

Multiple -View Imaging in GRAIN

P. Bernardini, R. Cataldo, G. De Matteis, A. Leaci, L. Martina,
A . Surdo

Università del Salento, Dipartimento di Matematica e Fisica " Ennio De Giorgi"
Sezione INFN, Lecce, Italy



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Outline

1 Single View Geometry

2 Multiple View

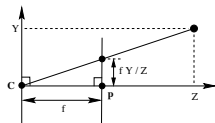
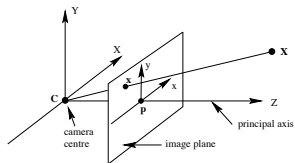


Coded masks for imaging of neutrino events

M. Andreotti^{1,2}, P. Bernardini^{3,4}, A. Bersani⁵, S. Bertolucci^{6,7}, S. Biagi⁸, A. Branca^{9,10}, C. Brizzolari^{9,10}, G. Brunetti^{9,10}, I. Cagnoli^{6,7}, R. Calabrese¹², A. Caminata⁵, A. Campani^{5,11}, P. Carniti^{9,10}, R. Cataldo⁵, C. Cattadori¹⁰, S. Cherubini⁸, V. Cicero^{6,7}, M. Citterio¹², S. Copello^{5,11}, P. Cova^{12,13}, E. Cristaldo Morales^{9,10}, S. Davini⁵, N. Delmonte^{12,13}, G. De Matteis^{3,4,14}, S. Di Domizio^{3,11}, L. Di Noto^{5,11}, C. Distefano⁸, T. Giammaria^{1,2}, M. Guarise^{1,2}, A. Falcone^{9,10}, F. Ferraro^{5,18}, M. Fiorini^{1,2}, N. Gallice^{15,12}, C. Gotti¹⁰, M. Guerzoni⁷, M. A. Hiescu^{16,a}, G. Ingratta^{6,7}, M. Lazzaroni^{12,15}, I. Lax⁷, G. Laurenti⁷, A. Leaci^{3,4}, E. Luppi^{1,2}, L. Martina^{3,4,b}, N. Mauri^{6,7}, A. Minotti^{1,2,19}, N. Moggi^{6,7}, E. Montagna^{6,7}, A. Montanari⁷, D. Montanino^{3,4}, M. Pallavicini^{5,11}, M. Panareo^{3,4}, E. G. Parozzi^{9,10}, L. Pasqualini^{6,7}, L. Patrizii⁷, G. Pessina¹⁰, F. Poppi^{6,7}, M. Pozzato⁷, V. Pia^{6,7}, S. Riboldi^{12,15}, G. Riccobene⁸, P. Sala¹², P. Sapienza⁸, F. Schifano^{1,2}, G. Sirri⁷, M. Spann^{9,10}, L. Stanco¹⁷, A. Surdo⁴, A. Taibi^{1,2}, M. Tenti⁷, F. Terranova^{9,10}, G. Testera⁸, L. Tomassetti^{1,2}, M. Torti^{9,10}, N. Tosi⁷, R. Travaglini⁷, L. Ubaldi^{12,15,20}, M. Vicenzi^{5,11}, A. Zani¹², S. Zucchelli^{6,7}, (NU@FNAL Collaboration)

¹ Dipartimento di Fisica e Scienze della Terra, Università di Ferrara, via G. Saragat 1, 44122 Ferrara, Italy² Istituto Nazionale di Fisica Nucleare, Sezione di Ferrara, via G. Saragat 1, 44122 Ferrara, Italy³ Dipartimento di Matematica e Fisica “Ennio De Giorgi”, Università del Salento, via per Arnesano, 73100 Lecce, Italy⁴ Istituto Nazionale di Fisica Nucleare, Sezione di Lecce, via per Arnesano, 73100 Lecce, Italy⁵ Dipartimento di Fisica, Università di Genova, via Dodecaneso 33, 16146 Genoa, Italy⁶ Dipartimento di Fisica, Università di Bologna, viale C. Bertini Pichat 6/2, 40127 Bologna, Italy⁷ Istituto Nazionale di Fisica Nucleare, Sezione di Bologna, viale C. Bertini Pichat 6/2, 40127 Bologna, Italy⁸ Istituto Nazionale di Fisica Nucleare, Laboratori Nazionali del Sud, via S. Sofia 62, 95125 Catania, Italy⁹ Università di Milano-Bicocca, Piazza della Scienza 3, 20126 Milan, Italy¹⁰ Istituto Nazionale Fisica Nucleare, Sezione di Milano-Bicocca, Piazza della Scienza 3, 20126 Milan, Italy¹¹ Istituto Nazionale Fisica Nucleare, Sezione di Genova, via Dodecaneso 33, 16146 Genoa, Italy¹² Istituto Nazionale Fisica Nucleare, Sezione di Milano, via Celoria 16, 20133 Milan, Italy¹³ Dipartimento di Ingegneria, Università di Parma, Parco Area delle Scienze 181/A, 43124 Parma, Italy¹⁴ GNFM-INDAM, Città Universitaria, piazzale Aldo Moro 5, 00185 Rome, Italy¹⁵ Dipartimento di Fisica, Università di Milano, via Celoria 16, 20133 Milan, Italy¹⁶ Istituto Nazionale Fisica Nucleare, Laboratori Nazionali di Frascati, via E. Fermi 54, 00044 Frascati, Italy¹⁷ Istituto Nazionale Fisica Nucleare, Sezione di Padova, Padua, Italy¹⁸ F. Ferraro: Present Address: Dipartimento di Fisica, Università di Milano, Milan, Italy¹⁹ A. Minotti: Present Address: Dipartimento di Fisica, Università di Milano-Bicocca, Milan, Italy²⁰ L. Ubaldi: Present Address: CERN, Geneva, Switzerland

