

Time-frequency energy distributions, old and new

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*thanks to François Auger, Pierre Borgnat, Éric Chassande-Mottin,
Paulo Gonçalves, Cédric Richard & Jun Xiao*

intuition

Idea



Give a mathematical sense to musical notation

Aim

*Write the “musical score” of a signal with multiple, evolutive components with that additional constraint of getting, in the case of an isolated chirp $x(t) = a(t) \exp\{i\varphi(t)\}$, a **localized** representation*

$$\rho(t, f) \sim a^2(t) \delta(f - \dot{\varphi}(t)/2\pi).$$

local methods and localization

- **The example of the short-time FT** — One defines the **local** quantity

$$F_x^{(h)}(t, f) = \int x(s) \overline{h(s-t)} e^{-i2\pi fs} ds,$$

where $h(t)$ is some short-time observation window.

- **Measurement** — The representation results from an interaction between the signal and a **measurement device** (the window $h(t)$).
- **Trade-off** — A short window favors the “resolution” in time at the expense of the “resolution” in frequency, and vice-versa.

adaptation

- **Chirps** — Adaptation to **pulses** if $h(t) \rightarrow \delta(t)$ and to **tones** if $h(t) \rightarrow 1 \Rightarrow$ adapting the analysis to arbitrary **chirps** suggests to make $h(t)$ **(locally) depending on the signal**.
- **Linear chirp** — In the linear case $f_x(t) = f_0 + \alpha t$, the equivalent frequency width δf_S of the **spectrogram** $S_x^{(h)}(t, f) := |F_x^{(h)}(t, f)|^2$ behaves as:

$$\delta f_S \approx \sqrt{\frac{1}{\delta t_h^2} + \alpha^2 \delta t_h^2}$$

for a window $h(t)$ with an equivalent time width $\delta t_h \Rightarrow$ minimum for $\delta t_h \approx 1/\sqrt{|\alpha|}$ (but α **unknown**...).

self-adaptation and Wigner-Ville distribution

- Matched filtering** — If one takes for the window $h(t)$ the **time-reversed** signal $x_-(t) := x(-t)$, one readily gets that $F_x^{(x_-)}(t, f) = W_x(t/2, f/2)/2$, where

$$W_x(t, f) := \int x(t + \tau/2) \overline{x(t - \tau/2)} e^{-i2\pi f\tau} d\tau$$

is the **Wigner-Ville Distribution** (Wigner, '32; Ville, '48).

- Linear chirps** — The WVD **perfectly** localizes on **straight lines** of the plane:

$$x(t) = \exp\{i2\pi(f_0 t + \alpha t^2/2)\} \Rightarrow W_x(t, f) = \delta(f - (f_0 + \alpha t)).$$

- Remark** — Localization via self-adaptation leads to a **quadratic** transformation (energy distribution).

interferences

- **Quadratic superposition** — For any pair of signals $\{x(t), y(t)\}$ and coefficients (a, b) , one gets

$$W_{ax+by}(t, f) = |a|^2 W_x(t, f) + |b|^2 W_y(t, f) + 2 \operatorname{Re} \{ a \bar{b} W_{x,y}(t, f) \},$$

with

$$W_{x,y}(t, f) := \int x(t + \tau/2) \overline{y(t - \tau/2)} e^{-i2\pi f\tau} d\tau$$

- **Drawback** — Interferences between **disjoint** component reduce readability.
- **Advantage** — Inner interferences between **coherent** components guarantee localization.

interferences

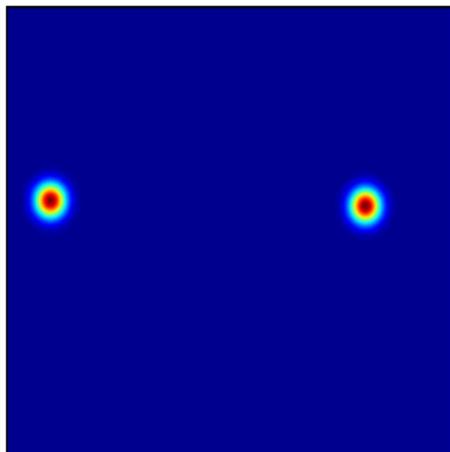
- **Janssen's formula (Janssen, '81)** — It follows from the **unitarity** of $W_x(t, f)$ that:

$$|W_x(t, f)|^2 = \iint W_x\left(t + \frac{\tau}{2}, f + \frac{\xi}{2}\right) W_x\left(t - \frac{\tau}{2}, f - \frac{\xi}{2}\right) d\tau d\xi$$

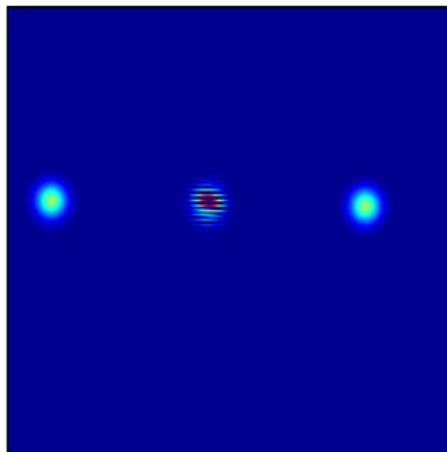
- **Geometry (Hlawatsch & F., '85)** — Contributions located in any two points of the plane plan interfere to create a third contribution
 - ① midway of the segment joining the two components
 - ② oscillating (positive and negative values) in a direction perpendicular to this segment
 - ③ with a “frequency” proportional to their “time-frequency distance”.

interferences and readability

somme des WV (N = 2)

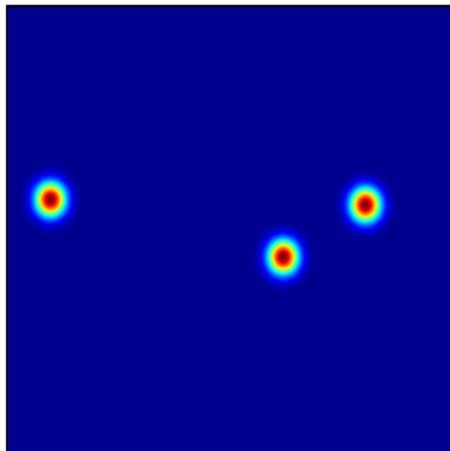


WV de la somme (N = 2)

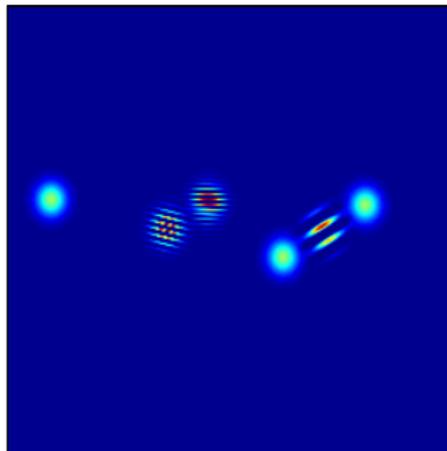


interferences and readability

somme des WV (N = 3)

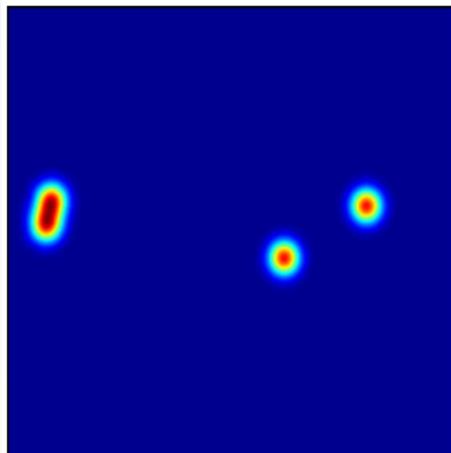


WV de la somme (N = 3)

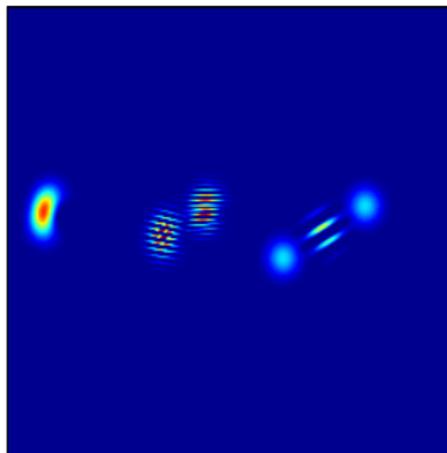


interferences and readability

somme des WV (N = 4)

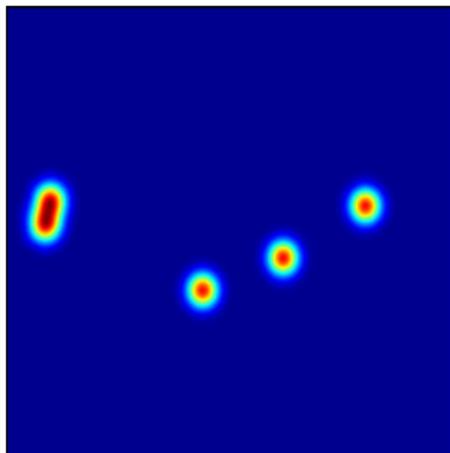


WV de la somme (N = 4)

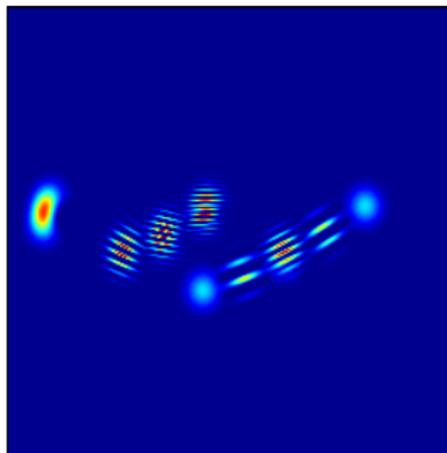


interferences and readability

somme des WV (N = 5)

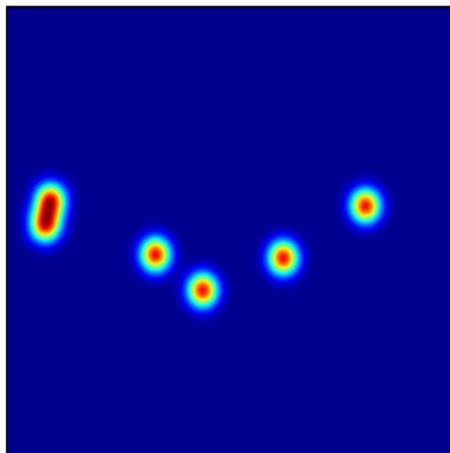


WV de la somme (N = 5)

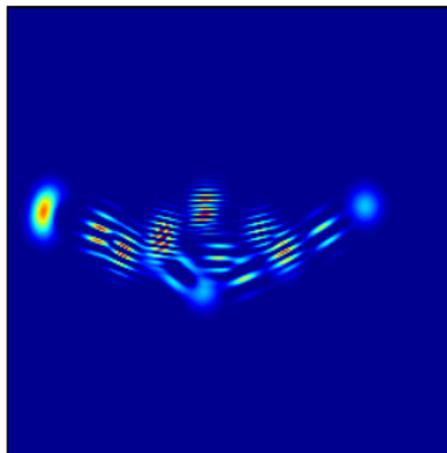


interferences and readability

somme des WV (N = 6)

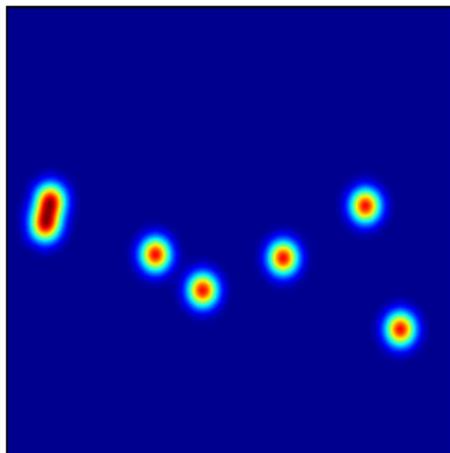


WV de la somme (N = 6)

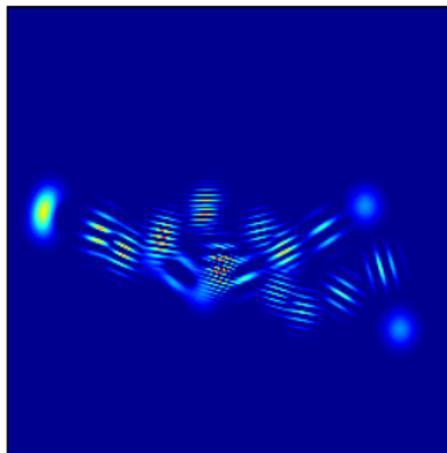


interferences and readability

somme des WV (N = 7)

