

# 3D Computer Vision

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# Multi-view reconstruction

- 1 Principles of multi-view reconstruction
- 2 Reconstruction for orthogonal and weak-perspective projection
  - Tomasi-Kanade factorization
- 3 Multi-view perspective reconstruction
- 4 Concatenation of stereo reconstructions
- 5 Bundle adjustment
- 6 Tomasi-Kanade factorization with missing data

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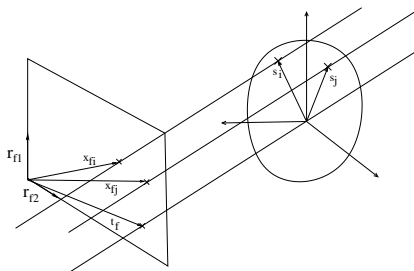
# Possibilities for multi-view reconstruction

- 1 Concatenation of stereo reconstructions
  - Complicated
  - Reconstruction error cummulated
- 2  $N$ -view solutons
  - Task is non-linear
  - Difficult solutions, implementation challenging
- 3 Reconstruction by simplified camera models
  - Task is linear if
    - orthogonal or
    - weak-perspective projections applied.

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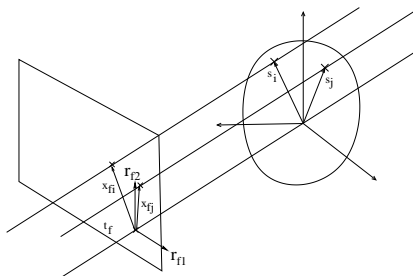
# Orthogonal projection



Projection of points

$$\begin{bmatrix} u_{fp} \\ v_{fp} \end{bmatrix} = \begin{bmatrix} \mathbf{r}_{f1}^T \\ \mathbf{r}_{f2}^T \end{bmatrix} \mathbf{s}_p - \mathbf{t}_f \quad (1)$$

# Orthogonal projection



Projection: origin is the center of gravity.

$$\begin{bmatrix} u_{fp} \\ v_{fp} \end{bmatrix} = \begin{bmatrix} \mathbf{r}_{f1}^T \\ \mathbf{r}_{f2}^T \end{bmatrix} \mathbf{s}_p \quad (2)$$

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# Tomasi-Kanade factorization

- Tracked (matched across multi-frames) coordinates are stacked in measurement matrix  $\mathbf{W}$ .
- It can be factorized into two matrices:

$$\mathbf{W} = \begin{bmatrix} U_{11} & U_{12} & \cdots & U_{1P} \\ V_{11} & V_{12} & \cdots & V_{1P} \\ U_{21} & U_{22} & \cdots & U_{2P} \\ V_{21} & V_{22} & \cdots & V_{2P} \\ \vdots & \vdots & \ddots & \vdots \\ U_{F1} & U_{F2} & \cdots & U_{FP} \\ V_{F1} & V_{F2} & \cdots & V_{FP} \end{bmatrix} = \begin{bmatrix} r_{11}^T \\ r_{12}^T \\ r_{21}^T \\ r_{22}^T \\ \vdots \\ r_{F1}^T \\ r_{F2}^T \end{bmatrix} \begin{bmatrix} \mathbf{s}_1 & \mathbf{s}_2 & \cdots & \mathbf{s}_p \end{bmatrix}$$

$$\mathbf{W} = \mathbf{M}\mathbf{S}$$

# Tomasi-Kanade factorization

- As  $\mathbf{W} = \mathbf{MS}$ , the rank of  $\mathbf{W}$  cannot exceed 3 (noiseless-case).
  - Size of  $\mathbf{M}$  is  $2F \times 3$
  - Size of  $\mathbf{S}$  is  $3 \times P$
  - Lemma: After factorization, the rank cannot increase
- Rank reduction of  $\mathbf{W}$  by Singular Value Decomposition (SVD)
  - Largest 3 singular values/vectors are kept, other ones are set to zero.
  - $\mathbf{W} = \mathbf{USV}^T \rightarrow \mathbf{W} = \mathbf{U}'\mathbf{S}'\mathbf{V}'^T$

$$\mathbf{S} = \begin{bmatrix} \sigma_1 & 0 & 0 & 0 & \dots \\ 0 & \sigma_2 & 0 & 0 & \dots \\ 0 & 0 & \sigma_3 & 0 & \dots \\ 0 & 0 & 0 & \sigma_4 & \dots \\ \vdots & \vdots & \vdots & \vdots & \ddots \end{bmatrix} \rightarrow \mathbf{S}' = \begin{bmatrix} \sigma_1 & 0 & 0 \\ 0 & \sigma_2 & 0 \\ 0 & 0 & \sigma_3 \end{bmatrix}$$

