Application of Image Restoration Techniques in Flow Scalar Imaging Experiments

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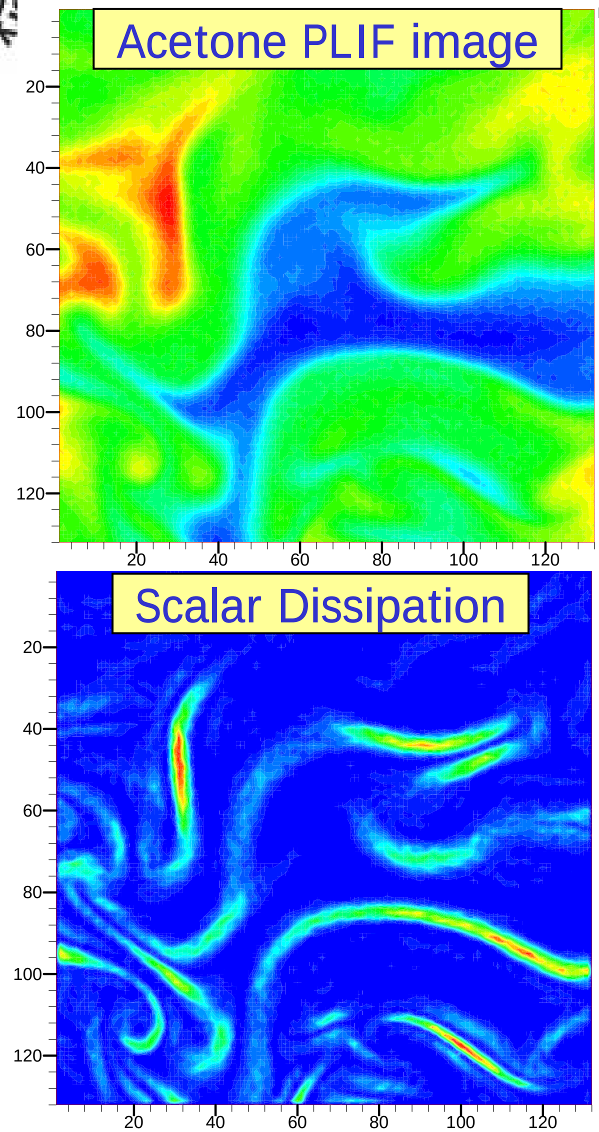
Introduction



PLIF (Planar Laser Induced Fluorescence) image
$Re_{d1/2}$=9600, Sc=1.5, [Tsurikov, 2002]

Flow scalar imaging experiments

- **Resolution requirements**

$$\lambda_V / \delta \propto \mathrm{Re}_\delta^{-3/4}$$

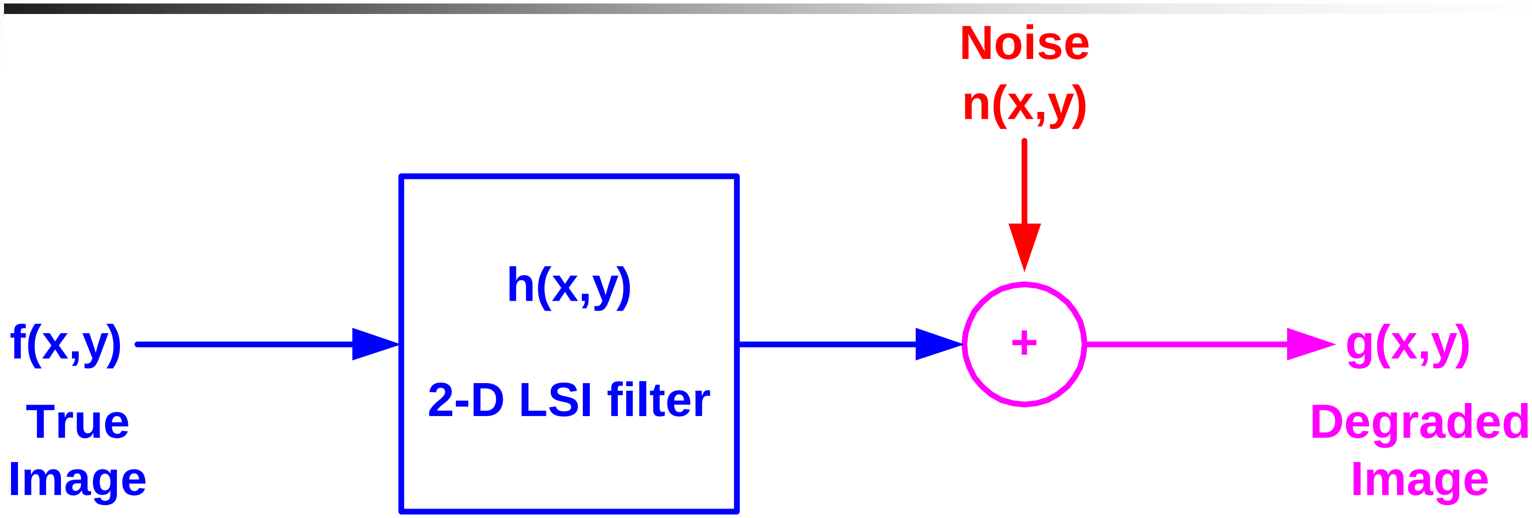
$$\lambda_D / \delta \propto Sc^{-1/2}\, \mathrm{Re}_\delta^{-3/4}$$

