

## Plane + Parallax, Tensors & Factorization

**Bill Triggs**

INRIA Rhône-Alpes  
Grenoble, France

<http://www.inrialpes.fr/movi/people/Triggs>

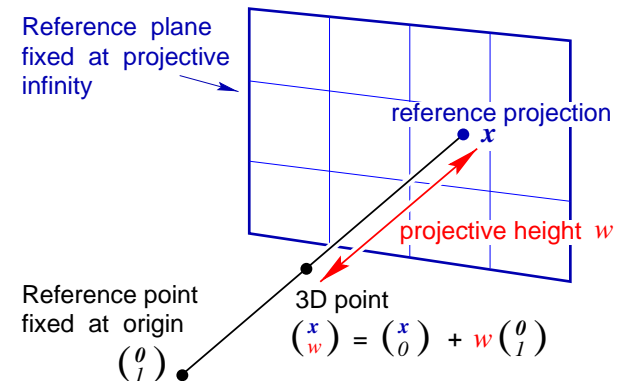
### Topics

- 1 Plane + parallax representation
- 2 Matching tensors in plane + parallax
- 3 Projective reconstruction by camera centre / projective height factorization.

## Plane + Parallax

- The effective orientation and calibration of a camera can be changed arbitrarily by image warping.
- As warping changes nothing in 3D, the intrinsic properties (singularities, *etc.*) of visual reconstruction and matching geometry must be independent of orientation and calibration
  - *i.e.* they depend *only* on the camera centres.
- To make this explicit, “fixate” a given 3D **reference plane**, warping all images so that the plane’s image is fixed.
  - this greatly simplifies 3D and matching tensor calculations
  - residual parallax displacements relative to the plane are often small, so feature detection and image processing are easier too.

## ‘Reference Plane at Infinity’ Coordinates



- This fixes 3D projective coordinates up to scale.
- Reference projection + height representation for 3D points:  $X = \begin{pmatrix} x \\ w \end{pmatrix}$ 
  - $w$  depends on normalization for  $x$ .

## Plane Aligned Cameras

- Plane-aligned cameras are parametrized by their projection centres:

$$P_i \simeq (I_{3 \times 3} \mid -c_i) \quad \text{with centre of projection} \quad \begin{pmatrix} c_i \\ 1 \end{pmatrix}$$

- $c_i$  is the displacement of camera from the origin.

**Plane aligned camera geometry is projectively equivalent to translating calibrated cameras**

- This simplifies many formulae and helps intuition!

## Point Projection and Parallax

- Each 3D point projects to its reference image, plus a **parallax** term:

$$\lambda_{ip} \mathbf{x}_{ip} = \mathbf{P}_i \begin{pmatrix} \mathbf{x}_p \\ w_p \end{pmatrix} = \mathbf{x}_p - w_p \mathbf{c}_i$$

- $\lambda_{ip}$  is a '**projective depth**' of  $\mathbf{x}_{ip}$  — an unknown homogeneous scale factor.
- Bilinearity**:  $(\text{parallax})_{ip} = (\text{height } w_p) (\text{camera displacement } \mathbf{c}_i)$   
— this suggests a **factorization based reconstruction** method  
— but first we must recover the missing depths  $\lambda_{ip}$ .
- Similarly, for the parallax between two cameras:

$$\lambda_{ip} \mathbf{x}_{ip} - \lambda_{jp} \mathbf{x}_{jp} = -w_p \mathbf{c}_{ij} \quad \mathbf{c}_{ij} \equiv \mathbf{c}_i - \mathbf{c}_j$$

## Matching Tensors & Their Relations

### Matching tensors $T$

- Quartic functions of  $\mathbf{P}$ 's, obtained by eliminating their 3D dependencies.

### Matching constraints

- Multilinear consistency relations between  $T$ 's and unscaled image features.

### Depth recovery relations

- Bilinear consistency relations between  $T$ 's and *coherently scaled* image features.

### Closure relations

- Bilinear consistency relations between  $T$ 's and  $\mathbf{P}$ 's.

### Grassmann relations

- Bilinear consistency relations on  $T$ 's.