# Ambiguity of factorization

- Infinite number of solutions exist:

$$\mathbf{W} = \mathbf{MS} = (\mathbf{MQ}^{-1})(\mathbf{QS}),$$

- where  $\mathbf{Q}$  is a  $3 \times 3$  (affine) matrix.
- $\mathbf{M}_{\text{aff}} = \mathbf{MQ}^{-1}$ : affine motion.
- $\mathbf{S}_{\text{aff}} = \mathbf{QS}$  affine structure.
- Constraint to resolve ambiguity: motion vectors  $\mathbf{r}_i$  are orthonormal.
  - Camera motion vectors is of length 1.0:

$$\mathbf{r}_{i1}^T \mathbf{r}_{i1} = 1$$

$$\mathbf{r}_{i2}^T \mathbf{r}_{i2} = 1$$

- They are perpendicular to each other:

$$\mathbf{r}_{i1}^T \mathbf{r}_{i2} = 0$$

# Ambiguity removal

- Affine  $\rightarrow$  real camera:

$$\mathbf{M}_{\text{aff}} = \begin{bmatrix} \mathbf{m}_{11}^T \mathbf{Q} \\ \mathbf{m}_{12}^T \mathbf{Q} \\ \vdots \\ \mathbf{m}_{F1}^T \mathbf{Q} \\ \mathbf{m}_{F2}^T \mathbf{Q} \end{bmatrix} \mathbf{M}_{\text{aff}} \mathbf{Q} = \mathbf{M} = \begin{bmatrix} \mathbf{r}_{11}^T \\ \mathbf{r}_{12}^T \\ \vdots \\ \mathbf{r}_{F1}^T \\ \mathbf{r}_{F2}^T \end{bmatrix}$$

- Constraints for camera vectors:

$$\begin{aligned} \mathbf{r}_{i1}^T \mathbf{r}_{i1} &= 1 &\rightarrow & \mathbf{m}_{i1}^T \mathbf{Q} \mathbf{Q}^T \mathbf{m}_{i1} = 1 \\ \mathbf{r}_{i2}^T \mathbf{r}_{i2} &= 1 &\rightarrow & \mathbf{m}_{i2}^T \mathbf{Q} \mathbf{Q}^T \mathbf{m}_{i2} = 1 \\ \mathbf{r}_{i1}^T \mathbf{r}_{i2} &= 0 &\rightarrow & \mathbf{m}_{i1}^T \mathbf{Q} \mathbf{Q}^T \mathbf{m}_{i2} = 0 \end{aligned}$$

# Estimation of matrix $\mathbf{Q}$

- Let us introduce the following notation:

$$\mathbf{L} = \mathbf{Q}\mathbf{Q}^T = \begin{bmatrix} l_1 & l_2 & l_3 \\ l_2 & l_4 & l_5 \\ l_3 & l_5 & l_6 \end{bmatrix}$$

- Important fact: matrix  $\mathbf{Q}\mathbf{Q}^T$  is symmetric
- Constraints can be written in linear form:  $\mathbf{A}_i \mathbf{l} = \mathbf{b}_i$

$$\mathbf{A}_i = \begin{bmatrix} m_{j1,x}^2 & 2m_{j1,x}m_{j1,y} & 2m_{j1,x}m_{j1,z} & m_{j1,y}^2 & 2m_{j1,y}m_{j1,z} & m_{j1,z}^2 \\ m_{j2,x}^2 & 2m_{j2,x}m_{j2,y} & 2m_{j2,x}m_{j2,z} & m_{j2,y}^2 & 2m_{j2,y}m_{j2,z} & m_{j2,z}^2 \\ m_{j1,x}m_{j2,x} & e_1 & e_2 & m_{j1,y}m_{j2,y} & m_{j1,y}m_{j2,z} + m_{j2,y}m_{j1,z} & m_{j1,z}m_{j2,z} \end{bmatrix}$$

$$\mathbf{l} = [l_1, l_2, l_3, l_4, l_5, l_6]^T \quad \mathbf{b}_i = [1, 1, 0]^T$$

- where  $m_{jk,x}$ ,  $m_{jk,y}$  and  $m_{jk,z}$  are the coordinates of vector  $\mathbf{m}_{jk}$ ,
- and  $e_1 = m_{j1,x}m_{j2,y} + m_{j2,x}m_{j1,y}$ ,  $e_2 = m_{j1,x}m_{j2,z} + m_{j2,x}m_{j1,z}$ .

