

Non-commutative tomography: A tool for data analysis and signal processing

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- Integral transforms: linear and bilinear
- Wavelet-type, quasi-distributions and tomograms: Examples and relations
- Tomograms and the conformal group operators
- Applications:
 - 1 Detection of small signals
 - 2 Filtering and component separation
 - 3 Plasma reflectometry

- **Integral transforms**

Tomographic data analysis. General setting

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Let $h \in \mathcal{N}^*$ be a reference vector such that the linear span of $\{U(\alpha)h \in \mathcal{N}^* : \alpha \in I\}$ is dense in \mathcal{N}^* . In the set $\{U(\alpha)h\}$, a complete set of vectors can be chosen to serve as a basis

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- **1 - Wavelet-type transform**

$$W_f^{(h)}(\alpha) = \langle U(\alpha)h | f \rangle,$$

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- **3 - Tomographic transform or tomogram**

$$M_f^{(B)}(X) = \langle f | \delta(B(\alpha) - X) | f \rangle$$

Examples for wavelet-type and quasi-distributions

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- **Bertrand transform:** $Q_f(\alpha)$ for B_W

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- The tomogram is a homogeneous function

$$M_f^{(B/p)}(X) = |p| M_f^{(B)}(pX)$$

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- $$Q_f^{(B)}(\alpha) = W_f^{(f)}(\alpha),$$

- $$W_f^{(h)}(\alpha) = \frac{1}{4} \int e^{iX} \left[\begin{array}{c} M_{f_1}^{(B)}(X) - iM_{f_2}^{(B)}(X) \\ -M_{f_3}^{(B)}(X) + iM_{f_4}^{(B)}(X) \end{array} \right] dX,$$

with

$$\begin{array}{ll} |f_1\rangle = |h\rangle + |f\rangle; & |f_3\rangle = |h\rangle - |f\rangle; \\ |f_2\rangle = |h\rangle + i|f\rangle; & |f_4\rangle = |h\rangle - i|f\rangle. \end{array}$$

- Other type of operator

$$U(\alpha) = e^{iB(\alpha)} P_h e^{-iB(\alpha)},$$

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Husimi–Kano type quasi-distribution

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- Quasidistribution of the Husimi–Kano type

$$H_f^{(b)}(\alpha) = \langle f | U(\alpha) | f \rangle.$$

The conformal group

- The generators of the conformal group

in \mathbb{R}^d

$$\omega_k = i \frac{\partial}{\partial t_k}$$

$$D = i \left(t \bullet \nabla + \frac{d}{2} \right)$$

$$R_{j,k} = i \left(t_j \frac{\partial}{\partial t_k} - t_k \frac{\partial}{\partial t_j} \right)$$

$$K_j = i \left(t_j^2 \frac{\partial}{\partial t_j} + t_j \right)$$

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- For $d = 1$

$$\begin{aligned} \text{in } \mathbb{R} \quad \omega &= i \frac{d}{dt} \\ D &= i \left(t \frac{d}{dt} + \frac{1}{2} \right) \\ K &= i \left(t^2 \frac{d}{dt} + t \right) \end{aligned}$$

Tomograms associated to the conformal group

- Time-frequency tomogram

$$B_1 = \mu t + iv \frac{d}{dt}$$

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$$B_4 = \mu t + iv \left(t^2 \frac{d}{dt} + t \right)$$

Tomograms associated to the conformal group

- General construction of the tomograms: Let

$$\int dY |Y\rangle \langle Y| = 1$$

be a decomposition of the unit, with generalized eigenvectors of the operator B . Then

$$M(\alpha, X) = \int dY \langle f | \delta(B(\alpha) - X) | Y\rangle \langle Y | f \rangle = |\langle X | f \rangle|^2$$

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- Therefore the construction of the tomograms reduces to the calculation of the generalized eigenvectors of each B operator
- $B_1 \psi_1(\mu, \nu, t, X) = X \psi_1(\mu, \nu, t, X)$

$$\psi_1(\mu, \nu, t, X) = \exp i \left(\frac{\mu t^2}{2\nu} - \frac{tX}{\nu} \right)$$

$$\int dt \psi_1^*(\mu, \nu, t, X) \psi_1(\mu, \nu, t, X') = 2\pi\nu \delta(X - X')$$

