{A}_{ij}^T \mathbf{B}_{ij} \quad \text{[9X3]}$$

V* is [3*n X 3*n]

W is [9*m X 3*n]

U* is [9*m X 9*m]

$$\begin{pmatrix} \mathbf{V}^* & \mathbf{W}^T \\ \mathbf{W} & \mathbf{U}^* \end{pmatrix} \begin{pmatrix} \delta_b \\ \delta_a \end{pmatrix} = \begin{pmatrix} \epsilon_b \\ \epsilon_a \end{pmatrix}$$

*calculate tPC = HPC^T*HPP^-1 = W*V^-1 [9m X 3n]

[9m X 3n]	[3n X 3n]	
W11 W21 W31 W41	* V1^-1 0 0 0	
W12 W22 W32 W42	0 V2^-1 0 0	
W13 W23 W33 W43	0 0 V3^-1 0	
	0 0 0 V4^-1	

W*V^-1= [9mX3n]

W11*V1^-1	W21*V2^-1	W31*V3^-1	W41*V4^-1
W12*V1^-1	W22*V2^-1	W32*V3^-1	W42*V4^-1
W13*V1^-1	W23*V2^-1	W33*V3^-1	W43*V4^-1

each block is [9X3]

i=1:nFeatures
j = 1:mImages
invVI, WIJ

[row J, col I] = WIJ*invVI

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M images = 3, j
N features = 4, i

$$\begin{aligned} H_{PP} &= J_P^\top J_P && \equiv && \mathbf{V}^* \\ H_{PC} &= J_P^\top J_C, && \equiv && \mathbf{W}^T \\ H_{CC} &= J_C^\top J_C, && \equiv && \mathbf{U}^* \\ b_P &= -J_P^\top f, && \equiv && \epsilon_b \\ b_C &= -J_C^\top f && \equiv && \epsilon_a \end{aligned}$$

$$\underbrace{(\mathbf{U}^* - \mathbf{W} \mathbf{V}^{*-1} \mathbf{W}^T)}_A \delta_a = \epsilon_a - \mathbf{W} \mathbf{V}^{*-1} \epsilon_b$$

$$\underbrace{(H_{CC} - H_{PC} H_{PP}^{-1} H_{PC}^\top)}_B dC = b_C - H_{PC}^\top H_{PP}^{-1} b_P$$

$$\mathbf{A}_{ij} = \frac{\partial \hat{x}_{ij}}{\partial \mathbf{a}_j} \text{ and } \mathbf{B}_{ij} = \frac{\partial \hat{x}_{ij}}{\partial \mathbf{b}_i}$$

$\boxed{2 \times 9}$ \mathbf{C} $\boxed{2 \times 3}$ \mathbf{P}

Note that $\mathbf{V}^{*-1} = \begin{pmatrix} \mathbf{V}_1^{*-1} & 0 & \dots \\ 0 & \mathbf{V}_2^{*-1} & \dots \\ \vdots & \vdots & \ddots \end{pmatrix}$

$$\mathbf{J}^\top \mathbf{J} = \begin{matrix} & \mathbf{b}_1^T & \mathbf{b}_2^T & \mathbf{b}_3^T & \mathbf{b}_4^T & \mathbf{a}_1^T & \mathbf{a}_2^T & \mathbf{a}_3^T \\ \begin{matrix} \mathbf{b}_1 \\ \mathbf{b}_2 \\ \mathbf{b}_3 \\ \mathbf{b}_4 \\ \mathbf{a}_1 \\ \mathbf{a}_2 \\ \mathbf{a}_3 \end{matrix} & \begin{pmatrix} \mathbf{V}_1 & 0 & 0 & 0 & \mathbf{W}_{11}^T & \mathbf{W}_{12}^T & \mathbf{W}_{13}^T \\ 0 & \mathbf{V}_2 & 0 & 0 & \mathbf{W}_{21}^T & \mathbf{W}_{22}^T & \mathbf{W}_{23}^T \\ 0 & 0 & \mathbf{V}_3 & 0 & \mathbf{W}_{31}^T & \mathbf{W}_{32}^T & \mathbf{W}_{33}^T \\ 0 & 0 & 0 & \mathbf{V}_4 & \mathbf{W}_{41}^T & \mathbf{W}_{42}^T & \mathbf{W}_{43}^T \\ \mathbf{W}_{11} & \mathbf{W}_{21} & \mathbf{W}_{31} & \mathbf{W}_{41} & \mathbf{U}_1 & 0 & 0 \\ \mathbf{W}_{12} & \mathbf{W}_{22} & \mathbf{W}_{32} & \mathbf{W}_{42} & 0 & \mathbf{U}_2 & 0 \\ \mathbf{W}_{13} & \mathbf{W}_{23} & \mathbf{W}_{33} & \mathbf{W}_{43} & 0 & 0 & \mathbf{U}_3 \end{pmatrix} \end{matrix}$$

$$\mathbf{U}_j \equiv \sum_{i=1}^4 \mathbf{A}_{ij}^T \mathbf{A}_{ij}, \quad \text{[9X9], for 1 image, sum over features}$$

$$\mathbf{V}_i \equiv \sum_{j=1}^3 \mathbf{B}_{ij}^T \mathbf{B}_{ij}, \quad \text{[3X3], for 1 feature, sum over images}$$

$$\mathbf{W}_{ij} = \mathbf{A}_{ij}^T \mathbf{B}_{ij} \quad \text{[9X3]}$$

\mathbf{V}^* is [3*n X 3*n]

\mathbf{W} is [9*m X 3*n]

\mathbf{U}^* is [9*m X 9*m]

$$\begin{pmatrix} \mathbf{V}^* & \mathbf{W}^T \\ \mathbf{W} & \mathbf{U}^* \end{pmatrix} \begin{pmatrix} \delta_b \\ \delta_a \end{pmatrix} = \begin{pmatrix} \epsilon_b \\ \epsilon_a \end{pmatrix}$$