## Matching Tensors in Plane + Parallax

- For aligned projections, the matching tensors and their relations reduce to *very simple* functions of the relative camera positions  $\mathbf{c}_{ij} \equiv \mathbf{c}_i - \mathbf{c}_j$ :

$$\begin{aligned} \mathbf{e}_{ij} &\simeq \mathbf{c}_{ij} && \text{epipole of c.o.p. } i \text{ in image } j \\ \mathbf{F}_{ij} &\simeq [\mathbf{c}_{ij}]_{\times} && \text{fundamental matrix} \\ \mathbf{T}_i^{jk} &\simeq \mathbf{I}_i^j \otimes \mathbf{c}_{ik} - \mathbf{c}_{ij} \otimes \mathbf{I}_i^k && \text{trifocal tensor} \\ \mathbf{Q}^{A_1 A_2 A_3 A_4} &\simeq \sum_{i=1}^3 (-1)^{i-1} \epsilon^{A_1 \dots \hat{A}_i \dots A_4} \cdot \mathbf{c}_{i4}^{A_i} && \text{quadrifocal tensor} \end{aligned}$$

- These have simple geometric interpretations, e.g.  $\mathbf{e}_{ij}$  is the intersection of the ray from  $\mathbf{c}_j$  to  $\mathbf{c}_i$  with the reference plane.
- The tensors have coherent, meaningful relative scalings given by the RHS.

## Matching Constraints in Plane + Parallax

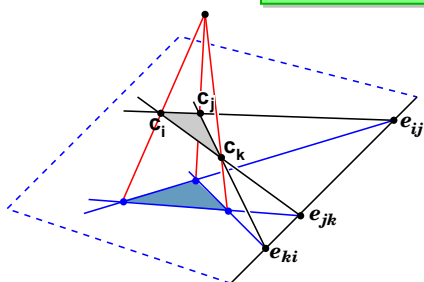
- Under plane alignment, the first few matching relations reduce to:

$$\begin{aligned} [\mathbf{x}_i, \mathbf{e}_{ij}, \mathbf{x}_j] &= 0 && \text{epipolar point} \\ (\mathbf{x}_i \wedge \mathbf{x}_j) (\mathbf{e}_{ik} \wedge \mathbf{x}_k)^\top - (\mathbf{e}_{ij} \wedge \mathbf{x}_j) (\mathbf{x}_i \wedge \mathbf{x}_k)^\top &= \mathbf{0} && \text{trifocal point} \\ (\mathbf{l}_i \wedge \mathbf{l}_j) (\mathbf{l}_k \cdot \mathbf{e}_{ik}) - (\mathbf{l}_j \cdot \mathbf{e}_{ij}) (\mathbf{l}_i \wedge \mathbf{l}_k) &= \mathbf{0} && \text{trifocal line} \end{aligned}$$

- The trifocal point constraint contains two epipolar constraints, and also a proportionality-of-parallax relation.

## Epipole Alignment and Desargues Configurations

- Cyclic sums of camera displacements vanish:  $\mathbf{c}_{ij} + \mathbf{c}_{jk} + \dots + \mathbf{c}_{mi} = \mathbf{0}$
- Given epipoles  $\mathbf{e}_{ij}$ , this can be used to reconstruct the  $\mathbf{c}_{ij}$ , i.e. to recover coherent scale factors.
- Circular triplets of epipoles are aligned:  $[\mathbf{e}_{ij}, \mathbf{e}_{jk}, \mathbf{e}_{ki}] = 0$



- It is *much easier* to work with the elementary 3-vector geometry of the  $\mathbf{c}$ 's than the Desargues geometry of the  $\mathbf{e}$ 's.

## Projective SFM by Matrix Factorization

- Gather the homogeneous image projections  $\lambda_{ip} \mathbf{x}_{ip} = \mathbf{P}_i \mathbf{X}_p$  of  $m$  general projective cameras  $\mathbf{P}_i$  viewing  $n$  3D points  $\mathbf{X}_p$  into a big matrix:

$$\begin{pmatrix} \lambda_{11} \mathbf{x}_{11} & \dots & \lambda_{1n} \mathbf{x}_{1n} \\ \vdots & \ddots & \vdots \\ \lambda_{m1} \mathbf{x}_{m1} & \dots & \lambda_{mn} \mathbf{x}_{mn} \end{pmatrix} = \begin{pmatrix} \mathbf{P}_1 \\ \vdots \\ \mathbf{P}_m \end{pmatrix} (\mathbf{X}_1 \dots \mathbf{X}_n)$$

- Any self-consistent set of projective depths  $\lambda$  contains an implicit projective reconstruction ("Joint image" viewpoint).
- SVD based **rank 4 matrix factorization** consolidates this and makes it explicit.