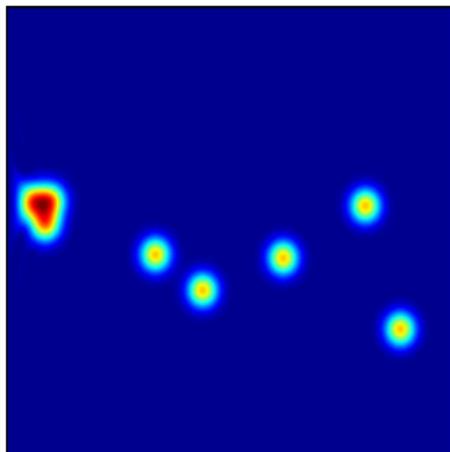


WV de la somme (N = 7)

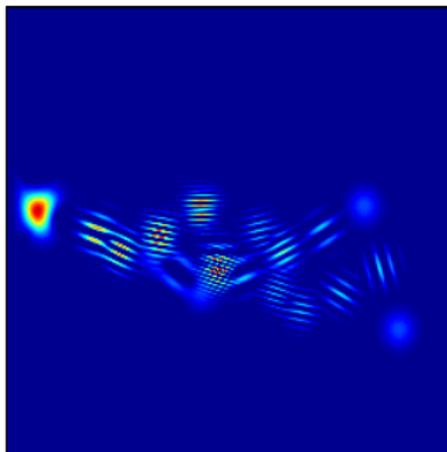


interferences and readability

somme des WV (N = 8)

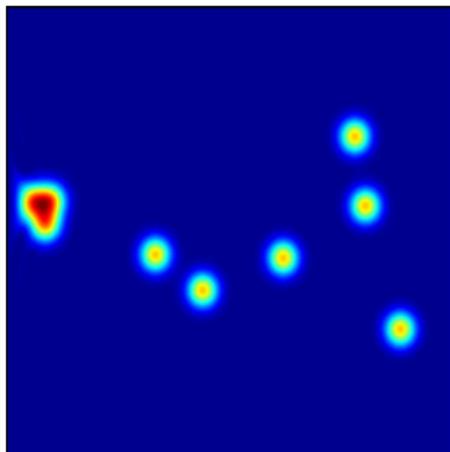


WV de la somme (N = 8)

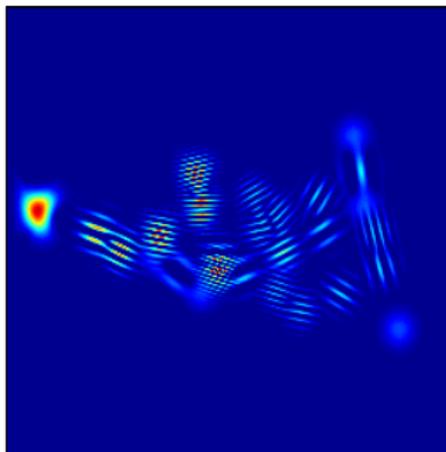


interferences and readability

somme des WV (N = 9)

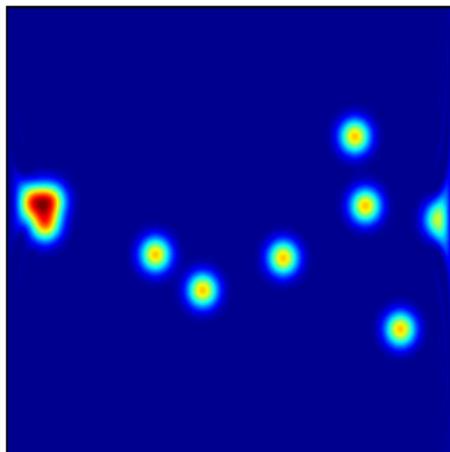


WV de la somme (N = 9)

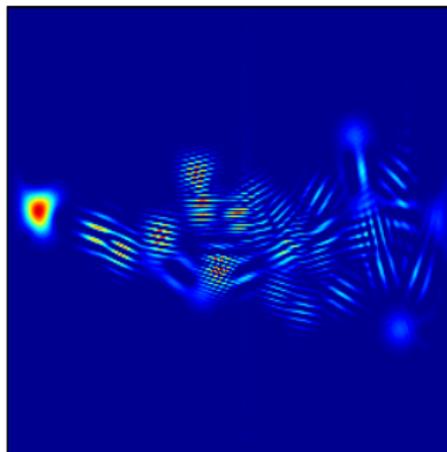


interferences and readability

somme des WV (N = 10)

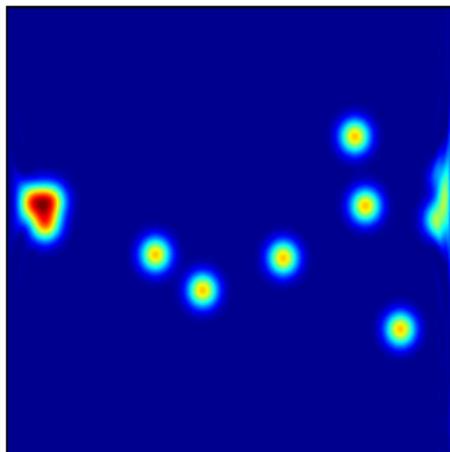


WV de la somme (N = 10)

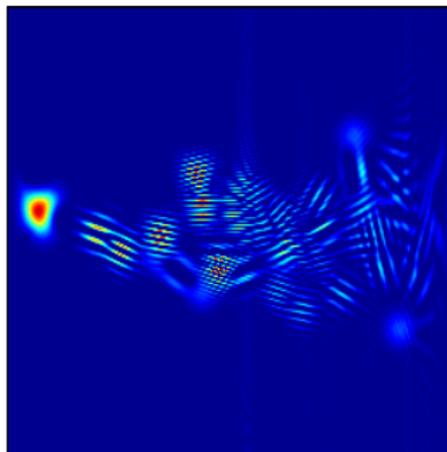


interferences and readability

somme des WV (N = 11)

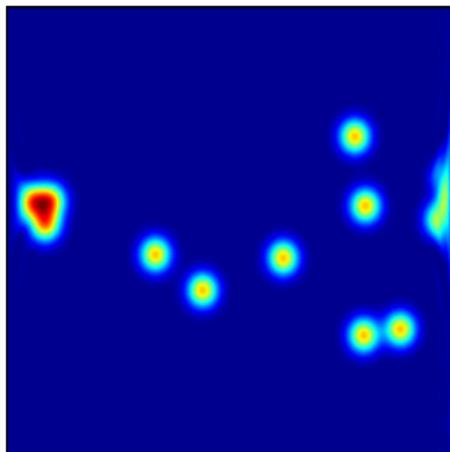


WV de la somme (N = 11)

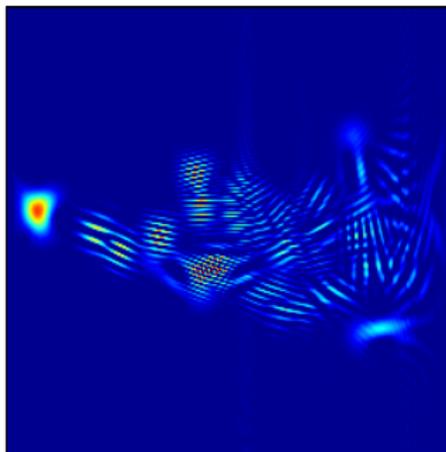


interferences and readability

somme des WV (N = 12)

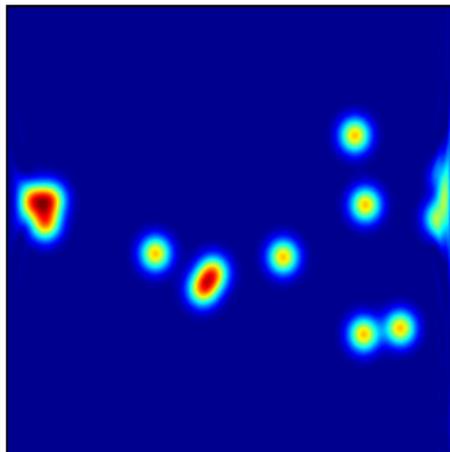


WV de la somme (N = 12)

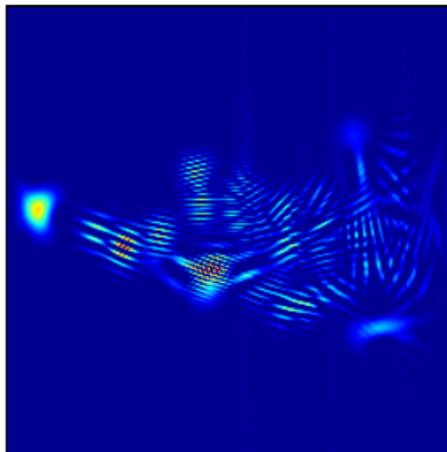


interferences and readability

somme des WV (N = 13)

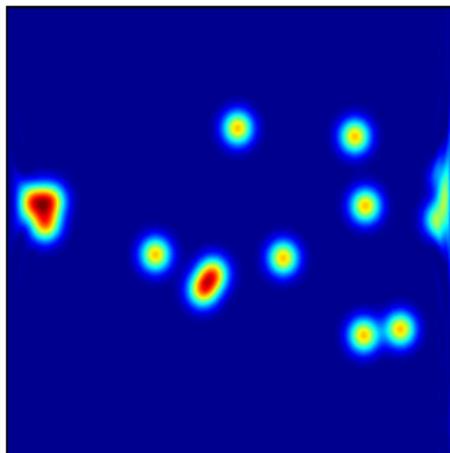


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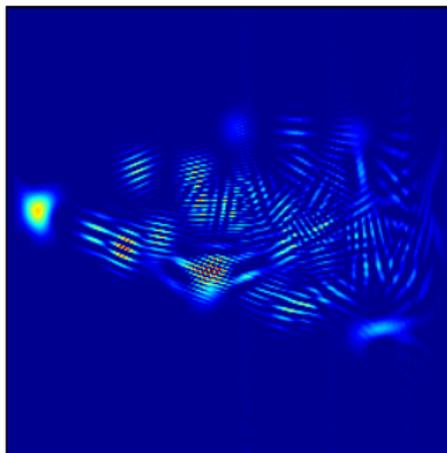


interferences and readability

somme des WV (N = 14)

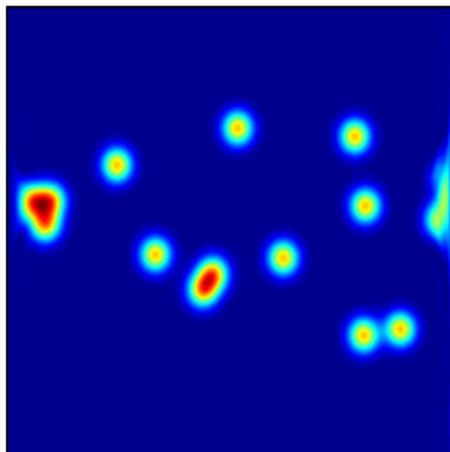


WV de la somme (N = 14)

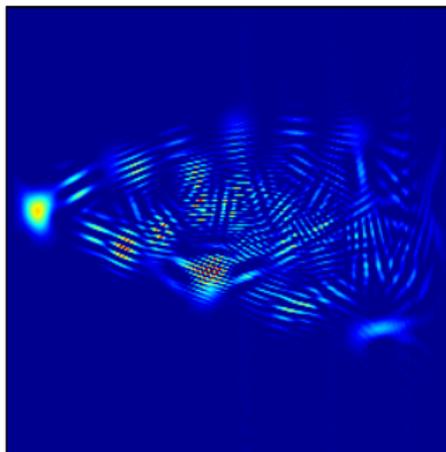


interferences and readability

somme des WV (N = 15)

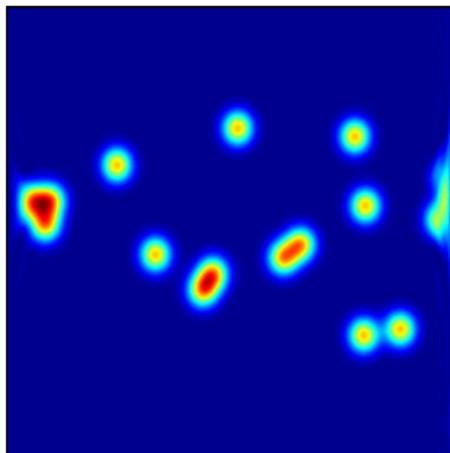


WV de la somme (N = 15)

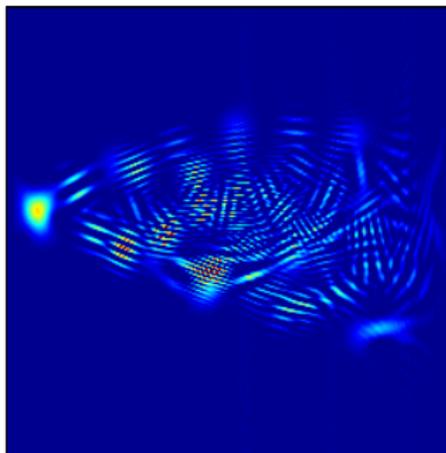


interferences and readability

somme des WV (N = 16)