*calculate rightside of mA: tPC*HPC2 = W*V^-1*W^T [9m X 9m]

W*V^-1= [9mX3n]

W11*V1^-1 W21*V2^-1 W31*V3^-1 W41*V4^-1 * W11T W12T W13T
W12*V1^-1 W22*V2^-1 W32*V3^-1 W42*V4^-1 W21T W22T W23T
W13*V1^-1 W23*V2^-1 W33*V3^-1 W43*V4^-1 W31T W32T W33T
W41T W42T W43T

each block is [9X3]

each block is [3X9]

W11*V1^-1*W11T + W21*V2^-1*W21T + W31*V3^-1*W31T + W41*V4^-1*W41T W11*V1^-1*W12T + W21*V2^-1*W22T + W31*V3^-1*W32T + W41*V4^-1*W42T W11*V1^-1*W13T + W21*V2^-1*W23T + W31*V3^-1*W33T + W41*V4^-1*W43T
W12*V1^-1*W11T + W22*V2^-1*W21T + W32*V3^-1*W31T + W42*V4^-1*W41T W12*V1^-1*W12T + W22*V2^-1*W22T + W32*V3^-1*W32T + W42*V4^-1*W42T W12*V1^-1*W13T + W22*V2^-1*W23T + W32*V3^-1*W33T + W42*V4^-1*W43T
W13*V1^-1*W11T + W23*V2^-1*W21T + W33*V3^-1*W31T + W43*V4^-1*W41T W13*V1^-1*W12T + W23*V2^-1*W22T + W33*V3^-1*W32T + W43*V4^-1*W42T W13*V1^-1*W13T + W23*V2^-1*W23T + W33*V3^-1*W33T + W43*V4^-1*W43T

i = 1:nFeatures

WIJ

j = 1:mImages

calc tPC = HPC^T * invHPP

j2 = 1:mImages

WIJ2

Subtract tPC*HPC2 (=HPC^T*invHPP*HPC2 = W*inv(V)*W2^T) from block (c, c2)

i=1,j=1,j2=1: block(1,1)= (W11 * inv(V1) * W11^T)

i=2,j=1,j2=1: block(1,1)= (W21 * inv(V2) * W21^T)

i=1,j=1,j2=2: block(1,2)= (W11 * inv(V1) * W12^T)

i=1,j=1,j2=3: block(1,3)= (W11 * inv(V1) * W13^T)

i=1,j=2,j2=1: block(2,1)= (W12 * inv(V1) * W11^T)

i=1 i=2 i=3... block(2,2)= (W12 * inv(V1) * W12^T)

M images = 3, j
N features = 4, i

$$\begin{array}{lll} H_{PP} = J_P^\top J_P & \equiv & \mathbf{V}^* \\ H_{PC} = J_P^\top J_C & \equiv & \mathbf{W}^T \\ H_{CC} = J_C^\top J_C & \equiv & \mathbf{U}^* \\ b_P = -J_P^\top f & \equiv & \epsilon_{\mathbf{b}} \\ b_C = -J_C^\top f & \equiv & \epsilon_{\mathbf{a}} \end{array}$$

$$\boxed{2 \times 9} \quad \mathbf{A}_{ij} = \frac{\partial \hat{\mathbf{x}}_{ij}}{\partial \mathbf{a}_j} \quad \text{and} \quad \boxed{2 \times 3} \quad \mathbf{B}_{ij} = \frac{\partial \hat{\mathbf{x}}_{ij}}{\partial \mathbf{b}_i} \quad \mathbf{P}$$

Note that $\mathbf{V}^{*-1} = \begin{pmatrix} \mathbf{V}_1^{*-1} & \mathbf{0} & \cdots \\ \mathbf{0} & \mathbf{V}_2^{*-1} & \cdots \\ \vdots & \vdots & \ddots \end{pmatrix}$

$$\begin{aligned} (\mathbf{U}^* - \mathbf{W} \mathbf{V}^{*-1} \mathbf{W}^T) \delta_{\mathbf{a}} &= \epsilon_{\mathbf{a}} - \mathbf{W} \mathbf{V}^{*-1} \epsilon_{\mathbf{b}} \\ \underbrace{(H_{CC} - H_{PC}^\top H_{PP}^{-1} H_{PC})}_{\mathbf{A}} d\mathbf{C} &= \underbrace{b_C - H_{PC}^\top H_{PP}^{-1} b_P}_{\mathbf{B}} \end{aligned}$$

$$\mathbf{J}^T \mathbf{J} = \begin{matrix} & \mathbf{b}_1^T & \mathbf{b}_2^T & \mathbf{b}_3^T & \mathbf{b}_4^T & \mathbf{a}_1^T & \mathbf{a}_2^T & \mathbf{a}_3^T \\ \begin{matrix} \mathbf{b}_1 \\ \mathbf{b}_2 \\ \mathbf{b}_3 \\ \mathbf{b}_4 \\ \mathbf{a}_1 \\ \mathbf{a}_2 \\ \mathbf{a}_3 \end{matrix} & \left(\begin{array}{ccccccc} \mathbf{V}_1 & 0 & 0 & 0 & \mathbf{W}_{11}^T & \mathbf{W}_{12}^T & \mathbf{W}_{13}^T \\ 0 & \mathbf{V}_2 & 0 & 0 & \mathbf{W}_{21}^T & \mathbf{W}_{22}^T & \mathbf{W}_{23}^T \\ 0 & 0 & \mathbf{V}_3 & 0 & \mathbf{W}_{31}^T & \mathbf{W}_{32}^T & \mathbf{W}_{33}^T \\ 0 & 0 & 0 & \mathbf{V}_4 & \mathbf{W}_{41}^T & \mathbf{W}_{42}^T & \mathbf{W}_{43}^T \\ \mathbf{W}_{11} & \mathbf{W}_{21} & \mathbf{W}_{31} & \mathbf{W}_{41} & \mathbf{U}_1 & 0 & 0 \\ \mathbf{W}_{12} & \mathbf{W}_{22} & \mathbf{W}_{32} & \mathbf{W}_{42} & 0 & \mathbf{U}_2 & 0 \\ \mathbf{W}_{13} & \mathbf{W}_{23} & \mathbf{W}_{33} & \mathbf{W}_{43} & 0 & 0 & \mathbf{U}_3 \end{array} \right) \end{matrix}$$

