

## **The Kravchuk transform**

A novel covariant representation for discrete signals amenable to zero-based detection tests

*March 18<sup>th</sup> 2022*

Barbara Pascal

**Séminaire Signal Image**

Institut de Mathématiques de Marseille

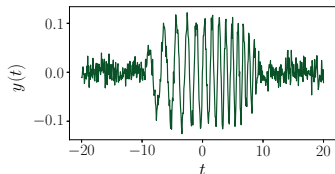
- Context and notations
  - Time-frequency analysis: the Short-Time Fourier Transform
- 

- Signal detection based on spectrogram zeros - I
  - Covariance principle and stationary point processes
- 

- The Kravchuk transform and its zeros
- Signal detection based on spectrogram zeros - II

# Continuous time-frequency analysis

Finite energy signal  $y \in L^2_{\mathbb{C}}(\mathbb{R})$ : function of time  $t$ .



- electrical cardiac activity,
- audio recording,
- seismic activity,
- light intensity on a photosensor
- ...

## Information of interest:

- time events, e.g., an earthquake and its replica
- frequency content, e.g., monitoring of the heart beating rate

### time

ever-changing world  
marker of events and evolutions

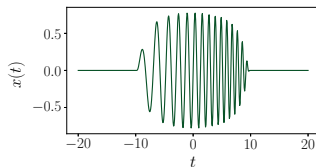
### frequency

waves, oscillations, rhythms  
intrinsic mechanisms

## Signal-plus-noise model

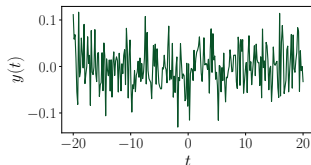
**E.g., chirp:** transient waveform modulated in amplitude and frequency:

$$x(t) = A_{\nu}(t) \sin \left( 2\pi \left( f_1 + (f_2 - f_1) \frac{t + \nu}{2\nu} \right) t \right)$$



**White noise:** random process  $\xi(t)$  such that

$$\mathbb{E}[\xi(t)] = 0 \quad \text{and} \quad \mathbb{E}[\overline{\xi(t)}\xi(t')] = \delta(t - t')$$

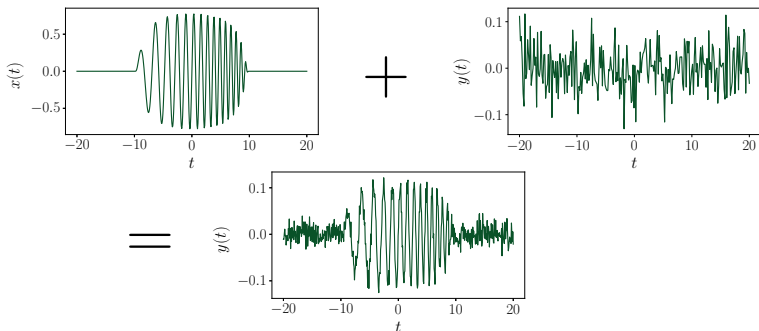


**P. Flandrin:** 'A signal is characterized by a structured organization.'

# Signal-plus-noise model

## Noisy observations

$$y(t) = \text{snr} \times x(t) + \xi(t)$$



**Classical tasks:** given an observation  $y(t)$

detection decides whether  $y(t) = \text{snr} \times x(t) + \xi(t)$ ,  $\text{snr} > 0$  or  $y(t) = \xi(t)$ ,

denoising retrieves the pure signal  $x(t)$ ,

feature extraction e.g., estimates  $f(t) = f_1 + (f_2 - f_1) \frac{t+\nu}{2\nu}$ .

# Outline of the presentation

- Context and notations
  - Time-frequency analysis: the Short-Time Fourier Transform
- 

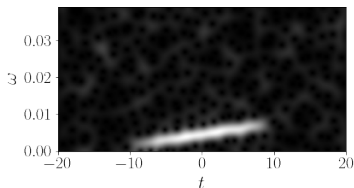
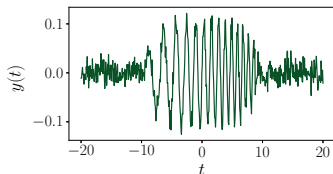
- Signal detection based on spectrogram zeros - I
  - Covariance principle and stationary point processes
- 

- The Kravchuk transform and its zeros
- Signal detection based on spectrogram zeros - II

## Time and frequency

Short-Time Fourier Transform with window  $h$ :

$$V_h y(t, \omega) \triangleq \int_{-\infty}^{\infty} \overline{y(u)} h(u - t) \exp(-i\omega u) du$$



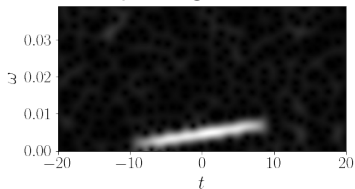
Energy density interpretation  $S_h y(t, \omega) = |V_h y(t, \omega)|^2$  the *spectrogram*

$$\int \int_{-\infty}^{+\infty} S_h y(t, \omega) dt \frac{d\omega}{2\pi} = \int_{-\infty}^{+\infty} |x(t)|^2 dt \quad \text{if} \quad \|h\|_2^2 = 1$$

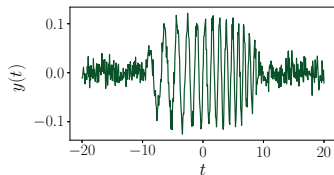
Signal, i.e., information of interest: regions of **maximal** energy.

