

Fourier and Wavelet Analysis

1

$$\hat{f}(\xi) = \int_{-\infty}^{\infty} e^{-2\pi i x \xi} f(x) dx$$

[this formula works equally well in \mathbb{R}^n , if $\int_{-\infty}^{\infty}$ is replaced by $\int_{\mathbb{R}^n}$, and $x \xi$ denotes the scalar product $\langle x, \xi \rangle$]

The course

- The Fourier transform
- Distribution theory
- Transforms related to the Fourier transform (Radon, Hankel, Z ...)
- The Wavelet transforms
- Multi resolution analysis
- Discrete transforms, sampling
- Applications (three lab assignments)

Notation

$$\hat{f}(\xi) = \int_{\mathbb{R}} e^{-2\pi i x \xi} f(x) dx$$

$$\hat{\hat{f}}(\xi) = (f)(\xi)$$

$$f(x) = \hat{\hat{f}}(\xi)$$

Basic properties

Linearity: $f + g \Rightarrow \hat{f} + \hat{g}$
 $\alpha f \Rightarrow \alpha \hat{f} \quad (\alpha \in \mathbb{R}, \mathbb{C})$

Scaling: $f \Rightarrow \hat{f} \Leftrightarrow \frac{1}{a} f(\frac{x}{a}) \Rightarrow \hat{f}(a\xi) \quad (a > 0)$

(better notation: $\frac{1}{a} f(\frac{\cdot}{a}) \Rightarrow \hat{f}(a\xi)$)

"if f is nice, then \hat{f} is nice"
(this will be made precise later)

Fourier transform in L^2

$$L^2(\mathbb{R}) = \left\{ f, \text{ measurable, such that } \int_{\mathbb{R}} |f(x)|^2 dx < \infty \right\}$$

Scalar product: $\langle f, g \rangle = \int_{\mathbb{R}} f(x) \overline{g(x)} dx$

$$\int_{\mathbb{R}} |f(x)|^2 dx = \int_{\mathbb{R}} |\hat{f}(\xi)|^2 d\xi$$

By nice we will mean: Schwartz class \mathcal{S}

Often: $f(t)$, a signal

$$f(t) = \sin(\omega t)$$

$$f(t) = H(t)$$

$$f(t) = \delta(t)$$



the Dirac " δ -function"

These are not in L^2 , nor in S .

Fundamental The Fourier inversion formula

$$\hat{f}(\xi) = \int_{\mathbb{R}} e^{-2\pi i x \xi} f(x) dx$$

$$\Leftrightarrow f(x) = \int_{\mathbb{R}} e^{2\pi i x \xi} \hat{f}(\xi) d\xi$$

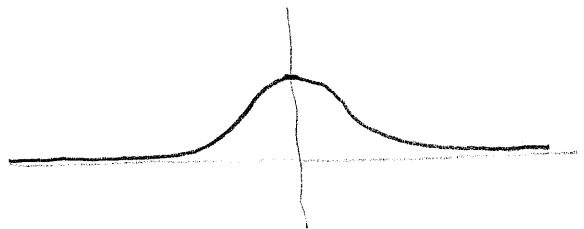
which means that

$$f(x) = \int_{\mathbb{R}} e^{2\pi i x \xi} \left[\int_{\mathbb{R}} e^{-2\pi i y \xi} f(y) dy \right] d\xi$$