# Computation of matrix $\mathbf{Q}$

- Constraints can be written in linear form:  $\mathbf{A}\mathbf{l} = \mathbf{b}$ ,

$$\mathbf{A} = [ \mathbf{A}_1^T \quad \mathbf{A}_2^T \quad \dots \quad \mathbf{A}_F^T ]^T$$

$$\mathbf{b} = [1, 1, 0, 1, 1, 0, \dots, 1, 1, 0]^T$$

- Solution by over-determined inhomogeneous linear system of equations
- Matrix  $\mathbf{Q}$  can be retrieved from  $\mathbf{L}$  by SVD:

$$\mathbf{L} \stackrel{(SVD)}{=} \mathbf{U}\mathbf{S}\mathbf{U}^T$$

$$\mathbf{Q} = \mathbf{U}\sqrt{\mathbf{S}}$$

# Weak-perspective projection

- Modified constraints:
  - motion vectors are perpendicular to each other:

$$\mathbf{r}_{i1}^T \mathbf{r}_{i2} = 0$$

- Length of vectors are not unit, but equal:

$$\mathbf{r}_{i1}^T \mathbf{r}_{i1} = \mathbf{r}_{i2}^T \mathbf{r}_{i2}$$

- Equations for affine ambiguity, represented by matrix  $\mathbf{Q}$  as follows:

$$\begin{aligned} \mathbf{m}_{i1}^T \mathbf{Q} \mathbf{Q}^T \mathbf{m}_{i1} - \mathbf{m}_{i2}^T \mathbf{Q} \mathbf{Q}^T \mathbf{m}_{i2} &= 0 \\ \mathbf{m}_{i1}^T \mathbf{Q} \mathbf{Q}^T \mathbf{m}_{i2} &= 0 \end{aligned}$$

- Linear, homogeneous system of equations obtained.

# Summary of Tomasi-Kanade factorization

- 1 Tracked points are stacked in measurement matrix  $\mathbf{W}$ .
- 2 Origin is moved to the center of gravity, translated coordinates are stacked in matrix  $\tilde{\mathbf{W}}$ .
- 3 SVD computed for  $\tilde{\mathbf{W}}$ :  $\tilde{\mathbf{W}} = \mathbf{U}\mathbf{S}\mathbf{V}^T$ .
- 4 Singular elements are replaced by zero, except the first three values in  $\mathbf{S}$ :  $\mathbf{S} \rightarrow \mathbf{S}'$ .
- 5 Affine factorization:  $\mathbf{M}_{\text{aff}} = \mathbf{U}\sqrt{\mathbf{S}'}$  and  $\mathbf{S}_{\text{aff}} = \sqrt{\mathbf{S}'}\mathbf{V}^T$ .
- 6 Calculation of matrix  $\mathbf{Q}$  by metric constraints.
- 7 Metric factorization:  $\mathbf{M} = \mathbf{M}_{\text{aff}}\mathbf{Q}$  and  $\mathbf{S} = \mathbf{Q}^{-1}\mathbf{S}_{\text{aff}}$ .



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# Multi-view perspective reconstruction

- Three-view geometry
  - Extension of epipolar geometry
  - Relationships can be written for 3D points and lines
  - Trifocal tensor introduced as the extension of the fundamental matrix
  - It has small practical impact
- Perspective Tomasi-Kanade factorization
  - Problem is a perspective auto-calibration
  - Difficulty: projective depths are different for all point/frames
  - Only iterative solutions exist
  - Very complicated
- Viable solution: Concatenation of stereo reconstructions

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# Reconstruction by concatenating multiple stereo vision

- For calibrated cameras, stereo reconstruction possible
- Camera calibration:
  - Intrinsic parameters: by chessboard-based Zhang calibration
  - Extrinsic parameters: by decomposition of essential matrix
- Spatial reconstruction: triangulation
- Results:
  - For each stereo image pair, 3D point clouds obtained.
  - Transformation(translation/rotation) between images computed as well

