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TSBB06 Multi-Dimensional Signal Analysis, Solutions 2022-01-11

1. (a) The intersection point can be found as $\mathbf{x}_{12} \sim \mathbf{l}_1 \times \mathbf{l}_2 = (3, 1, 1) \times (1, -1, 0) = (1, 1, -4)$. The distance between this point and the line \mathbf{l}_3 is

$$\left| (\text{norm}_{\text{D}} \mathbf{l}_{3})^{\top} (\text{norm}_{\text{P}} \mathbf{x}_{12}) \right| = \left| (0, -1, -1) \cdot \left(-\frac{1}{4}, -\frac{1}{4}, 1 \right) \right| = \frac{3}{4}$$

Answer: The Euclidean coordinates of the intersection point are $\left(-\frac{1}{4}, -\frac{1}{4}\right)$, and the distance from this point to \mathbf{l}_3 is $\frac{3}{4}$.

(b) We can parametrise $\mathbf{l} = (0, 1, s)$, and since the intersection point (1, 1, -4) should lie on \mathbf{l} , it follows that $(0, 1, s) \cdot (1, 1, -4) = \mathbf{0} \iff s = \frac{1}{4}$.

Answer: The line is $\mathbf{l} = (0, 1, \frac{1}{4})$.

(c) The ideal point on \mathbf{l}_3 can be found, e.g., as the intersection of \mathbf{l}_3 and the line at infinity, $\mathbf{l}_{\infty} = (0, 0, 1)$. This is found as $\mathbf{x}_{\infty} \sim \mathbf{l}_3 \times \mathbf{l}_{\infty} = (1, 0, 0)$. It is readily verified that $\mathbf{l}^{\top}\mathbf{x}_{\infty} = 0$ (of course, since the lines are parallel).

Answer: The ideal point on \mathbf{l}_3 is $\mathbf{x}_{\infty} = (1, 0, 0)$.

2. (a) With the assumption that $Ha \sim a$, it follows that

$$(\mathbf{H} + s[\mathbf{a}]_{\times})\mathbf{a} = \mathbf{H}\mathbf{a} + s[\mathbf{a}]_{\times}\mathbf{a} = \mathbf{H}\mathbf{a} \sim \mathbf{a},$$

 $\underbrace{\mathbf{u}}_{=\mathbf{0}}$

showing that $\mathbf{H} + s[\mathbf{a}]_{\times} \in \mathcal{H}_{\mathbf{a}}$, regardless of *s*.

(b) We need to check *closure*, *existence of an identity* (neutral element), *existence of inverse*, and *associativity*.

Associativity: This follows from the associativity of matrix multiplication. Closure: If $\mathbf{H}_1 \in \mathcal{H}_{\mathbf{a}}$ and $\mathbf{H}_2 \in \mathcal{H}_{\mathbf{a}}$, then $\mathbf{H}_2\mathbf{H}_1\mathbf{a} \sim \mathbf{H}_2\mathbf{a} \sim \mathbf{a}$, so $\mathbf{H}_2\mathbf{H}_1 \in \mathcal{H}_{\mathbf{a}}$. Identity: Clearly $\mathbf{I} \in \mathcal{H}_{\mathbf{a}}$, and for any $\mathbf{H} \in \mathcal{H}_{\mathbf{a}}$ it holds that $\mathbf{IH} = \mathbf{HI} = \mathbf{H}$. Existence of inverse: Homographies are by definition invertible but we set

Existence of inverse: Homographies are, by definition, invertible, but we still need to check that the inverse is actually in $\mathcal{H}_{\mathbf{a}}$. This is indeed the case, since any $\mathbf{H} \in \mathcal{H}_{\mathbf{a}}$ has \mathbf{a} as an eigenvector with a corresponding eigenvalue $\lambda \neq \mathbf{0}$, and thus $\mathbf{H}\mathbf{a} = \lambda \mathbf{a} \iff \mathbf{H}^{-1}\mathbf{a} = \frac{1}{\lambda}\mathbf{a} \sim \mathbf{a}$.

(c) A *general* homography has eight degrees of freedom, and we know that four point correspondences (where no three points are collinear) provide sufficient constraints to uniquely determine the homography. For a homography to belong to $\mathcal{H}_{\mathbf{a}}$, it is necessary to have a correspondence $\mathbf{a} \leftrightarrow \mathbf{a}$, leaving six degrees of freedom.

Answer: The homographies in \mathcal{H}_{a} have six degrees of freedom.