  - λ_v and λ_D: smallest local length scales

- **Resolution restrictions**
  - CCD camera pixel spacing/size
  - Imaging lens blurring effect, especially for FAST optics

- **In this project**
  - Improve resolution and measurement accuracy by image restoration techniques;
  - Estimate measurement error due to blurring;

Background

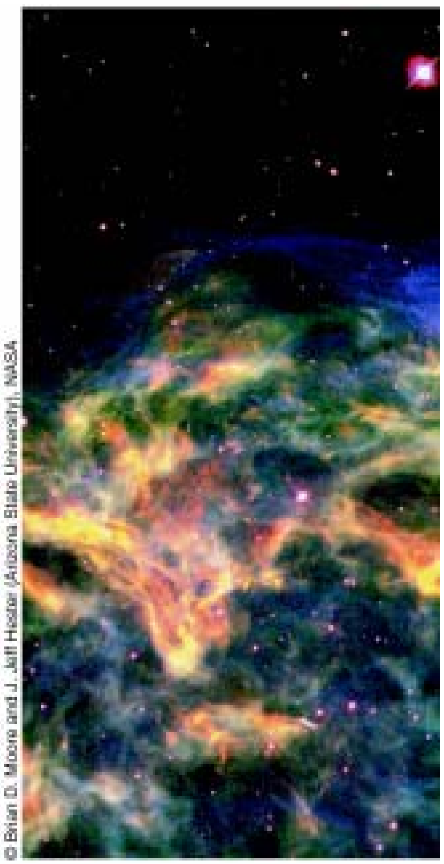


Linear degradation model

- Blurring model *g(x,y) = f(x,y)*h(x,y) + n(x,y)*
- True image f(x,y) *Flow Scalar field with Poisson noise*
- LSI Filter h(x,y) *Point Spread Function (PSF) of camera lens*
- Noise n(x,y) *Additive noise, i.e. CCD camera readout noise*
- **Interested in *f(x,y) and h(x,y)***

Key Paper #1

- R. Molina, J. Nunez, F.J. Cortijo and J. Mateos, "Image Restoration in Astronomy: a Bayesian perspective ", IEEE Signal Processing Magazine, vol.18, no. 2, pp.11-29, Mar. 2001