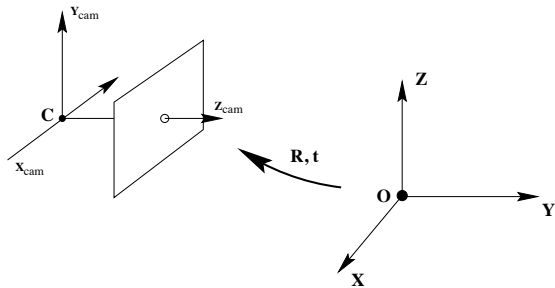
3D to 2D camera projection



Camera Model $\mathbf{x} = P \mathbf{X}$, $\mathbf{X} \in \mathbb{P}^3 \rightarrow \mathbf{x} \in \mathbb{P}^2$

$$P = \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ p_{21} & p_{22} & p_{23} & p_{24} \\ p_{31} & p_{32} & p_{33} & p_{34} \end{bmatrix} = \begin{bmatrix} \mathbf{P}^{1T} \\ \mathbf{P}^{2T} \\ \mathbf{P}^{3T} \end{bmatrix}$$

Camera projection matrix



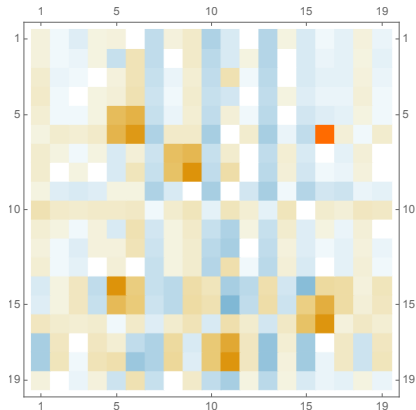
$$P = K [R | \mathbf{t}], \quad \lambda \mathbf{x} = P\mathbf{X}, \quad \forall \lambda \in \mathbb{R}/_0$$

$$R \in SO(3) \text{ and } \mathbb{R}^3 \ni \mathbf{t} = -R\mathbf{c} : \quad P\mathbf{C} = P \begin{pmatrix} \mathbf{c} \\ 1 \end{pmatrix} = 0$$

$$\text{Camera calibration matrix} \quad K = \begin{pmatrix} f_x & s & x_0 \\ 0 & f_y & y_0 \\ 0 & 0 & 1 \end{pmatrix}$$

Application to a MURA mask

A 19×19 MURA mask, with parameters
 $a \rightarrow 15, b \rightarrow 1.3637, p_m \rightarrow 0.11, p_d \rightarrow 0.12$ (cm)
6 point-like sources (minimal constraint)



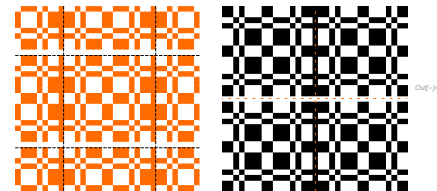
Calibration matrix

$$K = P_{ex}^{1-3} R^{-1} = \begin{pmatrix} 0.281 & 0.223 & 0.236 \\ 0 & 0.560 & -0.402 \\ 0 & 0 & 1 \end{pmatrix}$$