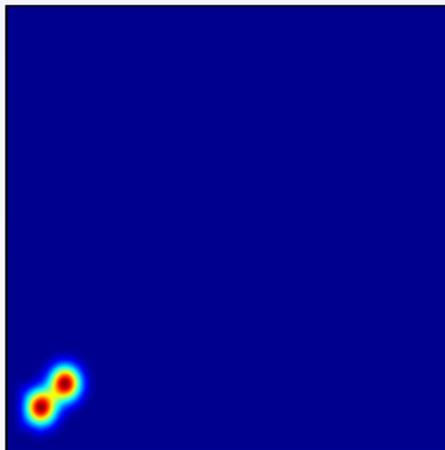


WV de la somme (N = 16)

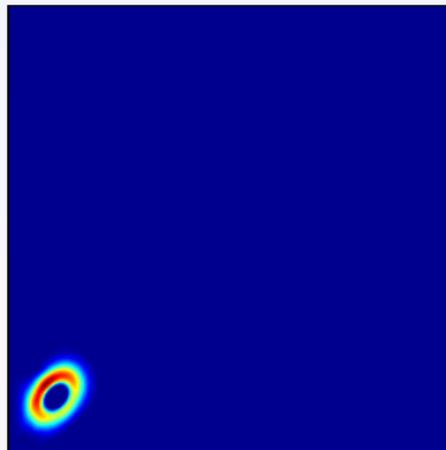


interferences and localization

sum(WV) (N = 2)

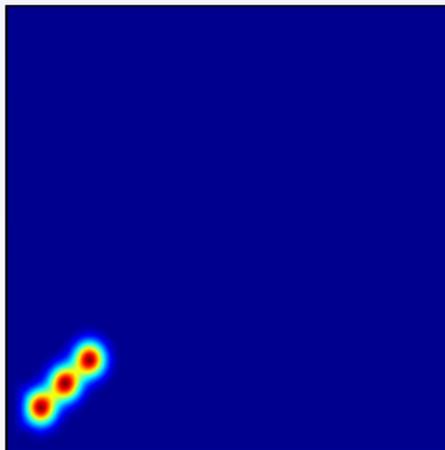


WV(sum) (N = 2)

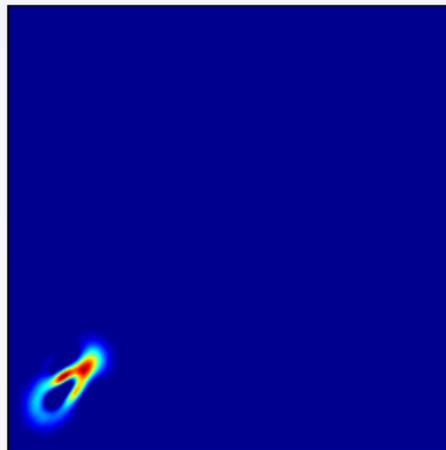


interferences and localization

sum(WV) (N = 3)

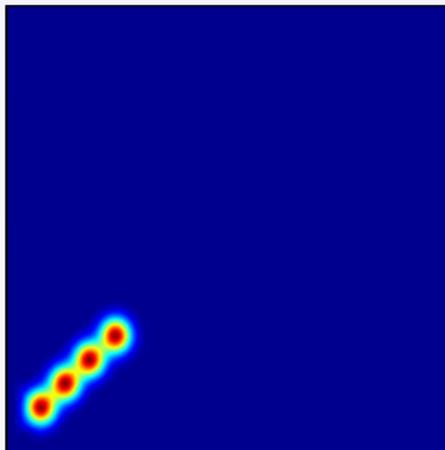


WV(sum) (N = 3)

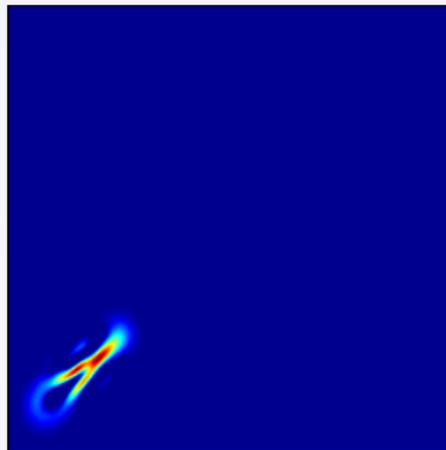


interferences and localization

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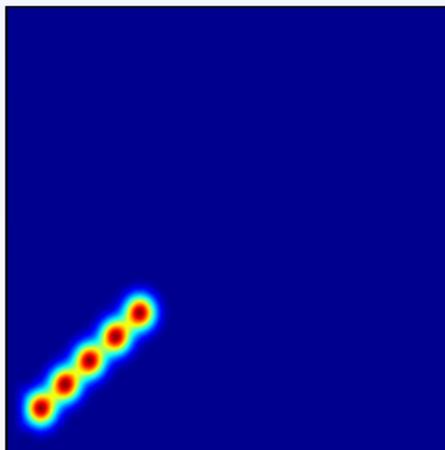


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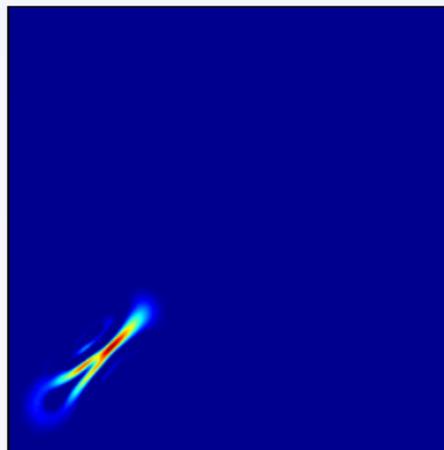


interferences and localization

sum(WV) (N = 5)

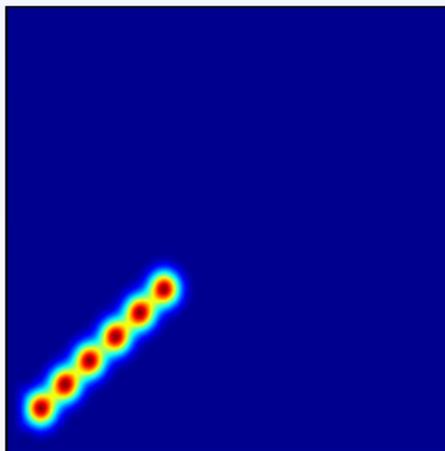


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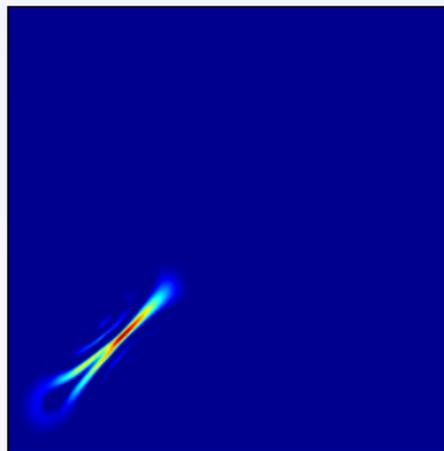


interferences and localization

sum(WV) (N = 6)

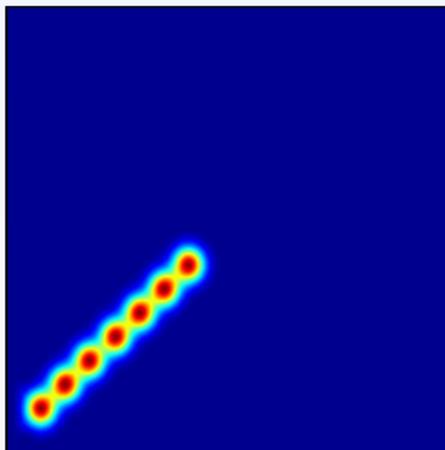


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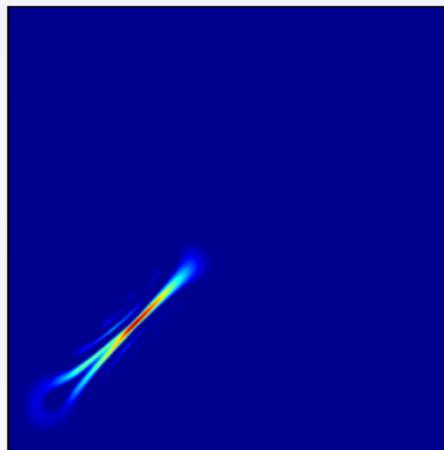


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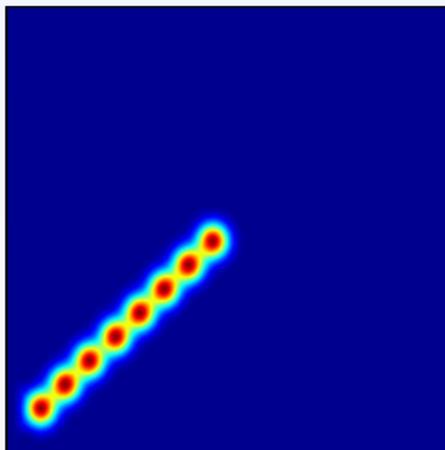


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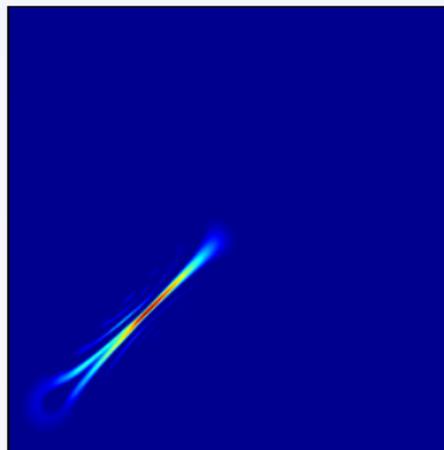


interferences and localization

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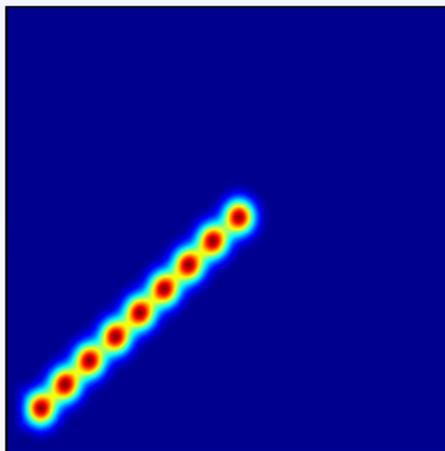


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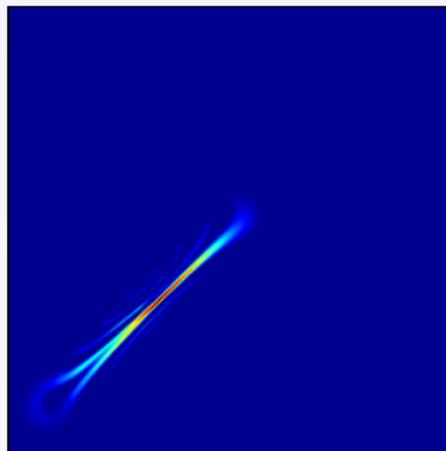


interferences and localization

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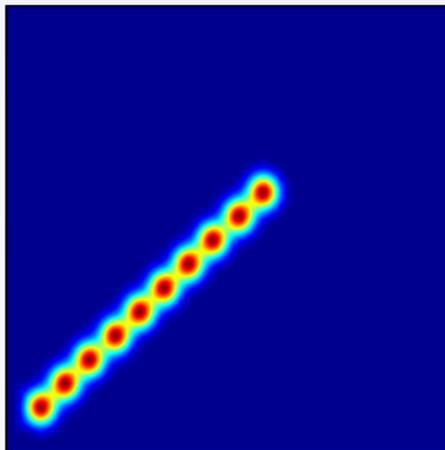


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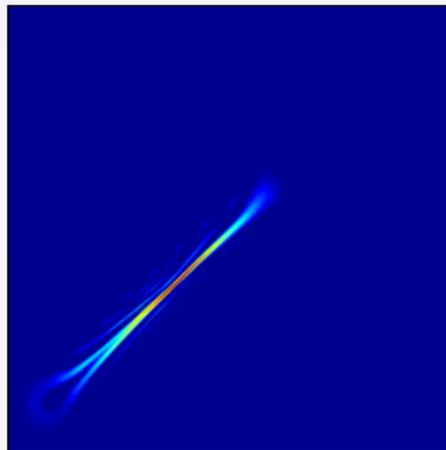


interferences and localization

sum(WV) (N = 10)

