



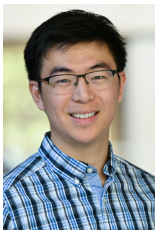
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TEXAS

The University of Texas at Austin

Going Beyond Pairs: Higher-Order Synchronization via Trifocal and Quadrifocal Constraints

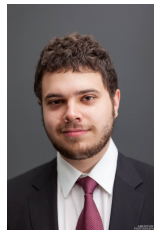


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GLOBAL STRUCTURE FROM MOTION (SfM)

The SfM problem estimates 3D structure and camera poses from 2D images.



Classical global SfM systems are based on pair-wise information. They may fail in

- ▶ near collinear situations.
- ▶ homogeneous scenes with insufficient feature points.

Can higher order measurements like trifocal and quadrifocal tensors help?

WHAT IS THE QUADRIFOCAI TENSOR?

- Consider a point correspondence between four views:

$$\mathbf{x} \longleftrightarrow \mathbf{x}' \longleftrightarrow \mathbf{x}'' \longleftrightarrow \mathbf{x}'''$$

associated with cameras $A, B, C, D \in \mathbb{R}^{3 \times 4}$, such that

$$AX = kx, BX = k'x', CX = k''x'', DX = k'''x'''$$

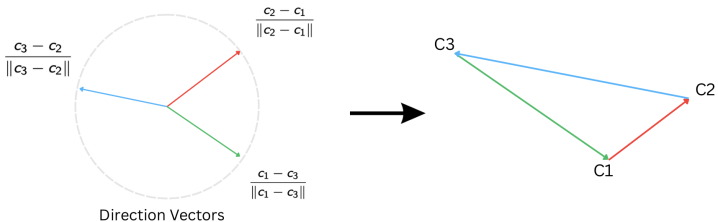
for some point X in 3D space and scales k, k', k'', k''' .

$$\begin{bmatrix} A & \mathbf{x} & & & \\ & B & \mathbf{x}' & & \\ & C & & \mathbf{x}'' & \\ & D & & & \mathbf{x}''' \end{bmatrix} \begin{pmatrix} \mathbf{X} \\ -k \\ -k' \\ -k'' \\ -k''' \end{pmatrix} = \mathbf{0}$$

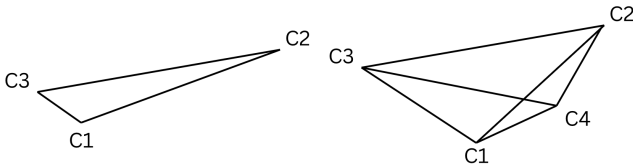
Since $\mathbf{x} \longleftrightarrow \mathbf{x}' \longleftrightarrow \mathbf{x}'' \longleftrightarrow \mathbf{x}'''$, this system has a solution, so that the 12×8 matrix on the left has at most rank 7, hence all 8×8 minors are zero.

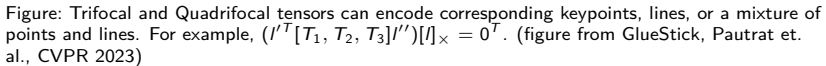
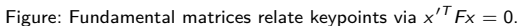
ADVANTAGES OF HIGHER ORDER MEASUREMENTS

Pairwise relative poses provide the relative direction but lacks scales.



Trifocal and quadrifocal tensors carry more information by inherently encoding the relative distances between triplets and quadruplets of camera locations. They also encode the scale in collinear settings.





FUNDAMENTAL MATRICES & HIGHER ORDER TENSORS

Image 1 - point matches

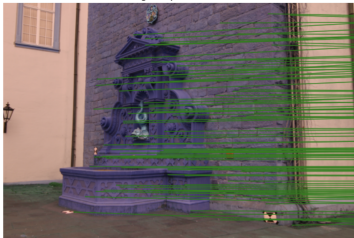


Image 2 - point matches



Fundamental matrices:

- ▶ Encode pair-wise relative camera orientation and relative directions of locations.

3rd and 4th order analogues:

- ▶ Encode relative pose info across multiple views and relates corresponding lines.
- ▶ Relative locations are encoded in triangles, much more stable than directions.