Denoising in the time-frequency plane:  $y = \text{snr} \times x + \xi$ ,  $\text{snr} = 2$

spectrogram

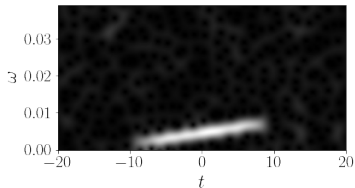


noisy observation

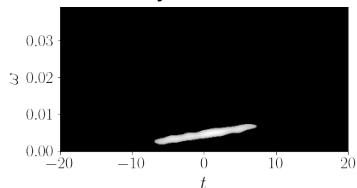


Denoising in the time-frequency plane:  $y = \text{snr} \times x + \xi$ ,  $\text{snr} = 2$

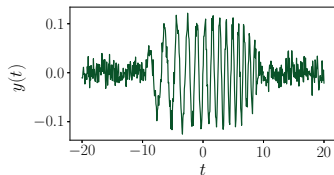
spectrogram



only maxima



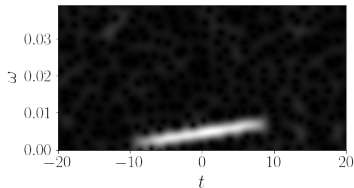
noisy observation



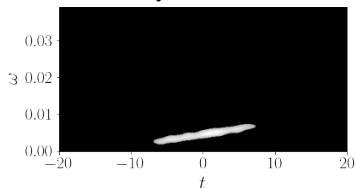
Denoising in the time-frequency plane:  $y = \text{snr} \times x + \xi$ ,  $\text{snr} = 2$

Inversion formula 
$$y(t) = \int \int_{-\infty}^{+\infty} \overline{V_h y(u, \omega)} h(t - u) \exp(i\omega u) du \frac{d\omega}{2\pi}$$

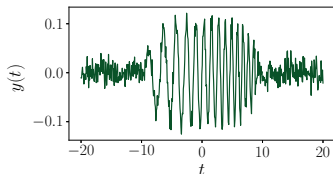
spectrogram



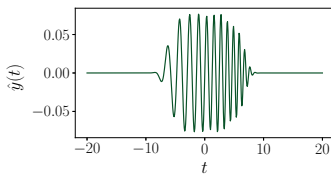
only maxima



noisy observation



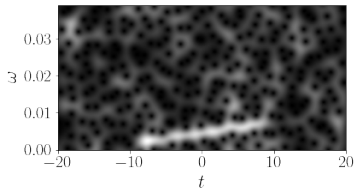
denoised estimate



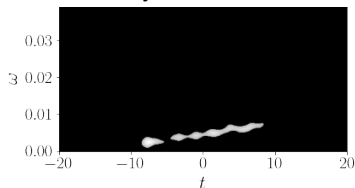
Denoising in the time-frequency plane:  $y = \text{snr} \times x + \xi$ ,  $\text{snr} = 0.5$

Inversion formula 
$$y(t) = \int \int_{-\infty}^{+\infty} \overline{V_h y(u, \omega)} h(t - u) \exp(i\omega u) du \frac{d\omega}{2\pi}$$

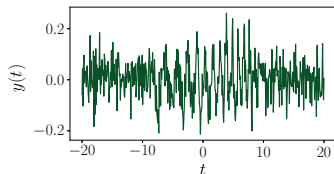
spectrogram



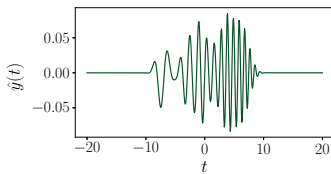
only maxima



noisy observation



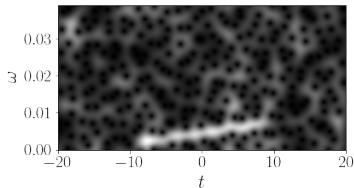
estimate



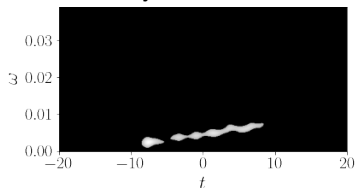
Denoising in the time-frequency plane:  $y = \text{snr} \times x + \xi$ ,  $\text{snr} = 0.5$

Inversion formula 
$$y(t) = \int \int_{-\infty}^{+\infty} \overline{V_h y(u, \omega)} h(t - u) \exp(i\omega u) du \frac{d\omega}{2\pi}$$

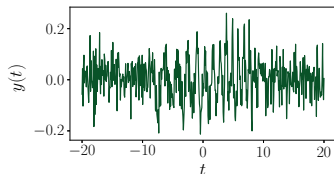
spectrogram



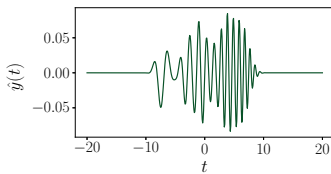
only maxima



noisy observation



estimate



**Maxima localization:** *reassignment, synchrosqueezing, ridge extraction*

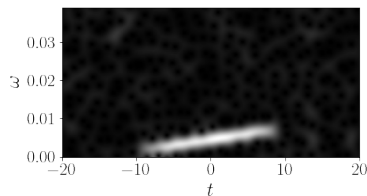
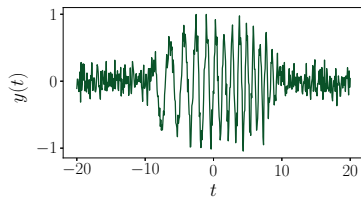
# Outline of the presentation

- Context and notations
  - Time-frequency analysis: the Short-Time Fourier Transform
- 

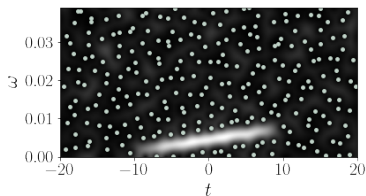
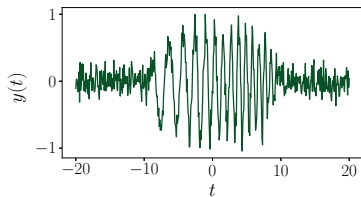
- Signal detection based on spectrogram zeros - I
  - Covariance principle and stationary point processes
- 

- The Kravchuk transform and its zeros
- Signal detection based on spectrogram zeros - II

Restriction to the **circular Gaussian window**:  $g(t) = \pi^{-1/4} e^{-t^2/2}$

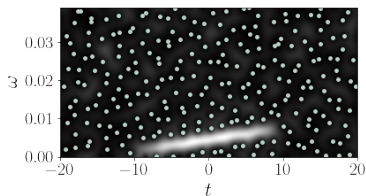
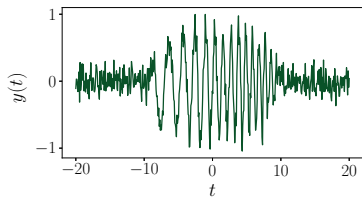


Restriction to the **circular Gaussian window**:  $g(t) = \pi^{-1/4} e^{-t^2/2}$



Instead of maxima, look for the **zeros**:  $(t_i, \omega_i)$  such that  $|V_g y(t_i, \omega_i)|^2 = 0$   
 (Gardner & Magnasco, 2006), (Flandrin, 2015)

