

The Hotelling Observer in Adaptive Optics

Luca Caucci

caucci@email.arizona.edu

College of Optical Sciences



December 7, 2011

Outline

- Brief review
- Application to AO
- Computational methods
- Conclusions

The Hotelling observer:

- Optimal linear discriminant
- Equivalent to ideal observer for Gaussian data
- Requires knowledge of data mean and covariance
- Inversion of a large covariance matrix (usually) required
- Given by:

$$t_{\text{Hot}}(\mathbf{g}) = \mathbf{w}^T \mathbf{g},$$

for an appropriate “template” vector \mathbf{w}

- Maximizes:

$$\text{SNR} = \frac{\langle t_{\text{Hot}}(\mathbf{g}) \rangle_{\mathbf{g}|S_+} - \langle t_{\text{Hot}}(\mathbf{g}) \rangle_{\mathbf{g}|S_-}}{\sqrt{\frac{1}{2}\sigma_{t_{\text{Hot}}(\mathbf{g})|S_+}^2 + \frac{1}{2}\sigma_{t_{\text{Hot}}(\mathbf{g})|S_-}^2}}$$

Brief review

- Noise-free image when the signal is absent: $\bar{\mathbf{g}}_0 = \langle \mathbf{g} \rangle_{S_-}$
- Noise-free image when the signal is present: $\bar{\mathbf{g}}_1 = \langle \mathbf{g} \rangle_{S_+}$
- Then the signal (ex: a planet) is $\mathbf{s} = \bar{\mathbf{g}}_1 - \bar{\mathbf{g}}_0$
- Let \mathbf{K}_g be the covariance matrix of the data:

$$\mathbf{K}_g = \Pr(S_-)\mathbf{K}_{g|S_-} + \Pr(S_+)\mathbf{K}_{g|S_+}$$

- The template is:

$$\mathbf{w} = \mathbf{K}_g^{-1}\mathbf{s}$$

Application to AO

- For the case of AO images:
- $\mathbf{G} = (\mathbf{g}^{(1)}, \dots, \mathbf{g}^{(J)})$: sequence of noisy random images
- $\mathbf{P} = (\mathbf{p}^{(1)}, \dots, \mathbf{p}^{(J)})$: sequence of random residual PSF's
- $\mathbf{F} = (\mathbf{f}^{(1)}, \dots, \mathbf{f}^{(J)})$: random and time-dependent objects
- Assume $\mathbf{f}^{(1)} = \dots = \mathbf{f}^{(J)} = \mathbf{f}$ (constant unknown object)
- \mathbf{f} can either be \mathbf{f}_{S_-} (signal absent) or \mathbf{f}_{S_+} (signal present)
- Two sources of randomness:
 - Residual random PSF
 - Measurement noise: Poisson noise, readout noise

Application to AO

- If we want to use the Hotelling observer in AO, we need to find the mean image sequences under both hypotheses and the mean data covariance matrix
- For the mean image sequence given \mathbf{f}_i ($i = S_-$ or $i = S_+$):

$$\overline{\mathbf{G}}_i = \left\langle \left\langle \mathbf{G} \right\rangle_{\mathbf{G}|\mathbf{P}, \mathbf{f}_i} \right\rangle_{\mathbf{P}|\mathbf{f}_i}$$

- Likewise:

$$\mathbf{K}_{\mathbf{G}|i} = \left\langle \left\langle \left[\mathbf{G} - \overline{\mathbf{G}}_i \right] \left[\mathbf{G} - \overline{\mathbf{G}}_i \right]^T \right\rangle_{\mathbf{G}|\mathbf{P}, \mathbf{f}_i} \right\rangle_{\mathbf{P}|\mathbf{f}_i}$$

- Dim signal: $\mathbf{K}_{\mathbf{G}|S_-} \approx \mathbf{K}_{\mathbf{G}|S_+} \approx \mathbf{K}_{\mathbf{G}}$
- It can be proved that:

$$\mathbf{K}_{\mathbf{G}} = \overline{\mathbf{K}}_{\mathbf{G}}^{\text{noise}} + \mathbf{K}_{\mathbf{G}}^{\text{PSF}}$$

Application to AO

- $\overline{\overline{\mathbf{G}_i}}$ estimated from simulated data
- Generate L realizations of AO-corrected system function

$$\left[\overline{\overline{\mathbf{G}_i}}\right]_m^{(j)} = \int_{\mathbb{R}^2} \overline{h}_m^{(j)}(x, y) \mathbf{f}_i(x, y) dx dy,$$

where:

$$\overline{h}_m^{(j)}(x, y) = \frac{1}{L} \sum_{\ell=1}^L h_{\ell, m}^{(j)}(x, y)$$

- $\mathbf{K}_{\overline{\mathbf{G}}}^{\text{PSF}}$ estimated from simulated data:

$$\left[\mathbf{K}_{\overline{\mathbf{G}}}^{\text{PSF}}\right]_{m,m'}^{(j,j')} = \frac{1}{L-1} \sum_{\ell=1}^L \Delta h_{\ell,m}^{(j)}(x,y) \Delta h_{\ell,m'}^{(j')}(x,y),$$

where:

$$\Delta h_{\ell,m}^{(j)}(x,y) = h_{\ell,m}^{(j)}(x,y) - \frac{1}{L} \sum_{\ell'=1}^L h_{\ell',m}^{(j)}(x,y)$$

- Formally:

$$\mathbf{W} = \mathbf{K}_{\overline{\mathbf{G}}}^{-1} \left[\overline{\overline{\mathbf{G}_{S_+}}} - \overline{\overline{\mathbf{G}_{S_-}}} \right]$$

- The big problem:

$$\mathbf{W} = \left[\mathbf{K} \mathbf{G} \right]^{-1} \left[\overline{\mathbf{G}}_{S_+} - \overline{\mathbf{G}}_{S_-} \right]$$

- For example, if images are 64×64 ($M = 64^2$ pixels) and there are $J = 25$ of them in each sequence, then $\mathbf{K} \mathbf{G}$ is 102400×102400
- Storing $\mathbf{K} \mathbf{G}$ as double-valued matrix requires about 39 GB of memory!
- And you still need to invert it...