$U_j \equiv \sum_{i=1}^4 A_{ij}^T A_{ij}$,	<u>[9X9], for 1 image, sum over features</u>
$V_i \equiv \sum_{j=1}^3 B_{ij}^T B_{ij}$,	<u>[3X3], for 1 feature, sum over images</u>
$W_{ij} = A_{ij}^T B_{ij}$	<u>[9X3]</u>

V^* is $[3^n \times 3^n]$

W is $[9 \times m \times 3 \times n]$

U^* is $[9^*m \times 9^*m]$

$$\begin{pmatrix} \mathbf{V}^* & \mathbf{W}^T \\ \mathbf{W} & \mathbf{U}^* \end{pmatrix} \begin{pmatrix} \delta_{\mathbf{b}} \\ \delta_{\mathbf{a}} \end{pmatrix} = \begin{pmatrix} \epsilon_{\mathbf{b}} \\ \epsilon_{\mathbf{a}} \end{pmatrix}$$

$$HPP^T = W \quad [9m \times 3n] \quad tP = V^{-1} * bP \quad [3n \times 2mn]$$

[illegible]

block multiplication: $[[9m \times 2mn]$. each larger block group is $[9m \times 2m]$

```

W11*v1~1*B11^T W11*v1~1*B12^T W11*v1~1*B13^T | W21*v2~1*B21^T W21*v2~1*B22^T W21*v2~1*B23^T | W31*v3~1*B31^T W31*v3~1*B32^T W31*v3~1*B33^T | W41*v4~1*B41^T W41*v4~1*B42^T W41*v4~1*B43^T
W12*v1~1*B11^T W12*v1~1*B12^T W12*v1~1*B13^T | W22*v2~1*B21^T W22*v2~1*B22^T W22*v2~1*B23^T | W32*v3~1*B31^T W32*v3~1*B32^T W32*v3~1*B33^T | W42*v4~1*B41^T W42*v4~1*B42^T W42*v4~1*B43^T
W13*v1~1*B11^T W13*v1~1*B12^T W13*v1~1*B13^T | W23*v2~1*B21^T W23*v2~1*B22^T W23*v2~1*B23^T | W33*v3~1*B31^T W33*v3~1*B32^T W33*v3~1*B33^T | W43*v4~1*B41^T W43*v4~1*B42^T W43*v4~1*B43^T
cell in block is [9X2]

```

```
i=1:nFeatures
    j = 1:mImages
        WIJ, invVI
        j2 = 1:mImages
            BIJ2,FIJ2
```

```
[1,1]=WI1J*invVI1*(Σ_j2(-BIJ2T*F1J2))
+ WI2J*invI2*(Σ_j2(-BIJ2T*F1J2))
+ WI3J*invI2*(Σ_j2(-BIJ2T*F1J2))
+ WI4J*invI2*(Σ_j2(-BIJ2T*F1J2))
[2,1]=same but j is now 2
[3,1]=same but j is now 3
```

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M images = 3, j
N features = 4, i

$$\begin{aligned} H_{PP} &= J_P^\top J_P && \equiv && \mathbf{V}^* \\ H_{PC} &= J_P^\top J_C, && \equiv && \mathbf{W}^T \\ H_{CC} &= J_C^\top J_C, && \equiv && \mathbf{U}^* \\ b_P &= -J_P^\top f, && \equiv && \epsilon_b \\ b_C &= -J_C^\top f && \equiv && \epsilon_a \end{aligned}$$

$$\underbrace{(\mathbf{U}^* - \mathbf{W} \mathbf{V}^{*-1} \mathbf{W}^T)}_A \delta_a = \epsilon_a - \underbrace{\mathbf{W} \mathbf{V}^{*-1}}_B \epsilon_b$$

$$\underbrace{(H_{CC} - H_{PC}^\top H_{PP}^{-1} H_{PC})}_{A} dC = \underbrace{b_C - H_{PC}^\top H_{PP}^{-1} b_P}_{B}$$

$$\mathbf{A}_{ij} = \frac{\partial \hat{x}_{ij}}{\partial \mathbf{a}_j} \text{ and } \mathbf{B}_{ij} = \frac{\partial \hat{x}_{ij}}{\partial \mathbf{b}_i}$$

2×9 2×3

C **P**

Note that $\mathbf{V}^{*-1} = \begin{pmatrix} \mathbf{V}_1^{*-1} & 0 & \dots \\ 0 & \mathbf{V}_2^{*-1} & \dots \\ \vdots & \vdots & \ddots \end{pmatrix}$

$$\mathbf{J}^\top \mathbf{J} = \begin{matrix} & \mathbf{b}_1^T & \mathbf{b}_2^T & \mathbf{b}_3^T & \mathbf{b}_4^T & \mathbf{a}_1^T & \mathbf{a}_2^T & \mathbf{a}_3^T \\ \begin{matrix} \mathbf{b}_1 \\ \mathbf{b}_2 \\ \mathbf{b}_3 \\ \mathbf{b}_4 \\ \mathbf{a}_1 \\ \mathbf{a}_2 \\ \mathbf{a}_3 \end{matrix} & \begin{pmatrix} \mathbf{V}_1 & 0 & 0 & 0 & \mathbf{W}_{11}^T & \mathbf{W}_{12}^T & \mathbf{W}_{13}^T \\ 0 & \mathbf{V}_2 & 0 & 0 & \mathbf{W}_{21}^T & \mathbf{W}_{22}^T & \mathbf{W}_{23}^T \\ 0 & 0 & \mathbf{V}_3 & 0 & \mathbf{W}_{31}^T & \mathbf{W}_{32}^T & \mathbf{W}_{33}^T \\ 0 & 0 & 0 & \mathbf{V}_4 & \mathbf{W}_{41}^T & \mathbf{W}_{42}^T & \mathbf{W}_{43}^T \\ \mathbf{W}_{11} & \mathbf{W}_{21} & \mathbf{W}_{31} & \mathbf{W}_{41} & \mathbf{U}_1 & 0 & 0 \\ \mathbf{W}_{12} & \mathbf{W}_{22} & \mathbf{W}_{32} & \mathbf{W}_{42} & 0 & \mathbf{U}_2 & 0 \\ \mathbf{W}_{13} & \mathbf{W}_{23} & \mathbf{W}_{33} & \mathbf{W}_{43} & 0 & 0 & \mathbf{U}_3 \end{pmatrix} \end{matrix}$$