Tomograms associated to the conformal group

- $B_2 \psi_2 (\mu, \nu, t, X) = X \psi_2 (\mu, \nu, t, X)$

$$\psi_2 (\mu, \nu, t, X) = \frac{1}{\sqrt{|t|}} \exp i \left(\frac{\mu t}{\nu} - \frac{X}{\nu} \log |t| \right)$$

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- $B_3\psi_3(\mu, \nu, \omega, X) = X\psi_3(\mu, \nu, \omega, X)$

$$\psi_3(\mu, \nu, \omega, X) = \exp(-i) \left(\frac{\mu}{\nu} \omega - \frac{X}{\nu} \log |\omega| \right)$$

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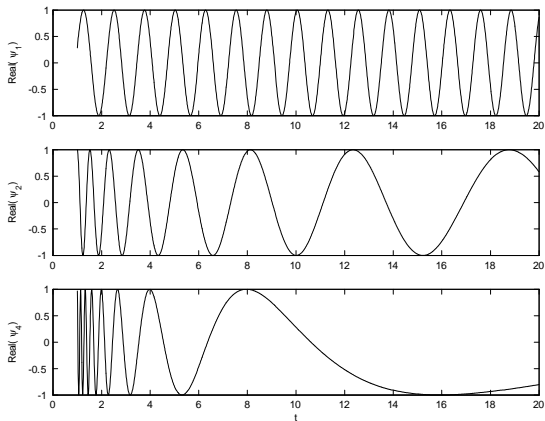
- $B_4\psi_4(\mu, \nu, t, X) = X\psi_4(\mu, \nu, t, X)$

$$\psi_4(\mu, \nu, t, X) = \frac{1}{|t|} \exp i \left(\frac{X}{\nu t} + \frac{\mu}{\nu} \log |t| \right)$$

$$\int dt \psi_4^*(\mu, \nu, t, s) \psi_4(\mu, \nu, t, s') = 2\pi\nu\delta(s - s')$$

Tomograms associated to the conformal group

$$\mu = 0$$



Tomograms associated to the conformal group

- Time-frequency tomogram

$$M_1(\mu, \nu, X) = \frac{1}{2\pi|\nu|} \left| \int \exp\left[\frac{i\mu t^2}{2\nu} - \frac{itX}{\nu}\right] f(t) dt \right|^2$$

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$$M_3(\mu, \nu, X) = \frac{1}{2\pi|\nu|} \left| \int d\omega \frac{f(\omega)}{\sqrt{|\omega|}} e^{-i\left(\frac{\mu}{\nu}\omega - \frac{X}{\nu} \log |\omega|\right)} \right|^2$$

$f(\omega)$ = Fourier transform of $f(t)$

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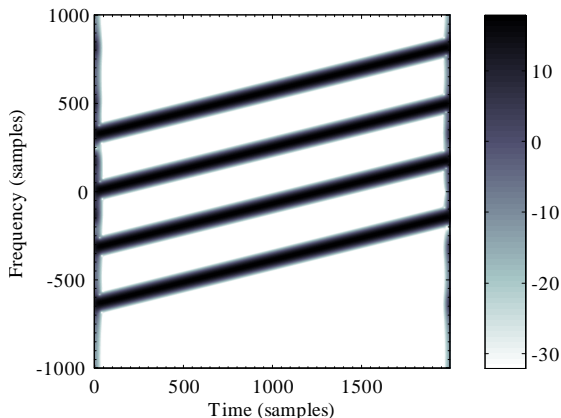
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- Time-conformal tomogram

$$M_4(\mu, \nu, X) = \frac{1}{2\pi|\nu|} \left| \int dt \frac{f(t)}{|t|} e^{i\left(\frac{X}{\nu t} + \frac{\mu}{\nu} \log |t|\right)} \right|^2$$

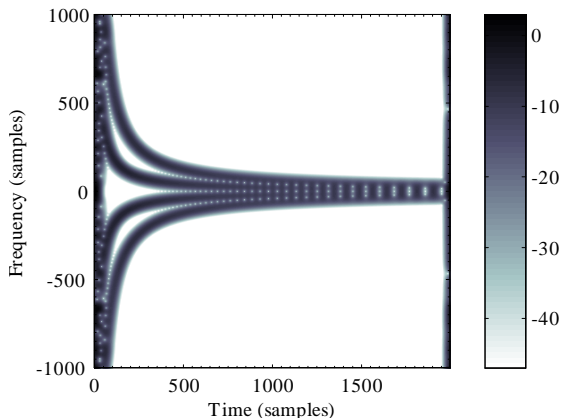
Basis functions of the tomograms in the time-frequency plane