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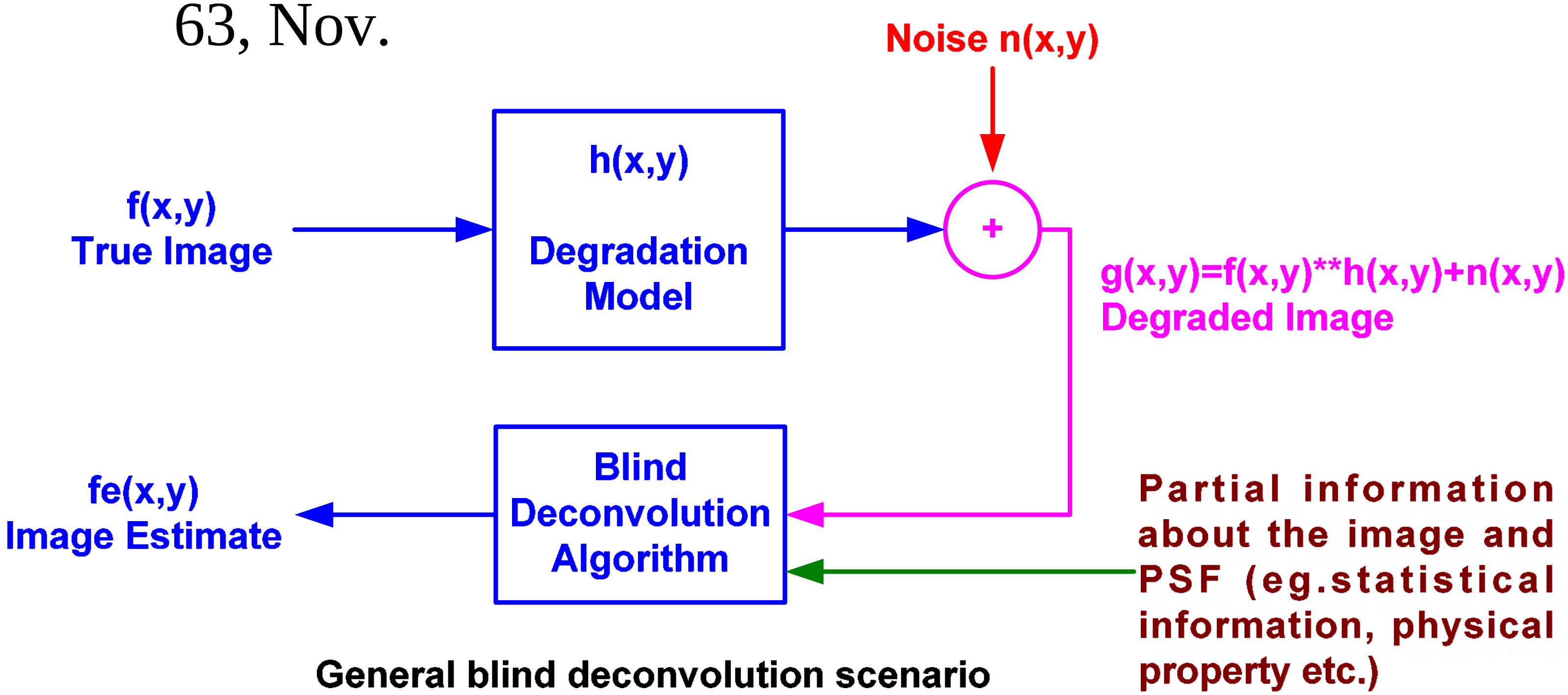
- **Lots in common:**
  - Low light level imaging;
  - Images degraded by imaging optics;
  - Signal related noise (Poisson noise);
  - CCD camera read-out noise;
- **Algorithms**
  - **Bayesian methods**
  - **Expectation Maximization algorithm**
  - **Successive substitution**
  - Acceleration and stopping rules
- **Provides good web resources**

Key Paper #2

- D. Kundur and D. Hatzinakos, IEEE Signal Processing Magazine, vol. 13, 1996
- "Blind Image Deconvolution", no. 3, pp.43-64, May
- "Blind Image Deconvolution Revisited", no. 6, pp.61-63, Nov.



