Image restoration

Introduction and examples —

Jean-François Giovannelli

Groupe Signal – Image Laboratoire de l'Intégration du Matériau au Système Univ. Bordeaux – CNRS – BINP

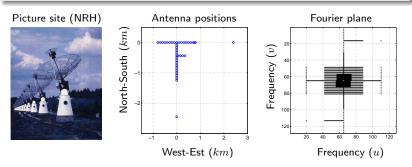
Topics

- Image restoration, deconvolution
 - Motivating examples: medical, astrophysical, industrial,...
 - Various problems: Fourier synthesis, deconvolution,...
 - Missing information: ill-posed character and regularisation
- Three types of regularised inversion
 - Quadratic penalties and linear solutions
 - Closed-form expression
 - Computation through FFT
 - Numerical optimisation, gradient algorithm
 - Non-quadratic penalties and edge preservation
 - Half-quadratic approaches, including computation through FFT
 - Numerical optimisation, gradient algorithm
 - Constraints: positivity and support
 - Augmented Lagrangian and ADMM, including computation by FFT
 - Optimisation (e.g., gradient), system solvers (e.g., splitting)
- Bayesian strategy: a few incursions
 - Tuning hyperparameters, instrument parameters,...
 - Hidden / latent parameters, segmentation, detection,...

Interferometry: principles of measurement

Physical principle [Thompson, Moran, Swenson, 2001]

- Antenna array → large aperture
- Frequency band, e.g., 164 MHz
- Couple of antennas interference → one measure in the Fourier plane



- Knowledge of the sun, magnetic activity, eruptions, sunspots,...
- Forecast of sun events and their impact,...

Interferometry: illustration

True map ES



True map PS



Dirty beam



Dirty map ES



Dirty map PS



 $\mathsf{Dirty}\;\mathsf{map}\;\mathsf{PS}+\mathsf{ES}$



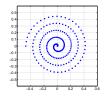
MRI: principles of measurement

Physical principle [Alaux 92]

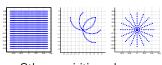
- ullet High / Ultra-high magnetic field $oldsymbol{B} \leadsto$ spin precession, $f \propto \|oldsymbol{B}\|$
- Gradient $\boldsymbol{B} = \boldsymbol{B}_0 + B(x) \leadsto \text{coding space}$ frequency
- Proton density → signal amplitude
- Tissue, motion (physiological, perfusion, diffusion),...
- Sequence and system parameters (times, magnetic field,...)



GE Phantom



Frequency coverage



Other acquisition schemes

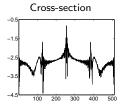
- Medical imaging, morphological and functional, neurology,...
- Fast MRI, cardiovascular applications, flow imaging,...

MRI: illustration



Instrument response

100
200
300
400
500
100
200
300
400
500

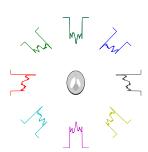




X-ray tomography (scanner): principles of measurement

- X-rays absorption → radiography
- Radon transform





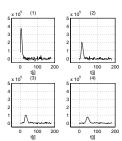
- Materials analysis and characterization, airport security,...
- Medical imaging: diagnosis, therapeutic follow-up,...

X-ray tomography: illustration

Hydrogeology and source identification

- Source: chemical, radioactive, odor,...
- Transport phenomena in porous media
- Groundwater sensors (drilling)

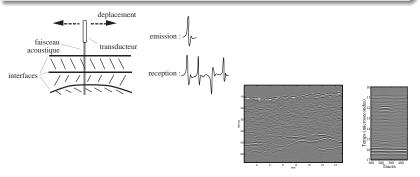




- Monitoring: electricity generation, chemical industry,...
- Knowledge for its own sake: subsoils, transportation, geology,...

Ultrasonic imaging

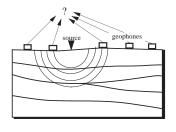
- Interaction: ultrasonic wave ↔ medium of interest
- Acoustic impedance: inhomogeneity, discontinuity, medium change

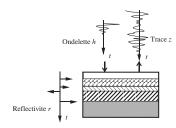


- Industrial control: very-early cracks detection (nuclear plants,...)
- Non destructive evaluation: aeronautics, aerospace,...
- Tissue characterisation, medical imaging,...

Seismic reflection method

- Acoustic impedance: inhomogeneity, discontinuity, medium change

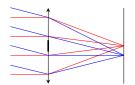




- Mineral and oil exploration,...
- Knowledge of subsoils and geology,...

