

Mathematical Modelling in Magnetic Resonance Imaging

Alessandro Sbrizzi





1973





part is different. It is a free association of nations drawn together by

a common will to bury the sword. To transform the cockpit of Europe into a power for

peace that was the ideal that took seed amid the rubble more than a quarter of a century ago.

The fine are shill sayly day, proneering day, min these are shill sayly day, proneering day, the say of the sa

For ten years the Dally Mail has campaigned for this commitment. We have not wavered in our conviction that Britain's best and brightest future is







Nature, 1973, pag. 190-191

Image Formation by Induced Local Interactions: Examples Employing Nuclear Magnetic Resonance P. C. LAUTERBUR

Department of Chemistry, State University of New York at Stony Brook, Stony Brook, New York 11790





Fig. 1 Relationship between a three-dimensional object, its twodimensional projection along the Y-axis, and four one-dimensional projections at 45° intervals in the XZ-plane. The arrows indicate the gradient directions. " the signal in the presence of a field gradient represents a **onedimensional projection** of the H_2O content of the object, **integrated over planes** perpendicular to the gradient direction, as a function of the gradient coordinate...."

"... combine several projections, ... using one of the available methods for reconstruction of objects from their projections."



"The variations in water contents and proton relaxation times among biological tissues should permit the generation (...) of useful zeugmatographic images (...). A possible application of considerable interest at this time would be to the in vivo study of malignant tumours ..."



Fig. 2 Proton nuclear magnetic resonance zeugmatogram of the object described in the text, using four relative orientations of object and gradients as diagrammed in Fig. 1.



A CENTURY OF 1 ature

WENTY-ONE DISCOVERIES

THAT CHANGED SCIENCE AND THE WORLD

EDITED BY LAURA GARWIN & TIM LINCOLN

ANALISTATIV & NEW SPACE OF WATTER FROM BUELLAN AMPLICE. ID NULLEAR WEAPONT HE DOLET THESE DARN OF STOLETURAL EDUDUCT. THE FIRST LESSE FAIL OF STOLETERS SEALLOSE MACHINERED OF TOUCHER ENTERING DESCRIPTION FOR THESE AND SELLATE ENTERING OWENER TO FAR THESE AND SELLATE ENTERING







1975: Enters Fourier transform

NMR Fourier Zeugmatography

ANIL KUMAR, DIETER WELTI, AND RICHARD R. ERNST

Laboratorium für Physikalische Chemie, Eidgenössische Technische Hochschule, 8006 Zürich, Switzerland

"(...) The spatial spin density function can then be reconstructed by a straightforward **two- or three-dimensional Fourier transformation**. One of the important features of this method is the **homogenous error distribution over the entire frequency range** such that low and high frequency components can be reconstructed with equal accuracy. The method can easily be implemented on a **small on-line computer**."



Spin warp NMR imaging and applications to human whole-body imaging

W A Edelstein, J M S Hutchison, G Johnson and T Redpath Physics in Medicine and Biology, Volume 25, Number 4



"In the spin warp technique, all the projections are along the same direction, and therefore inhomogeneity will manifest itself only as a geometric distortion in the final image; there will be no smearing of imaging information."

FFT for image reconstruction



Spin warp NMR imaging and applications to human whole-body imaging

W A Edelstein, J M S Hutchison, G Johnson and T Redpath Physics in Medicine and Biology, Volume 25, Number 4









64 x 64 FFT

A Simple Graphical Representation of Fourier-Based Imaging Methods

STIG LJUNGGREN

1983

Department of Physical Chemistry, The Royal Institute of Technology, S-100 44, Stockholm 70, Sweden

$$S(t) = \int \rho(\mathbf{r}) \exp\left(i\gamma \mathbf{r} \cdot \int_0^t \mathbf{G}(t')dt'\right) d\mathbf{r}$$
$$\mathbf{k}(t) = \gamma \int_0^t \mathbf{G}(t')dt'$$



A Simple Graphical Representation of Fourier-Based Imaging Methods

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$$S(S)(\mathbf{k}(f))(\mathbf{r}) = \exp\left(i\beta(\mathbf{r})\int_{0}^{t} \mathbf{G}(t')dt'\right)\mathbf{k}(t) = \gamma \int_{0}^{t} \mathbf{G}(t')dt'$$





FIG. 1. Scanning patterns in the k plane: (a) projection reconstruction method; (b) line scan method; (c) Fourier imaging; (d) echo planar imaging method; (e) modified EPI method; (f) modified projection reconstruction method.