$$\begin{aligned} \mathbf{U}_j &\equiv \sum_{i=1}^4 \mathbf{A}_{ij}^T \mathbf{A}_{ij}, && \text{[9X9], for 1 image, sum over features} \\ \mathbf{V}_i &\equiv \sum_{j=1}^3 \mathbf{B}_{ij}^T \mathbf{B}_{ij}, && \text{[3X3], for 1 feature, sum over images} \\ \mathbf{W}_{ij} &= \mathbf{A}_{ij}^T \mathbf{B}_{ij} && \text{[9X3]} \end{aligned}$$

\mathbf{V}^* is $[3*n \times 3*n]$

\mathbf{W} is $[9*m \times 3*n]$

\mathbf{U}^* is $[9*m \times 9*m]$

$$\begin{pmatrix} \mathbf{V}^* & \mathbf{W}^T \\ \mathbf{W} & \mathbf{U}^* \end{pmatrix} \begin{pmatrix} \delta_b \\ \delta_a \end{pmatrix} = \begin{pmatrix} \epsilon_b \\ \epsilon_a \end{pmatrix}$$

If camera c is free

{ $\mathbf{A}^T \mathbf{A}$
Add $J_c^\top J_c$ (optionally with an augmented diagonal) to upper triangular part of block (c, c) of left hand side matrix A (in our case a 6×6 matrix).
Compute block (p, c) of H_{PC} as $H_{pc} = J_p^\top J_c$ (in our case a 3×6 matrix) and store it until track is done.
Subtract $J_c^\top f$ from part c of right hand side vector B (related to b_C).
}

Augment diagonal of H_{pp} , which is now accumulated and ready. Invert H_{pp} , taking advantage of the fact that it is a symmetric matrix.

Compute $H_{pp}^{-1} b_p$ and store it in a variable t_p .

(Outer product of track) For each free camera c on track p

{
Subtract $H_{pc}^\top t_p = H_{pc}^\top H_{pp}^{-1} b_p$ from part c of right hand side vector B .
Compute the matrix $H_{pc}^\top H_{pp}^{-1}$ and store it in a variable T_{pc} .
For each free camera $c2 \geq c$ on track p
{
Subtract $T_{pc} H_{pc2} = H_{pc}^\top H_{pp}^{-1} H_{pc2}$ from block $(c, c2)$ of left hand side matrix A .
}
}
}

- 1 Initialize λ .
- 2 **Compute cost function** at initial camera and point configuration.
- 3 Clear the left hand side (matrix A) and right hand side (vector B)
- 4 For each track p (p is feature i of N)

{
Clear a variable H_{pp} to represent block p of H_{PP} (in our case a symmetric 3×3 matrix) and a variable b_p to represent part p of b_P (in our case a 3-vector).
}

(Compute derivatives) For each camera c on track p (c is image j of M)

{ Compute error vector f of reprojection in camera c of point p and its Jacobians J_p and J_c with respect to the

point parameters (in our case a 2×3 matrix) and the camera parameters (in our case a 2×6 matrix), respectively.

Add $J_p^\top J_p$ to the upper triangular part of H_{pp} .
Subtract $J_p^\top f$ from b_p .
}

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Note that $V^{*-1} = \begin{pmatrix} V_1^{*-1} & 0 & \cdots \\ 0 & V_2^{*-1} & \cdots \\ \vdots & \vdots & \ddots \end{pmatrix}$

$$\begin{aligned} H_{PP} &= J_P^T J_P && \equiv V^* && V_i \equiv \sum_{j=1}^3 B_{ij}^T B_{ij}, \text{ for 1 feature, sum over images} \\ H_{PC} &= J_P^T J_C, && \equiv W^T \\ H_{CC} &= J_C^T J_C, && \equiv U^* && U_j \equiv \sum_{i=1}^4 A_{ij}^T A_{ij}, \text{ for 1 image, sum over features} \\ b_P &= -J_P^T f, && \equiv \epsilon_b \\ b_C &= -J_C^T f && \equiv \epsilon_a \end{aligned}$$

δ_b is dP is $[3*n_features \times 1]$
 ϵ_b is b_P is $[3*n_features \times 1]$
 δ_a is dC is $[9*m_images \times 1]$
 ϵ_a is b_C is $[9*m_images \times 1]$

$$\begin{aligned} (U^* - W V^{*-1} W^T) \delta_a &= \epsilon_a - W V^{*-1} \epsilon_b \\ \underbrace{(H_{CC} - H_{PC}^T H_{PP}^{-1} H_{PC})}_{A} dC &= \underbrace{b_C - H_{PC}^T H_{PP}^{-1} b_P}_{B} \end{aligned}$$

$$\begin{aligned} V^* \delta_b &= \epsilon_b - W^T \delta_a \\ dP &= H_{PP}^{-1} b_P - H_{PP}^{-1} H_{PC} dC. \\ &= \begin{matrix} tP \\ [3n \times 1] \end{matrix} - \begin{matrix} tPC^T \\ [3n \times 9m] \end{matrix} \begin{matrix} dC \\ [9m \times 1] \end{matrix} \end{aligned}$$

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- 5 (Optional) Fix gauge by freezing appropriate coordinates and thereby reducing the linear system with a few dimensions.
- 6 **(Linear Solving)** Cholesky factor the left hand side matrix B and solve for dC . Add frozen coordinates back in.
- 7 **(Back-substitution)** For each track p
 - {
 - Start with point update for this track $dp = t_p$.
 - For each camera c on track p
 - {
 - Subtract $T_{pc}^T dc$ from dp (where dc is the update for camera c).
 - }
 - Compute updated point.
 - }
- 8 **Compute the cost function** for the updated camera and point configuration.
- 9 If cost function has improved, accept the update step, decrease λ and go to Step 3 (unless converged, in which case quit).
- 10 Otherwise, increase λ and go to Step 3 (unless exceeded the maximum number of iterations, in which case quit).