Time-frequency



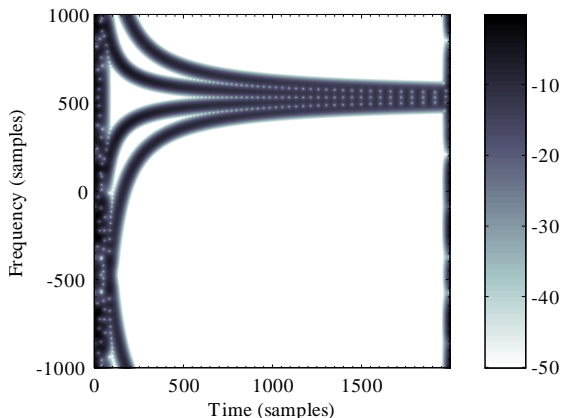
Basis functions of the tomograms in the time-frequency plane

Time-scale



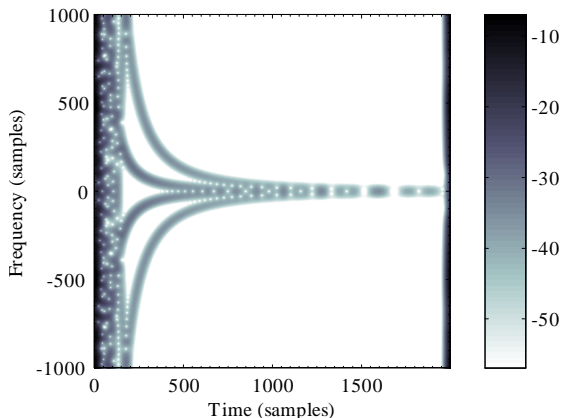
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Time-scale



Basis functions of the tomograms in the time-frequency plane

Time-conformal



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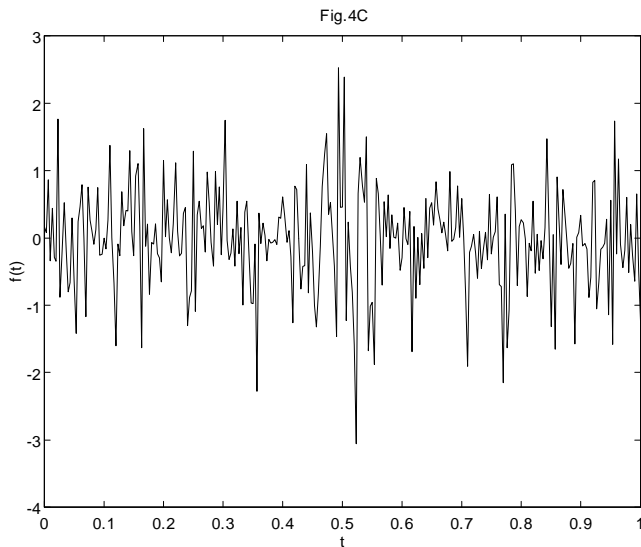
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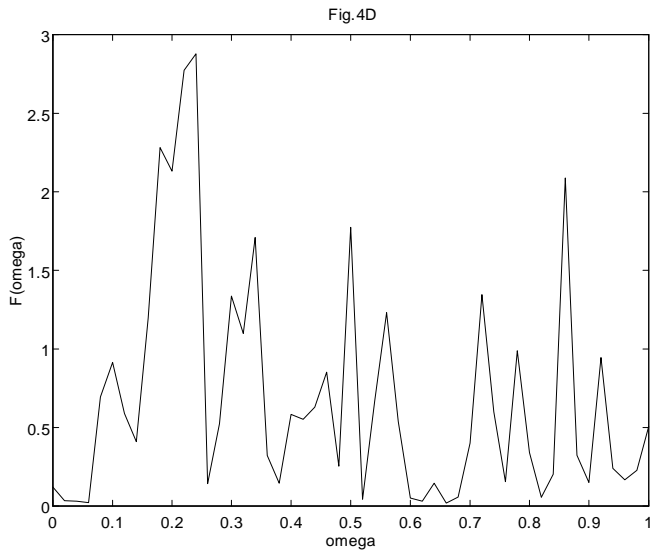
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- The following figures show the signal, its Fourier transform and the tomogram $M_f^{(S)}(s, \mu, \nu)$ ($T = 1$ and $\Omega = 1000$)