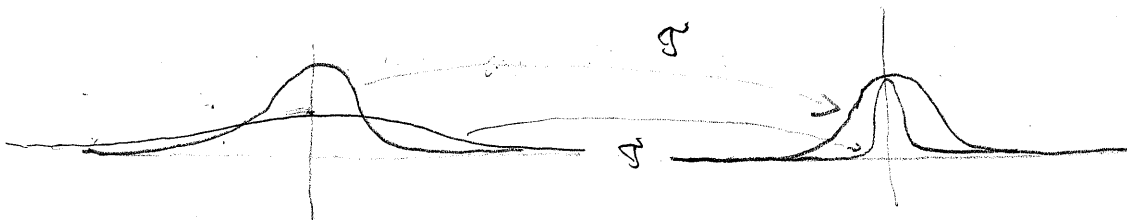
$\hat{f}(\xi)$

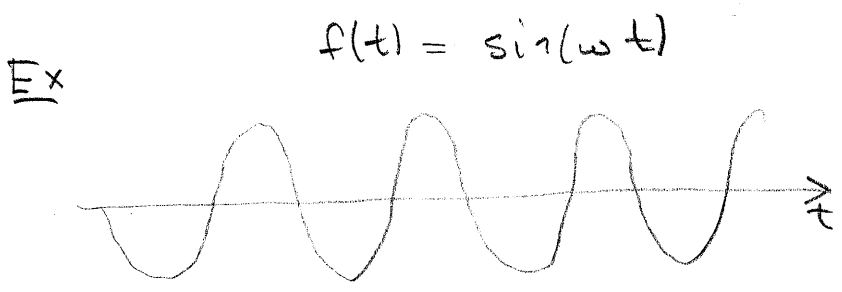
Example (important)

$$\mathcal{F}(e^{-\pi x^2}) = e^{-\pi \xi^2}$$

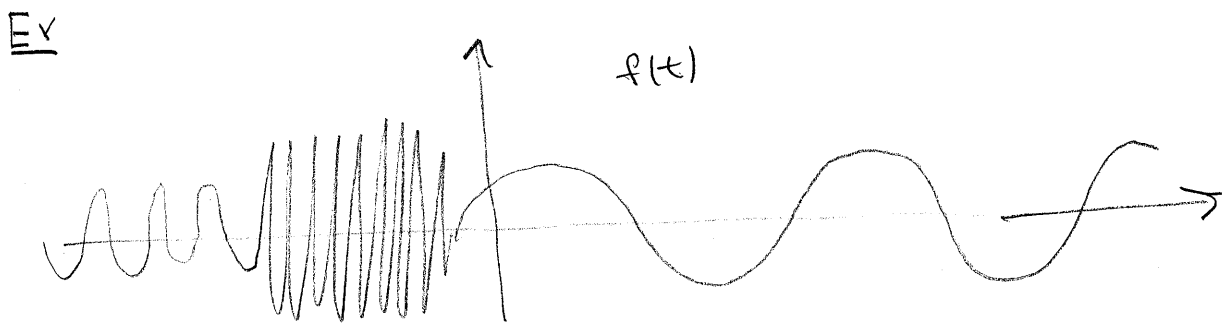
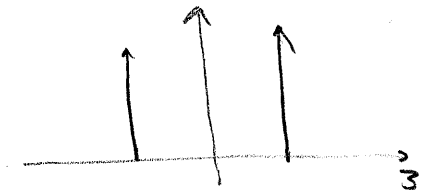


(scaling: $\frac{1}{2} e^{-\pi (\frac{x}{2})^2} = e^{-\pi (\frac{x}{2})^2}$)





$$\hat{f}(\xi) = \frac{1}{2} \delta_{-\omega/2\pi} + \delta_{\omega/2\pi}$$



The Fourier transform does not distinguish between what happened a long time ago, now, and in the future.

One solution: Wavelets

(another: windowed Fourier transform, STFT)

Our other transforms:

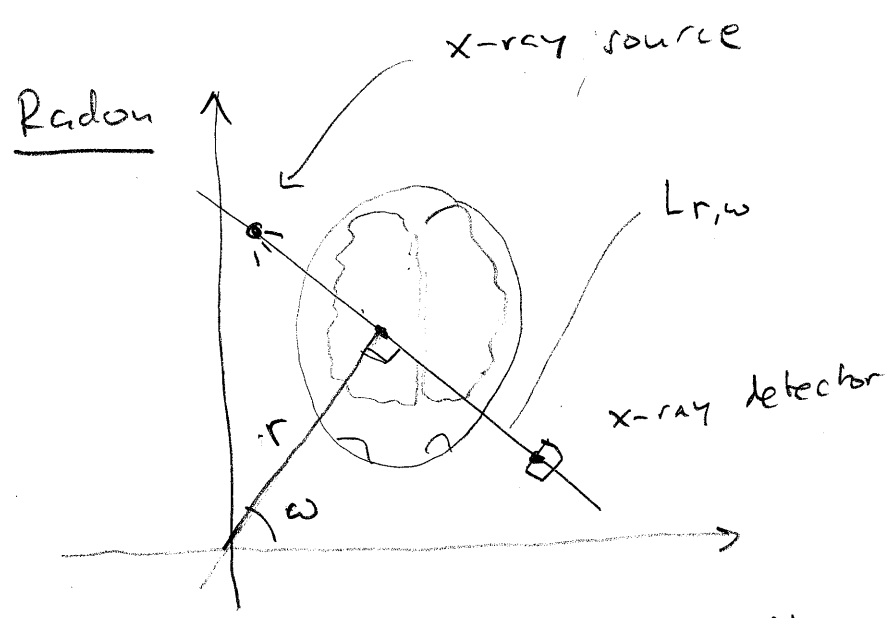
Hankel:
$$\hat{f}(\xi_1, \xi_2) = \iint_{\mathbb{R}^2} e^{-2\pi i(\xi_1 x_1 + \xi_2 x_2)} f(x_1, x_2) dx_1 dx_2$$