## Finding the Projective Depths

- To find the depths  $\lambda$  we use matching tensor based **depth recovery relations**:

$$\begin{aligned} \mathbf{F}_{ij} (\lambda_j \mathbf{x}_j) + \mathbf{e}_{ji} \wedge (\lambda_i \mathbf{x}_i) &= \mathbf{0} && \text{epipolar} \\ \mathbf{T}_i^{jk} (\lambda_i \mathbf{x}_i) - (\lambda_j \mathbf{x}_j) (\mathbf{e}_{ik})^\top + \mathbf{e}_{ij} (\lambda_k \mathbf{x}_k)^\top &= \mathbf{0} && \text{trifocal} \end{aligned}$$

- The matching tensors are estimated from the image correspondences as usual.

## Plane Aligned Depth Recovery Relations

- Under reference plane alignment, the depth recovery relations become:

$$\begin{aligned} \mathbf{e}_{ij} \wedge (\lambda_i \mathbf{x}_i - \lambda_j \mathbf{x}_j) &= \mathbf{0} && \text{epipolar} \\ \mathbf{e}_{ij} (\lambda_k \mathbf{x}_k - \lambda_i \mathbf{x}_i)^\top - (\lambda_j \mathbf{x}_j - \lambda_i \mathbf{x}_i) (\mathbf{e}_{ik})^\top &= \mathbf{0} && \text{trifocal} \end{aligned}$$

- These follow immediately from the relative parallax  $\lambda_i \mathbf{x}_i - \lambda_j \mathbf{x}_j = -w \mathbf{c}_{ij}$  and  $\mathbf{e}_{ij} \simeq \mathbf{c}_{ij}$ .
- The trifocal relations contain two epipolar ones, plus an additional relative scale constraint.

## Height / Camera Centre Factorization

- Plane alignment allows projective SFM factorization to be simplified.
- Rank 4 (projection) · (structure) factorization becomes Rank 1 (camera centre) · (height) factorization.

### Inputs

- Feature correspondences under plane + parallax alignment.
- Estimates of the epipoles for projective depth recovery.

### Output

- Projective 3D structure and camera centres, in a heuristic ‘average of camera centres’ frame.

## Algorithm

1 Find self-consistent projective depths  $\lambda_{ip}$  using epipolar or trifocal P+P depth recovery — as in the rank 4 method, a network of depth recovery relations are chained together.

2 Rescale the homogeneous image points:  $\mathbf{x}_{ip} \leftarrow \lambda_{ip} \mathbf{x}_{ip}$

3 Centre the rescaled data:  $\delta \mathbf{x}_{ip} \equiv \mathbf{x}_{ip} - \bar{\mathbf{x}}_p$  where  $\bar{\mathbf{x}}_p \equiv \frac{1}{m} \sum_{i=1}^m \mathbf{x}_{ip}$

4 Factorize to rank 1 to give the projection centres and heights:

$$\begin{pmatrix} \delta \mathbf{x}_{11} & \dots & \delta \mathbf{x}_{1n} \\ \vdots & \ddots & \vdots \\ \delta \mathbf{x}_{m1} & \dots & \delta \mathbf{x}_{mn} \end{pmatrix} \approx \begin{pmatrix} -\mathbf{c}_1 \\ \vdots \\ -\mathbf{c}_m \end{pmatrix} \begin{pmatrix} w_1 & \dots & w_n \end{pmatrix}$$

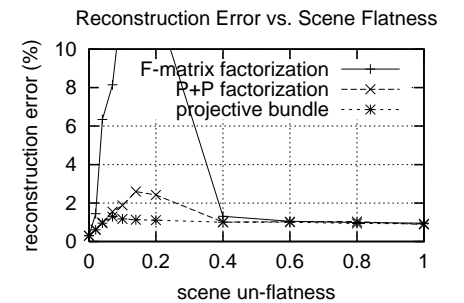
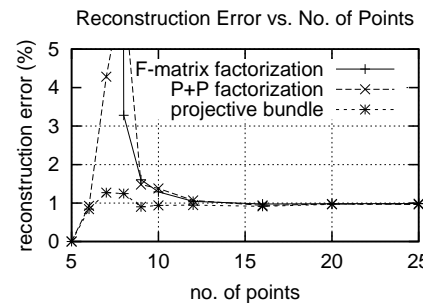
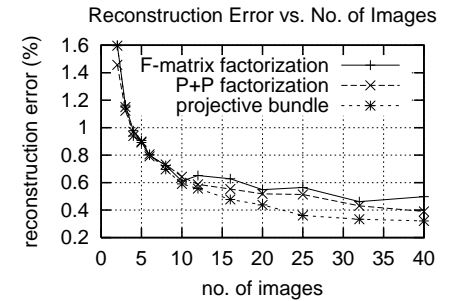
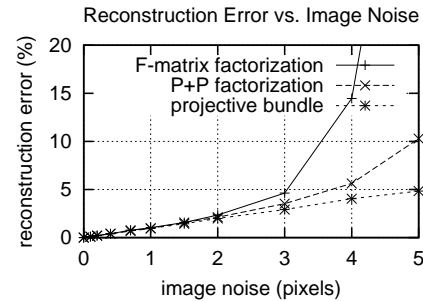
5 The final reconstruction is:  $\mathbf{P}_i = (\mathbf{I} | -\mathbf{c}_i)$  and  $\mathbf{X}_p = \begin{pmatrix} \bar{\mathbf{x}}_p \\ w_p \end{pmatrix}$