Ljunggren, 1983

"..., it is believed that many unnecessary mathematical complications such as the use of the so-called **projection functions may be avoided** in this way"

"The rather loosely outlined applications suggested above **should not be taken too seriously**."





 k_x

Image space



 \mathcal{X}



y

MRI through the '90s

- MRI becomes a mature/robust technique
- Numbers of clinical scanners (and scans) steadily increase in US and Europe



Exhibit 1. International Comparison of Spending on Health, 1980–2009





D.A. Squires, The Commonwealth Fund, 2012

Making MRI cheaper = faster





Employ several receiver antennas, **simultaneously**

Individual **additional** spatial information

Undersample the *k*-space



$$d_{\gamma,\kappa} = \int M(\mathbf{r}) \operatorname{enc}_{\gamma,\kappa}(\mathbf{r}) \, \mathrm{d}\mathbf{r}$$
$$\operatorname{enc}_{\gamma,\kappa}(\mathbf{r}) = s_{\gamma}(\mathbf{r}) e^{j\mathbf{k}_{\kappa}\mathbf{r}}$$
Coil dependent spatial weighting







Image from *Prussmann NMR Biomed 2006*

$$d_{\gamma,\kappa} = \int M(\mathbf{r}) \operatorname{enc}_{\gamma,\kappa}(\mathbf{r}) \,\mathrm{d}\mathbf{r}$$
$$\operatorname{enc}_{\gamma,\kappa}(\mathbf{r}) = s_{\gamma}(\mathbf{r})e^{j\mathbf{k}_{\kappa}\mathbf{r}}$$

Parallel imaging leads to (large scale) least-squares reconstruction

- \rightarrow iterative methods (CG, LSQR)
- \rightarrow preconditioning
- \rightarrow Tikhonov regularization



The magic of compressed sensing

- <u>Since 1970s</u> in several applied fields : exploit **sparse representation of data** through l_1 norm for regularization of illconditioned/underdetermined systems
- <u>Beginning 2000s, California</u>: Candes (Stanford), Romberg (Caltech/UCLA), Tao (UCLA), Donoho (Stanford). Theoretical foundations are laid. Correct recovery from highly undersampled data (!). Concept of **incoherence/randomization**.
- <u>2004</u>: *Convex Optimization* book by Boyd & vandenBerghe (more than 35,000 citations by May 2017). **Tractable algorithms**.

The Nobel Prize in Physiology or Medicine 2003





BACHG NEWS + BRE

erbur Sir Priz

Sir Peter Mansfield Prize share: 1/2



Sparse MRI: The Application of Compressed Sensing for Rapid MR Imaging 2007

Michael Lustig,^{1*} David Donoho,² and John M. Pauly¹





(10-fold undersampling)

Compressed sensing in MRI

- Development of l_2/l_1 minimization algorithms
- Optimal **undersampling** schemes?
- Optimal **sparse representation**?
- CS-MRI is now a **clinical product** from major vendors (<u>modern math</u> <u>enters the clinic!</u>)



Recent developments in CS MRI

- Recover image, M, such that M = L + S
- *L* : low-rank matrix (temporally correlated **background**)
- S : sparse matrix (**dynamic information** on top of background)





Recent developments in CS MRI

- Recover image, M, such that M = L + S
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8-fold undersampling



Otazo, Candes, Sodickson 2014

The future of MRI

Can we scan faster?



• So far, MRI reconstruction was more or less:

$$\min_{\mathbf{m}} \| F\mathbf{m} - \mathbf{d} \| + \lambda \| C\mathbf{m} \|$$

• Further undersampling by introducing physical constraints

 $\min_{\mathbf{m},\mathbf{p}} \| F\mathbf{m} - \mathbf{d} \| + \lambda \| C\mathbf{m} \|$ s.t. $g(\mathbf{m},\mathbf{p}) = 0$ (physical model)



The Bloch equation (1946)



Local behaviour of nuclear magnetization:

Felix Bloch (1905-1983) Nobel Prize in 1952



Experimental setting (t)State (t,\mathbf{r}) Parameter (\mathbf{r})





```
\min_{\mathbf{m},\mathbf{p}} \| F\mathbf{m} - \mathbf{d} \| + \lambda \| C\mathbf{m} \|
s.t. g(\mathbf{m},\mathbf{p}) = 0 (Bloch eq.)
```

- So far, **linear** operators (FFT, Parallel imaging spatial weight functions, sparsify transforms ...)
- Bloch equation is nonlinear in the model parameters
 1) computational complexity
 2) non-convexity





MR fingerprinting (Dan Ma et al, Nature 2013)





8 seconds scan





Jiang Y. et al, MRM 2015

MRF Dictionary. Computational complexity

Cost for constructing and storing the dictionary

# of parameters	Computing Time*	Memory*
4	17 hrs	400 Gb
6	43,000 hrs	960,000 Gb

Exponential growth for:

- a) Computing time
- b) Memory
- c) Exhaustive search (matching)⁻

Note: SVD compression accelerates matching but growth is still **exponential**.