Let $f(x_1, x_2) = F(\sqrt{x_1^2 + x_2^2}) = F(r)$

Then $\hat{f}(\xi_1, \xi_2) = \tilde{F}(\sqrt{\xi_1^2 + \xi_2^2}) = \tilde{F}(\rho)$

$x_1 = r \cos \theta$
 $x_2 = r \sin \theta$
 $\xi_1 = \rho \cos \alpha$
 $\xi_2 = \rho \sin \alpha$

$F(r) \mapsto \tilde{F}(\rho)$ is the Hankel transform.



If $f(x_1, x_2)$ is the density of the head at point (x_1, x_2) , then

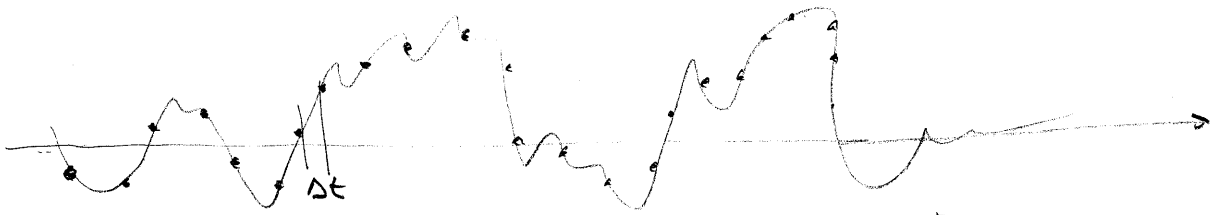
$\int_{L_{r,\omega}} f(x_1, x_2) dl$ gives a measure of the damping along $L_{r,\omega}$. This can be measured.

Notation: $R_{\omega} f(r) = \int_{L_{r,\omega}} f(x_1, x_2) dl$,
the Radon transform.

Important because there is a formula for recovering f from $R_{\omega} f(r)$,
(computer tomography).

Discrete transforms, sampling, filters

6



$$f(t) \longrightarrow \{f_n\}_{n=-\infty}^{\infty} = \{f(n \Delta t)\}_{n=-\infty}^{\infty}$$

$\{f_n\}$ is a discrete signal.

How often do we need to sample?

How do we construct digital filters?



Low pass, high pass

Fast Fourier Transform

What functions do have a Fourier transform:

$$L^2(\mathbb{R})$$

S (smooth functions with rapid decay)

$$L^1(\mathbb{R}) = \left\{ f : \int_{\mathbb{R}} |f(x)| dx < \infty \right\}$$

Note $f(x) \in L^1(\mathbb{R}) \Rightarrow |\hat{f}(\xi)| = \left| \int_{\mathbb{R}} e^{-i2\pi\xi x} f(x) dx \right|$
 $\leq \int_{\mathbb{R}} |e^{-i2\pi\xi x} f(x)| dx = \int_{\mathbb{R}} |f(x)| dx < \infty$

$$(f \in L^1 \Rightarrow \hat{f} \in L^\infty)$$

Hausdorff

Young's inequality $f \in L^p$ ($1 \leq p \leq 2$)
 $\Rightarrow \hat{f} \in L^q$ $q = \frac{1}{1-p}$

Convolution theorem

suppose that $f(x) \mapsto \hat{f}(\xi)$, $g(x) \mapsto \hat{g}(\xi)$.

Then

$$f * g(x) \equiv \int_{\mathbb{R}} f(x-y) g(y) dy \mapsto \hat{f}(\xi) \hat{g}(\xi)$$

Other properties of convolution:

commutative: $f * g = g * f$

associative: $f * (g * h) = (f * g) * h$

distributive: $f * (g + h) = f * g + f * h$