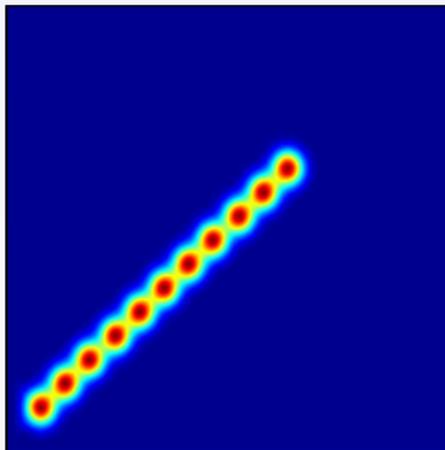


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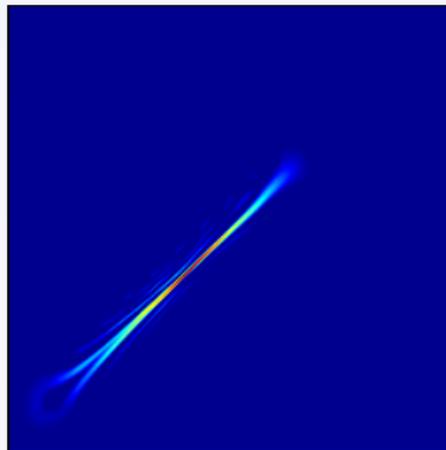


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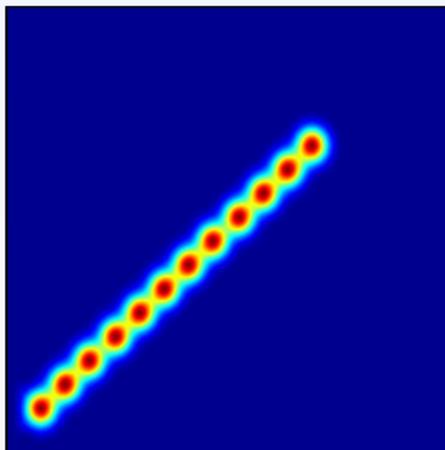


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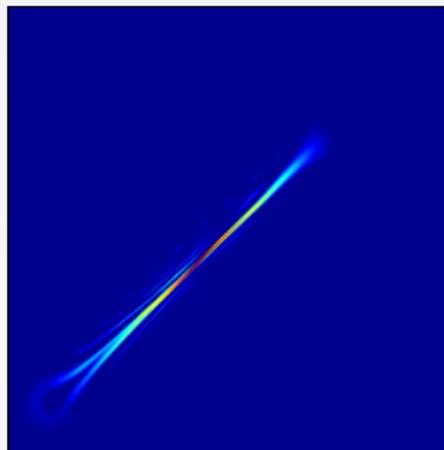


interferences and localization

sum(WV) (N = 12)

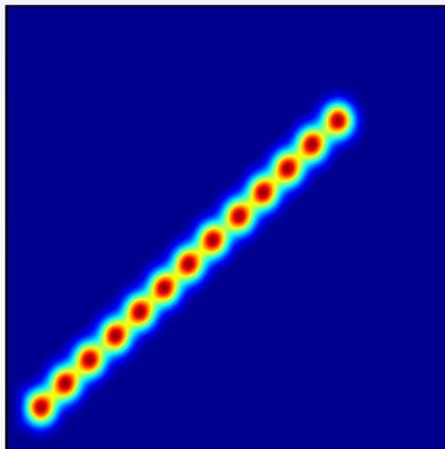


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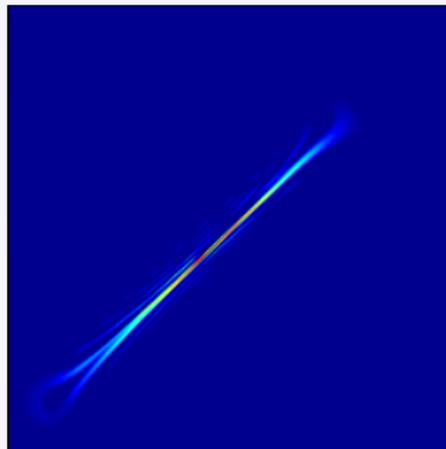


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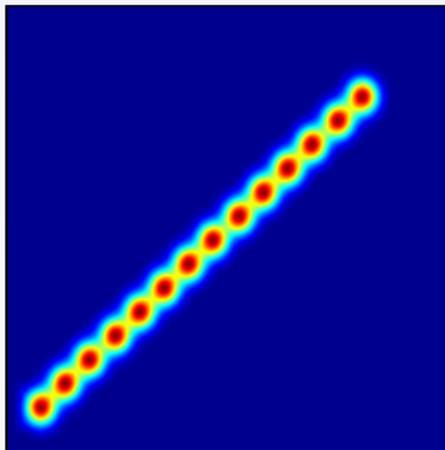


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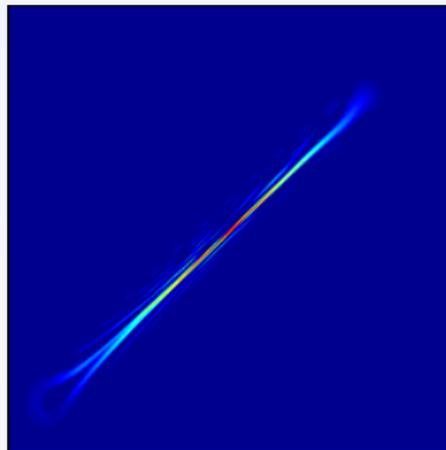


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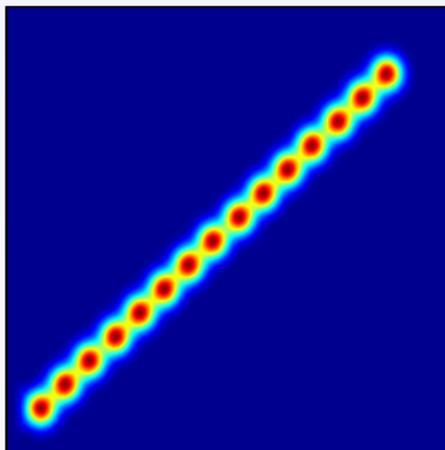


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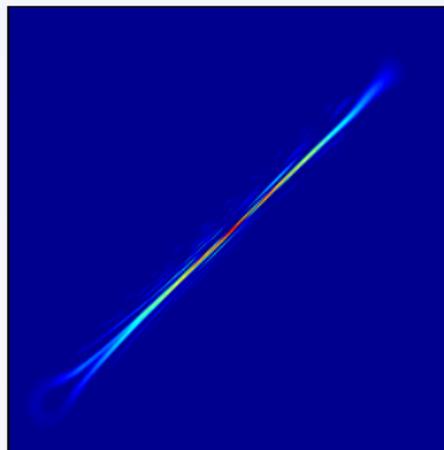


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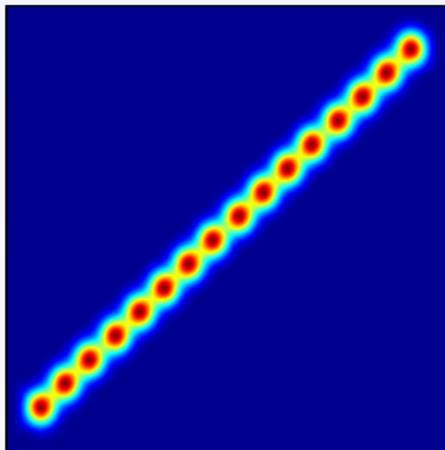


WV(sum) (N = 15)

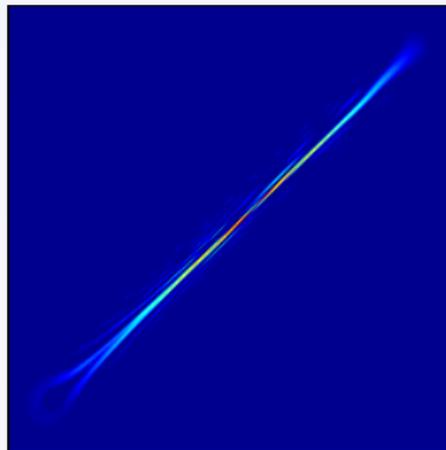


interferences and localization

sum(WV) (N = 16)



WV(sum) (N = 16)



classes of quadratic distributions

Observation

Many quadratic distributions have been proposed in the literature since more than half a century (e.g., spectrogram and DWV):
none fully extends the notion of spectrum density to the nonstationary case.

Principle of conditional unicity — **Classes** of quadratic distributions of the form $\rho_x(t, f) = \langle x, \mathbf{K}_{t,f} x \rangle$ can be constructed based on **covariance requirements** :

$$\begin{array}{ccc}
 x(t) & \rightarrow & \rho_x(t, f) \\
 \downarrow & & \downarrow \\
 (\mathbf{T}x)(t) & \rightarrow & \rho_{\mathbf{T}x}(t, f) = (\tilde{\mathbf{T}}\rho_x)(t, f)
 \end{array}$$

classes of quadratic distributions

- **Cohen's class** — Covariance wrt **shifts**

$(\mathbf{T}_{t_0, f_0} x)(t) = x(t - t_0) \exp\{i2\pi f_0 t\}$ leads to **Cohen's class** (Cohen, '66) :

$$C_x(t, f) := \iint W_x(s, \xi) \Pi(s - t, \xi - f) ds d\xi,$$

with $\Pi(t, f)$ “arbitrary” (and to be specified via additional constraints).

- **Variations** — Other choices possibles, e.g.,

$(\mathbf{T}_{t_0, f_0} x)(t) = (f/f_0)^{1/2} x(f(t - t_0)/f_0) \rightarrow$ **affine class** (Rioul & F, '92), etc.

Cohen's class and smoothing

- **Spectrogram** — Given a low-pass window $h(t)$, one gets the **smoothing** relation:

$$S_x^{(h)}(t, f) := |F_x^{(h)}(t, f)|^2 = \iint W_x(s, \xi) W_h(s-t, \xi-f) ds d\xi$$

- **From Wigner-Ville to spectrograms** — A generalization amounts to choose a smoothing function $\Pi(t, f)$ allowing for a **continuous** and **separable** transition between Wigner-Ville and a spectrogram (**smoothed pseudo-Wigner-Ville** distributions) :

Wigner – Ville ... \rightarrow *PWVL* ... \rightarrow *spectrogram*

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

$$g(t) H(f)$$

$$W_h(t, f)$$

from Wigner-Ville to spectrogram, and back

time-frequency spectrum

Definition (Martin, '82)

One of the most “natural” extensions of the power spectrum density is given by the **Wigner-Ville Spectrum** :

$$\mathbf{W}_x(t, f) := \int r_x\left(t + \frac{\tau}{2}, t - \frac{\tau}{2}\right) e^{-i2\pi f\tau} d\tau$$

- **Interpretation** — FT of a **local** correlation.
- **Properties** — PSD if $x(t)$ stationary, marginals, etc.
- **Relation with the WVD** — Under simple conditions, one has $\mathbf{W}_x(t, f) = \mathbb{E}\{W_x(t, f)\}$.

estimation of the Wigner-Ville spectrum

Aim

Approach $\mathbb{E}\{W_x(t, f)\}$ on the basis of only one realization.

- **Assumption** — **Local** stationarity (in time and in frequency).
- **Estimators** — Smoothing of the DWV :

$$\hat{W}_x(t, f) = (\Pi ** W_x)(t, f)$$

i.e., Cohen's class.

- **Properties** — **Statistical** (bias-variance) and **geometrical** (localization) trade-offs, both controlled by $\Pi(t, f)$.

global vs. local

- **Global approach** — The Wigner-Ville Distribution localizes perfectly on **straight lines** of the plane (linear chirps). One can construct other distributions localizing on more general **curves** (ex.: **Bertrand's** distributions adapted to hyperbolic chirps).
- **Local approach** — A different possibility consists in revisiting the smoothing relation defining the spectrogram and in considering localization wrt the instantaneous frequency as it can be measured **locally**, at the scale of the short-time window \Rightarrow **reassignment**.