Bill Triggs, Philip Mclauchlan, Richard Hartley, Andrew Fitzgibbon.

Bundle Adjustment – A Modern Synthesis.

International Workshop on Vision Algorithms,

Sep 2000, Corfu, Greece. pp.298–372,

10.1007/3-540-44480-7_21 . inria-00548290

see Appendix B, and page 23...

6.1 The Schur Complement and the Reduced Bundle System

Schur complement: Consider the following block triangular matrix factorization:

$$M = \begin{pmatrix} A & B \\ C & D \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ CA^{-1} & 1 \end{pmatrix} \begin{pmatrix} A & 0 \\ 0 & \bar{D} \end{pmatrix} \begin{pmatrix} 1 & A^{-1}B \\ 0 & 1 \end{pmatrix}, \quad \bar{D} \equiv D - CA^{-1}B \quad (16)$$

$$\begin{pmatrix} A & B \\ C & D \end{pmatrix}^{-1} = \begin{pmatrix} 1 & -A^{-1}B \\ 0 & 1 \end{pmatrix} \begin{pmatrix} A^{-1} & 0 \\ 0 & \bar{D}^{-1} \end{pmatrix} \begin{pmatrix} 1 & 0 \\ -CA^{-1} & 1 \end{pmatrix} = \begin{pmatrix} A^{-1} + A^{-1}B\bar{D}^{-1}CA^{-1} & -A^{-1}B\bar{D}^{-1} \\ -\bar{D}^{-1}CA^{-1} & \bar{D}^{-1} \end{pmatrix} \quad (17)$$

Here A must be square and invertible, and for (17), the whole matrix must also be square and invertible. \bar{D} is called the **Schur complement** of A in M . If both A and D are invertible, complementing on D rather than A gives \bar{D} , the Schur complement, is HPP is V^* .

$$\begin{pmatrix} A & B \\ C & D \end{pmatrix}^{-1} = \begin{pmatrix} \bar{A}^{-1} & -\bar{A}^{-1}B\bar{D}^{-1} \\ -\bar{D}^{-1}C\bar{A}^{-1} & \bar{D}^{-1} + \bar{D}^{-1}C\bar{A}^{-1}B\bar{D}^{-1} \end{pmatrix}, \quad \bar{A} = A - B\bar{D}^{-1}C$$

Equating upper left blocks gives the **Woodbury formula**:

$$(A \pm B\bar{D}^{-1}C)^{-1} = A^{-1} \mp A^{-1}B(D \pm CA^{-1}B)^{-1}CA^{-1} \quad (18)$$

This is the usual method of updating the inverse of a nonsingular matrix A after an update (especially a low rank one) $A \rightarrow A \pm B\bar{D}^{-1}C$. (See §8.1).

$$\begin{aligned} (U^* - W V^{*-1} W^T) \delta_a &= \epsilon_a - W V^{*-1} \epsilon_b \\ \underbrace{(H_{CC} - H_{PC}^T \underbrace{H_{PP}^{-1}}_{\bar{D}} H_{PC})}_{\bar{D}} dC &= \underbrace{b_C - H_{PC}^T H_{PP}^{-1} b_P}_B \end{aligned}$$

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10.1007/3-540-44480-7_21 . inria-00548290

see Appendix B, and page 23...

```

L = profile_cholesky_decomp(A)
for i = 1 to n do
  for j = first(i) to i do
    a = Aij -  $\sum_{k=\max(\text{first}(i), \text{first}(j))}^{j-1} L_{ik} L_{jk}$ 
    Lij = (j < i) ? a / Ljj :  $\sqrt{a}$ 
  
```

```

x = profile_cholesky_forward_subs(A, b)
for i = first(b) to n do
  xi =  $\left( b_i - \sum_{k=\max(\text{first}(i), \text{first}(b))}^{i-1} L_{ik} x_k \right) / L_{ii}$ 

```

```

y = profile_cholesky_back_subs(A, x)
y = x
for i = last(b) to 1 step -1 do
  for k = max(first(i), first(y)) to i do
    yk = yk - yi Lik
  yi = yi / Lii

```

Figure 10: A complete implementation of profile Cholesky decomposition.

cholesky:

$_A_ = L * D * L^T$
 $= L * \sqrt{D} * \sqrt{D} * L^T$

let C = L * \sqrt{D}

then $_A_ = C * C^T$

aside: L is invertible if none of its diagonal elements are 0.

for $_A_ = L * L^*$

$(_A_)^{-1} = (L^*) * (L * L^*)^{-1}$

but usually, for $A * x = b$:

(1) $A = L * L^*$

(2) $L * y = b \implies y$ via forward subst

(3) $L^* * x = y \implies x$ via backward subst

http://users.ics.forth.gr/~argyros/mypapers/2004_08_tr340_forth_sba.pdf

The Design and Implementation of a Generic
Sparse Bundle Adjustment Software Package
Based on the Levenberg-Marquardt Algorithm†