# Concatenating point clouds

- Two point clouds given
  - For stereo reconstruction, coordinate system is usually fixed to the first camera.
- Point clouds have  $N$  common points are stacked in vector sets:  $\{\mathbf{p}_i\}$  and  $\{\mathbf{q}_i\}$ , ( $i = 1 \dots N$ ).
- Similarity transformation between images has to be estimated.

$$\mathbf{q}_i = s\mathbf{R}\mathbf{p}_i + \mathbf{t}$$

- $s$ : scale
- $\mathbf{R}$ : rotation
- $\mathbf{t}$ : translation

# Concatenating stereo reconstructions

- Task: optimal registration to estimate similarity transformation

$$\sum_{i=1}^N \|\mathbf{q}_i - \mathbf{sR}\mathbf{p}_i - \mathbf{t}\|^2$$

- Proof given in separate document
  - Optimal translation  $\mathbf{t}$ : difference of centers of gravity
  - Optimal rotation:

$$\mathbf{H} = \sum_{i=1}^N \mathbf{q}'_i \mathbf{p}'_i{}^T$$

$$\mathbf{R} = \mathbf{V}\mathbf{U}^T \leftarrow \mathbf{H} = \mathbf{U}\mathbf{S}\mathbf{V}^T$$

- Optimal scale:

$$\mathbf{s} = \frac{\sum_{i=1}^N \mathbf{q}'_i{}^T \mathbf{R} \mathbf{p}'_i}{\sum_{i=1}^N \mathbf{p}'_i{}^T \mathbf{p}'_i}$$

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# Minimization by a numerical algorithm

- The projected coordinates of  $j$ -th point in  $i$ -th frame depend on
  - parameters of  $i$ th camera and
  - spatial coordinated of  $j$ -th point.
- Numerical optimization by Levenberg-Marquardt algorithm.
  - Jacobian matrix of the problem has to be determined.
  - Jacobian is very sparse.
- Thus, a sparse Levenberg-Marquardt algorithm should be applied.
  - It is called bundle Adjustment (BA) in the literature.



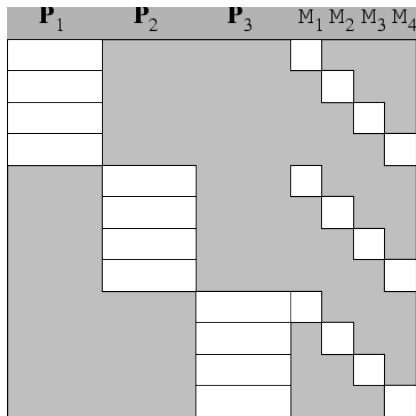
# Levenberg-Marquardt for 3D Reconstruction

- LM-rule for parameter tuning:

$$\Delta \mathbf{p} = \left( \mathbf{J}^T \mathbf{J} + \lambda \mathbf{I} \right)^{-1} \mathbf{J}^T \epsilon_p$$

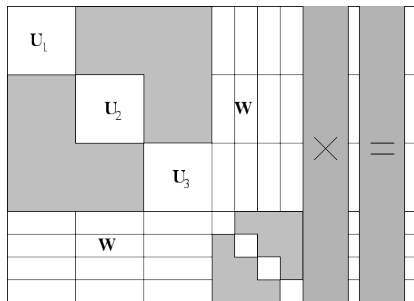
- Parameters to be tuned:
  - camera parameters
  - spatial coordinates
- E.g. for 20 perspective cameras and 1000 3D points:  
 $20 \cdot 11 + 3 \cdot 1000 = 3220$  parameters have to be estimated
  - Dimension of  $\mathbf{J}^T \mathbf{J}$  is  $3220 \times 3220$ .
  - Matrix inversion requires very high time demand.
  - Numerical stability of inversion is questionable

# Jacobian matrix



Jacobian matrix

# Jacobian matrix



Normal equation

# Bundle adjustment: normal equation

- Normal equation can be written by block of matrices:

$$\begin{bmatrix} \mathbf{U} & \mathbf{X} \\ \mathbf{X}^T & \mathbf{V} \end{bmatrix} \begin{bmatrix} \Delta \mathbf{m} \\ \Delta \mathbf{s} \end{bmatrix} = \begin{bmatrix} \epsilon_{\mathbf{m}} \\ \epsilon_{\mathbf{s}} \end{bmatrix}$$