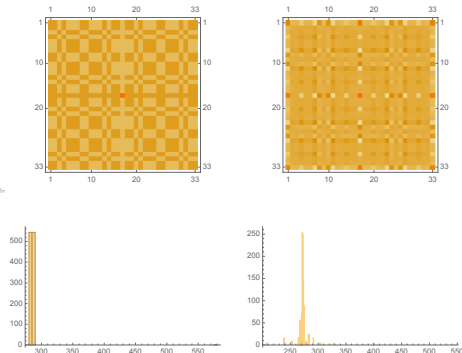
$$R = I_y R_z(0.22) R_y(0.82) R_z(0.12) \quad \mathbf{c} = (0.33, 1.62, 1.10)$$

- In first approximation a Coded Mask is a Projective Camera
- Different focal lengths $f_x \neq f_y$
- $(x_0, y_0) \neq \mathbf{0} \leftrightarrow$ image plane Origin \neq principal point
- Non vanishing skew parameter s
- Rotation relative to the world frame
- Translated camera center

Optimization of the Mosaic Masks



2 × 2 (left) mosaic EVEN side by side and
(right) ODD rotated superimposed 17 × 17 MURA



Autocorrelation function for the EVEN and the
ODD mosaic

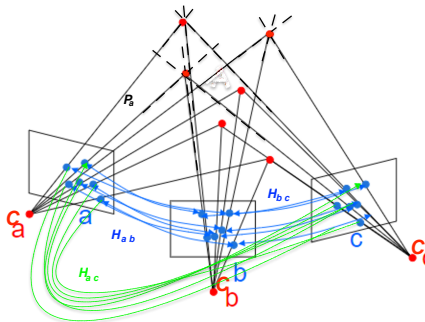
Methods of completing the lost/missed pixels
Valerio Pia thesis

Two - Triple - Many Views

- $P_i : \mathbb{P}^3 \rightarrow \mathbb{P}^2$
- $\lambda_{ij} \mathbf{x}_j = P_i \mathbf{X}_j, \quad \forall \lambda_{ij} \in \mathbb{R}_{/0}$
- $P_i = K_i [R_i | \mathbf{t}_i] \quad P_i \mathbf{C}_i = 0$
- $\mathbf{C}_i = \begin{pmatrix} \mathbf{c}_i \\ 1 \end{pmatrix} = \begin{pmatrix} -R_i^T \mathbf{t}_i \\ 1 \end{pmatrix}$
- Transition f. $H_{ab} : \mathbb{P}^2 \leftrightarrow \mathbb{P}^2$

$$\begin{cases} H_{aa} & = \mathbb{I} \\ H_{ab} H_{ba} & = \mathbb{I} \\ H_{ab} H_{bc} H_{ca} & = \mathbb{I} \end{cases}$$

Cocycle identities



Pseudo-Inverse and Reconstruction formula in double-view

$$P = K [R | \mathbf{t}] \quad \mathbf{x} = P \mathbf{X}$$

$$P^+ = \begin{bmatrix} R^T \\ \mathbf{t}^T \end{bmatrix} \left(\mathbb{I} - \frac{\mathbf{t} \otimes \mathbf{t}}{1 + |\mathbf{t}|^2} \right) K^{-1} = \begin{bmatrix} \mathbb{I} \\ -\mathbf{c}^T \end{bmatrix} \left(\mathbb{I} - \frac{\mathbf{c} \otimes \mathbf{c}}{1 + |\mathbf{c}|^2} \right) R^T K^{-1}$$

$$\Rightarrow \quad \mathbf{X} = P^+ \mathbf{x} + \mu \mathbf{C} \quad \mu \in \mathbb{R}$$

$$\lambda' \mathbf{x}' = P' \mathbf{X} \quad \lambda' \in \mathbb{R}_{/0}$$

$$\mathbf{x}' \wedge \mathbf{x}' = 0 \Rightarrow \mathbf{X} = P^+ \mathbf{x} + \frac{(P' P^+ \mathbf{x} \wedge \mathbf{x}') \cdot (\mathbf{x}' \wedge P' \mathbf{C})}{(\mathbf{x}' \wedge P' \mathbf{C})^2} \mathbf{C}$$

The Projective Reconstruction Theorem

The triplet $(P, P', \{\mathbf{X}_\alpha\}_{\alpha \geq 8})$ is called a 3D reconstruction of the images $\{\mathbf{x}_\alpha\}$ and $\{\mathbf{x}'_\alpha\}$ if it satisfies the relations

$$\lambda_\alpha \mathbf{x}_\alpha = P \mathbf{X}_\alpha, \quad \lambda'_\alpha \mathbf{x}'_\alpha = P' \mathbf{X}_\alpha$$

Th. A 3D reconstruction is unique up to a homography of \mathbb{P}^3 .