Manolis I.A. Lourakis and Antonis A. Argyros

In all cases, the function pointed to by `proj` is assumed to estimate in `xij` the projection in image `j` of the point `i`. Arguments `aj` and `bi` are respectively the parameters of the `j`-th camera and `i`-th point. In other words, `proj` implements the parameterizing function `Q()`. Similarly, `projac` is assumed to compute in `Aij` and `Bij` the functions $\frac{\partial Q(\mathbf{a}_j, \mathbf{b}_i)}{\partial \mathbf{a}_j}$ and $\frac{\partial Q(\mathbf{a}_j, \mathbf{b}_i)}{\partial \mathbf{b}_i}$, i.e. the jacobians with respect to `aj` and `bi` of the projection of point `i` in image `j`. If `projac` is NULL, the jacobians are

The employed world coordinate frame is taken to be aligned with the initial camera location. All subsequent camera motions are defined relative to the initial location, through the combination of a 3D rotation and a 3D translation. A 3D rotation by an angle θ about a unit vector $\mathbf{u} = (u_1, u_2, u_3)^T$ is represented by the quaternion $\mathbf{R} = (\cos(\frac{\theta}{2}), u_1 \sin(\frac{\theta}{2}), u_2 \sin(\frac{\theta}{2}), u_3 \sin(\frac{\theta}{2}))$ [26]. A 3D translation is defined by a vector \mathbf{t} . A 3D point is represented by its Euclidean coordinate vector \mathbf{M} . Thus, the parameters of each camera `j` and point `i` are $\mathbf{a}_j = (\mathbf{R}_j, \mathbf{t}_j^T)^T$ and $\mathbf{b}_i = \mathbf{M}_i$, respectively. With the previous definitions, the predicted projection of point `i` on image `j` is

$$\mathbf{Q}(\mathbf{a}_j, \mathbf{b}_i) = \mathbf{K} (\mathbf{R}_j \mathbf{N}_i \mathbf{R}_j^{-1} + \mathbf{t}_j), \quad (28)$$

where \mathbf{K} is the 3×3 intrinsic camera calibration matrix and $\mathbf{N}_i = (0, \mathbf{M}_i^T)$ is the vector quaternion corresponding to the 3D point \mathbf{M}_i . The expression $\mathbf{R}_j \mathbf{N}_i \mathbf{R}_j^{-1}$ corresponds to point \mathbf{M}_i rotated by an angle θ_j about unit vector \mathbf{u}_j , as specified by the quaternion \mathbf{R}_j . Source file `eucsbademo.c` accompanying the `sba` package im-

http://users.ics.forth.gr/~argyros/mypapers/2004_08_tr340_forth_sba.pdf

The Design and Implementation of a Generic
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Manolis I.A. Lourakis and Antonis A. Argyros

algorithm³. This procedure can be embedded into the LM algorithm of section 2 at the point indicated by the rectangular box in Fig. 1, leading to a sparse bundle adjustment algorithm.

Figure 2: Algorithm for solving the sparse normal equations arising in generic bundle adjustment; see text for details.

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Input: The current parameter vector partitioned into m camera parameter vectors \mathbf{a}_j and n 3D point parameter vectors \mathbf{b}_i , a function \mathbf{Q} employing the \mathbf{a}_j and \mathbf{b}_i to compute the predicted projections $\hat{\mathbf{x}}_{ij}$ of the i -th point on the j -th image, the observed image point locations \mathbf{x}_{ij} and a damping term μ for LM.

Output: The solution δ to the normal equations involved in LM-based bundle adjustment.

Algorithm:

Compute the derivative matrices $\mathbf{A}_{ij} := \frac{\partial \hat{\mathbf{x}}_{ij}}{\partial \mathbf{a}_j} = \frac{\partial \mathbf{Q}(\mathbf{a}_j, \mathbf{b}_i)}{\partial \mathbf{a}_j}$, $\mathbf{B}_{ij} := \frac{\partial \hat{\mathbf{x}}_{ij}}{\partial \mathbf{b}_i} = \frac{\partial \mathbf{Q}(\mathbf{a}_j, \mathbf{b}_i)}{\partial \mathbf{b}_i}$ and the error vectors $\epsilon_{ij} := \mathbf{x}_{ij} - \hat{\mathbf{x}}_{ij}$, where i and j assume values in $\{1, \dots, n\}$ and $\{1, \dots, m\}$ respectively.

Compute the following auxiliary variables:

$$\mathbf{U}_j := \sum_i \mathbf{A}_{ij}^T \Sigma_{\mathbf{x}_{ij}}^{-1} \mathbf{A}_{ij} \quad \mathbf{V}_i := \sum_j \mathbf{B}_{ij}^T \Sigma_{\mathbf{x}_{ij}}^{-1} \mathbf{B}_{ij} \quad \mathbf{W}_{ij} := \mathbf{A}_{ij}^T \Sigma_{\mathbf{x}_{ij}}^{-1} \mathbf{B}_{ij}$$

$$\epsilon_{\mathbf{a}_j} := \sum_i \mathbf{A}_{ij}^T \Sigma_{\mathbf{x}_{ij}}^{-1} \epsilon_{ij} \quad \epsilon_{\mathbf{b}_i} := \sum_j \mathbf{B}_{ij}^T \Sigma_{\mathbf{x}_{ij}}^{-1} \epsilon_{ij}$$

Augment \mathbf{U}_j and \mathbf{V}_i by adding μ to their diagonals to yield \mathbf{U}_j^* and \mathbf{V}_i^* .

Compute $\mathbf{Y}_{ij} := \mathbf{W}_{ij} \mathbf{V}_i^{*-1}$.

Compute $\delta_{\mathbf{a}}$ from $\mathbf{S} (\delta_{\mathbf{a}_1}^T, \delta_{\mathbf{a}_2}^T, \dots, \delta_{\mathbf{a}_m}^T)^T = (\mathbf{e}_1^T, \mathbf{e}_2^T, \dots, \mathbf{e}_m^T)^T$, where \mathbf{S} is a matrix consisting of $m \times m$ blocks; block jk is defined by

$$\mathbf{S}_{jk} = \delta_{jk} \mathbf{U}_j^* - \sum_i \mathbf{Y}_{ij} \mathbf{W}_{ik}^T, \text{ where } \delta_{jk} \text{ is Kronecker's delta}$$

and

$$\mathbf{e}_j = \epsilon_{\mathbf{a}_j} - \sum_i \mathbf{Y}_{ij} \epsilon_{\mathbf{b}_i}.$$

Compute each $\delta_{\mathbf{b}_i}$ from the equation $\delta_{\mathbf{b}_i} = \mathbf{V}_i^{*-1} (\epsilon_{\mathbf{b}_i} - \sum_j \mathbf{W}_{ij}^T \delta_{\mathbf{a}_j})$.