- If normal equation is multiplied by  $\begin{bmatrix} \mathbf{I} & -\mathbf{XV}^{-1} \\ \mathbf{0} & \mathbf{I} \end{bmatrix}$ , from the left, normal equation is modified as follows:

$$\begin{bmatrix} \mathbf{U} - \mathbf{XV}^T\mathbf{X}^T & \mathbf{0} \\ \mathbf{X}^T & \mathbf{V} \end{bmatrix} \begin{bmatrix} \Delta \mathbf{m} \\ \Delta \mathbf{s} \end{bmatrix} = \begin{bmatrix} \epsilon_{\mathbf{m}} - \mathbf{XV}^{-1}\epsilon_{\mathbf{s}} \\ \epsilon_{\mathbf{s}} \end{bmatrix}$$

# Bundle adjustment: solution for normal equation

- Solution:

$$\Delta \mathbf{m} = \left( \mathbf{U} - \mathbf{XV}^T \mathbf{X}^T \right)^{-1} \left( \epsilon_{\mathbf{m}} - \mathbf{XV}^{-1} \epsilon_{\mathbf{s}} \right)$$

$$\Delta \mathbf{s} = \mathbf{V}^{-1} \left( \epsilon_{\mathbf{s}} - \mathbf{X}^T \Delta \mathbf{m} \right)$$

- Inversion required:

- $\mathbf{V}$ :

- It contains small block matrices, they are inverted separately:

- $\left( \mathbf{U} - \mathbf{XV}^{-1} \mathbf{X}^T \right)^{-1}$

- Its size is relatively small.
- Is is also a special matrix, sub-blocks can be formed.

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# Reconstruction with missing data

- Missing data is not a problem for stereo vision
  - If a feature point visible only in one image, it cannot be reconstructed.
- Bundle adjustment can cope with missing data
  - Matrices  $\mathbf{U}_i$  and  $\mathbf{V}_j$  are calculated from less points.
- Tomasi-Kanade factorization requires modification.

# Outline: Calibration of weak-perspective camera

- Problem in algebraic form:

$$\begin{bmatrix} u_1 & \dots & u_P \\ v_1 & \dots & v_P \end{bmatrix} = [\mathbf{M}|\mathbf{b}] \begin{bmatrix} \mathbf{X}_1 & \dots & \mathbf{X}_P \\ 1 & \dots & 1 \end{bmatrix} \quad (3)$$

- where  $\mathbf{M} = q\hat{\mathbf{R}}$  and
  - $\hat{\mathbf{R}}$  consists of the first two rows of matrix  $\mathbf{R}$
- Camera parameters are unknown, task is a minimization:

$$\arg \min_{q, \hat{\mathbf{R}}, \mathbf{b}} \sum_j \left\| \begin{bmatrix} u_j \\ v_j \end{bmatrix} - [q\hat{\mathbf{R}}|\mathbf{b}] \begin{bmatrix} \mathbf{X}_j \\ 1 \end{bmatrix} \right\|_2^2 \quad (4)$$

- This is almost a point registration problem
  - On the left side, only two coordinates are written, not three.



# Outline: Calibration of weak-perspective camera

- Trick: left side is extended to have three dimensions
  - Two rows of  $\hat{\mathbf{R}}$  can be extended by the third coordinate: if  $\mathbf{r}_1^T$  and  $\mathbf{r}_2^T$  denote the two rows, the third one can be obtained by cross product:
 
$$\mathbf{r}_3^T = \mathbf{r}_1^T \times \mathbf{r}_2^T \quad (5)$$
  - Third coordinate of vector  $\mathbf{b}$  is selected to be zero.
  - Third coordinate of left side:  $w_i = q\mathbf{r}_3^T \mathbf{X}_i$
- Registration and completion repeated one after the other, until convergence.
- It can be proved that global optimum is reached.

# Tomasi-Kanade factorization

- Weak-perspective factorization is written as

$$\mathbf{W} = \mathbf{MS} \quad (6)$$

→ if the center of gravity is the origin.