- $(\tilde{P}, \tilde{P}', \{\tilde{\mathbf{X}}_\alpha\}_{\alpha \geq 8})$ is another reconstruction iff
 $\tilde{P} = P H^{-1}, \quad \tilde{P}' = P' H^{-1}, \quad \tilde{\mathbf{X}}_\alpha = H \mathbf{X}_\alpha, \quad H: \mathbb{P}^3 \leftrightarrow \mathbb{P}^3$ linear
- For any Camera Stereo Rig P_1, P_2, \dots its canonical form is

$$\tilde{P}_1 = [\mathbb{I} | \mathbf{0}], \quad \tilde{P}_2 = K_2 R_2 (K_1 R_1)^{-1} [\mathbb{I} | \det(K_1) K_1 R_2 (\mathbf{c}_1 - \mathbf{c}_2)], \dots$$

$$H = \begin{pmatrix} K_1 R_1 & -K_1 R_1 \mathbf{c}_1 \\ \mathbf{0}^T & 1/\det(K_1) \end{pmatrix}$$

The Fundamental Matrix

- Epipoles

$$\mathbf{e}' = P' \mathbf{C}, \quad \mathbf{e} = P \mathbf{C}'$$

- $\mathbf{x}' = P' \mathbf{X} = P' P^+ \mathbf{x} + \mu \mathbf{e}'$

- $\mathbf{l}' = \mathbf{e}' \wedge \mathbf{x}' = \mathbf{e}' \wedge P' P^+ \mathbf{x}$

- $F = [\mathbf{e}']_{\wedge} P' P^+$

rank 2 $\mathbb{P}^2 \rightarrow \mathbb{P}^2$, $\det F = 0$

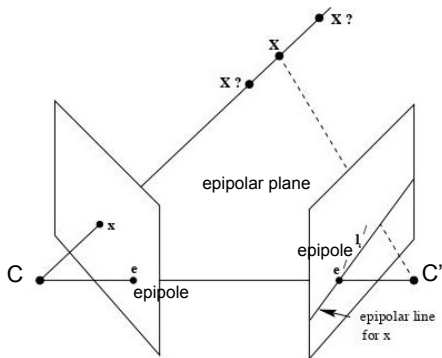
- Corresponding image points

$$\mathbf{x}' \cdot \mathbf{l}' = \mathbf{x}'^T F \mathbf{x} = 0$$

- $\sum_{ij} x'_i F_{ij} x_j = 0$

$$\det \begin{pmatrix} P' & \mathbf{x}' & 0 \\ P & 0 & \mathbf{x} \end{pmatrix} = 0$$

- $F = [\mathbf{e}']_{\wedge} K' R' K^{-1} = K'^{-T} R' K^T [\mathbf{e}]_{\wedge}$



Computing F from a pair of Camera Matrices - Examples I

Equally calibrated c.s $K' = K$

- front-to-front stereo rig:

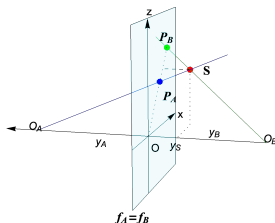
$$P' = K I_z [\mathbb{I}, -\mathbf{c}], \quad \mathbf{c} = (0, 0, c)^T, \quad I_z = \text{diag}(1, 1, -1)$$

$$\mathbf{e}' = c(x_0, y_0, 1)^T = c\mathbf{k}_3, \quad F_{ff-z} = [\mathbf{k}_3]_{\wedge} K I_z K^{-1}$$

$$\mathbf{x}'^T F_{ff-z} \mathbf{x} = (y' - y_0)x + (y_0 - y)x' + (y - y')x_0 = 0$$

$$\mathbf{X} = \left(\begin{array}{c} K^{-1}\mathbf{x} \\ \frac{(K I_z K^{-1}\mathbf{x} \wedge \mathbf{x}') \cdot (\mathbf{x}' \wedge \mathbf{k}_3)}{c(\mathbf{x}' \wedge \mathbf{k}_3)^2} \end{array} \right) \Rightarrow$$

$$\mathbf{X}_E = \frac{c(\mathbf{x}' \wedge \mathbf{k}_3)^2 K^{-1}\mathbf{x}}{(K I_z K^{-1}\mathbf{x} \wedge \mathbf{x}') \cdot (\mathbf{x}' \wedge \mathbf{k}_3)} = \frac{c(x' - x_0)}{x - 2x_0 + x'} K^{-1}\mathbf{x} = \frac{c(y' - y_0)}{y - 2y_0 + y'} K^{-1}\mathbf{x}$$