Optical imaging (and infrared, thermography)

- \bullet Fundamentals of optics (geometrical and physical) \leadsto stain
- CCD sensors or bolometers → spatial and time response





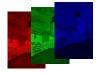


- Public space surveillance (car traffic, marine salvage,...)
- Satellite imaging: astronomy, remote sensing, environment
- Night vision, smokes / fogs / clouds, bad weather conditions

Digital photography and demosaicing

- Matrix / filter / Bayer mosaic: red, green, blue
- Chrominance and luminance





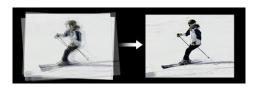


- Holiday pictures
- Surveillance (public space, car traffic,...)

The case of super-resolution

Physical principle

- Time series of images → over-resolved images
- ullet Sub-pixel motion \sim over-sampling
- Motion estimation + Restoration



• Same applications...with higher resolution

And other imaging... fields, modalities, problems,...

Fields

- Astronomy, geology, hydrology,...
- Thermography, fluid mechanics, transport phenomena,...
- Medical: diagnosis, prognosis, theranostics,...
- Remote sensing, airborne imaging,...
- Surveillance, security,...
- Non destructive evaluation, control,...
- Computer vision, under bad conditions,...
- Augmented reality, computer vision & graphics,...
- Photography, games, recreational activities, leisures,...
- . . .
 - → Health, knowledge, leisure,...
 - → Augmented Reality, Computer Vision & Graphics,...
 - → Aerospace, aeronautics, transport, energy, industry,...

And other imaging... fields, modalities, problems,...

Modalities

- Interferometry (radio, optical, coherent,...)
- Magnetic Resonance Imaging
- Tomography based on X-ray, optical wavelength, tera-Hertz,...
- Ultrasonic imaging, sound, mechanical
- Holography
- Polarimetry: optical and other
- Synthetic aperture radars
- Microscopy, atomic force microscopy
- Camera, photography
- Lidar, radar, sonar,...
- . .
 - \rightsquigarrow Essentially "wave \leftrightarrow matter" interaction

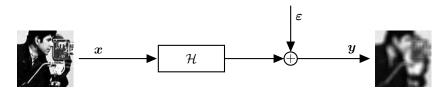
And other imaging... fields, modalities, problems,...

"Signal – Image" problems

- Denoising
- Edge / contrast enhancement
- Missing data
 - inpainting / interpolation
 - outpainting / extrapolation
- Deconvolution
- Inverse Radon
- Fourier synthesis
- . . .
- And also:
 - Segmentation
 - Detection of impulsions, salient points,...
 - ...
 - → In the following lectures: deconvolution-denoising

Inversion: standard question

$$y = \mathcal{H}(x) + \varepsilon = Hx + \varepsilon = h \star x + \varepsilon$$



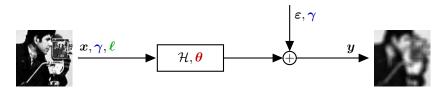
$$\widehat{m{x}} = \widehat{\mathcal{X}}(m{y})$$

Restoration, deconvolution-denoising

- General problem: ill-posed inverse problems, i.e., lack of information
- Methodology: regularisation, i.e., information compensation
 - Specificity of the inversion / reconstruction / restoration methods
 - Trade off and tuning parameters
- Limited quality results

Inversion: advanced question

$$oldsymbol{y} = \mathcal{H}(oldsymbol{x}) + oldsymbol{arepsilon} = oldsymbol{H}oldsymbol{x} + oldsymbol{arepsilon} = oldsymbol{h}\staroldsymbol{x} + oldsymbol{arepsilon}$$



$$egin{aligned} \widehat{oldsymbol{x}} &= \widehat{\mathcal{X}}(oldsymbol{y}) \ \left[\ \widehat{oldsymbol{x}}, \widehat{oldsymbol{\gamma}}, \widehat{oldsymbol{ heta}}, \widehat{\ell} \
ight] &= \widehat{\mathcal{X}}(oldsymbol{y}) \end{aligned}$$

More estimation problems

- Hyperparameters, tuning parameters: unsupervised
- Instrument parameters (resp. response): myopic (resp. blind)
- Hidden variables: edges, regions, singular points,...: augmented
- Different models for image, noise, response,...: model selection

Issues and framework

Inverse problems

- Instrument model, direct / forward model
- Involves physical principles of
 - the phenomenom at stake
 - the acquisition system, the sensor
- Inverse
 - undo the degradations, surpass natural resolution
 - from consequences to causes
 - restore / rebuild / retrieve
- Ill-posed / ill-conditioned character and regularisation

