DE LA RECHERCHE À L'INDUSTRIE



Astrophysics Division CosmoStat Lab

Sparse matrix factorization for PSFs field estimation

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Outline

- Context
- Monochromatic PSFs joint super-resolution
- Conclusion

GR





Gravitational lensing



Dark Universe





Weak gravitational lensing $(\leq 10\% \text{ of distortion})$

 Data from the ESA Euclid mission (to be launched in 2020)



Weak lensing measurement bottleneck: the PSF



Model-free PSFs estimation accounting for:

- noise and aliasing
- spatial and temporal variations
- wavelength dependency.

Observation model

$$\mathbf{y}_k = \mathbf{M}_k \mathbf{x}_k + \mathbf{n}_k, \ k = 1 \cdots p$$

y_k: kth low resolution image
M_k: shift and downsampling operator
x_k: kth well resolved image
n_k: gaussian noise

Constraints

- Piece-wise smoothness
- Low dimensionality
- Spatial regularity
- Positivity





Spatial frequency dictionary Observed stars spatial locations: $(\mathbf{u}_i)_{1 \le i \le p}$

$$\psi_{i} = \psi_{p-i+1} = -1/|\mathbf{u}_{i} - \mathbf{u}_{k+1}|^{e} \qquad a > 0, e > 0$$

$$\psi_{i} = \sum_{\substack{j=1\\j \neq k+1}}^{p} a/|\mathbf{u}_{j} - \mathbf{u}_{k+1}|^{e} \qquad \text{`Notch" filters: varying notch frequency }} depending on e and a$$

$$\Psi_{e,a}(\mathbf{v}) = \|\mathbf{v} \star \psi_{e,a}\|_{2}^{2}$$

$$\Psi : M_{rp}(\mathbb{R}) \mapsto \mathbb{R}^{+}, \mathbf{A} \rightarrow \sum_{i=1}^{r} \Psi_{e_{i,a}}(\mathbf{A}[i = 0 < e_{1} < e_{2} < \dots < e_{r}]$$

; :|)

Spatial frequency dictionary $\widehat{\Psi}_{e,a}: \mathbb{R}^p \mapsto \mathbb{R}^+, \mathbf{v} \to \sum_{k=1}^p (\sum_{\substack{i=1\\i \neq k}}^p \frac{av_k - v_i}{\|\mathbf{u}_k - \mathbf{u}_i\|_2^e})^2$ $\widehat{\Psi}_{e,a}(\mathbf{v}) = \|\mathbf{P}_{e,a}\mathbf{v}\|_2^2$ $\mathbf{P}_{e,a}[i,j] = -\frac{1}{\|\mathbf{u}_i - \mathbf{u}_j\|_2^e} \text{ if } i \neq j \qquad \mathbf{P}_{e,a}[i,i] = \sum_{i=1}^p \frac{a}{\|\mathbf{u}_i - \mathbf{u}_j\|_2^e}$ $\widehat{\Psi}_{e,a}(\mathbf{v}) = \mathbf{v}^T \mathbf{Q}_{e,a} \mathbf{v}, \quad \mathbf{Q}_{e,a} = \mathbf{P}_{e,a}^T \mathbf{P}_{e,a} = \mathbf{V}_{e,a} \mathbf{D}_{e,a} \mathbf{V}_{e,a}^T$ $\Psi(\mathbf{A}) = \sum_{i=1}^{r} \sum_{j=1}^{p} \mathbf{d}_{e_i,a}[j] \langle \mathbf{v}, \mathbf{V}_{e_i,a}[:,j] \rangle^2$ $i=1 \ i=1$

Spatial frequency dictionary

$$(e_i, a_i)_{1 \le i \le r}$$
 $\mathbf{V} = [\mathbf{V}_{e_1, a_1}, \dots, \mathbf{V}_{e_r, a_r}]$

 $\mathbf{P}_{e,1}$: laplacian matrix of a graph

Optimization problem

 $\Omega_1 = \{ \boldsymbol{\alpha} \in M_{r,N}(\mathbb{R}) / \| \boldsymbol{\alpha}[l,:] \|_0 \le \eta_l, \ l = 1 \dots r \}$

