Astronomical imaging & image processing

Seppo Mattila (sepmat@utu.fi) Department of Physics and Astronomy, University of Turku



Examples of astronomical imaging data

soft X-ray image (0.5 - 7 keV)



NASA Chandra X-ray observatory

optical image (435+814 nm)

Hubble Space Telescope (HST)



Hubble Space Telescope (HST) optical (435 + 814 nm) (PSF FWHM ~ 0.1 ")



2010P

NOT/NOTCam near-infrared (2.2 μ m) (PSF FWHM ~ 1")



Gemini-N/Altair near-infrared (1.1-2.2 μ m) (PSF FWHM ~ 0.1")



Very Large Array (VLA) radio image (8.46 GHz = 3.5 cm) (PSF FWHM ~ 0.5")





Detecting time-variability: astronomical and medical imaging

- Detection and study of stellar explosions (supernovae) by repeated imaging of galaxies
 - SN detection by precise image alignment, matching of the point spread functions (PSFs), intensity and background levels followed by image subtraction



Detecting time-variability: astronomical and medical imaging

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- Monitoring of volumetric changes, e.g., loss of tissue in Alzheimer's

Reference

Register new and reference images using natural landmarks, normalise image intensities and apply image subtraction to reveal tiny volumetric changes



(a) (b) (c) Bradley et al. 2002, British J. of Radiology, 75, 506



$$(f * g)(x) = \int_{-\infty}^{\infty} f(\tau)g(x - \tau) d\tau$$

 $(f * g)_j = \sum_{k=-m/2+1}^{m/2} f_k g_{j-k}$



$$F(u,v) = \operatorname{FT}\{f(x,y)\}$$

$$F(u,v) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x,y) \exp[2\pi i (ux+vy)] \, dx \, dy$$

Linearity

i.e.,

$$FT{f(x, y) + g(x, y)} = F(u, v) + G(u, v)$$

Convolution

$$FT{f(x, y) \star g(x, y)} = F(u, v) \cdot G(u, v)$$

Shift

$$FT{f(x - x_i, y - y_i)} = F(u, v) \exp[2\pi i(ux_i + vy_i)]$$

Similarity

$$FT{f(ax, by)} = \frac{1}{|ab|}F\left(\frac{u}{a}, \frac{v}{b}\right)$$

Convolution

With convolution can reduce the noise and therefore increase the S/N while degrading spatial resolution
 "real" signal additive noise

 $b(\vec{x}) = f(\vec{x}) * p(\vec{x}) + n(\vec{x})$

observed signal

PSF



 $ref(x, y) \otimes kernel(x, y, u, v) = im(x, y)$ Aland & Lupton 1998: A method for optimal image subtraction, arXiv:astro-ph/9712287

Convolution

• With convolution can reduce the noise and therefore increase the S/N while degrading spatial resolution "real" signal

$$b(\vec{x}) = f(\vec{x}) * p(\vec{x}) + n(\vec{x})$$

additive noise

observed signal **PSF**

In the case of 1-D functions

$$(f * g)(x) = \int_{-\infty}^{\infty} f(\tau)g(x - \tau) d\tau$$

In the case of discrete 1-D functions

$$(f * g)_j = \sum_{k=-m/2+1}^{m/2} f_k g_{j-k}$$

Deconvolution

We have observed data *I* (intensity distribution) corresponding to an observation of a "real image" O through an imaging system characterised by the PSF *P* and additive noise *N*.

$$I(x, y) = \int_{x_1 = -\infty}^{+\infty} \int_{y_1 = -\infty}^{+\infty} P(x - x_1, y - y_1) O(x_1, y_1) dx_1 dy_1$$

+
$$N(x, y)$$

= $(P * O)(x, y) + N(x, y),$

The Convolution Theorem: Convolution in either domain is equivalent to multiplication in the other.

In Fourier space:

$$\hat{I}(u, v) = \hat{O}(u, v)\hat{P}(u, v) + \hat{N}(u, v).$$

Starck, Pantin & Murtagh 2002: Deconvolution in Astronomy https://iopscience.iop.org/article/10.1086/342606/pdf

Deconvolution

In Fourier space:

$$\hat{I}(u, v) = \hat{O}(u, v)\hat{P}(u, v) + \hat{N}(u, v).$$

$$\frac{\hat{I}(u, v)}{\hat{P}(u, v)} = \hat{O}(u, v) + \frac{\hat{N}(u, v)}{\hat{P}(u, v)}.$$

This method, sometimes called the *Fourier-quotient method*, is very fast. We need to do only a Fourier transform and an inverse Fourier transform. However, in the presence of noise, this method cannot be used.