Framework of this course

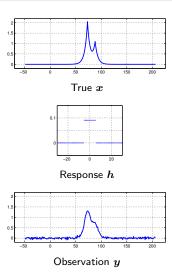
- Direct model
 - linear and shift invariant, i.e., convolutive
 - including additive error (model and measurement)
- Regularisation through penalties and constraints
- Criterion optimisation and convexity

Some historical landmarks

- ullet Quadratic approaches and linear filtering ~ 60
 - Phillips, Twomey, Tikhonov
 - Kalman
 - Hunt (and Wiener ~ 40)
- Extension: discrete hidden variables ~ 80
 - Kormylo & Mendel (impulsions, peaks,...)
 - Geman & Geman (lines, contours, edges,...)
 - Besag, Graffigne, Descombes (regions, labels,...)
- Convex penalties (also hidden variables,...) ~ 90
 - ullet L_2-L_1 , Huber, hyperbolic: Sauer, Blanc-Féraud, Idier...
 - ...et les POCS
 - L_1 : Alliney-Ruzinsky, Taylor ~ 79 , Yarlagadda ~ 85 . . .
 - And... L_1 -boom ~ 2005
- ullet Back to more complex models ~ 2000
 - · Unsupervised, myopic, semi-blind, blind
 - Stochastic sampling (MCMC, Metropolis-Hastings...)

Example due to Hunt ("square" response) [1970]

- ullet Convolutive model: $oldsymbol{y} = oldsymbol{h} \star oldsymbol{x} + oldsymbol{arepsilon}$
- Samples averaging



Example: photographed photographer ("square" response)

- ullet Convolutive model: $oldsymbol{y} = oldsymbol{h} \star oldsymbol{x} + oldsymbol{arepsilon}$
- Pixels averaging
- Think also about the Fourier domain



True x



Spatial response h



Observation y

Example: brain ("square" response)

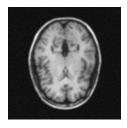
- ullet Convolutive model: $oldsymbol{y} = oldsymbol{h} \star oldsymbol{x} + oldsymbol{arepsilon}$
- Pixels averaging
- Think also about the Fourier domain



True x



Spatial response \boldsymbol{h}



Observation ${m y}$

Example: brain ("motion blur")

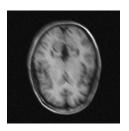
- ullet Convolutive model: $oldsymbol{y} = oldsymbol{h} \star oldsymbol{x} + oldsymbol{arepsilon}$
- Pixels averaging
- Think also about the Fourier domain



True $oldsymbol{x}$



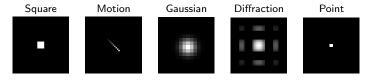
Spatial response h



Observation $oldsymbol{y}$

Convolution equation (discrete time / space)

Examples of response



Convolutive model

$$z(n) = \sum_{p=-P}^{+P} h(p) x(n-p)$$

$$z(n,m) = \sum_{p=-P}^{+P} \sum_{q=-Q}^{+Q} h(p,q) x(n-p,m-q)$$

- Response: h(p) or h(p,q)
 - impulse response, convolution kernel,...
 - ... point spread function, stain image

Convolution equation (discrete time, 1D): matrix form

- Linear \leadsto matricial relation: z = Hx
- Shift invariance → Toplitz structure
- Short response → band structure

```
z_{n-1} =
             h_P x_{n-P} + \cdots + h_1 x_{n-1} + h_0 x_n + h_{-1} x_{n+1} + \cdots + h_{-P} x_{n+P}
      z_{n+1}
```

See exercise regarding Toeplitz and circulant matrices...

Short and important incursion in "continuous statement"

- More realistic modelling of physical phenomenon
- Continuous variable convolution (1D, 2D and 3D,...)
- Observations
 - Sampling (discretization) of output
 - Finite number of samples
- Decomposition of unknown object
- Again "discrete" convolution

Convolution equation: continuous variable

Convolutive integral equation

$$z(t) = \int x(\tau) h(t-\tau) d\tau$$

$$z(u,v) = \iint x(u',v') h(u-u',v-v') du'dv'$$

$$z(u,v,w) = \iiint x(u',v',w') h(u-u',v-v',w-w') du'dv'dw'$$

More generally: Fredholm integral equation (first kind)

$$z(t) = \int x(\tau) h(t,\tau) d\tau$$

$$z(u,v) = \iint x(u',v') h(u,u',v,y') du'dv'$$

$$z(u,v,w) = \iiint x(u',v',w') h(u,u',v,y',w,w') du'dv'dw'$$

Continuous convolution and discrete observations

Convolutive integral equation

for
$$t \in \mathbb{R}$$
: $z(t) = \int_{-\infty}^{+\infty} x(\tau) h(t - \tau) d\tau$