3. (a) For **R** to be a valid rotation matrix, it must satisfy $\mathbf{R}^{\top}\mathbf{R} = \mathbf{I}$ and det $\mathbf{R} = 1$. In particular, all columns must have length one, which gives $\lambda = \frac{1}{\sqrt{1^2 + (-4)^2 + 8^2}} = \frac{1}{9}$. Now, the third column is given by

$$\frac{1}{9}(a,b,c) = \frac{1}{9}(1,-4,8) \times \frac{1}{9}(8,4,1) = \frac{1}{81}(-36,63,36) = \frac{1}{9}(-4,7,4).$$

Answer: The only possibility is to have $\lambda = \frac{1}{9}$ and (a, b, c) = (-4, 7, 4). With the values from (a), the rotation matrix is

(b)

$$\mathbf{R} = \frac{1}{9} \begin{pmatrix} 1 & 8 & -4 \\ -4 & 4 & 7 \\ 8 & 1 & 4 \end{pmatrix}.$$

Recall Rodrigues' formula, $\mathbf{R} = \mathbf{I} + \sin \varphi [\hat{\mathbf{n}}]_{\times} + (1 - \cos \varphi) [\hat{\mathbf{n}}]_{\times}^2$. It follows that

$$\sin \varphi \left[\hat{\mathbf{n}} \right]_{\times} = \frac{\mathbf{R} - \mathbf{R}^{\top}}{2} = \frac{1}{9} \begin{pmatrix} 0 & 6 & -6 \\ -6 & 0 & 3 \\ 6 & -3 & 0 \end{pmatrix} = \frac{1}{3} \begin{pmatrix} 0 & 2 & -2 \\ -2 & 0 & 1 \\ 2 & -1 & 0 \end{pmatrix}.$$

We can choose $\hat{\mathbf{n}} = -\frac{1}{3}(1, 2, 2)$, which is normalised, and $\sin \varphi = 1 \Rightarrow \varphi = \frac{\pi}{2} + 2k\pi$. NOTE: In general, $\sin \varphi = \sin(\pi - \varphi)$, so if $\varphi \neq \pm \frac{\pi}{2}$, we need to disambiguate the angle using the additional constraint $\cos \varphi = \frac{\operatorname{tr} \mathbf{R} - 1}{2}$.

Answer: One possible axis–angle representation of the rotation is $\hat{\mathbf{n}} = -\frac{1}{3}(1, 2, 2)$ and $\varphi = \frac{\pi}{2}$.

4. (a) Ideally, we want **p** to satisfy $\mathbf{X}_{j}^{\top}\mathbf{p} = 0$ for j = 1, ..., n. Together, this can be formulated as $\mathbf{A}\mathbf{p} = \mathbf{0}$ with a data matrix

$$\mathbf{A} = \begin{pmatrix} \mathbf{X}_1^\top \\ \vdots \\ \mathbf{X}_n^\top \end{pmatrix}.$$

(b) Answer: A geometric cost function for this problem is

$$\varepsilon_{\mathrm{G}}(\mathbf{p}) = \sum_{j=1}^{n} \left((\operatorname{norm}_{\mathrm{P}} \mathbf{X}_{j})^{\top} (\operatorname{norm}_{\mathrm{D}} \mathbf{p}) \right)^{2}.$$

5. (a) We seek a vector \mathbf{b}_3 such that $\langle \mathbf{b}_1 | \mathbf{b}_3 \rangle = \langle \mathbf{b}_2 | \mathbf{b}_3 \rangle = \mathbf{0}$ and $\langle \mathbf{b}_3 | \mathbf{b}_3 \rangle = \mathbf{1}$. The two orthogonality constraints tell us that

$$\begin{cases} \mathbf{b}_3^{\top} \mathbf{G}_0 \mathbf{b}_1 = \mathbf{0} \\ \mathbf{b}_3^{\top} \mathbf{G}_0 \mathbf{b}_2 = \mathbf{0} \end{cases} \Rightarrow \quad \mathbf{b}_3 \sim (\mathbf{G}_0 \mathbf{b}_1) \times (\mathbf{G}_0 \mathbf{b}_2) \sim (1, 1, 0) \times (0, 0, 1) \sim (1, -1, 0). \end{cases}$$

Now we need to normalise this with respect to the scalar product to obtain our \mathbf{b}_3 , so we let $\mathbf{b}_3 = (s, -s, 0)$. Since

$$\frac{1}{8} \begin{pmatrix} s & -s & 0 \end{pmatrix} \begin{pmatrix} 3 & 1 & 0 \\ 1 & 3 & 0 \\ 0 & 0 & 8 \end{pmatrix} \begin{pmatrix} s \\ -s \\ 0 \end{pmatrix} = \frac{1}{8} \begin{pmatrix} s & -s & 0 \end{pmatrix} \begin{pmatrix} 2s \\ -2s \\ 0 \end{pmatrix} = \frac{4s^2}{8},$$

we can choose $s = \pm \sqrt{2}$, resulting in either $\mathbf{b}_3 = (\sqrt{2}, -\sqrt{2}, 0)$ or $\mathbf{b}_3 = (-\sqrt{2}, \sqrt{2}, 0)$.

