The Fourier Transform in MRI/fMRI

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- \succ Introduction
- > One Dimensional FT
 - Time series constituents and Fourier spectrum.
- ≻ Two Dimensional FT
 - An image constituents and Fourier spectrum.
- ➤ Two Dimensional MR Image Formation.
 - *k*-space and MR Image Reconstruction.
- > Two Dimensional MR Image Processing
 - Smoothing/Edge detetection.
- > One Dimensional fMRI Time Series
 - fMRI time series Fourier spectrum and filtering.
- > FMRI Time Series Statistics

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Introduction

Place volunteer/patient into MRI scanner.



MCW GE 3T Long Bore

Introduction

In MRI we image a real-valued 3D object, R(x, y, z). Lattice of volume elements, voxels.



Volume

Slice

Consider a single slice R(x, y).

Introduction

In MRI we aim to image a real-valued object, R(x, y). Different tissues have different magnetic properties yielding contrast.





One Dimensional FT

The Complex-Valued (Discrete) Fourier Transform (n=256, TR=2s)



The FT of a continuous function f(x) is

$$F(k) = \int_{-\infty}^{+\infty} f(x)e^{-i2\pi kx} dx$$

also denoted as $\mathcal{F}{f(x)}$ and its inverse to be

$$f(x) = \int_{-\infty}^{+\infty} F(k) e^{+i2\pi kx} dk$$

also denoted as $\mathcal{F}^{-1}{F(k)}$.

Don't forget that

 $e^{i\alpha} = \cos(\alpha) + i\sin(\alpha)$.

$$F(k) = \int_{-\infty}^{\infty} f(x) [\cos(2\pi kx) - i\sin(2\pi kx)] dx$$

$$= \int_{-\infty}^{\infty} f(x) \cos(2\pi kx) dx - i \int_{-\infty}^{\infty} f(x) \sin(2\pi kx) dx$$

$$= F_C(k) - iF_S(k)$$

$$F_C(k) = \int_{-\infty}^{\infty} \left[\sum_j A_j \cos(2\pi \nu_j x) + \sum_j B_j \sin(2\pi \nu_j x) \right] \cos(2\pi kx) dx$$

$$F_S(k) = \int_{-\infty}^{\infty} \left[\sum_j A_j \cos(2\pi \nu_j x) + \sum_j B_j \sin(2\pi \nu_j x) \right] \sin(2\pi kx) dx$$

The $\cos()\sin()$ and $\sin()\cos()$ cross terms are zero. Nonzero values at constituent frequencies where A_j and B_j nonzero.

Fourier Transform properties.				
Property	Function	Transform		
Linearity	af(x) + bg(x)	aF(k) + bG(k)		
Similarity	$f(\alpha x)$	$\underline{1}F(\underline{k})$		
Similarity	$\int (ux)$	$\overline{ a }$ \mathbf{L} (\overline{a})		
Shifting	f(x-a)	$e^{-i2\pi ka}F(k)$		
Derivative	$\frac{d^{\ell}f(x)}{dx^{\ell}}$	$(i2\pi k)^\ell F(k)$		

Convolution of functions f(x) and g(x) is defined as

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

Further

$$\mathcal{F} \left\{ f(x) \cdot g(x) \right\} = F(k) * G(k) \ ,$$

and

$$\mathcal{F} \left\{ f(x) \ast g(x) \right\} = F(k) \cdot G(k) \; .$$

Convolution properties.

f(x) * g(x) =	g(x) * f(x)	commutative
$f(x) \ast [g(x) \ast h(x)] =$	$[f(x)\ast g(x)]\ast h(x)$	associative
$f(x) * [g_1(x) + g_2(x)] =$	$f(x) * g_1(x) + f(x) * g_2(x)$	distributive
$\frac{d f(x) * g(x)}{dx} =$	$\frac{d f(x)}{dx} * g(x) = f(x) * \frac{d g(x)}{dx}$	derivative
$h(x-x_0) =$	$f(x - x_0) * g(x) = f(x) * g(x - x_0)$	shift
	$\text{ if } h(x) = f(x) \ast g(x)$	

The (finite) Discrete FT can be derived from the continuous FT (with assumptions).

$$\underbrace{F(p\Delta k)}_{Complex} = \sum_{q=-n}^{n-1} \underbrace{f(q\Delta x)}_{Complex} e^{-\frac{i2\pi pq}{2n}}$$
for $p = -n, \dots, n-1$

$$\underbrace{f(q\Delta x)}_{Complex} = \frac{1}{2n} \sum_{p=-n}^{n-1} \underbrace{F(p\Delta k)}_{Complex} e^{\frac{i2\pi pq}{2n}}$$
for $q = -n, \dots, n-1$.

