The Chow form of the essential variety in computer vision

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Algebraic vision

Multiview geometry studies 3D scene reconstruction from images. Foundations in projective geometry. *Algebraic vision* bridges to algebraic geometry (combinatorial, computational, numerical, ...).



Oct 8-9, 2015, Berlin



May 2-6, 2016, San Jose

Example from Building Rome in a Day (2009) by S. Agarwal et al.

Input: 2106 Flickr images tagged "Colosseum"

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Output: configuration of cameras and 819,242 3D points



Over-simplification:

- Build a graph whose nodes are the images. Put an edge between two images if their views likely overlap.
- Do robust 2-view reconstruction along edges, with point pairs.

• Piece together. Refine estimate with nonlinear least squares.

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Moral: 'Tiny' reconstructions are subroutines in large-scale reconstructions. The 'tiny' reconstructions rely on super-fast, specialized polynomial equation solvers.

What is a camera?

A camera is a full rank 3×4 real matrix A. Determines a projection $\mathbb{P}^3 \dashrightarrow \mathbb{P}^2$; $\widetilde{X} \mapsto A\widetilde{X}$.

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| Math | Interpretation |
|----------------|-----------------------|
| \mathbb{P}^3 | world |
| \mathbb{P}^2 | image plane |
| $\ker(A)$ | camera center |
| K | internal parameters |
| | (e.g. focal length) |
| $[R \mid t]$ | external parameters |
| | (orientation, center) |

Above $A_{3\times4} =: K_{3\times3} [R_{3\times3} | t_{3\times1}]$ where K is upper triangular and R is a rotation. If K = I, so A = [R | t], then A is **calibrated**.

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 $A \text{ is calibrated } \iff \begin{pmatrix} A \text{ sends the conic } \{ (a:b:c:0) \mid a^2 + b^2 + c^2 = 0 \} \subset \mathbb{P}^3 \\ \text{ to the conic } \{ (a:b:c) \mid a^2 + b^2 + c^2 = 0 \} \subset \mathbb{P}^2 \end{pmatrix}$

Question (S. Agarwal et al. 2014)

Let m = 6. Given point pairs $\{(x^{(i)}, y^{(i)}) \in \mathbb{R}^2 \times \mathbb{R}^2 | i = 1, ..., m\}$. Consider the system of equations:

$$\begin{cases} A\widetilde{X^{(i)}} \equiv \widetilde{x^{(i)}} \\ B\widetilde{X^{(i)}} \equiv \widetilde{y^{(i)}}. \end{cases}$$
(1)

Here $\widetilde{x^{(i)}} = (x_1^{(i)} : x_2^{(i)} : 1)^T \in \mathbb{P}^2$ and $\widetilde{y^{(i)}} = (y_1^{(i)} : y_2^{(i)} : 1)^T \in \mathbb{P}^2$. The unknowns are two 3×4 matrices A, B with rotations in their left 3×3 block and m = 6 points $\widetilde{X^{(i)}} \in \mathbb{P}^3$. When does (1) admit a solution?

- Interpretation: characterize those m = 6 point pairs between two calibrated images that are mutually consistent.
- When m = 5, the system admits 10 complex solutions. Solvers for this are used in large-scale reconstructions.
- When m = 6, generically no exact solution. If there is a solution, then generically it is unique up to the natural symmetries.

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Recall m = 6, RHS given, LHS unknown with A, B calibrated:

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Theorem (Fløystad, K., Ottaviani 2016)

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There exists an explicit 20×20 skew-symmetric matrix M(x, y) of degree (6, 6) polynomials over \mathbb{Z} in the coordinates of $(x^{(i)}, y^{(i)})$ such that, for generic point correspondences, (1) admits a complex solution if and only if $M(x^{(i)}, y^{(i)})$ is rank-deficient.

Here's that matrix...

R =

$$\begin{split} & (0) = (1,1,2,1), q_1(1,1,2,2), q_2(1,1,2,2), q_2(1,1,2,3), q_2(1,1,2,3), q_2(1,1,2,3), q_2(1,1,3,3), q_2(1,1,3,2), q_2(1,1,3,2), q_2(1,1,3,3), q_1(1,1,3,3), q_1(1,$$

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What about noisy image point pairs?