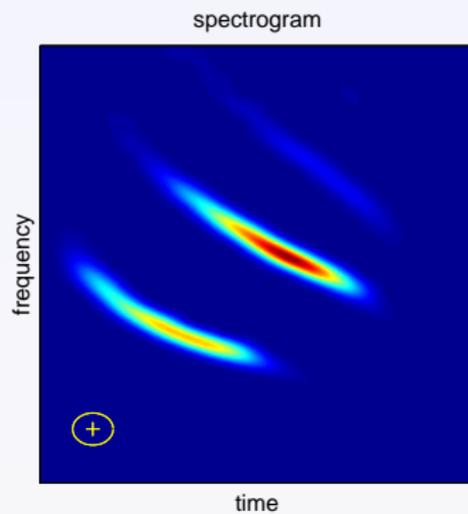
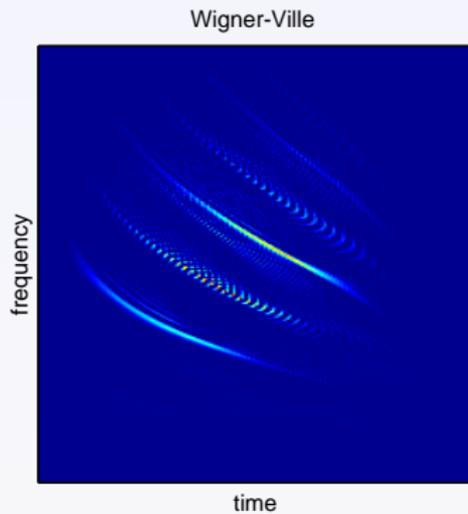
reassignment

- **Principle** — The key idea is (1) to replace the **geometrical** center of the smoothing time-frequency domain by the **center of mass** of the WVD over this domain, and (2) to **reassign** the value of the smoothed distribution to this local centroid:

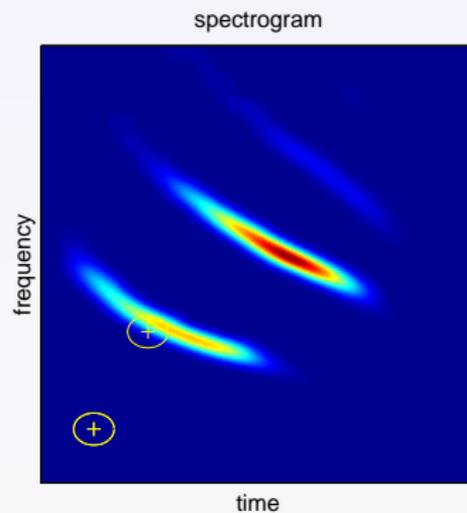
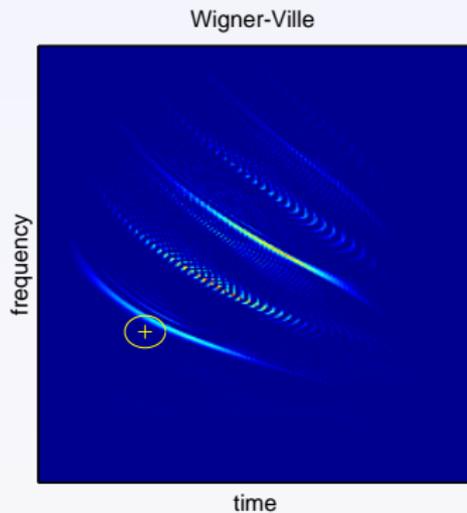
$$S_x^{(h)}(t, f) \mapsto \iint S_x^{(h)}(s, \xi) \delta\left(t - \hat{t}_x(s, \xi), f - \hat{f}_x(s, \xi)\right) ds d\xi.$$

- **Remark** — Reassignment has been first introduced for the only spectrogram (Kodera *et al.*, '76), but its principle has been further generalized to **any** distribution resulting from the smoothing of a localizable mother-distribution (Auger & F., '95).

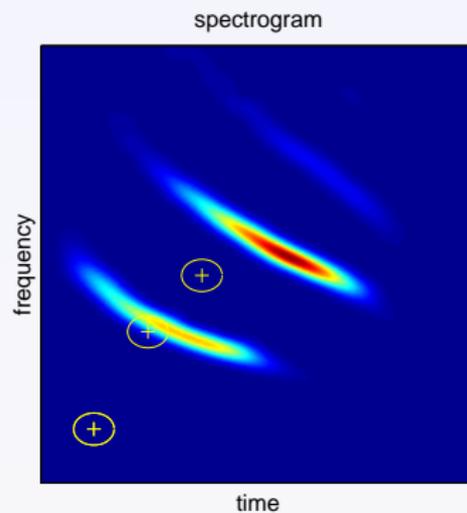
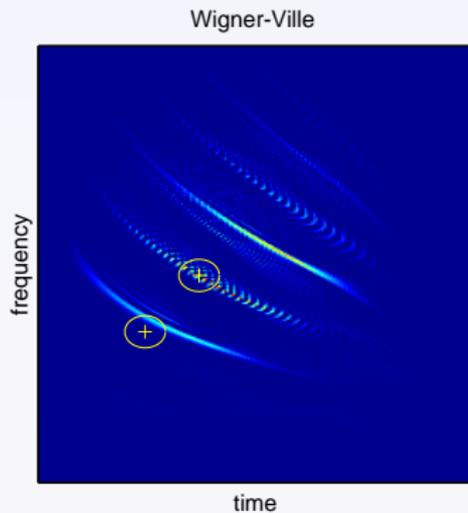
reassignment



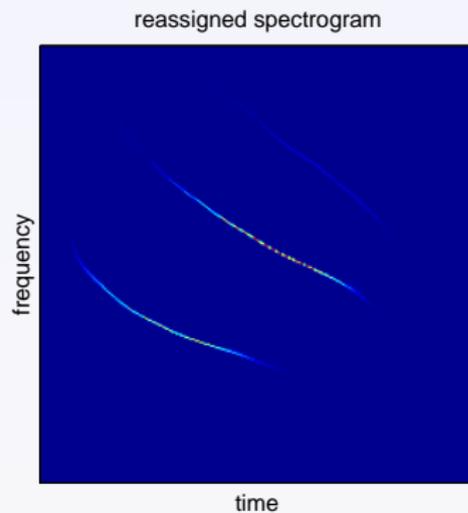
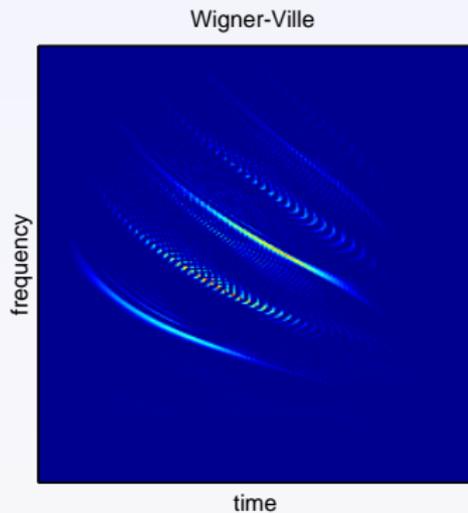
reassignment



reassignment



reassignment



reassignment in action

- **Spectrogram — Implicit** computation of the local centroids (Auger & F., '95) :

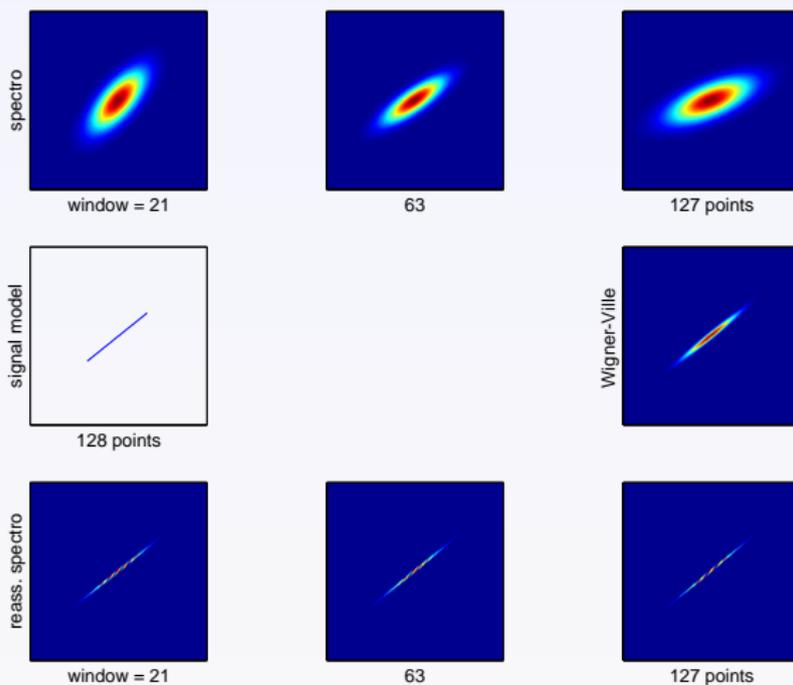
$$\hat{t}_x(t, f) = t + \operatorname{Re} \left\{ \frac{F_x^{(\mathcal{T}h)}}{F_x^{(h)}} \right\} (t, f)$$

$$\hat{f}_x(t, f) = f - \operatorname{Im} \left\{ \frac{F_x^{(\mathcal{D}h)}}{F_x^{(h)}} \right\} (t, f),$$

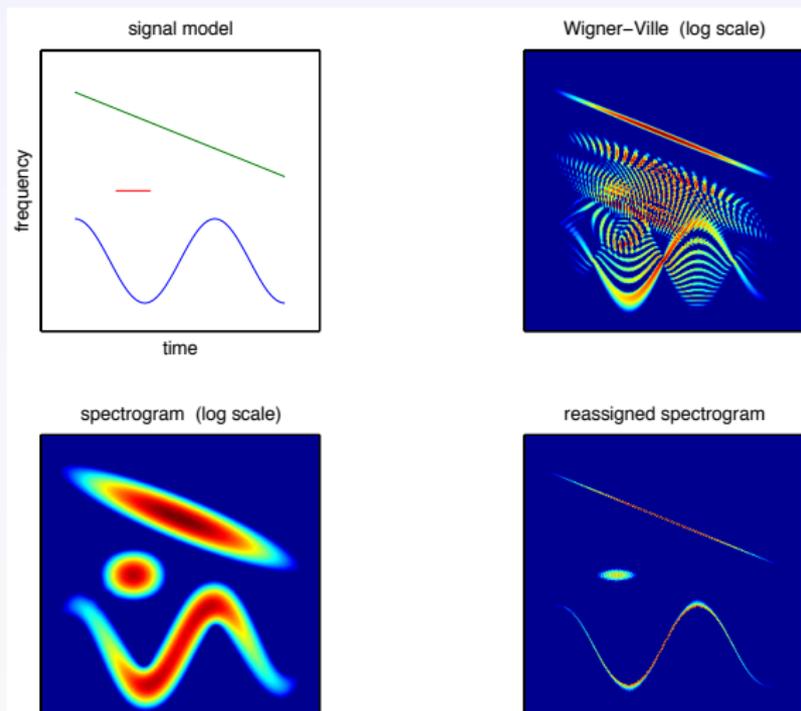
with $(\mathcal{T}h)(t) = t h(t)$ and $(\mathcal{D}h)(t) = (dh/dt)(t)/2\pi$.

- **Beyond spectrograms** — Possible generalizations to other smoothings (smoothed pseudo-Wigner-Ville, scalogram, etc.).

independence wrt window size



an example of comparison



reassignment and estimation

- **Advantage** — Very good properties of **localization** for chirps ($>$ spectrogram).
- **Limitation** — High **sensitivity to noise** ($<$ spectrogram).

Aim

Reduce fluctuations while preserving localization.

Idea (Xiao & F., '06)

*Adopt a **multiple windows** approach.*

back to spectrum estimation

- **Stationary processes** — The **power spectrum density** can be viewed as:

$$\mathbf{S}_x(f) = \lim_{T \rightarrow \infty} \mathbb{E} \left\{ \frac{1}{T} \left| \int_{-T/2}^{+T/2} x(t) e^{-i2\pi ft} dt \right|^2 \right\}$$

- **In practice** — Only one, finite duration, realization \Rightarrow crude periodogram (squared FT) = **non consistent estimator with large variance**

classical way out (Welch, '67)

- **Principle** — Method of **averaged periodograms**

$$\hat{S}_{x,K}^{(W)}(f) = \frac{1}{K} \sum_{k=1}^K S_x^{(h)}(t_k, f)$$

with $t_{k+1} - t_k$ of the order of the width of the window $h(t)$.