There are some assumptions here. The constituent frequencies do not change in time. The constituent frequencies are $\leq 1/(2\Delta x)$.

The DFT can be represented as



 $(f_R + if_I) = (\bar{\Omega}_R + i \bar{\Omega}_I) (y_R + iy_I)$

The Complex-Valued (Discrete) Fourier Transform (n=256, TR=2s)



The Complex-Valued (Discrete) Fourier Transform (n=256, TR=2s)



Represent complex-valued time series as an image.

The Complex-Valued (Discrete) Fourier Transform (n=256, TR=2s)



Pre-multiply by complex-valued forward Fourier Matrix as an image.

The Complex-Valued (Discrete) Fourier Transform (n=256, TR=2s)



There are lines at the frequency locations. Real part (image) represents constituent cosine frequencies. Imaginary part (image) represents constituent sine frequencies. The intensity of the lines represents amplitude of that frequency.

The Complex-Valued (Discrete) Fourier Transform (TR=2s)





 $10 * \cos 0/512$ Hz

 $3 * \sin 8/512$ Hz

 $\sin 32/512$ Hz

 $\cos 4/512$ Hz





 $\sum = \cos + \cos + \sin + \cos$

The Complex-Valued 2D (Discrete) Fourier Transform $(\bar{\Omega}_{yR} + i\bar{\Omega}_{yI}) * (Y_R + iY_I) * (\bar{\Omega}_{xR} + i\bar{\Omega}_{xI})^T = (F_R + iF_I)$



The Complex-Valued 2D (Discrete) Fourier Transform $(\bar{\Omega}_{yR} + i\bar{\Omega}_{yI}) * (Y_R + iY_I) * (\bar{\Omega}_{xR} + i\bar{\Omega}_{xI})^T = (F_R + iF_I)$



 $\overline{\text{FOV}}=192 \text{ mm}, \text{ mat}=96 \times 96, \text{ vox}=2 \text{ mm}^3$

The Complex-Valued 2D (Discrete) Fourier Transform $(\bar{\Omega}_{yR} + i\bar{\Omega}_{yI}) * (Y_R + iY_I) * (\bar{\Omega}_{xR} + i\bar{\Omega}_{xI})^T = (F_R + iF_I)$







Real *k*-space (Cosines)

Imaginary k-space (Sines)

Note: Rotate bottom half (complex conjugate) up to get top! Hermetian symmetry (property).

So why do we need Fourier Transforms?

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In MRI/fMRI our measurements are not voxel values!

So why do we need Fourier Transforms?

In MRI/fMRI our measurements are not voxel values!

Our measurements are spatial frequencies!



Real k-space (Cosines) Imaginary k-space (Sines)

How do we get spatial frequencies?

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We apply $G_x \& G_y$ magnetic field gradients to encode then we measure the complex-valued DFT of the object.

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We apply $G_x \& G_y$ magnetic field gradients to encode then we measure the complex-valued DFT of the object.

Images are formed (Reconstructed) by a 2D IFT



Kumar, Welti and Ernst: NMR Fourier Zeugmatography, J. Magn. Reson. 1975 Haacke et al.: *Magnetic Resonance Imaging: Physical Principles and Sequence Design*, 1999.

$F(k_x, k_y) = F_R(k_x, k_y) + iF_I(k_x, k_y)$, the complex-valued DFT of object



(a) real: 96×96

(b) imaginary: 96×96

$\begin{array}{rll} \text{complex-valued 2D IFT} \\ (\Omega_{yR} + i\Omega_{yI}) & \ast & (F_R + iF_I) & \ast & (\Omega_{xR} + i\Omega_{xI})^T & = & (Y_R + iY_I) \end{array}$



Due to the imperfect Fourier encoding, the IFT reconstructed object is complex-valued, $Y(x,y) = Y_R(x,y) + iY_I(x,y)$.



(a) Real image, y_R

(b) Imaginary image, y_I

Most fMRI studies transform from real-imaginary rectangular coordinates to magnitude-phase polar coordinates, $\rho(x, y) = m(x, y)e^{i\phi(x, y)}$.



(a) Magnitude, $m = \sqrt{y_R^2 + y_I^2}$

(b) Phase, $\phi = \operatorname{atan}_4(y_I/y_R)$

Most fMRI studies transform from real-imaginary rectangular coordinates to magnitude-phase polar coordinates, $\rho(x, y) = m(x, y)e^{i\phi(x, y)}$.