Advantages of higher order measurements:

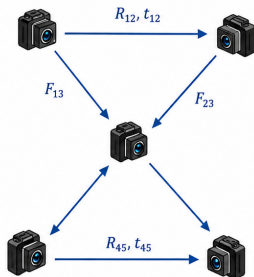
- ▶ May lead to more stable location estimation.
- ▶ Flexibility of using geometric information like lines.

SriRam and Marc mentioned in a paper they wrote in 2012 (Thirthala, S., & Pollefeys, M. 2012 IJCV), “*currently the quadrifocal and mixed trifocal tensors are useful only from a theoretical stand-point*”. Since then, these higher order tensors have been studied by many experts from different aspects.

- ▶ Aholt, C., & Oeding, L. (2014). The ideal of the trifocal variety. *Mathematics of Computation*, 83(289), 2553-2574.
- ▶ Oeding, L. (2017). The quadrifocal variety. *LAA*, 512, 306-330.
- ▶ Kileel, J. (2017). Minimal problems for the calibrated trifocal variety. *SIAM Journal on Applied Algebra and Geometry*, 1(1), 575-598.
- ▶ Kileel, J., Kukeleva, Z., Pajdla, T., & Sturm, B. (2018). Distortion varieties. *FOCM*, 18(4), 1043-1071.
- ▶ Fabbri, R., Duff, T., Fan, H., Regan, M. H., Pinho, D. D. C. D., Tsagaridas, E., ... & Pajdla, T. (2020). Trplp-trifocal relative pose from lines at points. *CVPR*.
- ▶ Hruby, P., Korotynskiy, V., Duff, T., Oeding, L., Pollefeys, M., Pajdla, T., & Larsson, V. (2023). Four-view geometry with unknown radial distortion. *CVPR*.
- ▶ many other works and still much to do!

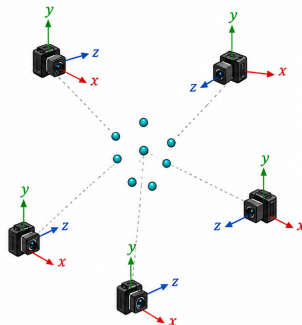
THE SYNCHRONIZATION PROBLEM

Relative measurements



Synchronization

Global solution



How can we use higher order relative pose measurements for synchronization in SfM?

THE n -VIEW FUNDAMENTAL MATRIX

- ▶ First explored by Sengupta et. al. in CVPR 2017.
- ▶ The n -view fundamental matrix $\mathcal{F}^n$ is formed by concatenating the $\binom{n}{2}$ fundamental matrices associated with n cameras into a $3n \times 3n$ matrix $\mathcal{F}^n$.
- ▶ $n \times n$ block matrix where the ij^{th} block is $F_{ij} \in \mathbb{R}^{3 \times 3}$.
- ▶ Calibrated setting: n -view essential matrix.

$$\mathcal{F}^n = \begin{pmatrix} 0_{3 \times 3} & F_{12} & \cdots & F_{1n} \\ F_{21} & 0_{3 \times 3} & \cdots & F_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ F_{n1} & F_{n2} & \cdots & 0_{3 \times 3} \end{pmatrix}$$

- ▶ Further explored by Kasten et. al., ICCV 2019, Kasten et. al., CVPR 2019, Geifman et. al., CVPR 2020.

ALGEBRAIC CHARACTERIZATION OF n -VIEW FUNDAMENTAL MATRIX

Theorem 1: Noncollinear Setting of n -view Fundamental Matrix

A given matrix $\mathcal{F}^n \in \mathbb{R}^{3n \times 3n}$ is consistent as a n -view fundamental matrix with a set of n cameras whose centers are not all collinear if and only if:

1. $\text{rank}(\mathcal{F}^n) = 6$ and $\mathcal{F}^n$ has exactly 3 positive and 3 negative eigenvalues.
2. $\text{rank}(\mathcal{F}_{i,:}^n) = 3$ for all $i = 1, \dots, n$.