Form δ as $(\delta_{\mathbf{a}}^T, \delta_{\mathbf{b}}^T)^T$.

http://users.ics.forth.gr/~argyros/mypapers/2004_08_tr340_forth_sba.pdf

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Figure 1: Levenberg-Marquardt non-linear least squares algorithm; see text and [16, 20] for details. The reason for enclosing a statement in a rectangular box will be explained in section 3.

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$\mathbf{p}_{new} := \mathbf{p} + \delta_{\mathbf{p}};$
 $\rho := (||\epsilon_{\mathbf{p}}||^2 - ||\mathbf{x} - f(\mathbf{p}_{new})||^2) / (\delta_{\mathbf{p}}^T (\mu \delta_{\mathbf{p}} + \mathbf{g}));$

gain ratio →

Input: A vector function $f : \mathcal{R}^m \rightarrow \mathcal{R}^n$ with $n \geq m$, a measurement vector $\mathbf{x} \in \mathcal{R}^n$ and an initial parameters estimate $\mathbf{p}_0 \in \mathcal{R}^m$.
Output: A vector $\mathbf{p}^+ \in \mathcal{R}^m$ minimizing $||\mathbf{x} - f(\mathbf{p})||^2$.
Algorithm:
 $k := 0; \nu := 2; \mathbf{p} := \mathbf{p}_0;$
 $\mathbf{A} := \mathbf{J}^T \mathbf{J}; \epsilon_{\mathbf{p}} := \mathbf{x} - f(\mathbf{p}); \mathbf{g} := \mathbf{J}^T \epsilon_{\mathbf{p}};$
stop: $(||\mathbf{g}||_{\infty} \leq \varepsilon_1); \mu := \tau * \max_{i=1, \dots, m} (A_{ii});$
while (not stop) and $(k < k_{max})$
 $k := k + 1;$
repeat

Solve $(\mathbf{A} + \mu \mathbf{I}) \delta_{\mathbf{p}} = \mathbf{g};$

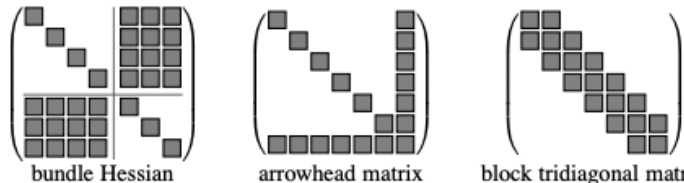
if $(||\delta_{\mathbf{p}}|| \leq \varepsilon_2 ||\mathbf{p}||)$
stop:=true;
else
 $\mathbf{p}_{new} := \mathbf{p} + \delta_{\mathbf{p}};$
 $\rho := (||\epsilon_{\mathbf{p}}||^2 - ||\mathbf{x} - f(\mathbf{p}_{new})||^2) / (\delta_{\mathbf{p}}^T (\mu \delta_{\mathbf{p}} + \mathbf{g}));$
if $\rho > 0$
 $\mathbf{p} = \mathbf{p}_{new};$
 $\mathbf{A} := \mathbf{J}^T \mathbf{J}; \epsilon_{\mathbf{p}} := \mathbf{x} - f(\mathbf{p}); \mathbf{g} := \mathbf{J}^T \epsilon_{\mathbf{p}};$
stop: $(||\mathbf{g}||_{\infty} \leq \varepsilon_1);$
 $\mu := \mu * \max(\frac{1}{3}, 1 - (2\rho - 1)^3); \nu := 2;$
else
 $\mu := \mu * \nu; \nu := 2 * \nu;$
endif
endif
until $(\rho > 0)$ or (stop)
endwhile

factoring an arrowhead Hessian matrix to get a reduced camera system or reduced structure system.

Bill Triggs, Philip Mclauchlan, Richard Hartley, Andrew Fitzgibbon.

Bundle Adjustment – A Modern Synthesis. International Workshop on Vision Algorithms, Sep 2000, Corfu, Greece. pp.298–372, 10.1007/3-540-44480-7_21 . inria-00548290

We seek variable orderings that approximately minimize the total operation count or fill-in over the whole elimination chain. For many problems a suitable ordering can be fixed in advance, typically giving one of a few standard pattern matrices such as band or arrowhead matrices, perhaps with such structure at several levels.



(25)

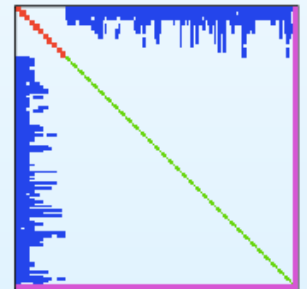
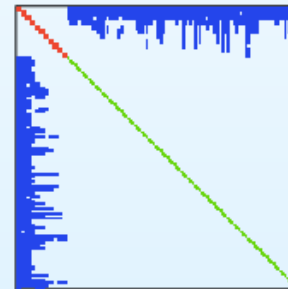
The diagram shows three matrix sparsity patterns. The first, labeled 'bundle Hessian', is a block matrix with a large square block on the top-left and a smaller square block on the bottom-right, with a vertical line of squares connecting them. The second, labeled 'arrowhead matrix', is a matrix with a large square block on the top-left and a single column of squares on the right. The third, labeled 'block tridiagonal matrix', is a matrix with a large square block on the top-left and a single column of squares on the right, with a vertical line of squares connecting them.