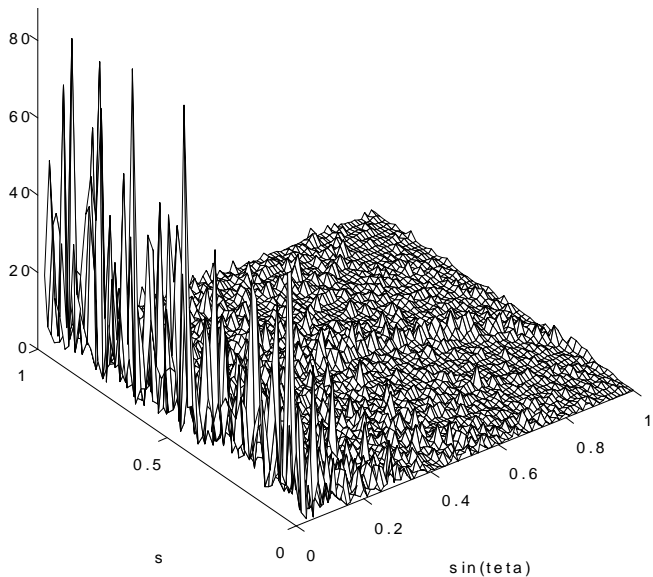
Detection of signals in noise



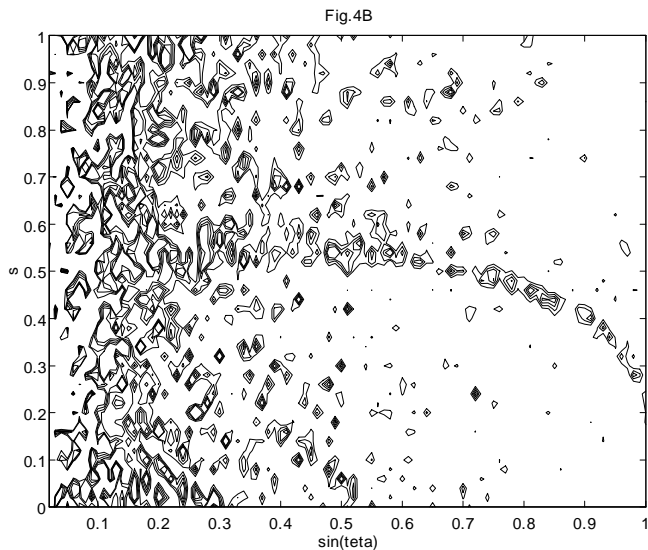
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- A ridge of small peaks is reliable because the rigorous probability interpretation of $M(\theta, X)$ renders the method immune to spurious effects.

Component decomposition

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Examples: Bat echolocation, whale sounds, radar, sonar, etc.
- The concept of signal component is not uniquely defined. The notion of *component* depends as much on the observer as on the observed object. When we speak about a component of a signal we are in fact referring to a particular feature of the signal that we want to emphasize.

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- Most natural and man-made signals are nonstationary and have a multicomponent structure.
Examples: Bat echolocation, whale sounds, radar, sonar, etc.
- The concept of signal component is not uniquely defined. The notion of *component* depends as much on the observer as on the observed object. When we speak about a component of a signal we are in fact referring to a particular feature of the signal that we want to emphasize.
- One possibility: Separation of components using its behavior in the time-frequency plane. Consider the finite-time tomogram

$$M(\theta, X) = \left| \int f(t) \psi_{\theta, X}(t) dt \right|^2 = |\langle f, \psi \rangle|^2$$

with

$$\psi_{\theta, X}(t) = \frac{1}{\sqrt{T}} \exp \left(\frac{-i \cos \theta}{2 \sin \theta} t^2 + \frac{iX}{\sin \theta} t \right)$$

$$\mu = \cos \theta, \nu = \sin \theta.$$

Component decomposition

- θ is a parameter that interpolates between the time and the frequency operators, running from 0 to $\pi/2$ whereas X is allowed to be any real number.