Computational methods

- Matrix-inversion lemma:

$$\begin{aligned} [\mathbf{N} + \mathbf{R}\mathbf{R}^T]^{-1} &= \\ &= \mathbf{N}^{-1} - \mathbf{N}^{-1}\mathbf{R}[\mathbf{I}_n + \mathbf{R}^T\mathbf{N}^{-1}\mathbf{R}]^{-1}\mathbf{R}^T\mathbf{N}^{-1} \end{aligned}$$

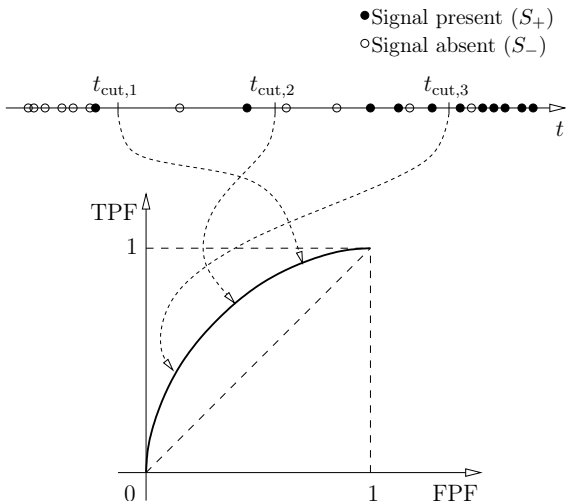
- Recall: $\mathbf{K}_G = \overline{\mathbf{K}}_G^{\text{noise}} + \mathbf{K}_G^{\text{PSF}}$
- $\mathbf{K}_G^{\text{PSF}}$ estimated from L sample sequences
- $\mathbf{K}_G^{\text{PSF}} = \mathbf{R}\mathbf{R}^T$ where \mathbf{R} is $MJ \times L$
- Substituting:

$$\mathbf{K}_G^{-1} = \left[\overline{\mathbf{K}}_G^{\text{noise}}\right]^{-1} + \left[\overline{\mathbf{K}}_G^{\text{noise}}\right]^{-1}\mathbf{R}\mathbf{Q}^{-1}\mathbf{R}^T\left[\overline{\mathbf{K}}_G^{\text{noise}}\right]^{-1}$$

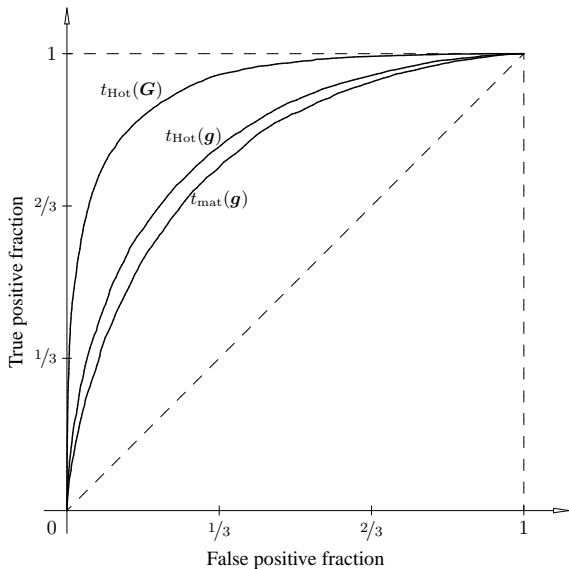
for $\mathbf{Q} = \mathbf{I}_L + \mathbf{R}^T\left[\overline{\mathbf{K}}_G^{\text{noise}}\right]^{-1}\mathbf{R}$

- \mathbf{Q} is $L \times L$ and L does not have to be large

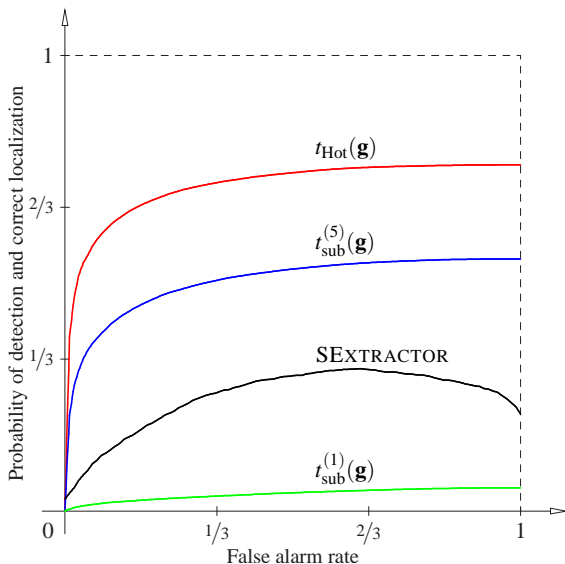
Computational methods



Results



Results



- Harrison H. Barrett, Kyle J. Myers, Nicholas Devaney, and Christopher Dainty, "Objective assessment of image quality. IV. Application to adaptive optics," *Journal of the Optical Society of America A*, vol. 23, issue 12, pp. 3080–3105 (2006)
- Luca Caucci, Harrison H. Barrett, and Jeffrey J. Rodríguez, "Spatio-temporal Hotelling observer for signal detection from image sequences," *Optics Express*, vol. 17, issue 13, pp. 10946–10958 (2009)