SVD of 1000 Tb matrix!



MRF without dictionary?



Gradient-based iterations. Advantages:

- No dictionary.
- Complexity is linear in # of parameters: Extra parameter → small increase



MRF without dictionary?



Gradient-based iterations. Tackle:

- 1. Poor performance for large data-model discrepancy
- 2. Local minima for nonconvex functions.



Minimization landscape



Large data/model discrepancy in MRF



Bloch equation response and **undersampling artifacts** both **high frequency**:

 \rightarrow difficult to **separate**, everything looks like noise



Low-pass experiment design Find the experimental setting $\theta(t)$: $\arg\min_{\theta} \max_{n} \left\{ \frac{\sigma(T_{1}^{n})}{T_{1}^{n}}, \frac{\sigma(T_{2}^{n})}{T_{2}^{n}}, \frac{\sigma(\rho^{n})}{\rho^{n}} \right\}$ Sensitivity such that: $\theta(0) = 0$ $\frac{\mathrm{d}\theta}{\mathrm{d}t} \leq \delta$ **Smooth response** $|\theta(t)| \leq \theta_{\max}$ **Physical limit**

Sbrizzi, Bruijnen, van den Berg ISMRM 2017





Sbrizzi, Bruijnen, van den Berg ISMRM 2017

Model-based reconstruction

 $\min_{\mathbf{m},\mathbf{p}} \| F\mathbf{m} - \mathbf{d} \| + \lambda \| C\mathbf{m} \|$ s.t. $g(\mathbf{m},\mathbf{p}) = 0$ (physical model)

MR Fingerprinting approach:

$$\mathbf{m}^* = \arg \min_{\mathbf{m},\mathbf{p}} \| F\mathbf{m} - \mathbf{d} \| + \lambda \| C\mathbf{m} \|$$
$$\mathbf{p}_j^* = \arg \min \| g(\mathbf{m}_j^*, \mathbf{p}_j) \| \text{ for all } j$$

What about *F* ?

"it should not be taken too seriously" (Ljunggren, 1983)





Sbrizzi, van der Heide, van den Berg. arXiv 2017

MR-STAT reconstruction

 $\vec{b} = (T_1(\vec{r}), T_2(\vec{r}), |B_1^+(\vec{r})|, \Delta B_0(\vec{r}))$ $a(\vec{r}) \equiv |B_1^-(\vec{r})| M_0(\vec{r}) e^{i\phi(\vec{r})}$ signal model Time-data $(a^*, \vec{b}^*) = \operatorname{arg\,min}_{a, \vec{b}} \int_{t \in \tau} \left| d(t) - s(a, \vec{b}, t) \right|^2 \mathrm{d}t,$ (Data consistency) such that $s(a, \vec{b}, t) = \int_V a m(\vec{b}, t) d\vec{r}, \quad t \in \tau$ (Faraday's law) $\frac{\mathrm{d}}{\mathrm{d}t}\vec{m} = \Pi\vec{m} + \vec{c}$ (Bloch equation) $\vec{m}(\vec{b},0) = \vec{e}_3$ (Initial condition) $\vec{b} \in \mathbb{B}$ (Physical bounds)

Sbrizzi, van der Heide, van den Berg. arXiv 2017



Sbrizzi, van der Heide, van den Berg. arXiv 2017

Summary

- <u>'70s and '80s:</u> toward a reliable, robust model. From radial projections to FFT. Experimental design is devoted to fit in the FFT framework (*k*-space)
- <u>'90s and '00s:</u> model is extended to parallel imaging and CS. FFT is still fundamental part of solution to linear systems. Iterative methods for large scale (ℓ_2/ℓ_1) regularized least squares.
- <u>Present (and future?)</u>: physical modelling and simulations directly included in reconstruction. Nonlinearity, non-convexity, computational complexity. Numerical experimental design. AI.