Theorem 2: Collinear Setting of n -view Fundamental Matrix

A given matrix $\mathcal{F}^n \in \mathbb{R}^{3n \times 3n}$ is consistent as a n -view fundamental matrix with a set of n collinear cameras if and only if:

1. $\text{rank}(\mathcal{F}^n) = 4$ and $\mathcal{F}^n$ has exactly 2 positive and 2 negative eigenvalues.
2. $\text{rank}(\mathcal{F}_{i,:}^n) = 2$ for all $i = 1, \dots, n$.

Ranks drop for collinear camera configurations. Need separate treatments to detect and reconstruct collinear situations such as constructing virtual cameras/points.

TUCKER DECOMPOSITION AND MULTILINEAR RANK

- ▶ A d^{th} order tensor $X \in \mathbb{R}^{n_1 \times \cdots \times n_d}$ is a d dimensional array.
- ▶ The tensor matrix product in the i th mode between X and $U \in m_i \times n_i$, is

$$(X \times_i U)_{j_1 \cdots j_{i-1} \ k \ j_{i+1} \cdots j_N} = \sum_{j_i=1}^{M_i} X_{j_1 \ j_2 \ \cdots \ j_N} U_{kj_i}.$$

Can see $Y = X \times_i U$ as multiplication in the unfolding, $Y_{(i)} = UX_{(i)}$, then rearranging back into a tensor.

- ▶ The Tucker Decomposition of X is any decomposition in the following form

$$X = G \times_1 A_1 \times_2 \cdots \times_d A_d = \llbracket G; A_1, A_2, \dots, A_d \rrbracket$$

where A_i are called the factor matrices, G is called the core tensor.
For third order tensors, elementwise:

$$X_{ijk} = \sum_{p=1}^P \sum_{q=1}^Q \sum_{r=1}^R G_{pqr} (A_1)_{ip} (A_2)_{jq} (A_3)_{kr}$$

HIGHER ORDER SINGULAR VALUE DECOMPOSITION

To calculate an approximate tucker factorization, we consider the following extension of the matrix SVD for a general order d tensor X , called the truncated higher order singular value decomposition (HOSVD):

Input: $X \in \mathbb{R}^{n_1 \times \cdots \times n_d}$, $r_1, r_2, \dots, r_d$

Algorithm:

For $i = 1:d$

$U_i = r_i$ leading left singular vectors of $X_{(i)}$

End Loop

$\mathcal{G} = X \times_1 U_1^T \times_2 \cdots \times_d U_d^T$

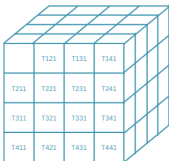
Return: $\mathcal{G}, U_1, \dots, U_d$

The multilinear rank is defined as the tuple of ranks of the flattenings of the tensor in each direction, $mlrank(X) = (r_1, \dots, r_d)$ (a higher order generalization of rank for matrices).

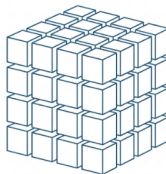
THE BLOCK TENSORS

- ▶ Given n cameras $\{P_i\}_{i=1}^n$.
- ▶ *Block trifocal tensor* $\mathcal{T}^n \in \mathbb{R}^{3n \times 3n \times 3n}$.
- ▶ The ijk^{th} block of $\mathcal{T}^n$ is the trifocal tensor $T_{ijk} \in \mathbb{R}^{3 \times 3 \times 3}$ corresponding to the cameras P_i, P_j, P_k .
- ▶ *Block quadrifocal tensor* $\mathcal{Q}^n \in \mathbb{R}^{3n \times 3n \times 3n \times 3n}$.
- ▶ The $ijkl^{th}$ block of $\mathcal{Q}^n$ is the quadrifocal tensor $Q_{ijkl} \in \mathbb{R}^{3 \times 3 \times 3 \times 3}$ corresponding to the cameras P_i, P_j, P_k, P_l .