- **Bias-variance trade-off** — Given T (finite), increasing $K \Rightarrow$ **reduces variance**, but **increases bias**

multitaper solution (Thomson, '82)

- **Principle** — Computing

$$\hat{\mathbf{S}}_{x,K}^{(T)}(f) = \frac{1}{K} \sum_{k=1}^K S_x^{(h_k)}(0, f)$$

with $\{h_k(t), k \in \mathbb{N}\}$ a family of orthonormal windows extending over the whole support of the observation \Rightarrow **reduced variance, without sacrificing bias**

- **Nonstationary extension** — **Multitaper spectrogram**

$$\hat{\mathbf{S}}_{x,K}^{(T)}(f) \rightarrow S_{x,K}(t, f) := \frac{1}{K} \sum_{k=1}^K S_x^{(h_k)}(t, f)$$

- **Limitation** — Localization controlled by most spread spectrogram.

multitaper reassignment

Idea

Combining the advantages of reassignment (wrt localization) with those of multitapering (wrt fluctuations) :

$$S_{x,K}(t, f) \rightarrow RS_{x,K}(t, f) := \frac{1}{K} \sum_{k=1}^K RS_x^{(h_k)}(t, f)$$

- ① **coherent averaging of chirps** (localization independent of the window)
- ② **incoherent averaging of noise** (different TF distributions for different windows)

in practice

- **Choice of windows — Hermite functions**

$$h_k(t) = (-1)^k \frac{e^{-t^2/2}}{\sqrt{\pi^{1/2} 2^k k!}} (\mathcal{D}^k \gamma)(t); \gamma(t) = e^{t^2}$$

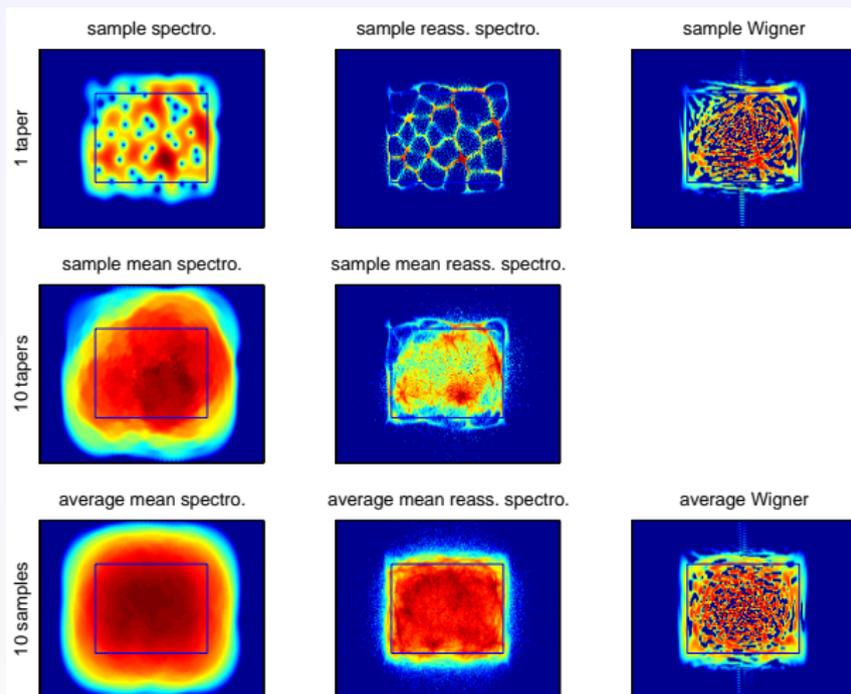
rather than **Prolate Spheroidal Wave functions**

- **Two main reasons**

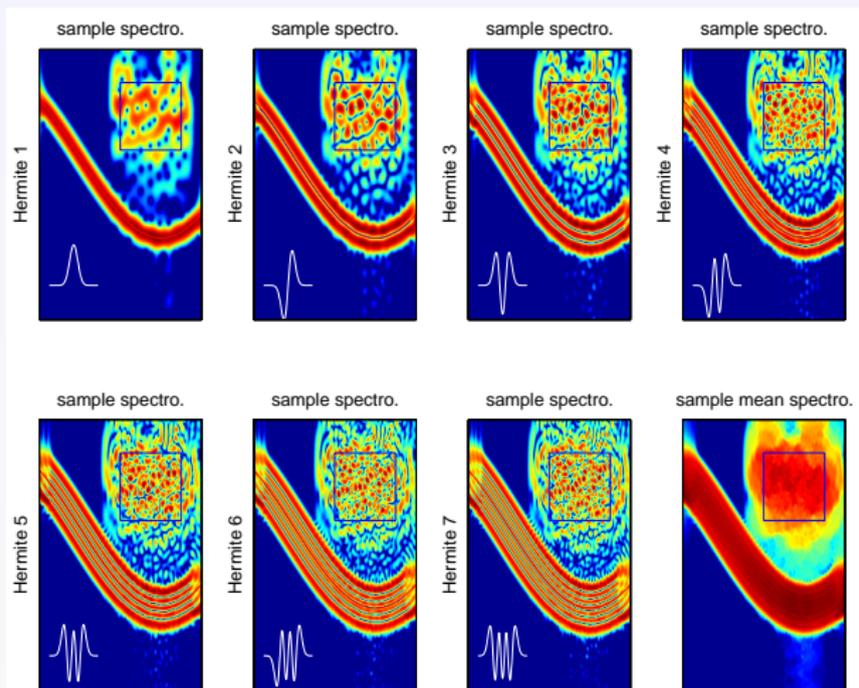
- ① WVD with **elliptic symmetry** and **maximum concentration** in the plane.
- ② **recursive** computation of $h_k(t)$, $(\mathcal{T}h_k)(t)$ and $(\mathcal{D}h_k)(t) \Rightarrow$ better implementation in **discrete-time**. In particular:

$$(\mathcal{D}h_k)(t) = (\mathcal{T}h_k)(t) - \sqrt{2(k+1)} h_{k+1}(t)$$

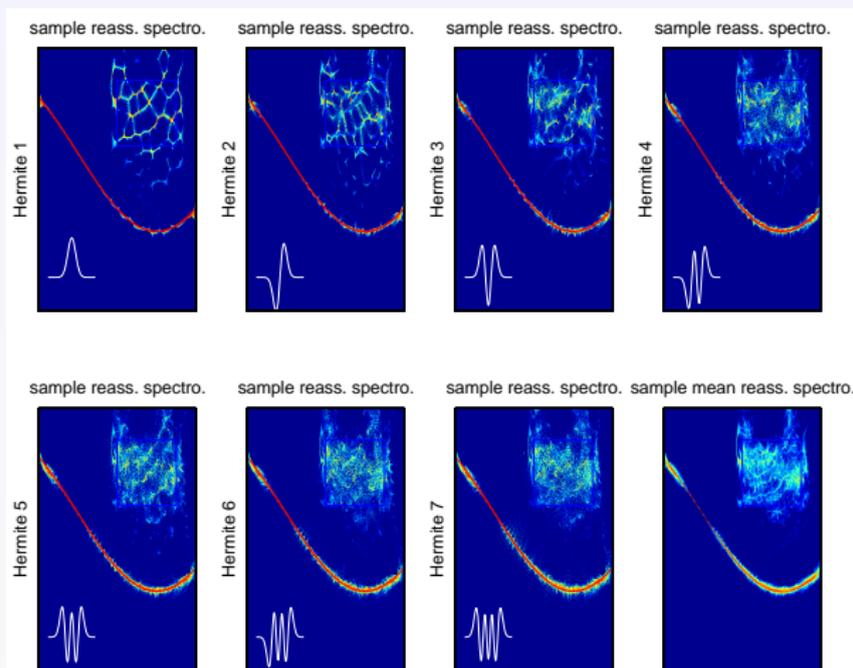
example 1



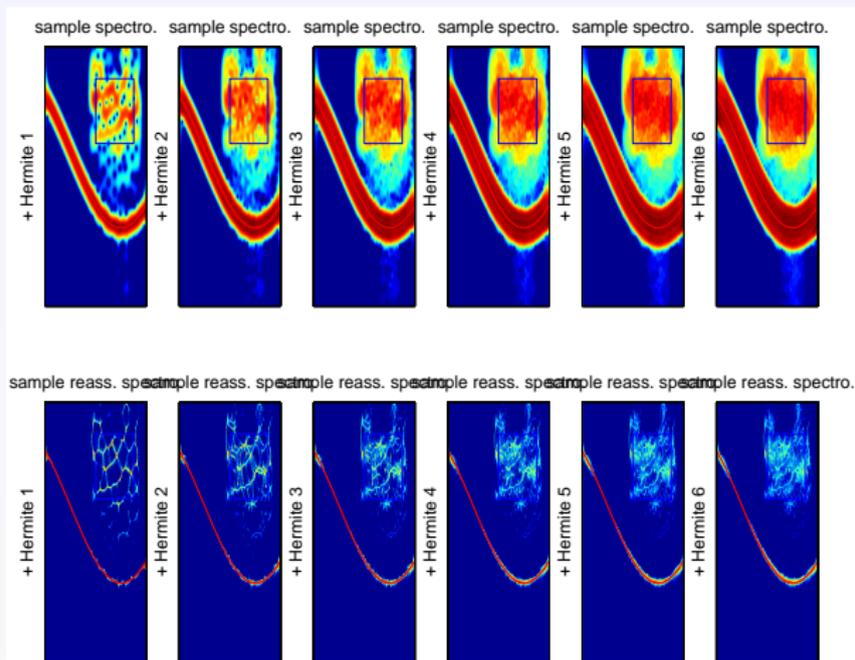
example 2



example 2



example 2



chirp enhancement

Idea

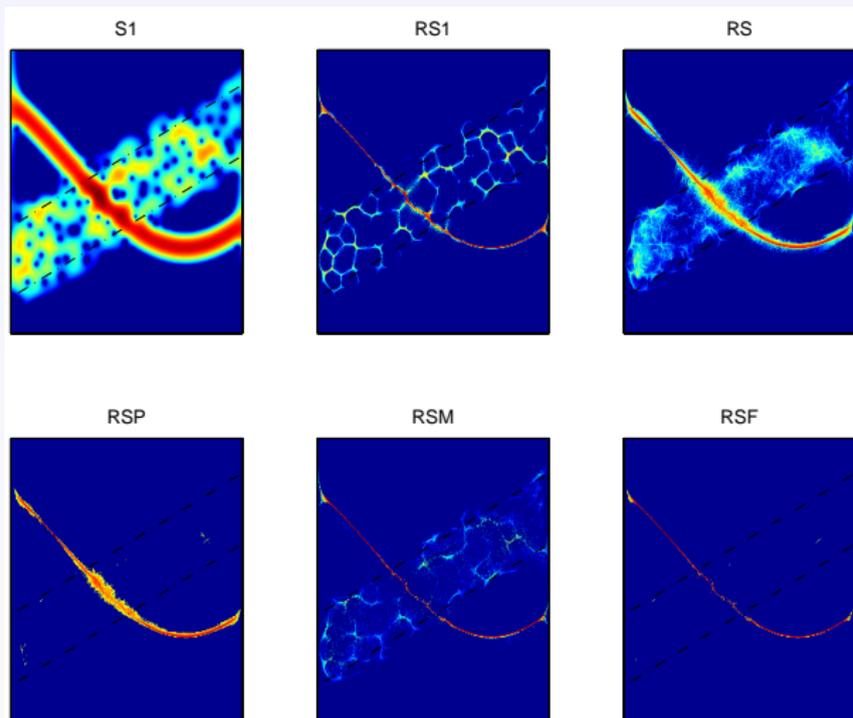
*Reassigned chirps **globally** invariant wrt tapers \Rightarrow "differences"
wrt successive tapers mostly non-zero in noisy regions*

- ① **average ratios (\sim log-differences)**

$$RSD_{x,K}(t, f) = \frac{1}{K-1} \sum_{k=1}^{K-1} \frac{RS_x^{(h_{k+1})}(t, f)}{RS_x^{(h_k)}(t, f)}.$$

- ② **threshold and mask**

example 3



a “compressed sensing” approach

Discrete time

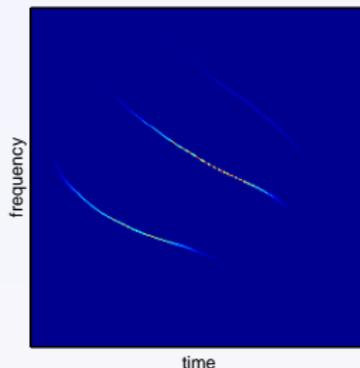
*signal of dimension $N \Rightarrow$ TF
distribution of dimension $\approx N^2$*

Few components

*$K \ll N \Rightarrow$ at most $KN \ll N^2$
non zero values in the TF plane*

Sparsity

*minimizing the ℓ_0 “norm” not feasible, but almost optimal solution
by minimizing the ℓ_1 norm*



a “compressed sensing” approach

Idea (F. & Borgnat, 2008-2010)

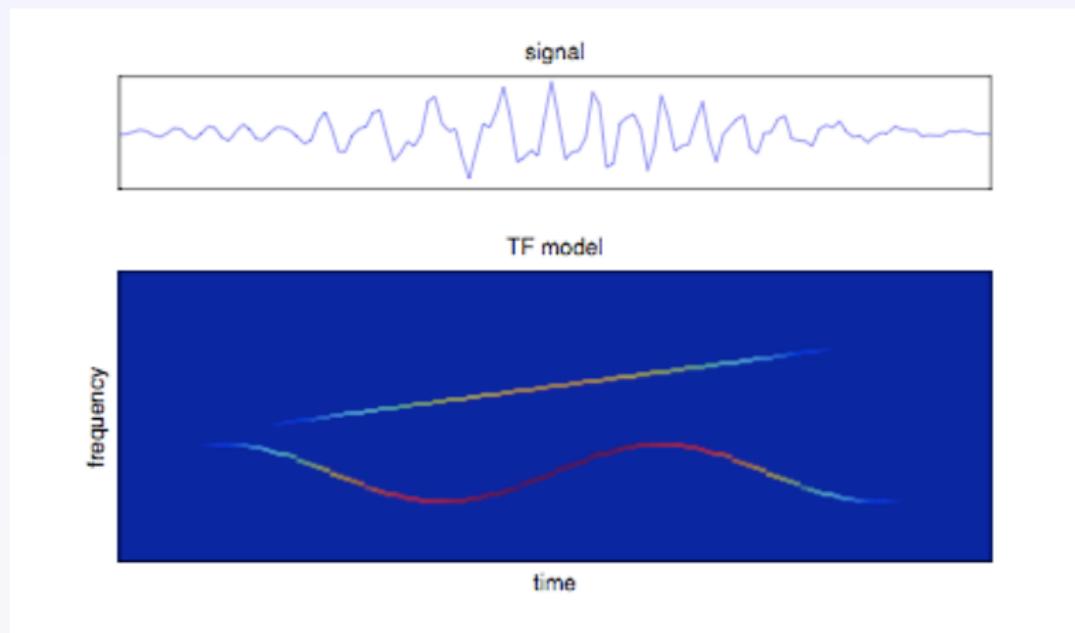
- ① *choose a domain Ω neighbouring the origin of the AF plane*
- ② *solve the program*

$$\min_{\rho} \|\rho\|_1 ; \mathcal{F}\{\rho\} - A_x = 0|_{(\xi, \tau) \in \Omega}$$