Computing F from a pair of Camera Matrices - Examples II

- Cameras at right angle:

$$P = K [\mathbb{I}, \mathbf{0}], \quad P' = K R_{-\pi/2}^y \left[\mathbb{I}, -r R_{\pi/4}^y \hat{\mathbf{z}} \right]$$

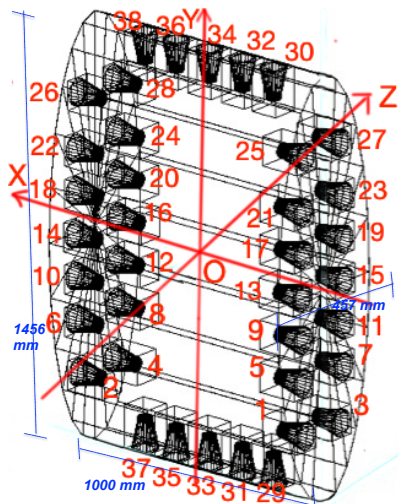
$$\mathbf{e} = r K R_{\pi/4}^y \hat{\mathbf{z}}, \quad \mathbf{e}' = -r K R_{-\pi/4}^y \hat{\mathbf{z}}$$

$$F_{\perp} = \left[K R_{-\pi/4}^y \hat{\mathbf{z}} \right]_{\times} K R_{-\pi/2}^y K^{-1} = \begin{pmatrix} 0 & 1 & -y_0 \\ -1 & 0 & x_0 - \alpha \\ y_0 & -\alpha - x_0 & 2\alpha y_0 \end{pmatrix}$$

Non anti-symmetric

$$\text{Horopter: } \mathbf{x}^T \frac{F_{\perp} + F_{\perp}^T}{2} \mathbf{x} = 0$$

GRAIN as a multiple-view (lens) system



GRAIN

Set of lenses centered at

$$\mathbf{c}_m^{\epsilon_1, \epsilon_2, \epsilon_3} = \begin{pmatrix} \zeta_m^{\epsilon_2, \epsilon_3} h \\ \psi_m^{\epsilon_1, \epsilon_3} b \\ \zeta_m^{\epsilon_2, \epsilon_3} \ell \end{pmatrix} = \begin{pmatrix} \left[(1 - \epsilon_3) \delta_m - \frac{(-1)^{\epsilon_2}}{2} \epsilon_3 \right] h \\ -(1 - \epsilon_3) (-1)^{\epsilon_1} \beta_m b \\ \left[-(1 - \epsilon_3) \frac{(-1)^{\epsilon_2}}{2} + \lambda \epsilon_3 m \right] \ell \end{pmatrix}$$

for $\epsilon_i = 0, 1$ and $0 \leq |m| \leq 3$

$\delta_{-m} = -\delta_m$, $\delta_0 = 0$ and $\beta_{-m} = \beta_m$ Set of Projection Matrices

$$P_m^{\epsilon_1 \epsilon_2 \epsilon_3} = K (R_\pi^x)^{\epsilon_2(1-\epsilon_3)} \left(R_{(-1)^{\epsilon_2} \frac{\pi}{2}}^y \right)^{\epsilon_3} [\mathbb{I}, -\mathbf{c}_m^{\epsilon_1, \epsilon_2, \epsilon_3}]$$

Fundamental Matrices

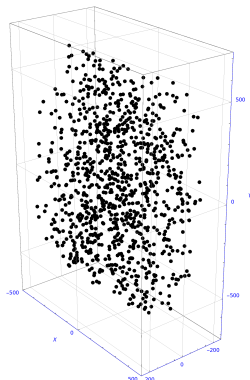
$$F_{m m'}^{\epsilon_1 \epsilon_2 \epsilon_3 \epsilon'_1 \epsilon'_2 \epsilon'_3} = \left(P_{m'}^{\epsilon'_1 \epsilon'_2 \epsilon'_3} \right)^+{}^T \left(P_m^{\epsilon_1 \epsilon_2 \epsilon_3} \right)^T \left[\mathbf{e}_{m m'}^{\epsilon_1 \epsilon_2 \epsilon_3 \epsilon'_1 \epsilon'_2 \epsilon'_3} \right]$$