- Factorization for arbitrary origin:

$$\mathbf{W} = \left[ \begin{array}{c|c} \mathbf{M}_1 & \mathbf{b}_1 \\ \vdots & \vdots \\ \mathbf{M}_F & \mathbf{b}_F \end{array} \right] \left[ \begin{array}{ccc} \mathbf{X}_1 & \cdots & \mathbf{X}_P \\ 1 & \cdot & 1 \end{array} \right] = [\mathbf{M}|\mathbf{b}] \left[ \begin{array}{ccc} \mathbf{X}_1 & \cdots & \mathbf{X}_P \\ 1 & \cdot & 1 \end{array} \right] \quad (7)$$

- 4-rank problem. It can be solved by an alternation:
  - Estimation of camera parameters: M-step
  - Estimation of 3D coordinates : S-step
  - Additional step (completion): extend 2D projected coordinates into 3D
  - All steps can be computed optimally.

# Tomasi-Kanade factorization: S-step

- For a spatial point, the following equation can be written for  $j$ -th frame:

$$\begin{bmatrix} u_{ij} \\ v_{ij} \\ w_{ij} \end{bmatrix} = [ \mathbf{M}_j \mid \mathbf{b}_j ] \begin{bmatrix} \mathbf{X}_i \\ 1 \end{bmatrix} = \mathbf{M}_j \mathbf{X}_i + \mathbf{b}_j \quad (8)$$

- Problem is linear, inhomogeneous,  $\mathbf{X}_i$  can be estimated by camera matrices:

$$\mathbf{X}_i = \left( \mathbf{M}^T \mathbf{M} \right)^{-1} \mathbf{M}^T (\mathbf{W}_i - \mathbf{b}) \quad (9)$$

- where  $\mathbf{W}_i$  is the  $i$ -th column of measurement matrix  $\mathbf{W}$ .
- Missing data: if a point is not visible in a frame, the corresponding camera matrix is discarded.

# Tomasi-Kanade factorization: M-step

- Estimation of motion matrix is a point registration problem:

$$\begin{bmatrix} u_{ij} \\ v_{ij} \\ w_{ij} \end{bmatrix} = \mathbf{M}_j \mathbf{X}_i + \mathbf{b}_j = q_j \mathbf{R}_j \mathbf{X}_i + \mathbf{b}_j \quad (10)$$

- Offset vector is denoted by  $\mathbf{b}_j$
- Rotation:  $\mathbf{R}_j$
- Scale:  $q_j$
- Missing data: if a point is not visible in a frame, the corresponding 3D coordinate vector is discarded.

# Tomasi-Kanade factorization: completion step

- Third coordinates in measurement matrix have to be recomputed
  - for all frames,
  - for all points,
  - after all steps.

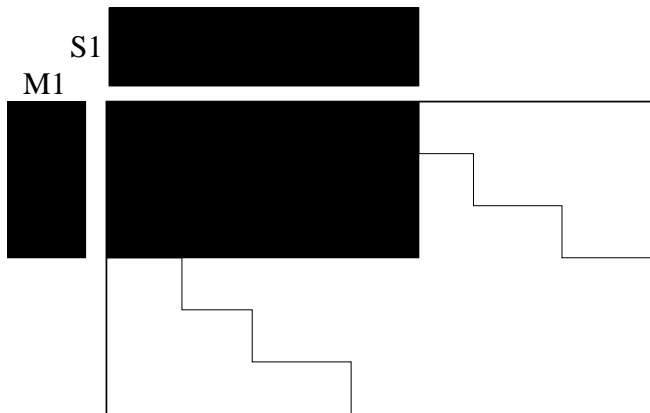
# Tomasi-Kanade factorization with missing data

- 1 Initial motion and 3D parameters are obtained by
  - merging full Tomasi-Kanade factorization, and
  - the third coordinates given by completion-steps.
- 2 Alternation until convergence:
  - M-step: camera matrix estimation as a 3D-3D point-registration
  - Third coordinates recomputed by completion step
  - 3D coordinates obtained by S-step (linear estimation)
  - Third coordinates recomputed by completion step
- All steps decrease the same least-squares cost function  $\rightarrow$  convergence guaranteed.
  - Unfortunately, local minima can occur.