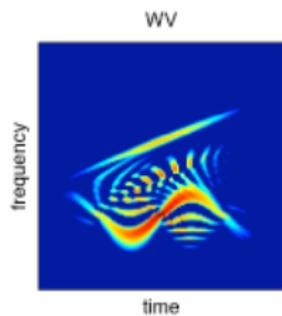
- ③ *the exact equality over Ω can be relaxed to*

$$\min_{\rho} \|\rho\|_1 ; \|\mathcal{F}\{\rho\} - A_x\|_2 \leq \epsilon|_{(\xi, \tau) \in \Omega}$$

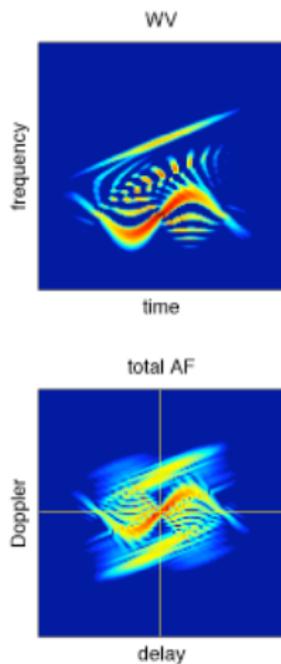
a toy example



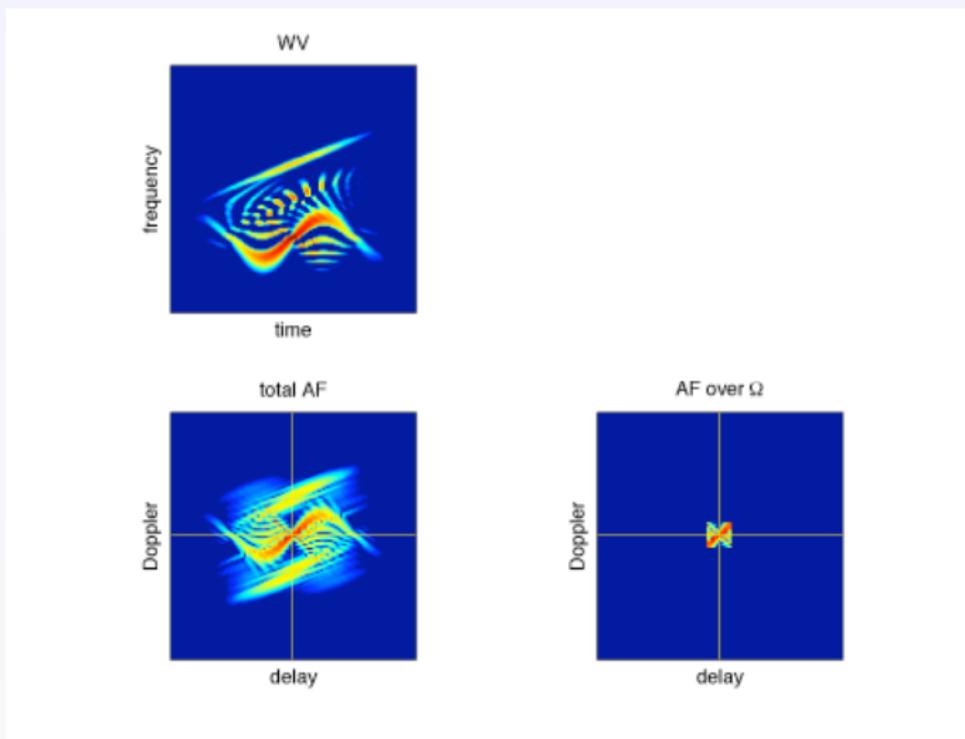
Wigner



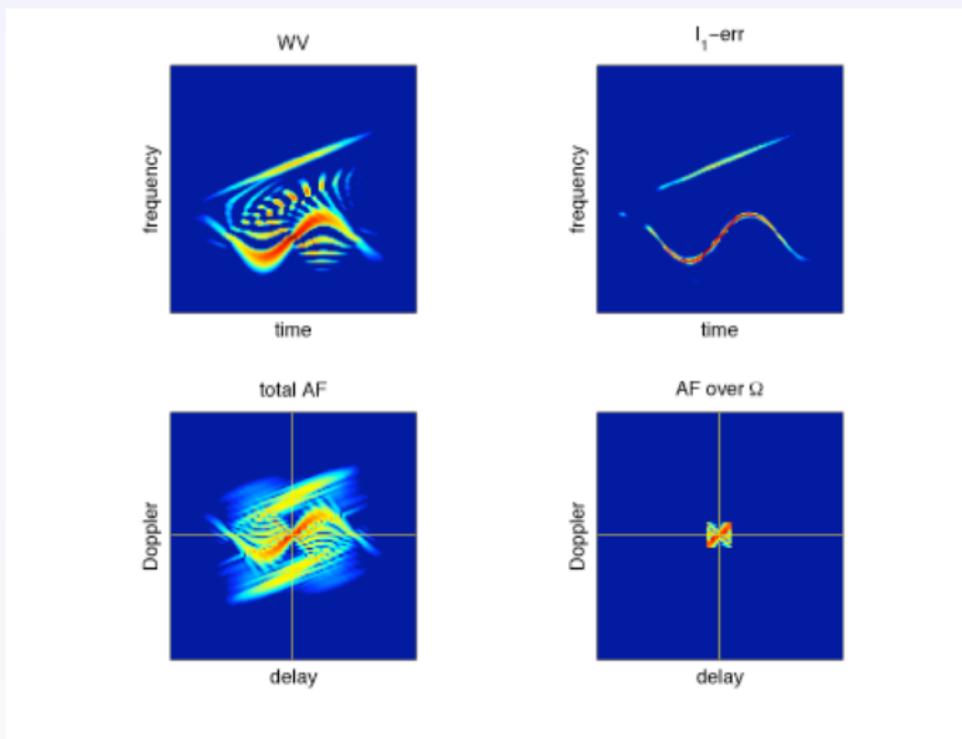
ambiguity



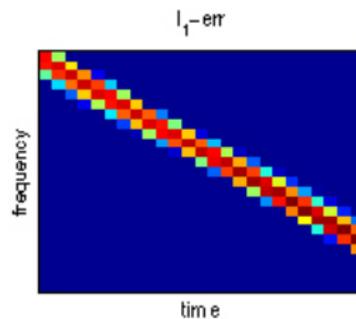
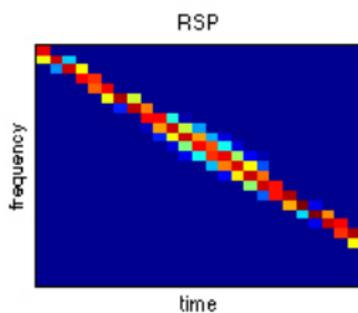
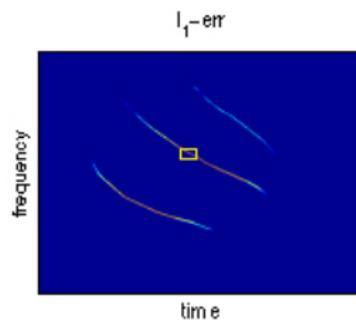
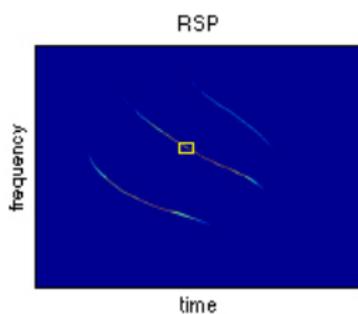
selection



sparse solution



comparison sparsity vs. reassignment



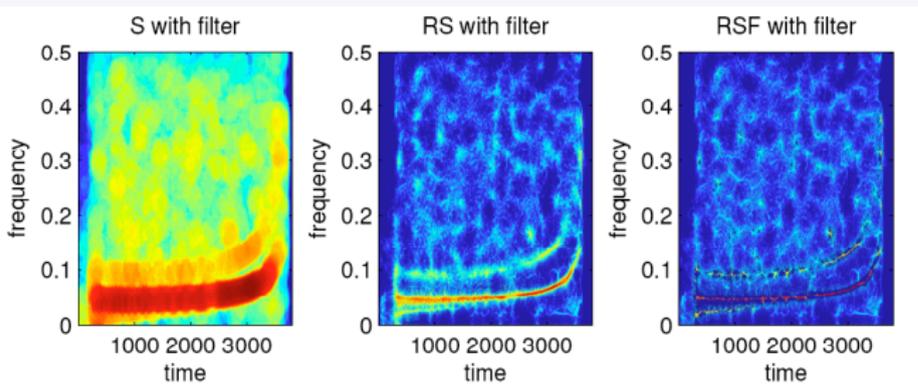
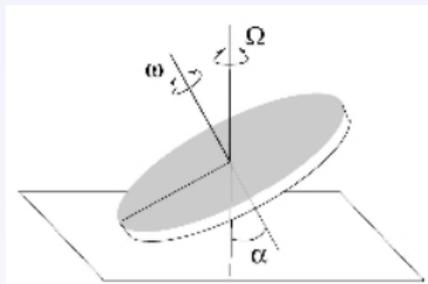
detection/estimation of chirps

- **Optimality** — Matched filtering, maximum likelihood, contrast, . . . : basic ingredient = **correlation** “received signal — copy of emitted signal”.
- **Time-frequency interpretation** — **Unitarity** of a time-frequency distribution $\rho_x(t, f)$ guarantees the equivalence:

$$|\langle x, y \rangle|^2 = \langle \langle \rho_x, \rho_y \rangle \rangle.$$

- **Chirps** — Unitarity + localization \Rightarrow detection/estimation via **path integration** in the plane (e.g., Wigner-Ville and linear chirps). Approximation = reassigned spectrogram and “any” chirp.

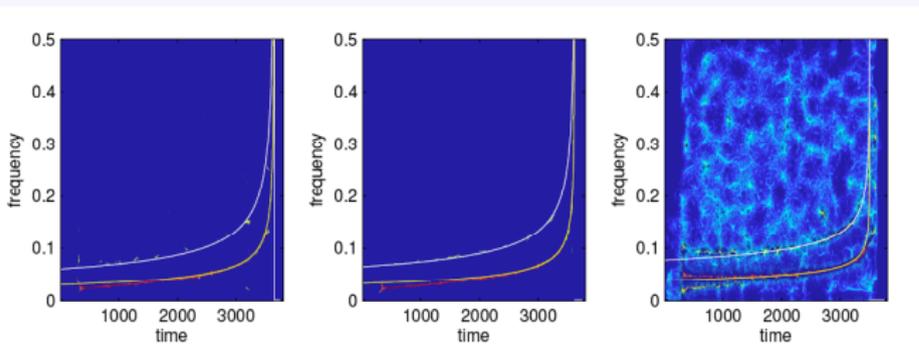
Euler's disk



Euler's disk — Hough 1

Idea

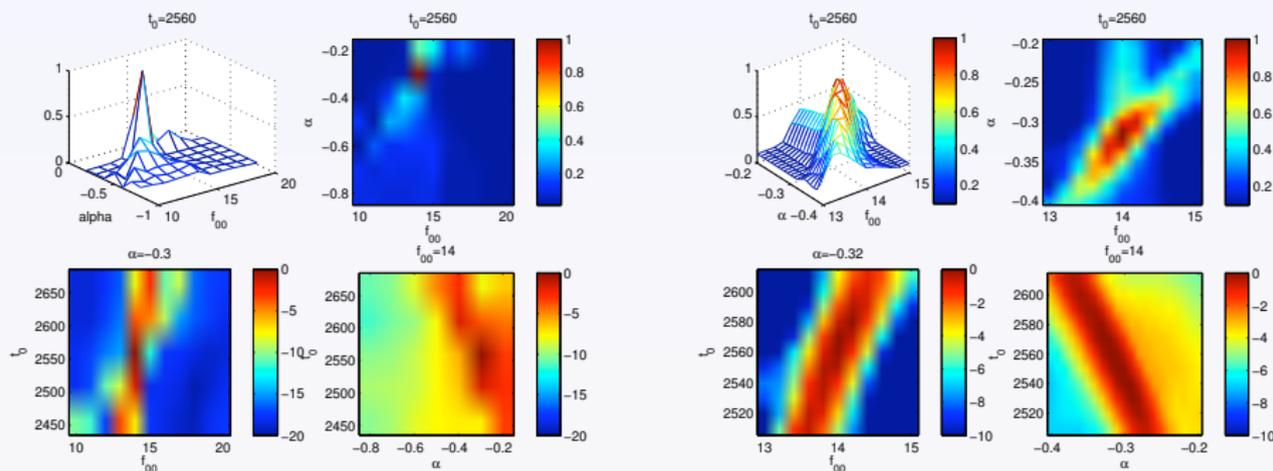
Path integration along power-law trajectories $f = f_0(t_0 - t)^\alpha$