Point-like Light sources in GRAIN and their reconstruction

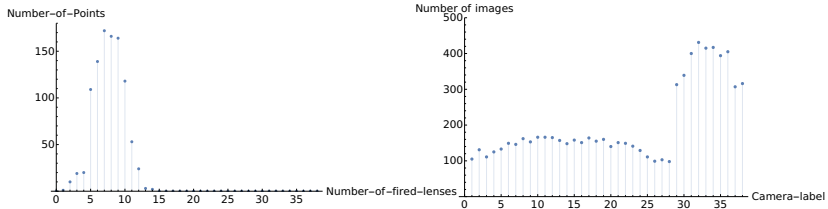
Joint work with L. Di Noto and M. Vicenzi

Case Study: 1000 selected light source points (randomly/uniformly)
in $800 \times 1200 \times 460 \text{ mm}^3$ **point Volume** \subset GRAIN

Energy release: 100 MeV per point



Points and Cameras Distribution I



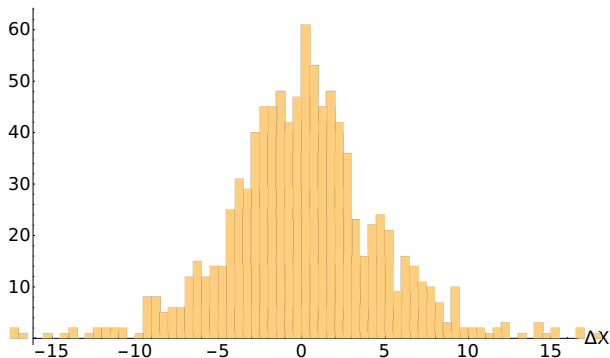
Reconstruction by double-View

- $K = \text{diag}(-f, -f, 1) \forall m, \epsilon_1, \epsilon_2, \epsilon_3$ of $P_m^{\epsilon_1 \epsilon_2 \epsilon_3}$, $f = 100\text{mm}$
- Each point is detected/seen by $N \leq 38$ cameras
- The image coordinates are given by the centroids of the photon distribution.
- There are $M = \frac{N!}{2!(N-2)!}$ possible double-views
- Check the consistency conditions

$$\mathbf{x}_{\epsilon'_1 \epsilon'_2 \epsilon'_3}^{m'} \cdot F_{m m'}^{\epsilon_1 \epsilon_2 \epsilon_3 \epsilon'_1 \epsilon'_2 \epsilon'_3} \cdot \mathbf{x}_{\epsilon_1 \epsilon_2 \epsilon_3}^m \approx 0$$
- Perform M reconstructions by the 3D formula
- take the mean value of the M possible reconstructions for each coordinate

$$X = \frac{\sum_{i < j}^N X_{ij}}{M}, \quad Y = \frac{\sum_{i < j}^N Y_{ij}}{M}, \quad Z = \frac{\sum_{i < j}^N Z_{ij}}{M}$$

Errors in reconstruction I

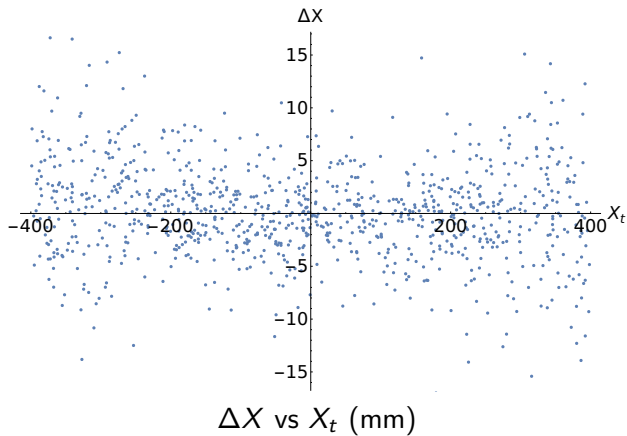


$\Delta X = X_c - X_t$ Distribution

X_c : calculated, X_t : original coordinates

$$\overline{\Delta X} \approx 10^{-2} \text{mm} \quad \overline{\Delta X^2}^{1/2} \approx 5 \text{mm}$$

Errors in reconstruction II



Errors in computing the corresponding points

$$S = \{\mathbf{x}_1, \dots, \mathbf{x}_N\}, S' = \{\mathbf{x}'_1, \dots, \mathbf{x}'_{N'}\} \rightarrow S \times S' = \left\{ \left(\mathbf{x}_\alpha, \mathbf{x}'_\beta \right) \right\}$$

$$\text{Corresponding points : } S_{cp} = \left\{ \left(\mathbf{x}_\alpha, \mathbf{x}'_\beta \right) : \mathbf{x}'_\beta F \mathbf{x}_\alpha = 0 \right\}$$

$$\text{Empirical data } 0 \leq E_{\alpha,\beta} = | \mathbf{x}'_\beta F \mathbf{x}_\alpha | \leq \epsilon$$