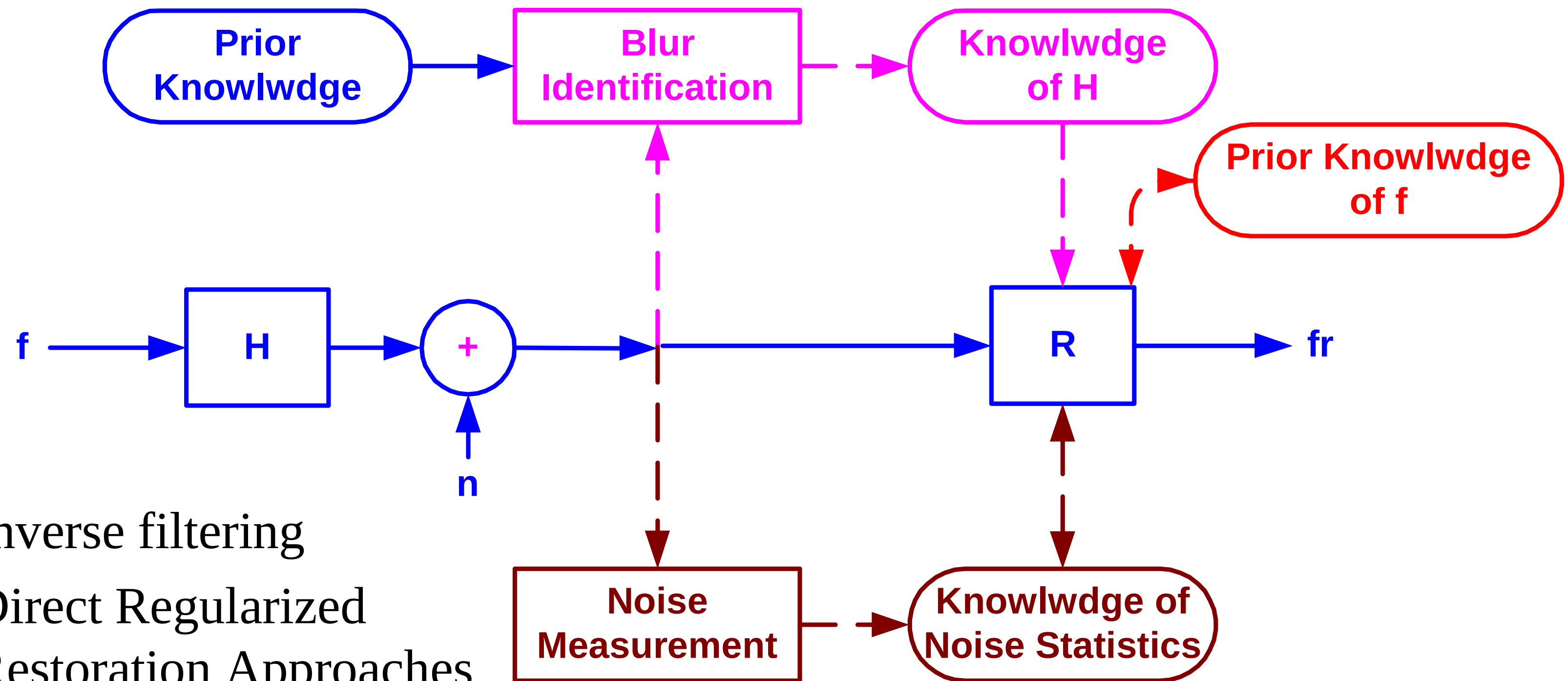
General blind deconvolution scenario

Key Paper #2 continued

Class of algorithms	Zero Sheet Separation	A priori blur identification	ARAM Parameter Extraction	Nonparametric Deterministic Constrains Algorithm	HOS method
Assumptions about the TRUE image	Finite support	Possibly contains edges or point sources	Modeled by an AR process	Deterministic constrains (non-negativity, support, blur invariant edge)	Accurately modeled by a non-Gaussian probability distribution
Assumptions about the blur	Finite support	Symmetric and non-minimum phase with a possibly known parametric form	Symmetric and modeled by an MA process of a possibly known parametric form	IBD and SA: positive with known finite support; NAS-RIF: invertible	invertible
Complexity	High	Very low (not iterative)	Moderate to high	Low to moderate	Moderate
Convergence properties	Sensitive to numerical accuracies; ill-convergence	Not iterative	ill-convergence to local minima; sensitive to initial condition	IBD: ill-convergence; sensitive to initial estimate; SA and NAS-RIF: converge to local minima	Ill-convergence; sensitive to initial estimate
Sensitivity to additive noise	High	Moderate to high	Moderate	IBD: low SA: moderate; NAS_RIF: moderate to high;	Low (Gaussian)
Application area	Astronomy	Astronomy, industrial x-ray imaging; photography	Photography; texture image reconstruction	Magnetic resonance imaging; x-ray imaging; astronomy	Astronomy; seismic data

Key Paper #3

- M. R. Banham and A. K. Katsaggelos, "Digital Image Restoration", IEEE Signal Processing Magazine, vol. 14, no. 2, pp.24-41, Mar. 1997



- Inverse filtering
- Direct Regularized Restoration Approaches
- Iterative Approaches
- Recursive Approaches