Restriction to the **circular Gaussian window**:  $g(t) = \pi^{-1/4} e^{-t^2/2}$

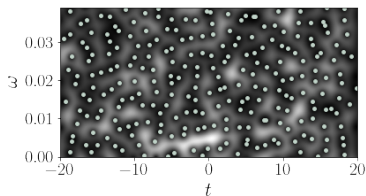
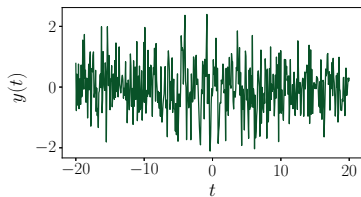


Instead of maxima, look for the **zeros**:  $(t_i, \omega_i)$  such that  $|V_g y(t_i, \omega_i)|^2 = 0$   
(Gardner & Magasco, 2006), (Flandrin, 2015)

### Observations:

- In the noise region zeros are evenly spread.
- There exists a short-range repulsion between zeros.
- Zeros are repelled by the signal.

Restriction to the **circular Gaussian window**:  $g(t) = \pi^{-1/4} e^{-t^2/2}$



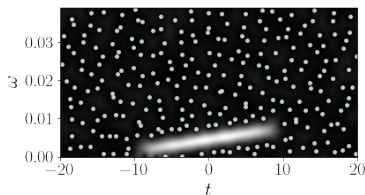
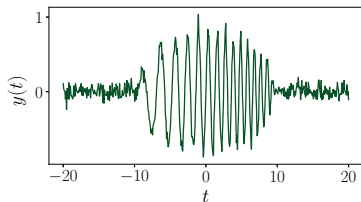
Instead of maxima, look for the **zeros**:  $(t_i, \omega_i)$  such that  $|V_g y(t_i, \omega_i)|^2 = 0$

(Gardner & Magnasco, 2006), (Flandrin, 2015)

### Observations:

- In the noise region zeros are evenly spread.
- There exists a short-range repulsion between zeros.
- Zeros are repelled by the signal.

Restriction to the **circular Gaussian window**:  $g(t) = \pi^{-1/4} e^{-t^2/2}$



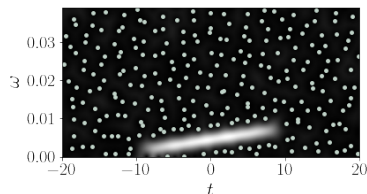
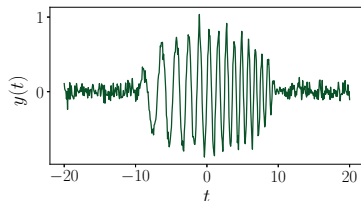
Instead of maxima, look for the **zeros**:  $(t_i, \omega_i)$  such that  $|V_g y(t_i, \omega_i)|^2 = 0$

(Gardner & Magnasco, 2006), (Flandrin, 2015)

### Observations:

- In the noise region zeros are evenly spread.
- There exists a short-range repulsion between zeros.
- Zeros are repelled by the signal.

Restriction to the **circular Gaussian window**:  $g(t) = \pi^{-1/4} e^{-t^2/2}$



Instead of maxima, look for the **zeros**:  $(t_i, \omega_i)$  such that  $|V_g y(t_i, \omega_i)|^2 = 0$   
(Gardner & Magnasco, 2006), (Flandrin, 2015)

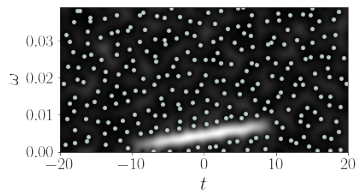
### Observations:

- In the noise region zeros are evenly spread.
- There exists a short-range repulsion between zeros.
- Zeros are repelled by the signal.

**What can be said theoretically about the zeros pattern?**

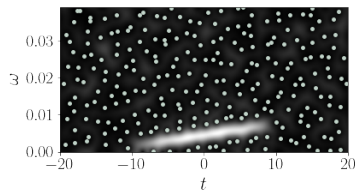
# Unorthodox time-frequency analysis: spectrogram zeros

**Idea** assimilate the time-frequency plane with  $\mathbb{C}$  through  $z = (\omega + it)/\sqrt{2}$



# Unorthodox time-frequency analysis: spectrogram zeros

**Idea** assimilate the time-frequency plane with  $\mathbb{C}$  through  $z = (\omega + it)/\sqrt{2}$



Bargmann factorization

$$V_g y(t, \omega) = e^{-|z|^2/2} e^{-i\omega t/2} B_y(z)$$

$g$  the circular Gaussian window

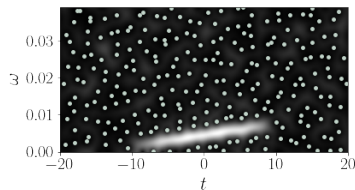
Bargmann transform of the signal  $y$

$$B_y(z) \triangleq \pi^{-1/4} e^{-z^2/2} \int_{\mathbb{R}} \overline{y(u)} \exp\left(\sqrt{2}uz - u^2/2\right) du,$$

$B_y$  is an **entire** function, almost characterized by its infinitely many zeros:

$$B_y(z) = z^m e^{C_0 + C_1 z + C_2 z^2} \prod_{n \in \mathbb{N}} \left(1 - \frac{z}{z_n}\right) \exp\left(\frac{z}{z_n} + \frac{1}{2} \left(\frac{z}{z_n}\right)^2\right)$$

**Idea** assimilate the time-frequency plane with  $\mathbb{C}$  through  $z = (\omega + it)/\sqrt{2}$



Bargmann factorization

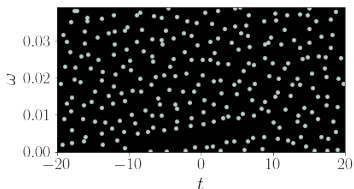
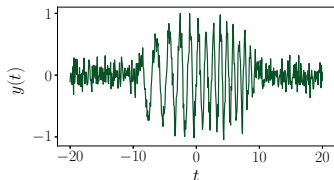
$$V_g y(t, \omega) = e^{-|z|^2/2} e^{-i\omega t/2} B_y(z)$$

$g$  the circular Gaussian window

**Theorem** The zeros of the Gaussian spectrogram  $V_g y(t, \omega)$

- coincide with the zeros of the **entire** function  $B_y$ ,
- hence are **isolated** and constitute a **Point Process**,
- which almost completely **characterizes** the spectrogram.