Block Trifocal Tensor
($3n \times 3n \times 3n$)



Block Quadrifocal Tensor
($3n \times 3n \times 3n \times 3n$)



LOW RANKNESS OF BLOCK TENSORS

Block Fundamental Matrix
($3n \times 3n$)

	F12	F23	F34
F21		F23	F24
F31	F32		F34
F41	F42	F43	

Non-Collinear: $\text{rank}(\mathcal{F}^n) = 6$

Collinear: $\text{rank}(\mathcal{F}^n) = 4$

Block Trifocal Tensor
($3n \times 3n \times 3n$)

	T121	T131	T141
T211		T231	T241
T311	T321		T341
T411	T421	T431	

$\text{mlrank}(\mathcal{T}^n) = (6, 4, 4)$

$\text{mlrank}(\mathcal{T}^n) = (5, 4, 4)$

Block Quadrifocal Tensor
($3n \times 3n \times 3n \times 3n$)

$\text{mlrank}(\mathcal{Q}^n) = (4, 4, 4, 4)$

$\text{mlrank}(\mathcal{Q}^n) = (4, 4, 4, 4)$

Theorem 3: Low Rankness of Block Tensors (Informal)

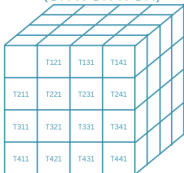
Trifocal Tensor: Given a block trifocal tensor $\mathcal{T}^n$ with $n \geq 4$, $\text{mlrank}(\mathcal{T}^n) = (6, 4, 4)$, when cameras are non collinear. $\text{mlrank}(\mathcal{T}^n) = (5, 4, 4)$ when they are collinear but do not share the same camera center.

Quadrifocal Tensor: Given a block quadrifocal tensor $\mathcal{Q}^n$ with $n \geq 5$, $\text{mlrank}(\mathcal{Q}^n) = (4, 4, 4, 4)$, **if the cameras don't share the same center.**

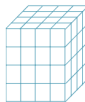
Note that these ranks are independent of the number of cameras and hold under a suitable set of scales for each block.

We establish an explicit tucker factorization for the block trifocal/quadrifocal tensor.

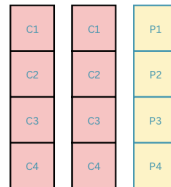
Block Trifocal Tensor
($3n \times 3n \times 3n$)



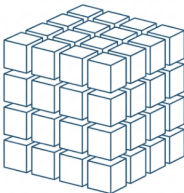
Core Tensor
($6 \times 4 \times 4$)



Two Stacked Camera Matrix
One Stacked Line Projection Matrix



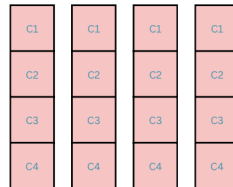
Block Quadrifocal Tensor
($3n \times 3n \times 3n \times 3n$)



Core Tensor
($4 \times 4 \times 4 \times 4$)



Four Stacked Camera Matrix
($3n \times 4$)



ADDITIONAL PROPERTIES

Proposition 1: Basic Properties

We have the following observations for the block trifocal tensor $\mathcal{T}^n$. For all distinct $i, j \in [n]$,

1. $\mathcal{T}_{iii}^n = 0_{3 \times 3 \times 3}$
2. The $\mathcal{T}_{jii}^n$: elements of fundamental matrix F_{ij} .
3. The $\mathcal{T}_{jij}^n$ and $\mathcal{T}_{iji}^n$: epipoles (projections of camera centers).
4. The horizontal slices $\mathcal{T}^n(i, :, :)$ are skew symmetric.
5. When all cameras are calibrated (so that the calibration matrices $K_i = I_{3 \times 3}, \forall i \in [n]$), three singular values of $\mathcal{T}_{(1)}^n$ are equal.

The block quadrifocal tensor $\mathcal{Q}^n$ admits the following properties.

1. The super-diagonal blocks vanish, $\mathcal{Q}_{iiii}^n = 0_{3 \times 3 \times 3 \times 3}, \forall i = 1, \dots, n$.
2. Three of the indices the same: epipoles.
3. Two of the indices the same and other two different: elements of trifocal tensors.
4. Two of the indices the same, the other two also the same: elements in the fundamental matrix.