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- For all different θ 's the $U(\theta)$ are unitarily equivalent operators, hence all the tomograms share the same information. The component separation technique is based on the search for an intermediate value of θ where a good compromise might be found between time localization and frequency information.
- First select a subset X_n in such a way that the corresponding family $\left\{ \psi_{\theta, X_n}(t) \right\}$ is orthogonal and normalized,

$$\langle \psi_{\theta, X_n} \psi_{\theta, X_m} \rangle = \delta_{m,n}$$

This is possible by taking the sequence

$$X_n = X_0 + \frac{2n\pi}{T} \sin \theta$$

where X_0 is freely chosen (in general we take $X_0 = 0$)

Component decomposition

- We then consider the projections of the signal $f(t)$

$$c_{X_n}^\theta(f) = \langle f, \psi_{\theta, X_n} \rangle$$

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- Multi-component analysis is done by selecting subsets \mathcal{F}_k of the X_n and reconstructing partial signals (k -components) by restricting the sum to

$$f_k(t) = \sum_{n \in \mathcal{F}_k} c_{X_n}^\theta(f) \psi_{\theta, X_n}(t)$$

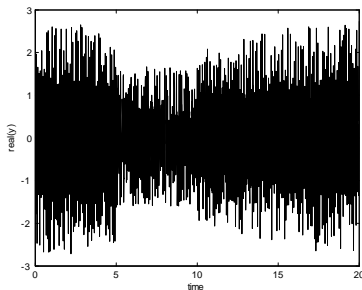
for each k .

Component decomposition. Examples

- $$y(t) = y_1(t) + y_2(t) + y_3(t) + b(t)$$
$$y_1(t) = \exp(i25t), t \in [0, 20]$$
$$y_2(t) = \exp(i75t), t \in [0, 5]$$
$$y_3(t) = \exp(i75t), t \in [10, 20]$$

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- Real part of the time signal

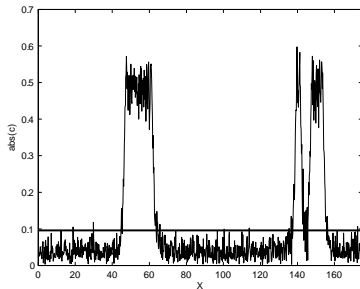


Component decomposition. Examples

- Separation at $\theta = \frac{\pi}{5}$

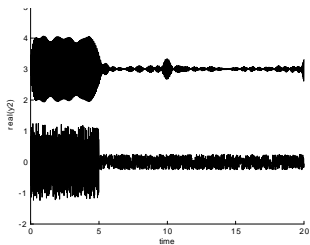
Component decomposition. Examples

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-



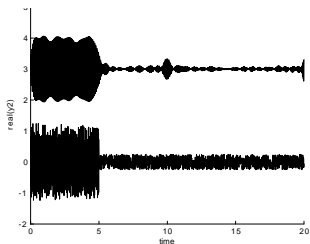
Component decomposition. Examples

- Reconstruction of the $y_2(t)$

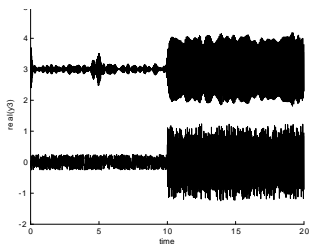


Component decomposition. Examples

- Reconstruction of the $y_2(t)$



- and $y_3(t)$ components



Component decomposition. Examples

- Sum $y(t) = y_0(t) + y_R(t) + b(t)$ of an “incident” $y_0(t)$ and a “deformed reflected” chirp $y_R(t)$ delayed by 3s with white noise added.