(Flandrin, 2015)



## Advantages of working with the zeros

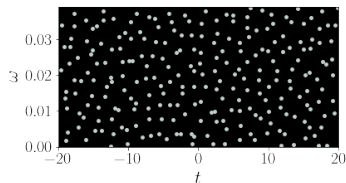
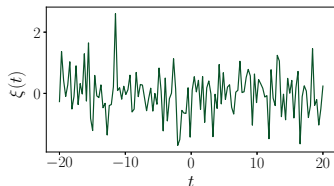
- Easy to find compared to relative maxima.
- Form a robust pattern in the time-frequency plane.
- Require little memory space for storage.
- Efficient tools were recently developed in **stochastic geometry**.

**Need for a rigorous characterization of the distribution of the zeros.**

# The zeros of the spectrogram of white noise

## Continuous complex white Gaussian noise

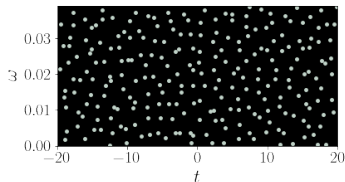
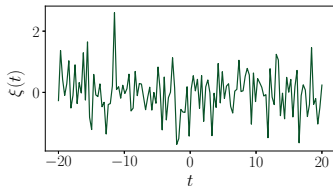
$$\xi(t) = \sum_{n=0}^{\infty} \xi[n] h_n(t), \quad \xi[n] \sim \mathcal{N}_{\mathbb{C}}(0, 1), \quad \{h_n, k = 0, 1, \dots\} \text{ Hermite functions}$$



# The zeros of the spectrogram of white noise

## Continuous complex white Gaussian noise

$$\xi(t) = \sum_{n=0}^{\infty} \xi[n] h_n(t), \quad \xi[n] \sim \mathcal{N}_{\mathbb{C}}(0, 1), \quad \{h_n, k = 0, 1, \dots\} \text{ Hermite functions}$$

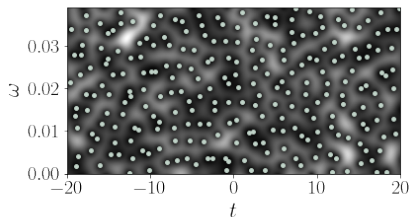


### Theorem

$$V_g \xi(t, \omega) = e^{-|z|^2/4} e^{-i\omega t/2} \text{GAF}_{\mathbb{C}}(z) \quad (\text{Bardenet \& Hardy, 2021})$$

$$\text{GAF}_{\mathbb{C}}(z) = \sum_{n=0}^{\infty} \xi[n] \frac{z^n}{\sqrt{n!}} \text{ the planar Gaussian Analytic Function and } z = \frac{\omega + it}{\sqrt{2}}.$$

# The zeros of the planar Gaussian Analytic Function



$$V_g \xi(t, \omega) \stackrel{\text{non-vanishing}}{\propto} \text{GAF}_{\mathbb{C}}(z)$$

$$z = (\omega + it)/\sqrt{2}$$

$$|V_g y(t_i, \omega_i)|^2 = 0 \iff \text{GAF}_{\mathbb{C}}(z_i) = 0$$

→ zeros of Gaussian Analytic Functions studied by probabilists

## Zeros of the Planar Gaussian Analytic Function

$$\{z_i \in \mathbb{C}, \quad \text{GAF}_{\mathbb{C}}(z_i) = 0\}$$

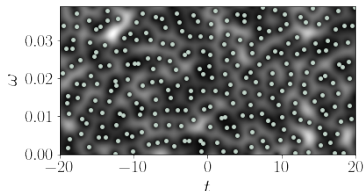
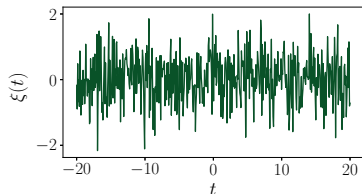
- form a *point process* : random configuration of points
- is stationary : invariant under translations
- has a uniform density  $\rho^{(1)}(z) = \rho^{(1)} = 1/\pi$

# Signal detection based on spectrogram zeros

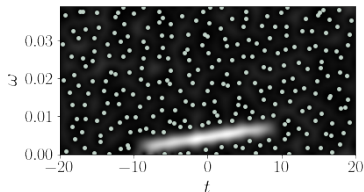
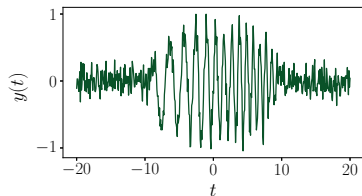
(Bardenet, Flamant & Chainais, 2020)

- $H_0$  white noisy only, i.e.,  $y(t) = \xi(t)$
- $H_1$  presence of a signal, i.e.,  $y(t) = \text{snr} \times x(t) + \xi(t)$ ,  $\text{snr} > 0$

null hypothesis



alternative hypothesis

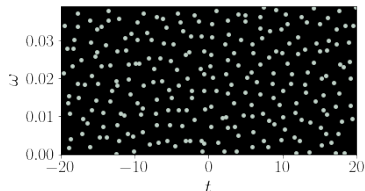
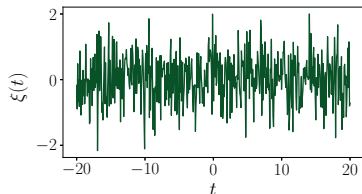


# Signal detection based on spectrogram zeros

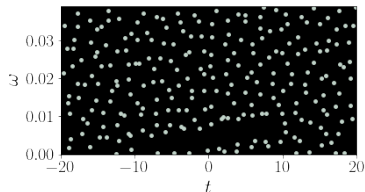
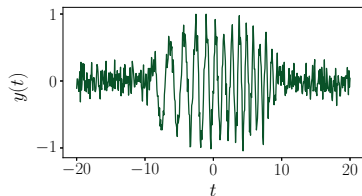
(Bardenet, Flamant & Chainais, 2020)