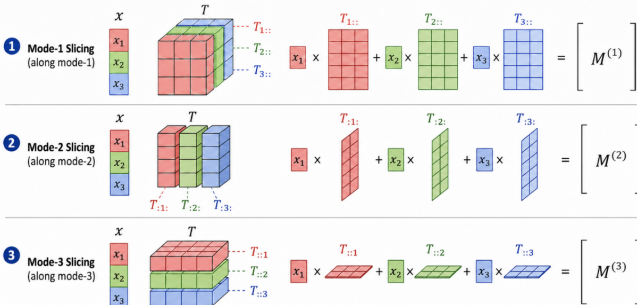
ADDITIONAL PROPERTIES - PROJECTIVE RANK

We establish the projection rank for $\mathcal{Q}^n$ and $\mathcal{T}^n$.

Definition 1: Projection Rank

The projection rank is defined as the tuple of ranks of the various projections from an order n tensor to matrices by contraction with any generic tuple of $n - 2$ vectors, where $n \geq 3$.

Projection Rank for a 3rd-Order Tensor



Given the block quadrifocal tensor Q^n and for generic vectors $x, y \in \mathbb{R}^{3n}$, Q^n 's projection rank is a tuple of 6 numbers, corresponding to the ranks of the matrices

$$\begin{aligned} \sum_{i,j} x_i y_j Q^n_{ij::}, \quad \sum_{i,j} x_i y_j Q^n_{i:j:}, \quad \sum_{i,j} x_i y_j Q^n_{i::j} \\ \sum_{i,j} x_i y_j Q^n_{:ij:}, \quad \sum_{i,j} x_i y_j Q^n_{:i:j}, \quad \sum_{i,j} x_i y_j Q^n_{::ij} \end{aligned}$$

Theorem 4: Projection Rank for Q^n and $\mathcal{T}^n$

Let Q^n be a block quadrifocal tensor and $\mathcal{T}^n$ be a block trifocal tensor. Then

$$\text{P-Rank}(Q^n) = (2, 2, 2, 2, 2, 2), \quad \text{P-Rank}(\mathcal{T}^n) = (4, 3, 3).$$

- ▶ Not implied by low multilinear rank.
- ▶ Depends just on the core.
- ▶ By optimizing with the fixed core, and preserving the symmetries in the factor matrices, we will enforce the P-Rank constraint.

ADDITIONAL PROPERTIES OF THE BLOCK TENSORS

- **Pose Retrieval:** A simple HOSVD on $\mathcal{Q}^n, \mathcal{T}^n$ gives the camera poses. The leading 4 singular vectors will give the camera matrices up to a projective transformation.
- **Sufficiency of constraints to determine scales:** In the noiseless case, we prove that regardless of the scales on the blocks, if the block quadrifocal tensor has low rank of $(4, 4, 4, 4)$, the camera matrices are then uniquely determined (up to scale). An analogous results exists for the block trifocal tensor.

Theorem 5: Sufficiency of Low Rank for Determining Scales

Let $\mathcal{Q}^n \in \mathbb{R}^{3n \times 3n \times 3n \times 3n}$ be a block quadrifocal tensor corresponding to $n \geq 5$ generic cameras. Let $\Lambda \in \mathbb{R}^{n \times n \times n \times n}$ be a block scaling with $\lambda_{ijkl} \neq 0$ if and only if i, j, k, l are not all equal. If $\Lambda \odot_b \mathcal{Q}^n \in \mathbb{R}^{3n \times 3n \times 3n \times 3n}$ has multilinear rank $(4, 4, 4, 4)$, then there exists $\alpha, \beta, \gamma, \delta \in \mathbb{R}^n$ such that $\lambda_{ijkl} = \alpha_i \beta_j \gamma_k \delta_l$ whenever i, j, k, l are not all the same. That is, Λ and $\alpha \otimes \beta \otimes \gamma \otimes \delta$ are equal away from the super diagonal.

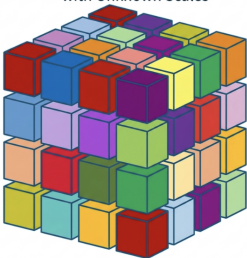
OPTIMIZING THE NOISY BLOCK TENSORS

In practice, there are two big issues to be dealt with algorithmically.

Issue I. Trifocal/Quadrifocal tensors are estimated up to a scale.

Issue II. Missing and noisy blocks in the block trifocal/quadrifocal tensor.