Answer: The possible choices are $\mathbf{b}_3 = (\sqrt{2}, -\sqrt{2}, \mathbf{0})$ and $\mathbf{b}_3 = (-\sqrt{2}, \sqrt{2}, \mathbf{0})$. (b) The best subspace approximation \mathbf{u} of \mathbf{v} can be found as

$$\mathbf{u} = \langle \tilde{\mathbf{b}}_1 | \mathbf{v} \rangle \mathbf{b}_1 + \langle \tilde{\mathbf{b}}_2 | \mathbf{v} \rangle \mathbf{b}_2,$$

where $\tilde{\mathbf{b}}_1$ and $\tilde{\mathbf{b}}_2$ are the corresponding dual basis vectors to \mathbf{b}_1 and \mathbf{b}_2 . However, since the basis is orthogonal, it is its own dual basis, and consequently

$$\mathbf{u} = \langle \mathbf{b}_1 | \mathbf{v} \rangle \mathbf{b}_1 + \langle \mathbf{b}_2 | \mathbf{v} \rangle \mathbf{b}_2.$$

Computing the subspace coordinates

$$\begin{cases} \langle \mathbf{b}_1 \mid \mathbf{v} \rangle = \frac{1}{8} \begin{pmatrix} 1 & 2 & 3 \end{pmatrix} \begin{pmatrix} 3 & 1 & 0 \\ 1 & 3 & 0 \\ 0 & 0 & 8 \end{pmatrix} \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix} = \frac{1}{8} \begin{pmatrix} 1 & 2 & 3 \end{pmatrix} \begin{pmatrix} 4 \\ 4 \\ 0 \end{pmatrix} = \frac{3}{2}, \\ \langle \mathbf{b}_2 \mid \mathbf{v} \rangle = \frac{1}{8} \begin{pmatrix} 1 & 2 & 3 \end{pmatrix} \begin{pmatrix} 3 & 1 & 0 \\ 1 & 3 & 0 \\ 0 & 0 & 8 \end{pmatrix} \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} = \frac{1}{8} \begin{pmatrix} 1 & 2 & 3 \end{pmatrix} \begin{pmatrix} 0 \\ 0 \\ 8 \end{pmatrix} = 3, \end{cases}$$

we finally have $\mathbf{u} = \frac{3}{2}\mathbf{b}_1 + 3\mathbf{b}_2 = \left(\frac{3}{2}, \frac{3}{2}, 3\right)$.

Answer: The best approximation of **v** is $\mathbf{u} = (\frac{3}{2}, \frac{3}{2}, 3)$.

6. (a) The frame operator is

$$\mathbf{F} = \mathbf{B}\mathbf{B}^{\top}\mathbf{G}_{0} = \begin{pmatrix} 1 & 0 & a \\ 0 & 2 & a \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & 2 \\ a & a \end{pmatrix} \begin{pmatrix} 2 & 0 \\ 0 & 1 \end{pmatrix} = \begin{pmatrix} 2 + 2a^{2} & a^{2} \\ 2a^{2} & 4 + a^{2} \end{pmatrix}.$$

Answer: The frame operator is $\mathbf{F} = \begin{pmatrix} 2+2a^2 & a^2 \\ 2a^2 & 4+a^2 \end{pmatrix}$.

(b) The lower frame bound L = 3 is the smallest eigenvalue of **F**, and the upper frame bound U = 6 is the largest eigenvalue of **F**. Since **F** only has two eigenvalues (it is a 2×2 matrix), we know that

$$\begin{cases} \operatorname{tr} \mathbf{F} = L + U \\ \det \mathbf{F} = LU \end{cases} \iff \begin{cases} 2 + 2a^2 + 4 + a^2 = 3 + 6 \\ (2 + 2a^2)(4 + a^2) - 2a^4 = 3 \cdot 6 \end{cases} \iff \begin{cases} 6 + 3a^2 = 9 \\ 8 + 10a^2 = 18 \end{cases}$$

This means that a = 1.

Answer: a = 1 gives the desired frame bounds.