- $H_0$  white noisy only, i.e.,  $y(t) = \xi(t)$
- $H_1$  presence of a signal, i.e.,  $y(t) = \text{snr} \times x(t) + \xi(t)$ ,  $\text{snr} > 0$

null hypothesis



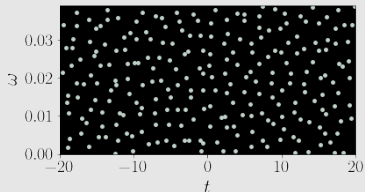
alternative hypothesis



# Monte Carlo envelope test

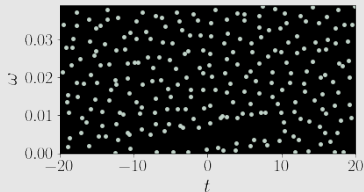
**Purpose:** summary statistic  $s$ , such that for  $y = \text{snr} \times x + \xi$

$$\mathbb{E}[s(y)|\mathbf{H}_0] = 0$$



$\text{snr} = 0$

$$\mathbb{E}[s(y)|\mathbf{H}_1] > 0$$

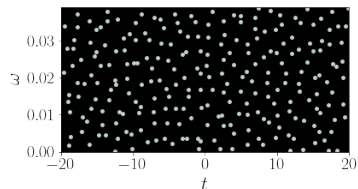


$\text{snr} > 0$

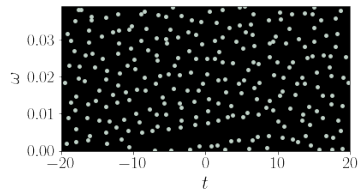
**‘Large value of  $s(y)$  is a strong indication that there is a signal.’**

Tools from **stochastic geometry** to capture spatial statistics of the zeros.

# Unorthodox path: zeros of Gaussian Analytic Functions



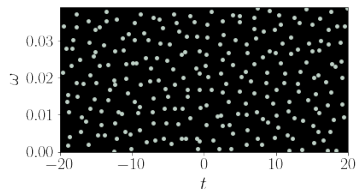
$\text{snr} = 0$



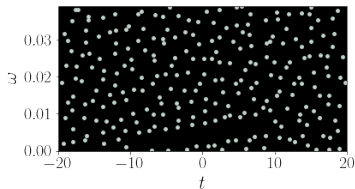
$\text{snr} > 0$

The signal creates **holes** in the zeros pattern: **second order** statistics.

# Unorthodox path: zeros of Gaussian Analytic Functions



$\text{snr} = 0$



$\text{snr} > 0$

The signal creates **holes** in the zeros pattern: **second order** statistics.

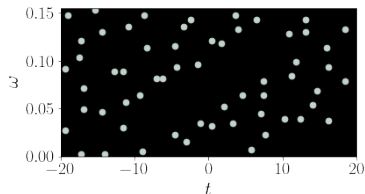
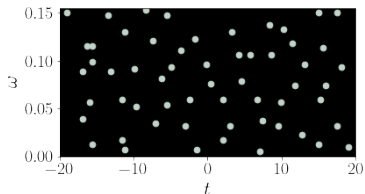
## A functional statistic: the empty space function

$Z$  a stationary point process,  $z_0$  any reference point

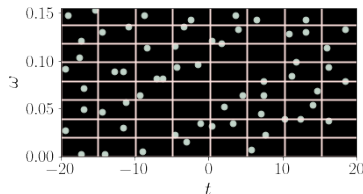
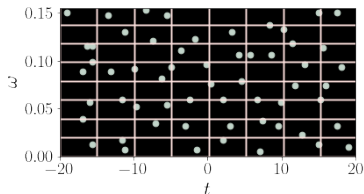
$$F(r) = \mathbb{P} \left( \inf_{z_i \in Z} d(z_0, z_i) < r \right)$$

→ probability to find a zero at distance less than  $r$  from  $z_0$

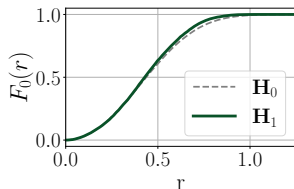
$$F(r) = \mathbb{P} \left( \inf_{z_i \in Z} d(z_0, z_i) < r \right) : \text{empty space function}$$



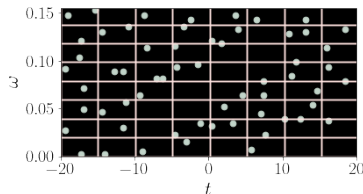
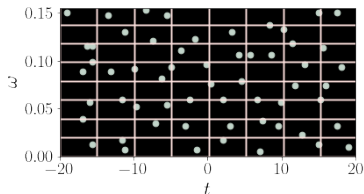
$$F(r) = \mathbb{P} \left( \inf_{z_i \in Z} d(z_0, z_i) < r \right) : \text{empty space function}$$



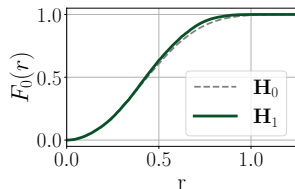
$$\hat{F}(r) = \frac{1}{N_{\#}} \sum_{j=1}^{N_{\#}} \mathbf{1} \left( \inf_{z \in \text{Zeros}} d(z_j, z) < r \right)$$



$$F(r) = \mathbb{P} \left( \inf_{z_i \in Z} d(z_0, z_i) < r \right) : \text{empty space function}$$



$$\hat{F}(r) = \frac{1}{N_{\#}} \sum_{j=1}^{N_{\#}} \mathbf{1} \left( \inf_{z \in \text{Zeros}} d(z_j, z) < r \right)$$



- Monte Carlo envelope test based on the discrepancy between  $\hat{F}$  and  $F_0$

## Monte Carlo envelope test from an observation $y$

Settings:  $\alpha$  level of significance,  $m$  number of samples under  $\mathbf{H}_0$

Index  $k$ , chosen so that  $\alpha = k/(m + 1)$

## Monte Carlo envelope test from an observation $y$

Settings:  $\alpha$  level of significance,  $m$  number of samples under  $\mathbf{H}_0$

Index  $k$ , chosen so that  $\alpha = k/(m + 1)$

(i) generate  $m$  independent samples of complex white Gaussian noise

$$\xi_1, \xi_2, \dots, \xi_m$$

compute their spectrograms and find their zeros;

## Monte Carlo envelope test from an observation $y$

Settings:  $\alpha$  level of significance,  $m$  number of samples under  $\mathbf{H}_0$

Index  $k$ , chosen so that  $\alpha = k/(m+1)$

- (i) generate  $m$  independent samples of complex white Gaussian noise

$$\xi_1, \xi_2, \dots, \xi_m$$

compute their spectrograms and find their zeros;