# Tomasi-Kanade factorization: initialization

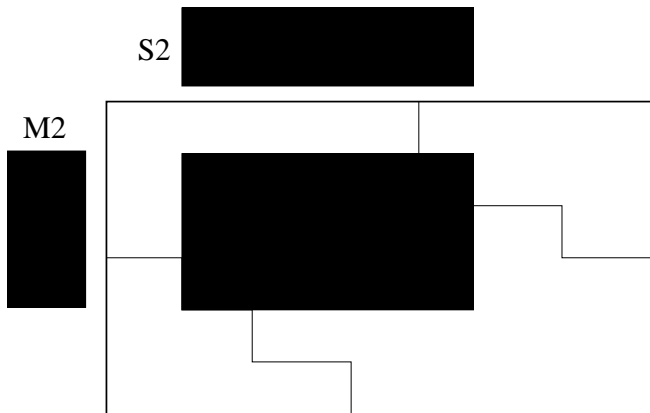
- Mergin full sub-factorization
  - At least 3 images required for a weak-perspective full factorization.
  - Frames 1–3, 2–4, 3–5, etc. have to be processed
- Factorization is carried out for frame-triplets
- Results are merged.

## Tomasi-Kanade factorization: partial reconstructions

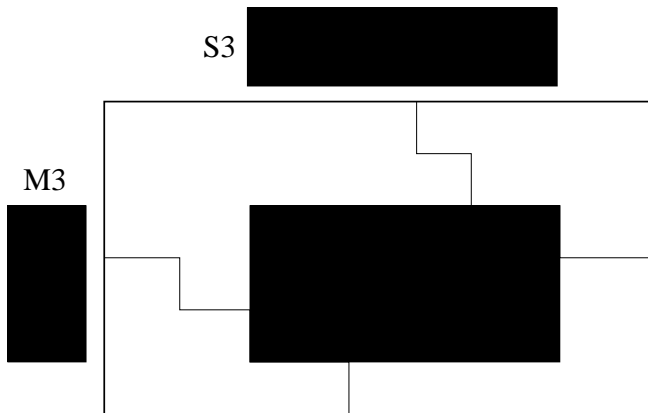




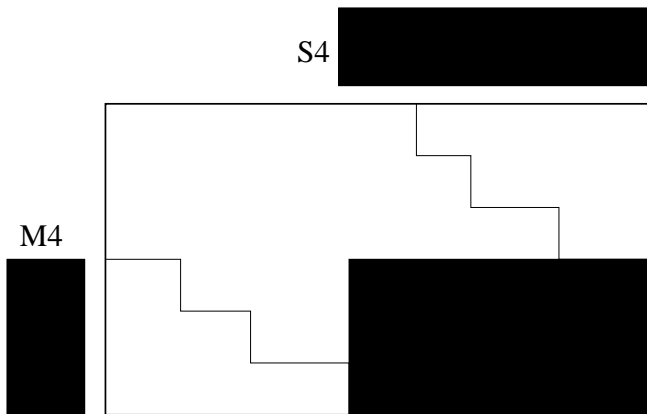
## Tomasi-Kanade factorization: partial reconstructions



## Tomasi-Kanade factorization: partial reconstructions



## Tomasi-Kanade factorization: partial reconstructions



# Tomasi-Kanade factorization: initialization

- Concatenation of subfactorizations is not trivial.
- Let us assume that two factorizations are computed
  - Scalar  $q_j$ , matrices  $\mathbf{R}_j$ ,  $\mathbf{S}_j$ , and vector  $\mathbf{b}_j$  known for  $j$ -th image,
  - as well as  $q_{j+1}$ ,  $\mathbf{R}_{j+1}$ ,  $\mathbf{b}_{j+1}$ , and  $\mathbf{S}_{j+1}$  for  $(j + 1)$ -th frame.
- Concatenation of 3D point clouds is a point registration problem
  - Obtained parameters after point registration: rotation  $\mathbf{R}$ , scale  $q$ , and offset  $\mathbf{t}$ .
  - The the registraton for the  $i$ -th point:

$$\mathbf{s}'_i = q\mathbf{R}(\mathbf{s}_i - \mathbf{o}_1) + \mathbf{o}_2 \quad (11)$$

- Concatenation of motion matrices
  - $\mathbf{M}_{j+1} \leftarrow \frac{1}{q}\mathbf{M}_{j+1}\mathbf{R}^T$
  - $\mathbf{b}_{j+1} \leftarrow \mathbf{b}_{j+1} + q\mathbf{M}_{j+1}\mathbf{R}\mathbf{o}_1 - \mathbf{M}_{j+1}\mathbf{o}_2$