$$y_0(t) = e^{i\Phi_0(t)} \qquad y_R(t) = e^{i\Phi_R(t)}$$

$$\Phi_0(t) = a_0 t^2 + b_0 t \text{ and}$$

$$\Phi_R(t) = a_R(t - t_R)^2 + b_R(t - t_R) + 10(t - t_R)^{\frac{3}{2}}.$$

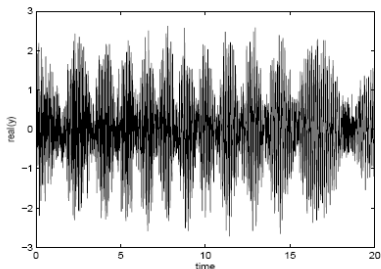
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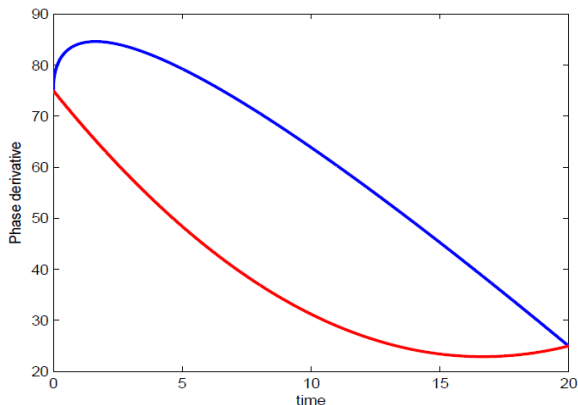


Component decomposition. Examples

- Comparison of the phase derivatives $\frac{d}{dt}\Phi_0(t)$ and $\frac{d}{dt}\Phi_R(t)$. Except for the three first seconds, the spectrum of the signals $y_0(t)$ and $y_R(t)$ is almost the same

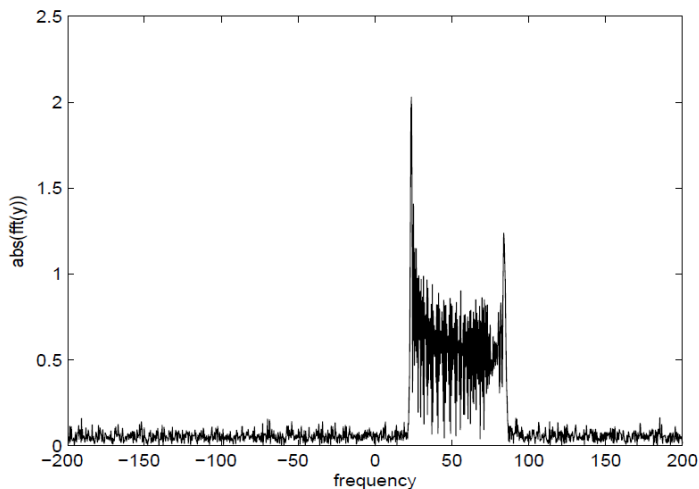
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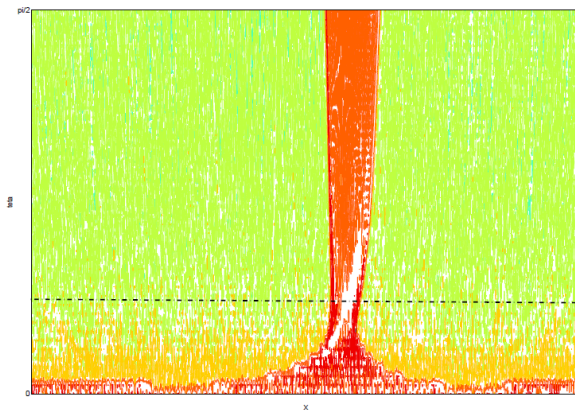
Component decomposition. Examples