- (ii) compute the summary statistics from the zeros

$$\forall \mu = 1, 2, \dots, m, \quad s(\mu) = \sqrt{\int_{r_1}^{r_2} |\hat{F}_\mu(r) - F_0(r)|^2}$$

and sort them in decreasing order  $s_1 \geq s_2 \geq \dots \geq s_m$ ;

## Monte Carlo envelope test from an observation $y$

Settings:  $\alpha$  level of significance,  $m$  number of samples under  $\mathbf{H}_0$

Index  $k$ , chosen so that  $\alpha = k/(m+1)$

- (i) generate  $m$  independent samples of complex white Gaussian noise

$$\xi_1, \xi_2, \dots, \xi_m$$

compute their spectrograms and find their zeros;

- (ii) compute the summary statistics from the zeros

$$\forall \mu = 1, 2, \dots, m, \quad s(\mu) = \sqrt{\int_{r_1}^{r_2} |\hat{F}_\mu(r) - F_0(r)|^2}$$

and sort them in decreasing order  $s_1 \geq s_2 \geq \dots \geq s_m$ ;

- (iii) compute the summary statistics of the observations  $y$  under concern;

## Monte Carlo envelope test from an observation $y$

Settings:  $\alpha$  level of significance,  $m$  number of samples under  $\mathbf{H}_0$

Index  $k$ , chosen so that  $\alpha = k/(m+1)$

- (i) generate  $m$  independent samples of complex white Gaussian noise

$$\xi_1, \xi_2, \dots, \xi_m$$

compute their spectrograms and find their zeros;

- (ii) compute the summary statistics from the zeros

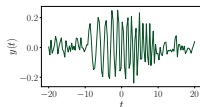
$$\forall \mu = 1, 2, \dots, m, \quad s(\mu) = \sqrt{\int_{r_1}^{r_2} |\hat{F}_\mu(r) - F_0(r)|^2}$$

and sort them in decreasing order  $s_1 \geq s_2 \geq \dots \geq s_m$ ;

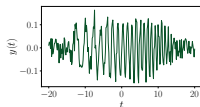
- (iii) compute the summary statistics of the observations  $y$  under concern;

- (iv) if  $s(y) \geq s_k$ , then reject the null hypothesis with confidence  $1 - \alpha$ .

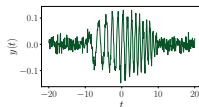
Detection of a noisy chirp of duration  $2\nu = 30$  s



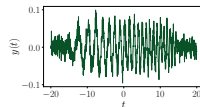
$N = 128$



$N = 256$

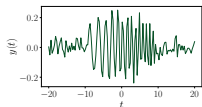


$N = 512$

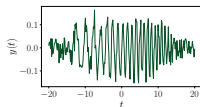


$N = 1024$

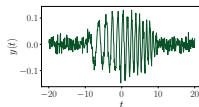
Detection of a noisy chirp of duration  $2\nu = 30$  s



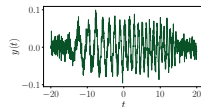
$N = 128$



$N = 256$

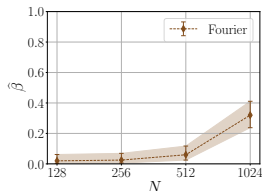


$N = 512$

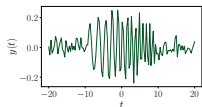


$N = 1024$

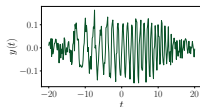
**Performance:** power of the test computed over 200 samples



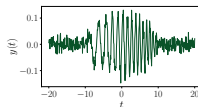
Detection of a noisy chirp of duration  $2\nu = 30$  s



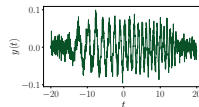
$N = 128$



$N = 256$

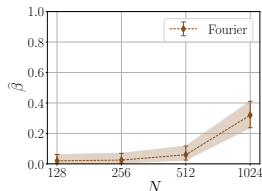


$N = 512$

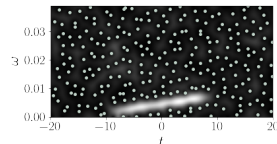


$N = 1024$

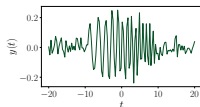
**Performance:** power of the test computed over 200 samples



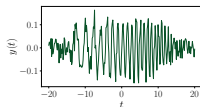
- ✓ Fast Fourier Transform
- ✗ low detection power
- ✗ requires large number of samples



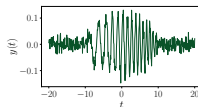
Detection of a noisy chirp of duration  $2\nu = 30$  s



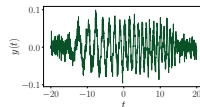
$N = 128$



$N = 256$

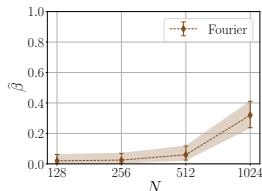


$N = 512$



$N = 1024$

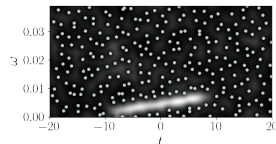
**Performance:** power of the test computed over 200 samples



- ✓ Fast Fourier Transform
- ✗ low detection power
- ✗ requires large number of samples

**Limitations:**

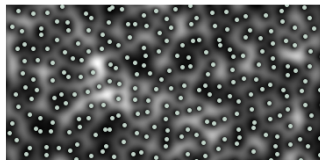
- necessary discretization of the STFT: arbitrary resolution
- observe only a bounded window: edge correction to compute  $\hat{F}(r)$



## Short-Time Fourier Transform

$$V_g \xi(t, \omega) \propto \text{GAF}_{\mathbb{C}}(z) = \sum_{n=0}^{\infty} \xi[n] \frac{z^n}{\sqrt{n!}}$$

Unbounded phase space  $\mathbb{C}$



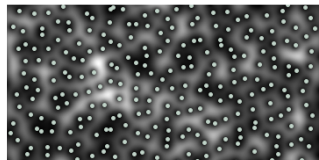
→ edge corrections

---

## Short-Time Fourier Transform

$$V_g \xi(t, \omega) \propto \text{GAF}_{\mathbb{C}}(z) = \sum_{n=0}^{\infty} \xi[n] \frac{z^n}{\sqrt{n!}}$$

Unbounded phase space  $\mathbb{C}$



→ edge corrections

---

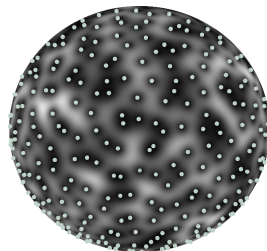
## New transform?

$$? \propto \text{GAF}_{\mathbb{S}}(z) = \sum_{n=0}^N \xi[n] \sqrt{\binom{N}{n}} z^n$$

stereographic projection  $z = \cot(\vartheta/2)e^{i\varphi}$

→ spherical coordinates  $(\vartheta, \varphi) \in S^2$

Compact phase space  $S^2$ ?