Bounded spread criterion

$$\left(\mathbf{x}_\alpha, \mathbf{x}'_\beta \right) = \left(\mathbf{x}_\alpha^0 + \Delta \mathbf{x}, \mathbf{x}'_\beta^0 + \Delta \mathbf{x}' \right)$$

$$|\Delta \mathbf{x}| \leq \frac{\epsilon}{|\mathbf{x}'_\beta^0| \|F\|}, |\Delta \mathbf{x}'| \leq \frac{\epsilon}{|\mathbf{x}_\alpha^0| \|F\|}$$

The Fundamental matrix from data

The set S_{cp} of the corresponding points is known and $\#S_{cp} \geq 8$

$$\mathbf{x}'_{\alpha} F \mathbf{x}_{\alpha} = 0 \quad \Rightarrow \quad A \mathbf{F} = 0 \text{ with } A \in \mathbb{R}^{n \times 9}$$

$\text{rank}(A) = 8 \Rightarrow F$ is determined mod. scalar $\neq 0$

$\text{rank}(A) = 9$ a least square solution is found by solving

$$\text{Min}_A \|\mathbf{A}\mathbf{F}\| \text{ subject to } \|\mathbf{F}\| = 1$$

Extraction of Camera Matrices from F

- Singular Value Decomposition : $F = U D V^T$ with $D = \text{diag}(p, q, \epsilon)$, $\epsilon \ll q < p$, U, V orthogonal
- Introduce the matrices $Z = \begin{pmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$ and $W = \begin{pmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix}$
- Compute $S = UZU^T$ and $M = UW^T D V^T$, which satisfy $F = SM$
- An associated to F pair of cameras is $P = [\mathbb{I}|\mathbf{0}]$, $P' = [M|U_3]$

Three view reconstruction

$$\lambda_{\alpha} \mathbf{x}_{\alpha} = P \mathbf{X}_{\alpha}, \quad \lambda'_{\alpha} \mathbf{x}'_{\alpha} = P' \mathbf{X}_{\alpha}, \quad \lambda''_{\alpha} \mathbf{x}''_{\alpha} = P'' \mathbf{X}_{\alpha}$$

$$\begin{pmatrix} P & \mathbf{x}_{\alpha} & 0 & 0 \\ P' & 0 & \mathbf{x}'_{\alpha} & 0 \\ P'' & 0 & 0 & \mathbf{x}''_{\alpha} \end{pmatrix} \begin{pmatrix} \mathbf{X}_{\alpha} \\ -\lambda_{\alpha} \\ -\lambda'_{\alpha} \\ -\lambda''_{\alpha} \end{pmatrix} = 0$$

Since a solution exists, then all 7×7 sub-matrices have 0 determinant \Rightarrow

$\sum_{i,j,k,q,r=1}^3 x^i x'^j x''^k \epsilon_{jqu} \epsilon_{krv} \mathcal{T}_i^{qr} = 0$ 4 independent eq.s
 9 trilinear conditions involving the trifocal tensor (27 components)

$$\mathcal{T}_i^{qr} = (-1)^{i+1} \det \left(P \hat{i}, P'_q, P''_r \right)$$

- 7 triplets of corresponding points completely determine \mathcal{T}_i^{qr}
- Known \mathcal{T}_i^{qr} , three views allow to reconstruct \mathbf{X}
- tri-linear equations hold for corresponding points, lines and mixed point-line ones.

Conclusions I

- A proof of principle for the application and implementation of the coded masks
- Different reconstruction algorithms are in development.
- A coded mask can be treated as a projective camera
- Camera projection, Fundamental matrices and trifocal tensors are common tools in a multiple - view treatment.
- 3D Reconstruction formulas are displayed for generic and special arrangements of cameras.
- Camera projection matrices, fundamental matrices and trifocal tensors can be derived from constructive design data
- Alternatively, they can be derived from calibration methods, exploiting a minimal finite number of empirical data.

Conclusions II

- Optimization methods in the above calculations are already at our disposal.
- Several tests addressed to evaluate the capability of 3D reconstruction point like sources in different regions of GRAIN have been performed.
- Adopting the trifocal tensor approach, point and line sources can be treated at the same foot.
- Generalized methods in presence of more than three view should be developed.
- Accurate reconstruction methods are intended to be developed for lines, performing both analytical and numerical studies.