- Frequency representation



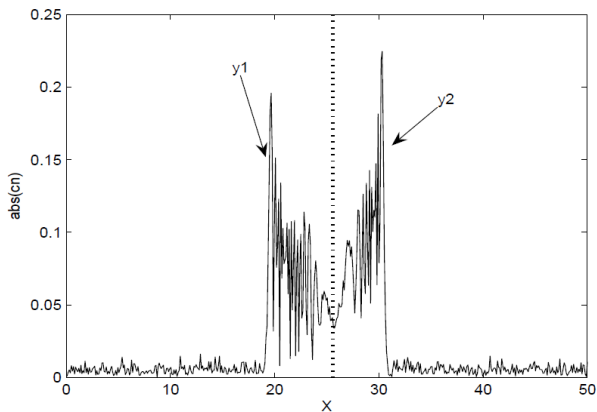
Component decomposition. Examples

- Tomogram of the chirps signal



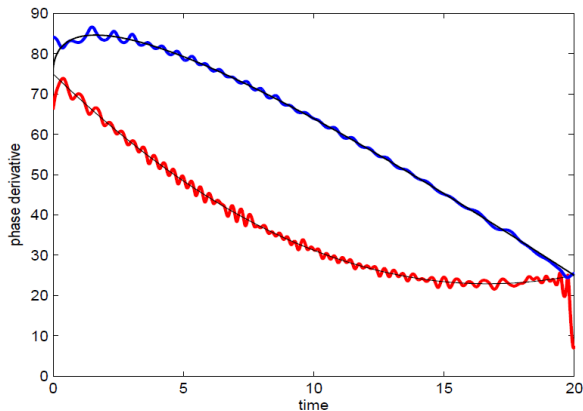
Component decomposition. Examples

Separable spectrum at $\theta = \frac{\pi}{5}$



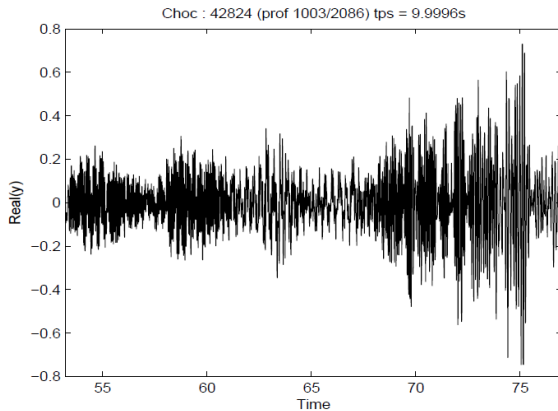
Component decomposition. Examples

The phase derivative

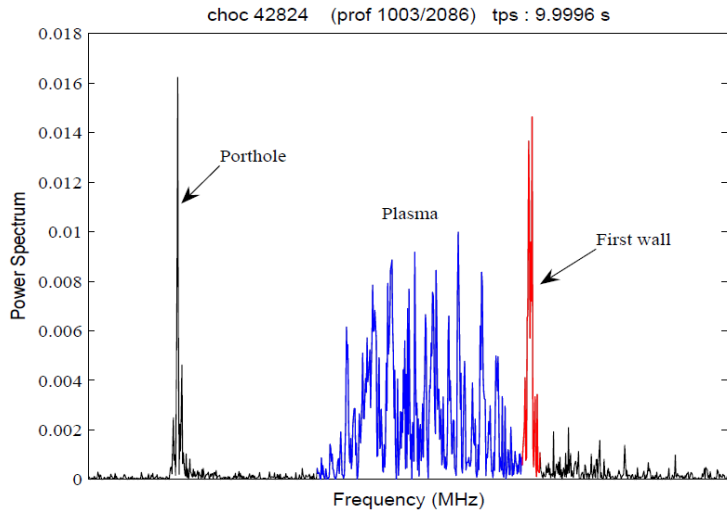


Component decomposition. Examples

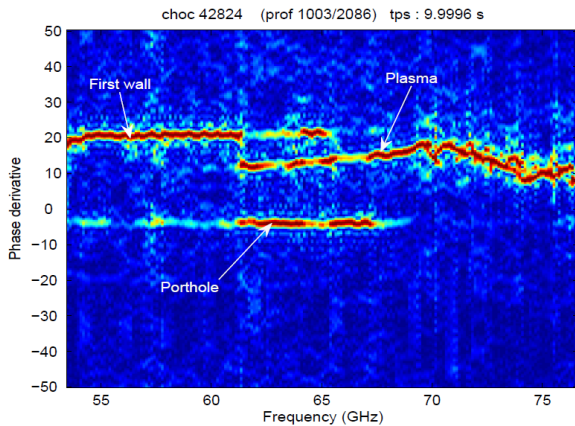
- Reflectometry signal



Component decomposition. Examples