→ no border!

# Outline of the presentation

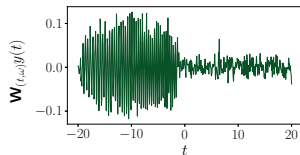
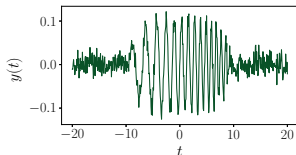
- Context and notations
  - Time-frequency analysis: the Short-Time Fourier Transform
- 

- Signal detection based on spectrogram zeros - I
  - Covariance principle and stationary point processes
- 

- The Kravchuk transform and its zeros
- Signal detection based on spectrogram zeros - II

## Time and frequency shifts

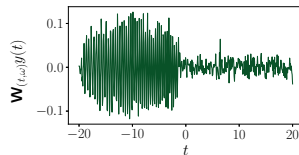
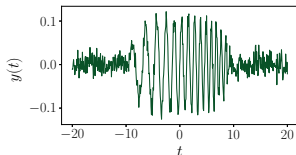
$$W_{(t,\omega)}y(u) = e^{-i\omega u}y(u - t)$$



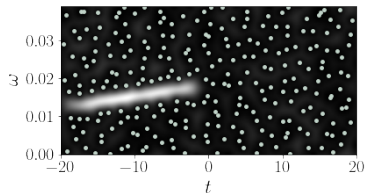
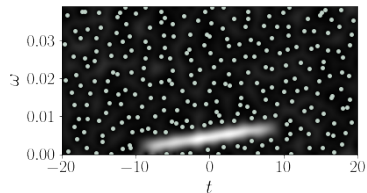
# Algebraic interpretation: covariance under a symmetry group

## Time and frequency shifts

$$\mathcal{W}_{(t,\omega)}y(u) = e^{-i\omega u}y(u - t)$$



$$V_h[\mathcal{W}_{(t,\omega)}y](t', \omega') \stackrel{(\text{covariance})}{=} e^{-i(\omega' - \omega)t} V_h y(t' - t, \omega' - \omega),$$



**Time and frequency shifts**

$$\mathbf{W}_{(t,\omega)}y(u) = e^{-i\omega u}y(u - t)$$

$$|V_h[\mathbf{W}_{(t,\omega)}y](t', \omega')|^2 \stackrel{(\text{covariance})}{=} |V_hy(t' - t, \omega' - \omega)|^2,$$

### Time and frequency shifts

$$\mathbf{W}_{(t,\omega)}y(u) = e^{-i\omega u}y(u - t)$$

$$|V_h[\mathbf{W}_{(t,\omega)}y](t', \omega')|^2 \stackrel{(\text{covariance})}{=} |V_hy(t' - t, \omega' - \omega)|^2,$$

### Complex white Gaussian noise

$$\tilde{\xi} = \mathbf{W}_{(t,\omega)}\xi$$

- $\mathbb{E}[\tilde{\xi}(u)] = e^{-i\omega u}\mathbb{E}[\xi(u - t)] = 0$

### Time and frequency shifts

$$\mathbf{W}_{(t,\omega)}y(u) = e^{-i\omega u}y(u - t)$$

$$|V_h[\mathbf{W}_{(t,\omega)}y](t', \omega')|^2 \stackrel{(\text{covariance})}{=} |V_h y(t' - t, \omega' - \omega)|^2,$$

### Complex white Gaussian noise

$$\tilde{\xi} = \mathbf{W}_{(t,\omega)}\xi$$

- $\mathbb{E}[\tilde{\xi}(u)] = e^{-i\omega u}\mathbb{E}[\xi(u - t)] = 0$
- $\mathbb{E}[\overline{\tilde{\xi}(u)}\tilde{\xi}(u')] = e^{i\omega(u-u')}\mathbb{E}[\overline{\xi(u)}\xi(u')] = \delta(u - u')$

## Time and frequency shifts

$$\mathbf{W}_{(t,\omega)}y(u) = e^{-i\omega u}y(u - t)$$

$$|V_h[\mathbf{W}_{(t,\omega)}y](t', \omega')|^2 \stackrel{(\text{covariance})}{=} |V_hy(t' - t, \omega' - \omega)|^2,$$

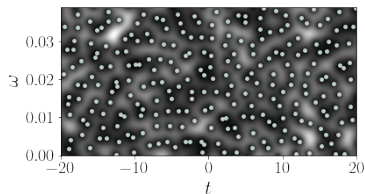
## Complex white Gaussian noise

$$\tilde{\xi} = \mathbf{W}_{(t,\omega)}\xi$$

- $\mathbb{E}[\tilde{\xi}(u)] = e^{-i\omega u}\mathbb{E}[\xi(u - t)] = 0$
- $\mathbb{E}[\overline{\tilde{\xi}(u)}\tilde{\xi}(u')] = e^{i\omega(u-u')}\mathbb{E}[\overline{\xi(u)}\xi(u')] = \delta(u - u')$

## Invariance under time-frequency shifts:

$$\tilde{\xi} = \mathbf{W}_{(t,\omega)}\overset{(\text{law})}{=} \xi$$



# Algebraic interpretation: covariance under a symmetry group

## Time and frequency shifts

$$\mathbf{W}_{(t,\omega)}y(u) = e^{-i\omega u}y(u - t)$$

$$|V_h[\mathbf{W}_{(t,\omega)}y](t', \omega')|^2 \stackrel{(\text{covariance})}{=} |V_h y(t' - t, \omega' - \omega)|^2,$$