Estimated Block Quadrifocal Tensor
with Unknown Scales

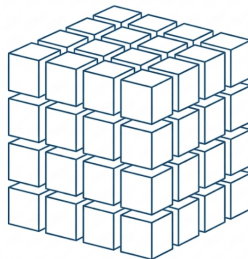


Optimize for Scales



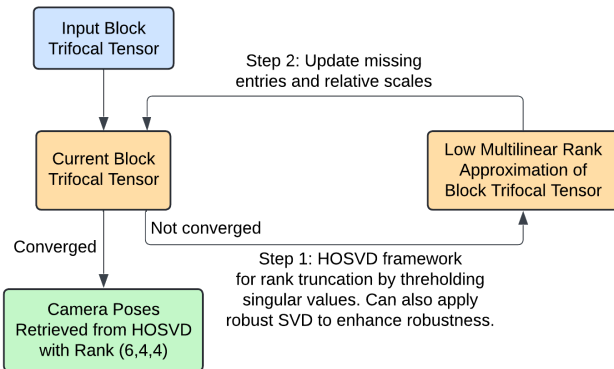
Disregard Missing Entries

Optimized Block Quadrifocal Tensor with Correct Scales



TRIFOCALSYNC: A HEURISTIC WAY TO OPTIMIZE THE NOISY BLOCK TRIFOCAL TENSOR

Use the relative scales and entries in a multilinear rank truncated tensor as a heuristic.



II : UPDATE SCALES AND IMPUTATION

We also use the information on the tensor obtained from our previous procedure to update **scales**. At each step, we solve

$$\begin{aligned} \Lambda^{(t+1)} = \arg \min_{\Lambda} & \|\Lambda \odot \hat{T}^n - \mathcal{P}_{ht}(\Lambda^{(t)} \odot \hat{T}^n)\|^2 \\ \text{s.t. } & \Lambda_{ijk} = 0_{3 \times 3 \times 3} \text{ for } (i, j, k) \in \Omega^c \end{aligned} \quad (1)$$

Denoting $\mathcal{P}_{ht}(\Lambda^{(t)} \odot \hat{T}^n)$ as $(\hat{T}_r^n)^{(t)}$, we have

$$\Lambda_{ijk}^{(t+1)} = \arg \min_{\mu} \|\mu \cdot \hat{T}_{ijk}^n - (\hat{T}_r^n)^{(t)}_{ijk}\|^2 = \frac{\text{trace}((\hat{T}_{ijk}^n)^T_{(1)} ((\hat{T}_r^n)^{(t)})_{(1)})}{\|((\hat{T}_r^n)^{(t)})_{(1)}\|_F^2}. \quad (2)$$

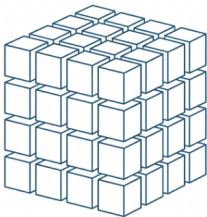
Thus, given the current tensor $(\hat{T}^n)^{(t)}$, we calculate the new scales $\Lambda^{(t+1)}$, and impute for **completion**:

$$(\hat{T}^n)^{(t+1)} = (\Lambda^{(t+1)} \odot (\hat{T}^n)^{(t)} \odot W_{\Omega}) + (\hat{T}_r^n)^{(t)} \odot W_{\Omega^c}. \quad (3)$$

QUADSYNC: OPTIMIZING THE NOISY BLOCK QUADRIFOCAL TENSOR

- Better symmetry for block quadrifocal tensor $\rightarrow$ A more principled approach.

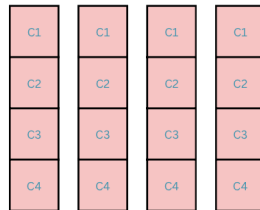
Block Quadrifocal Tensor
($3n \times 3n \times 3n \times 3n$)



Core Tensor
($4 \times 4 \times 4 \times 4$)



Four Stacked Camera Matrix
($3n \times 4$)



We exploit the factorization's common factor matrix and develop an Alternating Direction Method of Multipliers (ADMM) and Iteratively Reweighted Least Squares (IRLS) based optimization method to retrieve the scales and complete the tensor.