(c) The reconstructing coefficients with smallest Euclidean norm are given as

$$\mathbf{c} = \tilde{\mathbf{B}}^{\top} \mathbf{G}_{0} \mathbf{v} = \frac{1}{18} \begin{pmatrix} 5 & -2 \\ -2 & 8 \\ 4 & 2 \end{pmatrix} \begin{pmatrix} 2 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} 3 \\ 15 \end{pmatrix} = \frac{1}{18} \begin{pmatrix} 0 \\ 108 \\ 54 \end{pmatrix} = \begin{pmatrix} 0 \\ 6 \\ 3 \end{pmatrix}.$$

Answer: The sought reconstructing coefficients are $\mathbf{c} = (0, 6, 3)$. (If you used a = -1, then $\mathbf{c} = (0, 6, -3)$.)

(a) The homogeneous coordinates of the camera centre are found as the null space of the camera matrix. The homogeneous coordinates of (-1, 1, -1) are (-1, 1, -1, 1), and we see that

$$\mathbf{C}_{1} \begin{pmatrix} -1 \\ 1 \\ -1 \\ 1 \end{pmatrix} = \begin{pmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 2 \end{pmatrix} \begin{pmatrix} -1 \\ 1 \\ -1 \\ 1 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}$$

and

$$\mathbf{C}_{2} \begin{pmatrix} -1 \\ 1 \\ -1 \\ 1 \end{pmatrix} = \begin{pmatrix} 2 & -3 & 0 & 5 \\ 2 & 1 & 2 & 3 \\ -4 & -1 & 1 & -2 \end{pmatrix} \begin{pmatrix} -1 \\ 1 \\ -1 \\ 1 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}.$$

Answer: The camera C_2 is located at (-1, 1, -1).

(b) From (a), we know that the centre of the camera C_2 is $n_2 = (-1, 1, -1, 1)$, meaning that the epipole e_{12} is $e_{12} = C_1 n_2 = (0, 0, 1)$. To compute the epipole in the other view, we first need to compute the camera centre of C_1 . This is found as

$$\begin{pmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 2 \end{pmatrix} \begin{pmatrix} x \\ y \\ z \\ w \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} \iff \begin{pmatrix} x \\ y \\ z \\ w \end{pmatrix} = t \begin{pmatrix} -2 \\ 2 \\ -2 \\ 1 \end{pmatrix}, \quad t \in \mathbb{R},$$

so we can take $\mathbf{n}_1 = (-2, 2, -2, 1)$. Projecting it into the second view gives the epipole $\mathbf{e}_{21} = \mathbf{C}_2 \mathbf{n}_1 = (-5, -3, 2)$.

Answer: The epipoles are $e_{12} = (0, 0, 1)$ and $e_{21} = (-5, -3, 2)$.

(c) The most direct way is to use the fact that $\mathbf{Fe}_{21} = \mathbf{0}$, which immediately gives us a = -4.

Another possibility is project a 3D point **X** into the two views, and then use the epipolar constraint. This will also result in a = -4.

Answer: For **F** to be the fundamental matrix for this camera pair, we need a = -4.

8. (a) In the case where $\mathbf{B} = \mathbf{b}_1$, we have

$$\varepsilon_1 = \mathbb{E}[\mathbf{v}^\top \mathbf{b}_1 \mathbf{b}_1^\top \mathbf{v}] = \mathbb{E}[\mathbf{b}_1^\top \mathbf{v} \mathbf{v}^\top \mathbf{b}_1] = \mathbf{b}_1^\top \mathbb{E}[\mathbf{v} \mathbf{v}^\top] \mathbf{b}_1 = \mathbf{b}_1^\top \mathbf{C} \mathbf{b}_1.$$

With the constraint $g(\mathbf{b}_1) = \mathbf{b}_1^{\mathsf{T}} \mathbf{b}_1 = 1$, the constrained optima of ε_1 are found where $\nabla \varepsilon_1 \parallel \nabla g \iff 2\mathbf{C}\mathbf{b}_1 = 2\lambda\mathbf{b}_1 \iff \mathbf{C}\mathbf{b}_1 = \lambda\mathbf{b}_1$, which means that \mathbf{b}_1 is an eigenvalue of \mathbf{C} with corresponding eigenvalue λ . The largest eigenvalue λ is the one that maximises $\varepsilon_1 = \mathbf{b}_1^{\mathsf{T}}\mathbf{C}\mathbf{b}_1 = \lambda\mathbf{b}_1^{\mathsf{T}}\mathbf{b}_1 = \lambda$.

(b) The expected reconstruction error is the sum of the eigenvalues corresponding to the unused eigenvectors of **C**. Assuming the eigenvalues are ordered in decreasing order, this means that

$$\varepsilon = \sum_{j=2}^n \lambda_j = \operatorname{tr} \mathbf{C} - \lambda_1.$$

Answer: See above.