- Measurement
 - Discrete data (just sampling, no approximation)...

$$z_n = z(nT_s) = \int_{-\infty}^{+\infty} x(\tau) h(nT_s - \tau) d\tau$$

- ullet ...and finite number of data: $n=1,2,\ldots,N$.
- Unknown object remains "continuous variable": x(t), for $t \in \mathbb{R}$

Object "decomposition-recomposition"

"General" decomposition of continuous time object

$$x(\tau) = \sum_{k} x_{k} \varphi_{k}(\tau)$$

- Fourier series and finite time extend (finite duration)
- Cardinal sine and finite bandwidth
- Spline, wavelets, Gaussian kernel...
- . . .
- Infinite dimensional linear algebra
 - Hilbert spaces, Sobolev spaces...
 - Basis, representations...
 - Inner products, norms, projections...

Object "de / re - composition": example of finite bandwidth

"General" decomposition of continuous time object

$$x(\tau) = \sum_{k} x_{k} \varphi_{k}(\tau)$$

ullet Case of shifted version of a basic function $arphi_0$

$$\varphi_k(\tau) = \varphi_0(\tau - k\delta)$$

Special case with cardinal sine

$$\varphi_0(\tau) = \operatorname{sinc}[t/\delta]$$
 with $\operatorname{sinc}[u] = \frac{\sin \pi u}{\pi u}$

• That is the Shannon reconstruction formula

$$x(\tau) = \sum_{k \in \mathbb{Z}} x_k \varphi_0(\tau - k\delta) = \sum_{k \in \mathbb{Z}} x_k \operatorname{sinc}\left[\frac{\tau - k\delta}{\delta}\right]$$

- ...and there is no approximation, no error if
 - the signal is •
 - ullet and with $x_k = ullet$

Object "de / re - composition": example of finite bandwidth

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- ...and there is no approximation, no error if
 - the signal is of finite bandwidth
 - ullet and with $x_k=x(kT_{
 m s})$ with $T_{
 m s}$ ullet

Object "de / re - composition": example of finite bandwidth

• "General" decomposition of continuous time object

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- ... and there is no approximation, no error if
 - the signal is of finite bandwidth
 - and with $x_k = x(kT_{
 m s})$ with $T_{
 m s}$ small enough: $F_{
 m s} > 2F_{
 m M}$

Convolution: continuous → discrete

ullet Given that (discrete observation at time $nT_{
m s}$)

$$z_n = \int_{-\infty}^{+\infty} x(\tau) h(nT_s - \tau) d\tau$$
 for $n = 1, 2, \dots, N$

• and that (case of shifted version of a basic function φ_0)

$$x(\tau) = \sum_{k} x_k \varphi_0(\tau - k\delta) \quad \text{for } \tau \in \mathbb{R}$$

By substitution, we have

$$z_{n} = \int_{-\infty}^{+\infty} \left[\sum_{k} x_{k} \varphi_{0}(\tau - k\delta) \right] h(nT_{s} - \tau) d\tau$$

$$= \sum_{k} x_{k} \int_{-\infty}^{+\infty} \varphi_{0}(\tau - k\delta) h(nT_{s} - \tau) d\tau$$

$$= \sum_{k} x_{k} \int_{-\infty}^{+\infty} \varphi_{0}(\tau) h([nT_{s} - k\delta] - \tau) d\tau$$

Convolution: continuous → discrete

• Let us denote: $\bar{h}=\varphi_0\star h$

$$\bar{h}(u) = \int_{-\infty}^{+\infty} \varphi_0(\tau) h(u - \tau) d\tau$$

We then have

$$z_n = \sum_k x_k \int_{-\infty}^{+\infty} \varphi_0(\tau) h([nT_s - k\delta] - \tau) d\tau$$
$$= \sum_k x_k \bar{h}(nT_s - k\delta)$$

- The z_n are given as a function of the x_k
- It is a "discrete linear" transform
- There is no apprximation

Convolution: continuous → discrete

 \bullet A specific case when $\delta = T_{\rm s}/K$

$$z_{n} = \sum_{k} x_{k} \bar{h} [nT_{s} - k\delta]$$

$$= \sum_{k} x_{k} \bar{h} [nK\delta - k\delta]$$

$$= \sum_{k} x_{k} \bar{h} [(nK - k)\delta]$$

- Subsampled discrete convolution
- ullet A specific case when $\delta=T_{
 m s}$, i.e., K=1

$$z_n = \sum_k x_k \, \bar{h} \left[(n-k)\delta \right]$$

A standard discrete convolution