## Rationale

- For noiseless data, the parallax equations  $\lambda_{ip} \mathbf{x}_{ip} = \mathbf{x}_p - w_p \mathbf{c}_i$  give:

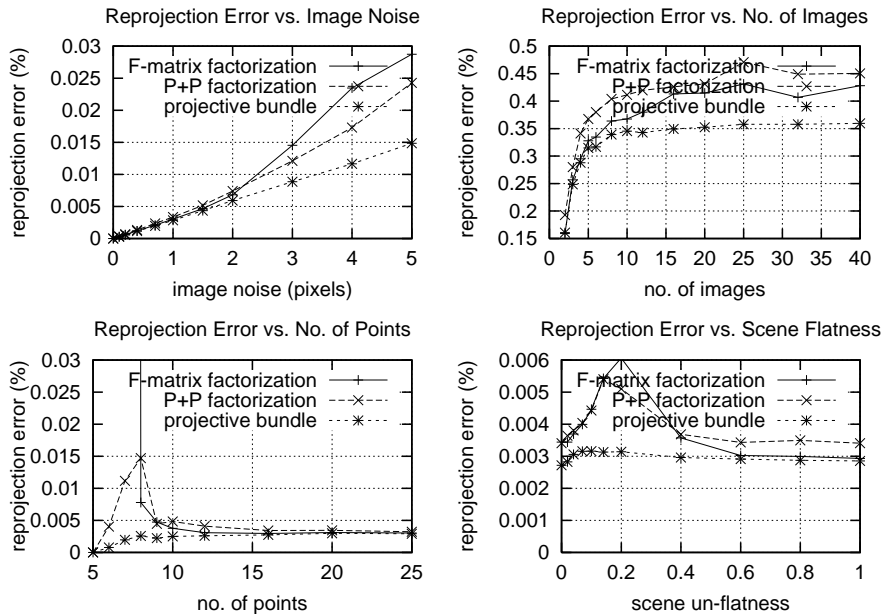
$$\begin{aligned} \bar{\mathbf{x}}_p &\equiv \frac{1}{m} \sum_{i=1}^m \mathbf{x}_{ip} \longrightarrow \mathbf{x}_p - w_p \bar{\mathbf{c}} & \bar{\mathbf{c}} &\equiv \frac{1}{m} \sum_{i=1}^m \mathbf{c}_i \\ \delta \mathbf{x}_{ip} &\equiv \mathbf{x}_{ip} - \bar{\mathbf{x}}_p \longrightarrow w_p \delta \mathbf{c}_i & \delta \mathbf{c}_i &\equiv \mathbf{c}_i - \bar{\mathbf{c}} \end{aligned}$$

- $\bar{\mathbf{c}}$  is the same for all points and amounts to a change of origin.
- We can fix the origin freely, so we choose  $\bar{\mathbf{c}} = \mathbf{0}$ .



## Summary

- 1 Plane + parallax greatly simplifies matching tensor geometry and reconstruction.
- 2 Rather than working with epipole based Desargues constructions, it is easier to recover scale factors  $e_{ij} \rightarrow c_{ij}$  and use explicit 3-vector geometry.
- 3 Plane + parallax factorization looks promising, especially for near-planar scenes.



## Extensions

- Other 3D features including lines and planes have simple plane + parallax representations.
- Both lines and planes can be added to the plane + parallax factorization
  - for lines take via points
  - for planes take homographies and treat their columns as point triplets.
- In both cases, the correct projective depths (homogeneous scalings) can be found by natural depth recovery methods.