 $\Omega_2 = \{ (\mathbf{S}, \boldsymbol{\alpha}) \in M_{nr}(\mathbb{R}) \times M_{r,N}(\mathbb{R}) / \mathbf{S} \boldsymbol{\alpha} \mathbf{V}^T \geq_{M_{np}(\mathbb{R})} 0 \}$

 $\min_{\boldsymbol{\alpha},\mathbf{S}} \frac{1}{2} \|\mathbf{Y} - \mathcal{F}(\mathbf{S}\boldsymbol{\alpha}\mathbf{V}^{T})\|_{F}^{2} + \sum_{i=1}^{r} \|\mathbf{w}_{i} \odot \boldsymbol{\Phi}_{s} \odot \mathbf{s}_{i}\|_{1} + \iota_{\Omega_{1}}(\boldsymbol{\alpha}) + \iota_{\Omega_{2}}(\mathbf{S},\boldsymbol{\alpha})$

Algorithm 1 Resolved components analysis (RCA)

1: Parameters estimation and initialization: Harmonic constraint parameters $(e_i, a_i)_{1 \le i \le r} \to \mathbf{V}, \mathbf{A}_0$ Noise level, $A_0 \rightarrow W_{0,0}$ 2: Alternate minimization 3: for k = 0 to k_{max} do for j = 0 to j_{max} do 4: $\mathbf{S}_{k} = \operatorname{argmin}_{\mathbf{S}} \frac{1}{2} \|\mathbf{Y} - \mathcal{F}(\mathbf{S}\mathbf{A}_{k})\|_{F}^{2} + \sum_{i=1}^{r} \|\mathbf{W}_{k,j}[:,i] \odot \boldsymbol{\Phi}_{s}\mathbf{S}[:,i]\|_{1} \text{ s.t. } \mathbf{S}\mathbf{A}_{k} \ge 0$ 5: update: $\mathbf{W}_{k,0}, \mathbf{S}_k \rightarrow \text{update}(\mathbf{W}_{k,i+1})$ 6: end for 7: $\boldsymbol{\alpha}_{k+1} = \operatorname{argmin}_{\frac{1}{2}} \|\mathbf{Y} - \mathcal{F}(\mathbf{S}_k \boldsymbol{\alpha} \mathbf{V}^T)\|_F^2 \text{ s.t. } \|\boldsymbol{\alpha}[l, :]\|_0 \le \eta_l$ 8: update: Noise level, $\alpha_{k+1} \rightarrow \mathbf{W}_{k+1,0}$ 9: $\mathbf{A}_{k+1} = \boldsymbol{\alpha}_{k+1} \mathbf{V}^T$ 10: $\mathbf{A}_{k+1}[i,:] = \mathbf{A}_{k+1}[i,:]/\|\mathbf{A}_{k+1}[i,:]\|_2$, for $i = 1 \dots r$ 11: 12: end for 13: Return: $\mathbf{S}_{k_{\max}}$, $\mathbf{A}_{k_{\max}}$.

Numerical results

Data

- 500 42x42 simulated Euclid telescope optical PSFs
- Realistic effects included such polishing and alignement defects
- Upsampling factor of 2 in the SR case

Numerical results

Dimension reduction



Numerical results

Dimension reduction and super-resolution





Conclusion

- Noise robust dimension reduction and superresolution method taking advantage of the PSFs field spatial regularity
- Good accuracy on both PSFs shape and pixels values

Bibliography

- F. M. Ngolè Mboula, J.-L. Starck, K. Okomura, J. Amiaux, P. Hudelot. "*Constraint matrix factorization for space variant PSFs field restoration*", Inverse Problems, In press.
- Condat, Laurent. "A primal-dual splitting method for convex optimization involving Lipschitzian, proximable and linear composite terms." Journal of Optimization Theory and Applications 158.2 (2013): 460-479..

Thank you for your attention!