QUADSYNC: AN OPTIMIZATION FRAMEWORK

We wish to solve for the scales and the camera matrices given the estimated block quadrifocal tensor $\tilde{\mathcal{Q}}^n$. We form the following optimization problem with a robust loss,

$$\begin{aligned} \min_{\Lambda, C} \quad & \sum_{(i,j,k,l) \in \Omega} \|\Lambda_{ijkl}(\tilde{\mathcal{Q}}^n)_{ijkl} - [\![\mathcal{G}_Q; C, C, C, C]\!]\|_F \\ \text{s.t.} \quad & \Lambda \in S^4(\mathbb{R}^n) \text{ and } \|\Lambda\|_F^2 = 1, \end{aligned}$$

We solve it using an ADMM-IRLS scheme. The problem becomes

$$\begin{aligned} \max_{\Gamma_i} \min_{\Lambda, C_i, B} \quad & \|W \odot_b ((\Lambda \odot_b \tilde{\mathcal{Q}}^n) - [\![\mathcal{G}_Q; C_1, C_2, C_3, C_4]\!])\|_F^2 + \\ & \frac{\rho}{2} \sum_{i=1}^4 \|C_i - B + \Gamma_i\|_F^2 \quad \text{s.t. } \Lambda \in S^4(\mathbb{R}^n) \text{ and } \|\Lambda\|_F^2 = 1 \end{aligned} \quad (4)$$

- For each IRLS iteration, we solve for a new set of scales W . We then solve for $C_i, \Lambda, B, \Gamma_i$ via alternating minimization.
- Initialization: HOSVD.

COMPUTATIONALLY COMPLEXITY AND PARTIAL REMEDIES

Computational Complexity:

- Initialization ($\mathbf{O}(n^4)$): The factors are initialized via truncated HOSVD of a tensor of size $3n \times 3n \times 3n$.
- Algorithm:
 1. $C_i : \mathbf{O}(n^4)$. The expense comes from multiplying large matrices many times. Through randomized updates, we can decrease the complexity drastically.

$$n(4 \times 27n^3) \cdot \text{diag}(27n^3 \times 27n^3) \cdot (27n^3 \times 4) \rightarrow n(4 \times m) \cdot (m \times m) \cdot (m \times 4)$$
$$\mathbf{O}(n^4) \rightarrow \mathbf{O}(n)$$

2. $\Lambda : \mathbf{O}(n^4)$: For a full estimated tensor it is $\mathbf{O}(n^4)$. However, for a carefully constructed viewing graph, the number of blocks can be significantly reduced. This step can be parallelized.
3. $B, \Gamma_i : \mathbf{O}(n)$.

Takeaways:

- Randomized updates; Careful construction of the viewing graph; Parallel computing

A DEMONSTRATION OF STOCHASTIC UPDATES

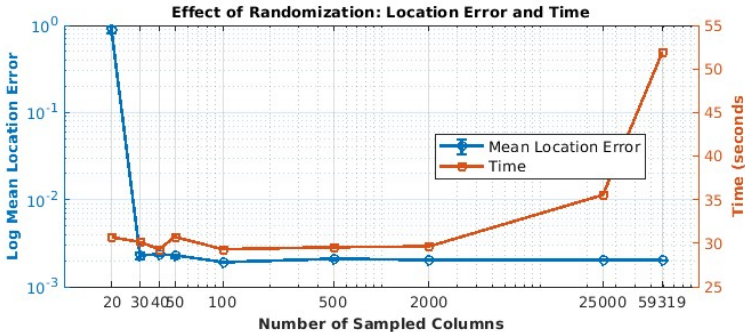


Figure: Randomized updates in QuadSync. Tested on ETH3D 'relief' dataset. Max number of columns is 59319. Using 30 random columns achieves similar accuracy with notable speed-ups.