Euler's disk — Hough 2

Result

Coarse and refined estimation of parameters f_0 , t_0 and α



revisiting stationarity

Observation

*Discrepancy between **theory** (invariance over all times, stochastic framework) and **practice** (observation scale, deterministic signals)*

Aim

*Get an **operational** (i.e., equipped with interpretation + test) definition of stationarity*

Idea

*Operate in the time-frequency plane and compare with a **stationarized** reference*

time-frequency stationarity

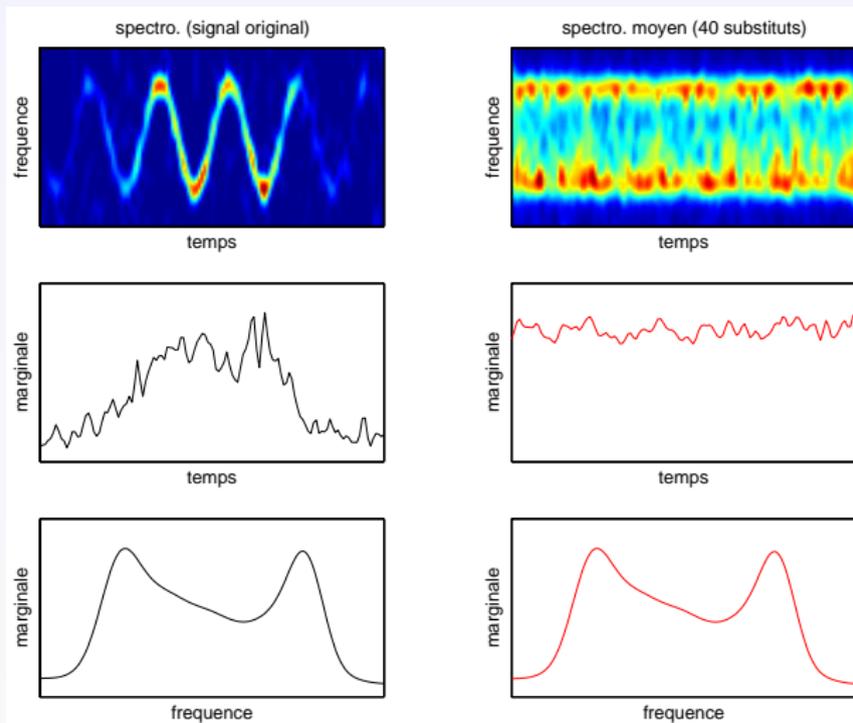
- **Principle**

- 2nd-order stationarity $\Rightarrow \mathbf{W}_x(t, f) = \Gamma_x(f)$ (PSD) for **any** t
- adaptation to sub-regions of the TF plane, in **time** (observation scale) and/or in **frequency** (subbands)
- test by comparing **local** vs. **global** spectral features

- **Significance**

- nonstationarity = **structured** organization of spectral content over time: local “ \neq ” global
- null hypothesis of stationarity = **stationarized** (i.e., unstructured in time) reference: local “ $=$ ” global
- phase randomization in the Fourier domain (method of **surrogate** data)

stationarization via surrogates



a distance-based test

- **Dissimilarity measures**

- $\kappa_{\text{KL}}(G, H) := \int_{\Omega} (G(f) - H(f)) \log(G(f)/H(f)) df$
(Kullback-Leibler divergence)
- $\kappa_{\text{LS}}(G, H) := \int_{\Omega} |\log(G(f)/H(f))| df$ (log-spectral deviation)
- $\kappa(G, H) := \kappa_{\text{KL}}(G, H) \cdot (1 + \lambda \kappa_{\text{LS}}(G, H))$ (combined)

- **Comparison local vs. global**

$$\{c_n^{(y)} := \kappa(S_{y,K}(t_n, \cdot), \langle S_{y,K}(t_n, \cdot) \rangle_{n=1, \dots, N}), n = 1, \dots, N\}$$

with either

- $y(t) = x(t)$ (observed signal)
- $\{y(t) = s_j(t); j = 1, \dots, J\}$ (stationarized surrogates)

proposed test

- **Fluctuations** — “Nonstationarity” assessed by the l_2 -norm

$$L(g, h) := \sum_{n=1}^N (g_n - h_n)^2 / N$$

- $\Theta_1 = L(c^{(x)}, \langle c^{(x)} \rangle_{n=1, \dots, N})$ (signal)
 - $\Theta_0(j) = L(c^{(s_j)}, \langle c^{(s_j)} \rangle_{n=1, \dots, N})$, $j = 1, \dots, J$ (surrogates)
- **Test**

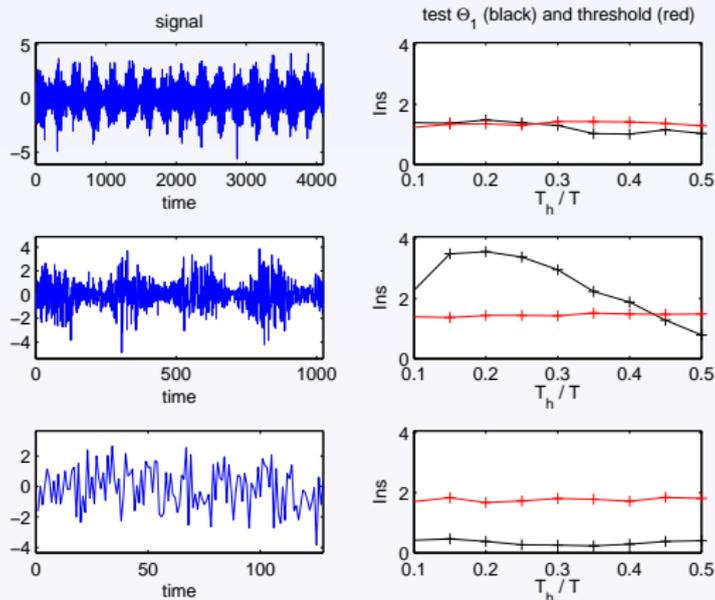
$$\begin{cases} \Theta_1 > \gamma & : \text{“nonstationarity”}; \\ \Theta_1 < \gamma & : \text{“stationarity”}. \end{cases}$$

with threshold γ deduced from the distribution of $\Theta_0(j)$ for a given level of significance (probability of rejecting the null hypothesis of stationarity)

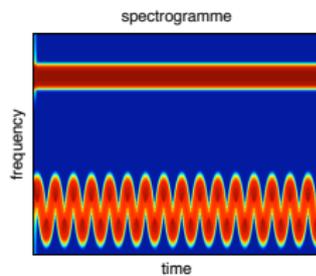
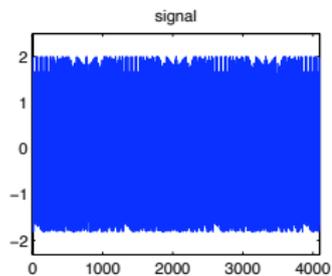
- **From detection to estimation**

- **index** of nonstationarity: $\text{INS} := \sqrt{\frac{\Theta_1}{\frac{1}{J} \sum_{j=1}^J \Theta_0(j)}}$
 - **scale** of nonstationarity: $\text{SNS} := \frac{1}{N_x} \arg \max_{N_h} \{\text{INS}(N_h)\}$

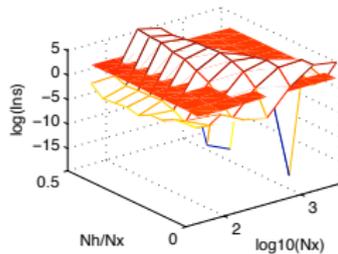
test in action (stochastic case)



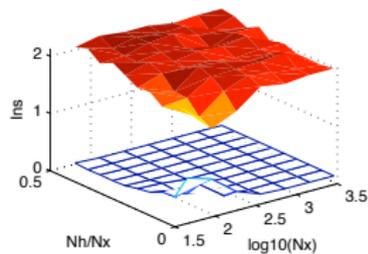
test in action (deterministic case)



test et seuil dans la bande [0.01 - 0.2]



test et seuil dans la bande [0.3 - 0.49]



a kernel-based test

Idea

Surrogates = learning set \Rightarrow kernel methods machinery

- **Nonlinear** mapping $\varphi(\cdot)$ from input space to **feature** space, with a kernel such that $K(x_i, x_j) = \langle \varphi(x_i), \varphi(x_j) \rangle$
- **One-class SVM** (Support Vector Machines)
 - **implicit** density estimation for outlier rejection
 - optimal **hyperplane** solution of the quadratic program

$$\min_{w, \rho, \xi} \frac{1}{2} \|w\|^2 + \frac{1}{\nu J} \sum_{j=1}^J \xi_j - \rho$$

subject to $\langle w, \varphi(x_j) \rangle \geq \rho - \xi_j, \xi_j \geq 0$

- **decision** function given by $d(z) = \text{sgn}(\langle w, \varphi(z) \rangle - \rho)$

feature space

- **Normalized** spectral “slices” of multitaper spectrograms

$$\tilde{S}_n(f) = S_{x,K}(t_n, f) / \int_0^\infty S_{x,K}(t_n, f) df; n = 1, \dots, N$$

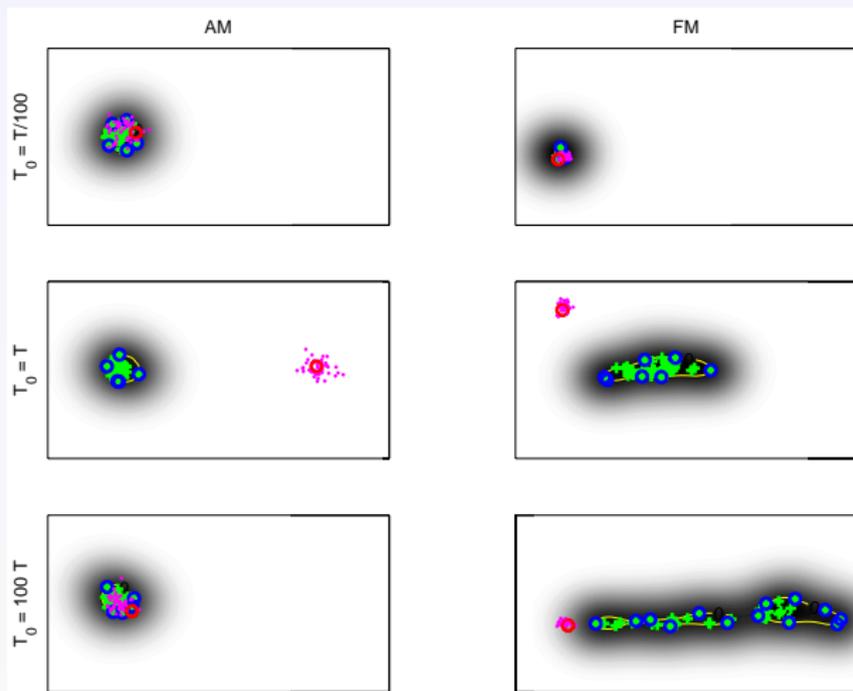
- Time evolution of local **power** P_n and **frequency** F_n

$$P_n = \langle 1 \rangle_{\tilde{S}_n}; F_n = \langle f \rangle_{\tilde{S}_n}; F_n^2 = \langle f^2 \rangle_{\tilde{S}_n}$$

- **Local** vs. **global** features

$$\begin{cases} P = \text{std}(\{P_n\}_{n=1..N}) / \text{mean}(\{P_n\}_n) \\ F = \text{std}(\{F_n\}_{n=1..N}) / \text{mean}(\{\sqrt{\{F_n^2 - (F_n)^2\}}_n\}) \end{cases}$$

an example



monographs

- L. Cohen, *Time-Frequency Analysis*, Prentice-Hall, 1995.
- S. Mallat, *A Wavelet Tour of Signal Processing*, Academic Press, 1997.
- R. Carmona, H.L. Hwang & B. Torrèsani, *Practical Time-Frequency Analysis*, Academic Press, 1998.
- F. Hlawatsch, *Time-Frequency Analysis and Synthesis of Linear Signal Spaces*, Kluwer, 1998.
- P. Flandrin, *Time-Frequency/Time-Scale Analysis*, Academic Press, 1999.

collective books

- A. Papandreou-Suppappola (*ed.*), *Applications in Time-Frequency Signal Processing*, CRC Press, 2003.
- B. Boashash (*ed.*), *Time-Frequency Signal Analysis and Processing*, Elsevier, 2003.
- Ch. Doncarli & N. Martin (*eds.*), *Décision dans le Plan Temps-Fréquence*, Traité IC2, Hermes, 2004.
- F. Auger & F. Hlawatsch (*eds.*), *Temps-Fréquence — Concepts et Outils*, Traité IC2, Hermes, 2005.

(p)reprints, Matlab codes & contact

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- `http://tftb.nongnu.org/`
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