Starck, Pantin & Murtagh 2002: Deconvolution in Astronomy https://iopscience.iop.org/article/10.1086/342606/pdf

Difference imaging in astronomy



Sep, 1994



Mar, 1995



Feb, 1996



Jul, 1997



Feb, 1998



Apr, 1999



Nov, 2000



Jan, 2003



Nov, 2003



Sep, 2005



Apr, 2006



Dec, 2001

Dec, 2006



May, 2007



Feb, 2008



Apr, 2009



Dec, 2009



Jan, 2011



Feb, 2013



Jun, 2014



Ahola (2018)

$ref(x, y) \otimes kernel(x, y, u, v) = im(x, y) + bg(x, y)$



 $ref(x, y) \otimes kernel(x, y, u, v) = im(x, y) + bg(x, y)$

 $kernel(x, y, u, v) = \sum_{n} \sum_{d_n^x} \sum_{d_n^y} \sum_{\delta^x} \sum_{\delta^y} \left[a_n \underbrace{x^{\delta^x} y^{\delta^y}}_{3} \underbrace{e^{-(u^2 + v^2)/2\sigma_n^2}}_{1} \underbrace{u^{d_n^x} v^{d_n^y}}_{2}\right]$



$$ref(x,y) \otimes kernel(x,y,u,v) = im(x,y) + bg(x,y)$$

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The convolution kernel consists of a set of Gaussian functions (1) which are modified by polynomials (2) and a model for the spatial variations of the kernel (3) where $0 < d_n^y + d_n^x \leq D_n$, and $0 < \delta^y + \delta^x \leq D^k$.



 $ref(x, y) \otimes kernel(x, y, u, v) = im(x, y) + bg(x, y)$

 $kernel(x, y, u, v) = \sum_{n} \sum_{d_n^x} \sum_{d_n^y} \sum_{\delta^x} \sum_{\delta^y} \sum_{\delta^y} \left[a_n \underbrace{x^{\delta^x} y^{\delta^y}}_{3} \underbrace{e^{-(u^2 + v^2)/2\sigma_n^2}}_{1} \underbrace{u^{d_n^x} v^{d_n^y}}_{2}\right]$

$$bg(x,y) = \sum_{i} \sum_{j} a_{i} x^{i} y^{j}$$



Discovery of new astrophysical transients by precise alignment, PSF matching and subtraction of images





VLT/VIMOS B 10 hours V 5 hours R 15 hours I 30 hours

Melinder et al. 2011, 2012



Examples of deconvolution

Application of the Richardson-Lucy algorithm in astronomy

THE ASTRONOMICAL JOURNAL

VOLUME 79, NUMBER 6

JUNE 1974

An iterative technique for the rectification of observed distributions

L. B. Lucy*

Departments of Physics and Astronomy, The University of Pittsburgh, Pittsburgh, Pennsylvania 15213 (Received 15 January 1974; revised 26 March 1974)

An iterative technique is described for generating estimates to the solutions of rectification and deconvolution problems in statistical astronomy. The technique, which derives from Bayes' theorem on conditional probabilities, conserves the constraints on frequency distributions (i.e., normalization and non-negativeness) and, at each iteration, increases the likelihood of the observed sample. The behavior of the technique is explored by applying it to problems whose solutions are known in the limit of infinite sample size, and excellent results are obtained after a few iterations. The astronomical use of the technique is illustrated by applying it to the problem of rectifying distributions of $v \sin i$ for aspect effect; calculations are also reported illustrating the technique's possible use for correcting radio-astronomical observations for beam-smoothing. Application to the problem of obtaining unbiased, smoothed histograms is also suggested.



Dopita et al. 1996: Hubble Space Telescope observations of planetary nebulaea

Application of the Richardson-Lucy algorithm to medical images



Lai et al. 2003, Journal of Microscopy





Coubin et al. 2011, arXiv:1009.1473



1 arcm

Ε ◄



Adaptive optics (AO) imaging

Davies R. 2012: Adaptive Optics for Astronomy https://arxiv.org/pdf/1201.5741.pdf



Figure 3-1: Principle of Adaptive Optics VLT/NACO User manual

The principles of Adaptive Optics



Davies et al. 2012

The principles of Adaptive Optics



Davies et al. 2012





FWHM = 1" natural seeing



The motion of a star around the central black hole in the Milky Way



Multi-AO Imaging Camera for Deep Observations (MICADO) will enable ELT to perform diffraction limited: observations $\theta \sim 1.22 \text{ x } \lambda / D$

• 4 mas pixel scale providing 50" x 50" field of view with fully sampled diffraction limited PSF of the 39-m diameter ELT (FWHM = 12 mas at 2 μ m)



Davies et al. 2018