JOINT OPTIMIZATION OF BLOCK MATRIX AND TENSORS

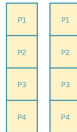
Block Essential Matrix
($3n \times 3n$)



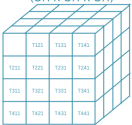
Core Matrix
(6×6)



Two Stacked Line Projection Matrix



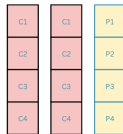
Block Trifocal Tensor
($3n \times 3n \times 3n$)



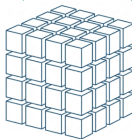
Core Tensor
($6 \times 4 \times 4$)



Two Stacked Camera Matrix
One Stacked Line Projection Matrix



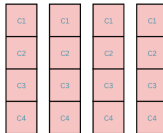
Block Quadrifocal Tensor
($3n \times 3n \times 3n \times 3n$)



Core Tensor
($4 \times 4 \times 4 \times 4$)



Four Stacked Camera Matrix
($3n \times 4$)



We find factorizations of block essential matrix, block trifocal tensor, block quadrifocal tensor, **where many factor matrices are the same.**

We develop a similar algorithm to synchronize all three entities simultaneously, exploiting the shared factors.

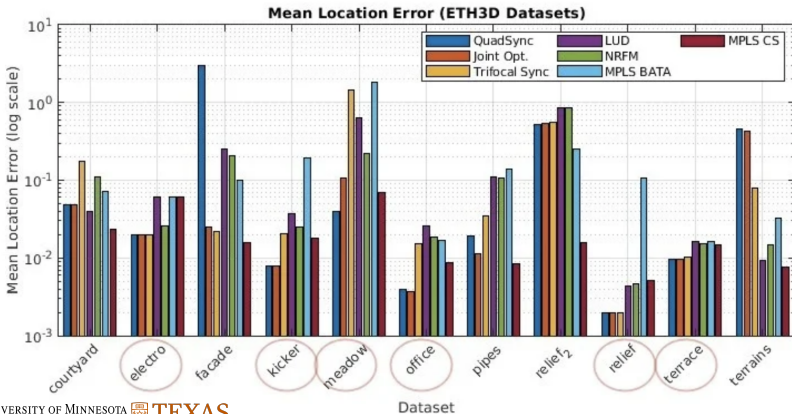
EXPERIMENTS

We test our results on the ETH3D multiview stereo dataset and the EPFL stereo dataset. It is a real dataset with a wide variety of scenes, from natural to artificial, from indoor to outdoor.



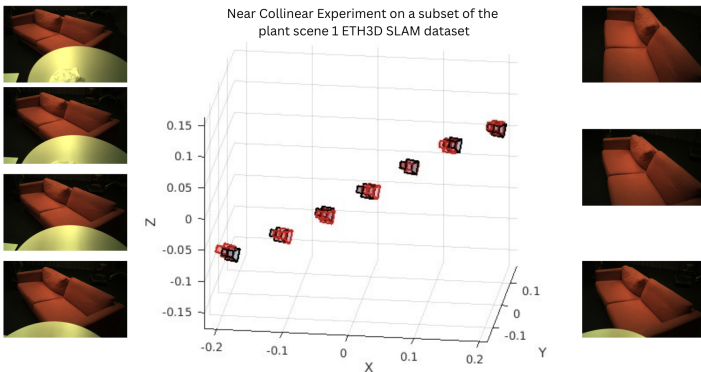
SFM EXPERIMENTAL RESULTS ETH3D

- ▶ No bundle adjustment.
- ▶ Initial estimation quality much worse compared to pairwise pose estimates.
- ▶ **Superior results over pairwise methods on circled datasets.**
- ▶ **Struggle with datasets with bad estimation quality and density.** Succeeds in dense reconstruction scenes, yet can be computationally expensive.
- ▶ Rotation averaging can be improved.



EXPERIMENTAL RESULTS FOR NEAR COLLINEAR DATASET

- ▶ A near collinear excerpted scenario from ETH3D-SLAM.
- ▶ Note that this is a classical **failure mode**, which can't be solved by location **synchronization methods** based on pair-wise measurements without 3D points.



IMPACT AND FUTURE DIRECTIONS

Impact

- ▶ We establish **novel algebraic constraints on a set of trifocal and quadrifocal tensors**, expressed as low rank block tensors.
- ▶ We develop the **first global synchronization algorithms for trifocal and quadrifocal tensors** and provide a path for practical algorithms.
- ▶ Experimental results show that using higher order tensors may lead to better camera location estimations.

Future Directions

- ▶ The estimation of single trifocal and quadrifocal tensors.
- ▶ Sparsification and refinement of the initial viewing graph for large scale adoption.