The most prominent pattern structure in bundle adjustment is the primary subdivision of the Hessian into structure and camera blocks. To get the reduced camera system (19), we treat the Hessian as an arrowhead matrix with a broad final column containing all of the camera parameters. Arrowhead matrices are trivial to factor or reduce by block 2×2 Schur complementation, *c.f.* (16, 19). For bundle problems with many independent images and only a few features, one can also complement on the image parameter block to get a reduced *structure* system.

http://users.ics.forth.gr/~lourakis/sba/PRCV_colloq.pdf

Bundle adjustment gone public
Manolis Lourakis

- A few interesting practical situations violate its underlying assumption regarding the problem's sparsity pattern, rendering it inapplicable. E.g., fixed but unknown intrinsics shared by all cameras
- Example: Hessians corresponding to BA for motion and structure (left) and BA for motion, structure and shared intrinsics (right)



applying local updates rather than global

How to Avoid Singularity For Euler Angle Set?

Puneet Singla*, Daniele Mortari[†], and John L. Junkins[‡]

Since all rotations are performed about the principal axes of the reference frame, we define $\mathbf{M}_i = \exp(-[\tilde{\mathbf{e}}_i]\theta_i)$ as an elementary rotation matrix about the \mathbf{e}_i -body axis. Here, $[\tilde{\mathbf{e}}_i]$ represents the skew-symmetric cross product matrix given by the following expression:

$$[\tilde{\mathbf{a}}] = \begin{bmatrix} 0 & -a_3 & a_2 \\ a_3 & 0 & -a_1 \\ -a_2 & a_1 & 0 \end{bmatrix} \quad (1)$$

From the expression of \mathbf{M}_i , we can construct the following three elementary rotation matrices:

$$\mathbf{M}_1(\theta) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos \theta & \sin \theta \\ 0 & -\sin \theta & \cos \theta \end{bmatrix} \quad (2)$$

$$\mathbf{M}_2(\theta) = \begin{bmatrix} \cos \theta & 0 & -\sin \theta \\ 0 & 1 & 0 \\ \sin \theta & 0 & \cos \theta \end{bmatrix} \quad (3)$$

$$\mathbf{M}_3(\theta) = \begin{bmatrix} \cos \theta & \sin \theta & 0 \\ -\sin \theta & \cos \theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (4)$$

if i, j , and k , indicate the coordinate axes about which each subsequent rotation is performed, that is, they can be any integer from 1-3, provided that $i \neq j$ and $j \neq k$, are satisfied then the resultant direction cosine matrix can be written as

$$\mathbf{C}_{ijk}(\theta_1, \theta_2, \theta_3) = \mathbf{M}_k(\theta_3) \mathbf{M}_j(\theta_2) \mathbf{M}_i(\theta_1) \quad (5)$$

applying local updates rather than global

How to Avoid Singularity For Euler Angle Set?

Puneet Singla*, Daniele Mortari†, and John L. Junkins‡

It is a fundamental topological fact that singularities can never be eliminated in any 3-dimensional representation of orientation. But we can avoid this singularity by describing the attitude at a particular instant by the Euler angle set *which is farthest away from singularity*. In this paper, we present an algorithm to switch between different sets of Euler angles to avoid this singularity.

Table 1: Classical Parameterizations of Attitude Rotation Matrix

Paramet-rization	Dimension	Attitude Matrix	Kinematic Equations	Singularities	Constraints
DCM, (C_{ij})	9	$\mathbf{C} = [C_{ij}]$	$\dot{\mathbf{C}} = -[\tilde{\boldsymbol{\omega}}]\mathbf{C}$	None	$\mathbf{C}^T \mathbf{C} = \mathbf{I}$
Euler Angles EA (θ_i)	3	$\mathbf{C} = \begin{bmatrix} \text{transcendental} \\ \text{functions of} \\ \theta'_i s \end{bmatrix}$	$\dot{\boldsymbol{\theta}} = \begin{bmatrix} \text{transcendental} \\ \text{functions of} \\ \theta'_i s \end{bmatrix} \boldsymbol{\omega}$	$\theta_2 = \pm \frac{\pi}{2}$	None
Euler-Rodrigues Symmetric Parameters ERSP (q_i)	4	$\mathbf{C} = \begin{bmatrix} \text{algebraic} \\ \text{functions of} \\ q'_i s \end{bmatrix}$	$\dot{\mathbf{q}} = \begin{bmatrix} \text{linear} \\ \text{functions of} \\ q'_i s \end{bmatrix} \begin{Bmatrix} 0 \\ \boldsymbol{\omega} \end{Bmatrix}$	None	$\mathbf{q}^T \mathbf{q} = 1$
RP (r_i)	3	$\mathbf{C} = \begin{bmatrix} \text{quadratic} \\ \text{functions of} \\ r'_i s \end{bmatrix}$	$\dot{\mathbf{r}} = \begin{bmatrix} \text{non-linear} \\ \text{functions of} \\ r'_i s \end{bmatrix} \boldsymbol{\omega}$	$\phi = \pm \pi$	None
MRP (σ_i)	3	$\mathbf{C} = \begin{bmatrix} \text{quartic} \\ \text{functions of} \\ \sigma'_i s \end{bmatrix}$	$\dot{\boldsymbol{\sigma}} = \begin{bmatrix} \text{non-linear} \\ \text{functions of} \\ \sigma'_i s \end{bmatrix} \boldsymbol{\omega}$	$\phi = \pm 2\pi$	None

applying local updates rather than global

How to Avoid Singularity For Euler Angle Set?

Puneet Singla^{*}, Daniele Mortari[†], and John L. Junkins[‡]

second reason comes out from the capability of the Shuster's Method of Sequential Rotations[4] (MSR) to avoid the *un-avoidable* singularity affecting all the minimum attitude parameter. Not only the original QUEST[4] algorithm has taken advantage from the MSR technique, but also some recent attitude determination approaches, like ESOQ2[5] and OLAE[6].

Snavely's GitHub `bundler_sfm/lib/sba-1.5/sba_levmar.c`