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(b) Phase, $\phi = \operatorname{atan}_4(y_I/y_R)$

There are two basic image (filtering) processing categories.

1) Image smoothing

2) Image sharpening

Both can be performed with the DFT.

For image processing, we first define a kernel (AKA mask). A 3×3 kernel with weights denoted by w's.



We take this kernel and move it around the image.

A new image is made by summing the product of the kernel weights with the pixel intensity values under the kernel.

The kernel weights typically sum to unity.





Make new image Z with value at (q_x, q_y) that is

 $Z(q_x, q_y) = \frac{1}{16 \cdot 202 + 1/8 \cdot 198 + \dots + 1/8 \cdot 189 + 1/16 \cdot 208}$

The previous procedure of moving the kernel around and making new voxel values is the definition of convolution!

$$Z(q_x, q_y) = \sum_{s=-m}^{m} \sum_{r=-n}^{n} Y(q_x - r, q_y - s)u(r, s)$$

where n and m are the x and y dimensions of Y. u is zero padded to be of the same dimension as Y.

Image filtering (Smoothing) is computationally faster in freq space.

.0001

.0001

.0001

.0000

.0000

.0000

kernel=

.0017

.0026

.0017

.0004

.0000

.0000

.0154

.0239

.0154

.0041

.0004

.0000

.0581

.0906

.0581

.0154

.0017

.0001

.0906

.1412

.0906

.0239

.0026

.0001

.0581

.0906

.0581

.0154

.0017

.0001

.0154

.0239

.0154

.0041

.0004

.0000

.0017

.0026

.0017

.0004

.0000

.0000

.0001

.0001

.0001

.0000

.0000

.0000

Two Dimensional MR Image Processing-Smoothing



Two Dimensional MR Image Processing-Smoothing



Image FT Imag. Kernel FT Imag. Prod. FT Imag. IFT Prod. Imag.

Two Dimensional MR Image Processing-Smoothing





Original Image

Smoothed Image

Two Dimensional MR Image Processing-Smoothing

Smothing Caveats:

1) Increases/Induces local voxel correlation





Original Image Corr Smoothed Image Corr 2) t-statistics need to be renormalized

 $K = \sqrt{\sum w_j}$ under independence

In fMRI we get complex-valued images over time and voxel time course observations, $y_t = y_{Rt} + iy_{It}$.



Collect a sequence of these reconstructed images over time. Form voxel time courses, $y_t = r_t e^{i\phi_t}$.



Collect a sequence of these reconstructed images over time. Form voxel time courses, $y_t = r_t e^{i\phi_t}$.



One Dimensional fMRI Time Series

Time series are complex-valued or bivariate with phase coupled means.



The y_R and y_I time courses have related vector length info! This is a time series from a actual human experimental data!

One Dimensional fMRI Time Series

Time series are complex-valued or bivariate with phase coupled means.



MO time courses only have vector length info! PO time courses only has vector angle info! Real-Imaginary or Magnitude-Phase time courses have all info!

One Dimensional fMRI Time Series

Time series are complex-valued or bivariate with phase coupled means.



Real-Imaginary or Magnitude-Phase time courses have all info! Recent work indicates that phase time courses may exhibit TRPCs Menon, 2002; Hoogenrad et al., 1998; Borduka et al., 1999; Chow et al., 2006;

Block-designed experiment: Off-On-Off-...-On-Off task



> Real Phase-Only (PO) Activation⁶

¹Rowe and Logan: NeuroImage, 23:1078-1092, 2004.
 ³Rowe: NeuroImage, 25:1310-1324, 2005b.
 ⁵Friston et al.: Hum Brain Mapp, 2:189-210, 1995.

²Rowe: NeuroImage 25:1124-1132, 2005a.
⁴Bandettini et al.: Magn Reson Med, 30:161-173, 1993.
[®]Rowe, Meller, & Hoffmann: J Neuro Meth, in press, 2006.

Let's consider the magnitude of the time series and its FT.



101,102,110,118,152,160,168,169

One Dimensional fMRI Time Series

Let's filter some FT frequencies of the time series.



101,102,110,118,152,160,168,169

One Dimensional fMRI Time Series







This filtering will reduce your residual variance! A smaller variance means larger activation statistics! But you have changed the temporal autocorrelation!

FMRI time series statistics

Activation statistic (measure of association) is computed in every voxel.

Many ways to compute activation statistics. Magnitude vs. Complex

Activation is another topic all to itself! Happy to return.

Need to separate activation signal from noise!

Thresholding and the multiple comparisons problem.

Thresholding is another topic all to itself!







FWE Activation



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- Thank You.