Practical Question

While the matrix M(x, y) drops rank when there is an exact solution to (1), how can we tell if there is an approximate solution?

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Answer

Calculate the Singular Value Decomposition of M(x, y) when a noisy six-tuple of image point correspondences is plugged in. Look for a big **spectral gap** between smallest singular values.



Essential matrices

Definition

Given two calibrated cameras A, B. Consider the linear map:

$$\mathbb{P}^2 \dashrightarrow \mathsf{Gr}(\mathbb{P}^1, \mathbb{P}^3) \dashrightarrow (\mathbb{P}^2)^{\vee}$$

$$\widetilde{x} \mapsto A^{-1}(\widetilde{x}) \mapsto B(A^{-1}(\widetilde{x})).$$

Here the first map takes preimage. Let $E_{A,B}$ be the 3×3 real matrix representing the composite with respect to standard bases. Then $E_{A,B}$ is called an essential matrix. It represents the relative pose of A and B.

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Facts

- Let $\widetilde{x}, \widetilde{y} \in \mathbb{P}^2$. Then there exists $\widetilde{X} \in \mathbb{P}^3$ such that $A\widetilde{X} \equiv \widetilde{x}$ and $B\widetilde{X} \equiv \widetilde{y}$ if and only if $\widetilde{y}^T E_{A,B} \widetilde{x} = 0$.
- The singular values of $E_{A,B}$ satisfy $\sigma_1 = \sigma_2$ and $\sigma_3 = 0$.

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Definition/Proposition

Let $\mathcal{E} := \{E \in \mathbb{R}^{3 \times 3} : \sigma_1(E) = \sigma_2(E), \sigma_3 = 0\}$. Then the real radical ideal is $\mathcal{E} = \{E \in \mathbb{R}^{3 \times 3} : \det(E) = 0, 2(EE^T)E - \operatorname{tr}(EE^T)E = 0\}$. Let $\mathcal{E}_{\mathbb{C}} \subset \mathbb{P}^8_{\mathbb{C}}$ be the set of complex solutions, called the essential variety. Dim 5, degree 10.

Seformulate: want the Chow form of E_C. Degree 10 equation in Plücker coordinates for the divisor {L ∈ Gr(P², P⁸) | L ∩ E_C ≠ ∅} ⊂ Gr(P², P⁸).

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- Reformulate: want the Chow form of *E*_C. Degree 10 equation in Plücker coordinates for the divisor {*L* ∈ Gr(P², P⁸) | *L* ∩ *E*_C ≠ ∅} ⊂ Gr(P², P⁸).
- **3** New geometric description: we prove that the singular locus of $\mathcal{E}_{\mathbb{C}}$ is the surface $\text{Sing}(\mathcal{E}_{\mathbb{C}}) = \{ab^T \in \mathbb{P}^8 \mid a^T a = b^T b = 0\}$. Also, the line secant variety of the singular locus equals $\mathcal{E}_{\mathbb{C}}$, i.e. $\sigma_2(\text{Sing}(\mathcal{E}_{\mathbb{C}})) = \mathcal{E}_{\mathbb{C}}$.

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- **3** Easier equations: we deduce that $\mathcal{E}_{\mathbb{C}}$ is a hyperplane section of the projective variety $PX_{4,2}^s$ of rank ≤ 2 symmetric 4×4 matrices.
- **3** Eisenbud-Schreyer theory: we construct a rank 2 Ulrich sheaf on $PX_{4,2}^s$. This means the corresponding graded module is Cohen-Macaulay with a linear minimal free resolution. Here it is GL(4)-equivariant and self-dual:



Through the Bernstein-Gel'fand-Gel'fand correspondence, the product of the differential matrices over the **exterior algebra** gives a Pfaffian formula for the Chow form of $PX_{4,2}^s$. For $\mathcal{E}_{\mathbb{C}}$, we restrict to the hyperplane. \Box

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References

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Thank you!

Joe Kileel (Berkeley) The Chow form of the essential variety in computer vision

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