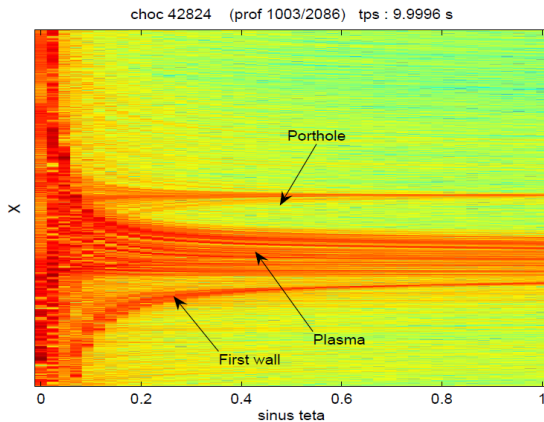


Component decomposition. Examples



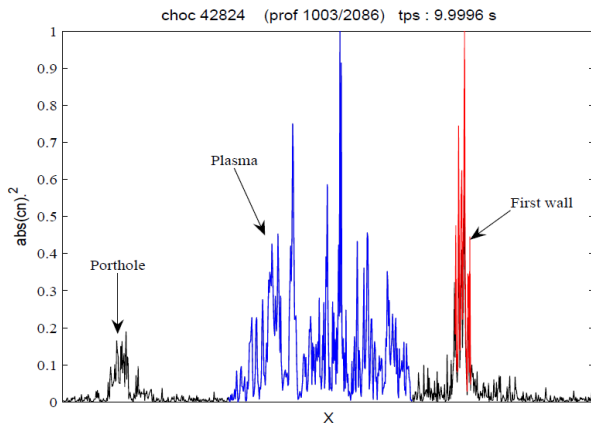
Component decomposition. Examples

- Tomogram of the reflectometry signal

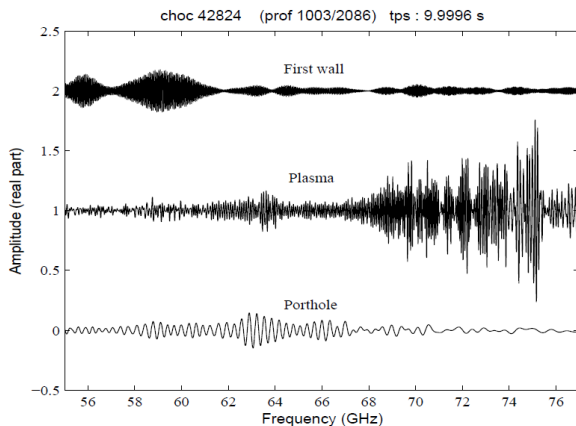


Component decomposition. Examples

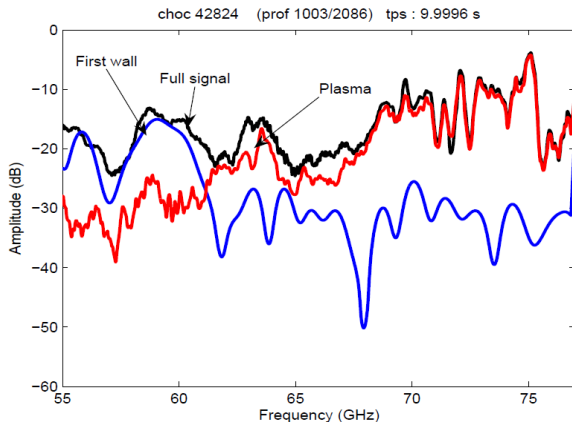
- "Spectrum" at $\theta = \pi - \frac{\pi}{5}$



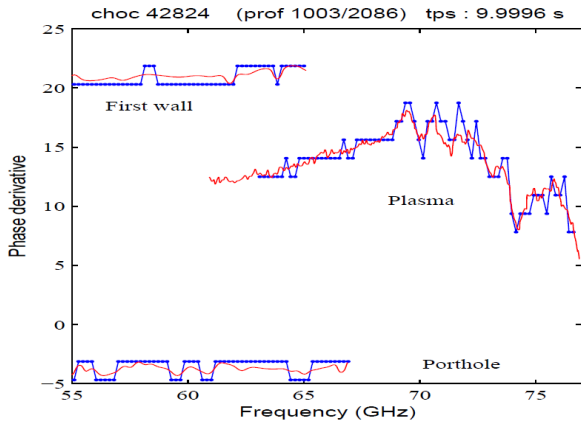
Component decomposition. Examples



Component decomposition. Examples



Component decomposition. Examples



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