Determining equation for P

n source points

$$\mathbf{X}_i \leftrightarrow \mathbf{x}_i \Leftrightarrow \exists \lambda_i : \lambda_i \mathbf{x}_i = \lambda_i (x_i, y_i, w_i)^T = P \mathbf{X}_i \quad i = 1, \dots, n$$

$$\mathbf{x}_i \wedge P \mathbf{X}_i = 0 \Leftrightarrow \begin{bmatrix} \mathbf{0}^T & -w_i \mathbf{X}_i^T & y_i \mathbf{X}_i^T \\ w_i \mathbf{X}_i^T & \mathbf{0}^T & -x_i \mathbf{X}_i^T \\ -y_i \mathbf{X}_i^T & x_i \mathbf{X}_i^T & \mathbf{0}^T \end{bmatrix} \begin{pmatrix} p^1 \\ p^2 \\ p^3 \end{pmatrix} = 0$$

$$A = \begin{bmatrix} \mathbf{0}^T & -w_1 \mathbf{X}_1^T & y_1 \mathbf{X}_1^T \\ w_1 \mathbf{X}_1^T & \mathbf{0}^T & -x_1 \mathbf{X}_1^T \\ \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots \\ \mathbf{0}^T & -w_n \mathbf{X}_n^T & y_n \mathbf{X}_n^T \\ w_n \mathbf{X}_n^T & \mathbf{0}^T & -x_n \mathbf{X}_n^T \end{bmatrix} : A \begin{pmatrix} p^1 \\ p^2 \\ p^3 \end{pmatrix} = 0$$

$$A \in \mathbb{R}^{2n \times 12} \quad \det A = 0, \quad \text{rank } A = 11$$

P is defined by $n \geq 6$ points (modulo a scale factor)

Sorgenti (cm)			Punti Immagine (cm)	
-6.6	-6.6	16.5	-0.44	-0.44
7.92	7.92	15.75	0.66	0.66
-5.28	7.92	15.	-0.44	0.66
-2.64	-1.32	14.25	-0.22	-0.11
9.24	1.32	13.5	0.88	0.11
5.28	-5.28	12.75	0.44	-0.55

$$\Rightarrow A_{ex}, \quad \det A_{ex} \neq 0, \quad A_{ex} P_{ex} = 0$$

Solving for P

Direct Linear Algorithm

- Assemble $A \in \mathbb{R}^{2n \times 12}$
- Performe the Singular Valued Decomposition $A = U D V^T$, with $D = \text{diag}(\lambda_{max}, \dots, \lambda_{min}) \in \mathbb{R}^{12 \times 12}$, $\lambda_i > 0$
- $P = V_{12^{th}}$ column

λ_{min} of $A_{ex} = 0.05042$

$$P_{ex} = \begin{pmatrix} -0.081 & -0.404 & 0.480 & 0.174 \\ 0.209 & -0.839 & -0.534 & 1.851 \\ -1.074 & 0.136 & 1. & -0.920 \end{pmatrix}$$

$$P_{ex} \cdot \text{Sorgenti} \rightarrow \frac{\Delta \text{Immagini}}{\text{Immagini}} = \begin{pmatrix} 0.005 & 0.005 \\ 0.02 & 0.01 \\ 0.01 & 0.02 \\ 0.02 & 0.03 \\ 0.03 & 0.01 \\ 0.003 & 0.01 \end{pmatrix}$$

Optimization

for $n \geq 6$ find the Maximum Likelihood estimate of P by
The Standard Algorithm (Hartley)

1 Estimate P by a linear procedure

2 Normalize source and image points : $\tilde{\mathbf{X}}_i = U \mathbf{X}_i$, $\tilde{\mathbf{x}}_i = T \mathbf{x}_i$,

$$\text{such that } \sum_i \tilde{\mathbf{X}}_i = \mathbf{0}, \sum_i \tilde{\mathbf{x}}_i = \mathbf{0} \quad \frac{\sum_i |\tilde{\mathbf{X}}_i|^2}{n-1} = 3, \quad \frac{\sum_i |\tilde{\mathbf{x}}_i|^2}{n-1} = 2$$

3 Generate $A \left(\left\{ \tilde{\mathbf{X}}_i \right\}, \left\{ \tilde{\mathbf{x}}_i \right\} \right)$ and take its normalized eigenvector
 $\tilde{\mathbf{p}}_{\min} \leftrightarrow \lambda_{\min} \neq 0 \Rightarrow \tilde{P}$

4 Minimize recursively $\min_P \left(\sum_{i=1}^n |\mathbf{x}_i - P \mathbf{X}_i|^2 \right)$

5 Back in the original coordinates : $P = T^{-1} \tilde{P} U$