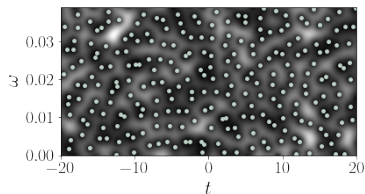
## Complex white Gaussian noise

$$\tilde{\xi} = \mathbf{W}_{(t,\omega)}\xi$$

- $\mathbb{E}[\tilde{\xi}(u)] = e^{-i\omega u}\mathbb{E}[\xi(u - t)] = 0$
- $\mathbb{E}[\overline{\tilde{\xi}(u)}\tilde{\xi}(u')] = e^{i\omega(u-u')}\mathbb{E}[\overline{\xi(u)}\xi(u')] = \delta(u - u')$

## Invariance under time-frequency shifts:

$$\tilde{\xi} = \mathbf{W}_{(t,\omega)}\xi \stackrel{(\text{law})}{=} \xi$$



**Covariance** is the key to get **stationarity**: how to get covariant transforms?

**Time and frequency shifts**

$$\mathbf{W}_{(t,\omega)}y(u) = e^{-i\omega u}y(u - t)$$

$$|V_h[\mathbf{W}_{(t,\omega)}y](t', \omega')|^2 \stackrel{(\text{covariance})}{=} |V_hy(t' - t, \omega' - \omega)|^2,$$

## Time and frequency shifts

$$\mathbf{W}_{(t,\omega)} y(u) = e^{-i\omega u} y(u - t)$$

$$|V_h[\mathbf{W}_{(t,\omega)} y](t', \omega')|^2 \stackrel{(\text{covariance})}{=} |V_h y(t' - t, \omega' - \omega)|^2,$$

**Weyl-Heisenberg group**  $\{e^{i\gamma} \mathbf{W}_{(t,\omega)}, (\gamma, t, \omega) \in [0, 2\pi] \times \mathbb{R}^2\}$

$$\mathbf{W}_{(t',\omega')} \mathbf{W}_{(t,\omega)} = e^{i\omega t'} \mathbf{W}_{(t+t',\omega+\omega')}.$$

# Algebraic interpretation: covariance under a symmetry group

## Time and frequency shifts

$$\mathbf{W}_{(t,\omega)}y(u) = e^{-i\omega u}y(u - t)$$

$$|V_h[\mathbf{W}_{(t,\omega)}y](t', \omega')|^2 \stackrel{(\text{covariance})}{=} |V_hy(t' - t, \omega' - \omega)|^2,$$

**Weyl-Heisenberg group**  $\{e^{i\gamma} \mathbf{W}_{(t,\omega)}, (\gamma, t, \omega) \in [0, 2\pi] \times \mathbb{R}^2\}$

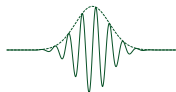
$$\mathbf{W}_{(t',\omega')} \mathbf{W}_{(t,\omega)} = e^{i\omega t'} \mathbf{W}_{(t+t', \omega+\omega')}.$$



$$g(t) = \pi^{-1/4} \exp(-t^2/2)$$



$$\mathbf{T}_u g(t) = g(t - u)$$



$$\mathbf{M}_\omega g(t) = g(t) \exp(-i\omega t)$$

# Algebraic interpretation: covariance under a symmetry group

## Time and frequency shifts

$$\mathbf{W}_{(t,\omega)}y(u) = e^{-i\omega u}y(u-t)$$

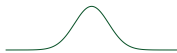
$$|V_h[\mathbf{W}_{(t,\omega)}y](t',\omega')|^2 \stackrel{(\text{covariance})}{=} |V_hy(t'-t,\omega'-\omega)|^2,$$

**Weyl-Heisenberg group**  $\{e^{i\gamma}\mathbf{W}_{(t,\omega)}, (\gamma, t, \omega) \in [0, 2\pi] \times \mathbb{R}^2\}$

$$\mathbf{W}_{(t',\omega')}\mathbf{W}_{(t,\omega)} = e^{i\omega t'}\mathbf{W}_{(t+t',\omega+\omega')}.$$

Coherent state interpretation  $\{\mathbf{W}_{(t,\omega)}h, t, \omega \in \mathbb{R}\}$  covariant family

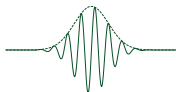
$$V_hy(t,\omega) = \int_{-\infty}^{\infty} \overline{y(u)}h(u-t)\exp(-i\omega u)\,du = \langle y, \mathbf{W}_{(t,\omega)}h \rangle$$



$$g(t) = \pi^{-1/4} \exp(-t^2/2)$$



$$\mathbf{T}_ug(t) = g(t-u)$$



$$\mathbf{M}_\omega g(t) = g(t)\exp(-i\omega t)$$

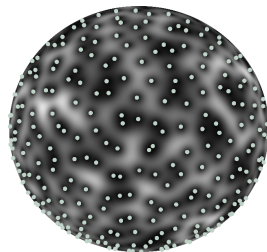
# Outline of the presentation

- Context and notations
  - Time-frequency analysis: the Short-Time Fourier Transform
- 

- Signal detection based on spectrogram zeros - I
  - Covariance principle and stationary point processes
- 

- **The Kravchuk transform and its zeros**
- Signal detection based on spectrogram zeros - II

## The Kravchuk transform: covariance under $SO(3)$

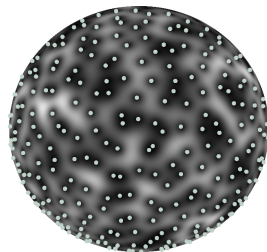


# The Kravchuk transform: covariance under $SO(3)$

Coherent state interpretation      $\mathbf{y} \in \mathbb{C}^{N+1}$

$$T\mathbf{y}(\vartheta, \varphi) = \langle \mathbf{y}, \Psi_{(\vartheta, \varphi)} \rangle$$

$$\vartheta \in [0, \pi], \varphi \in [0, 2\pi]$$

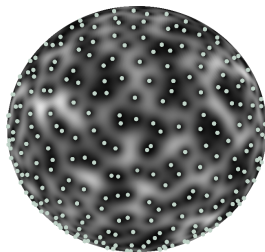


# The Kravchuk transform: covariance under $\text{SO}(3)$

Coherent state interpretation      $\mathbf{y} \in \mathbb{C}^{N+1}$

$$T\mathbf{y}(\vartheta, \varphi) = \langle \mathbf{y}, \Psi_{(\vartheta, \varphi)} \rangle$$

$$\vartheta \in [0, \pi], \varphi \in [0, 2\pi]$$



$\text{SO}(3)$  **coherent states** (Gazeau, 2009)

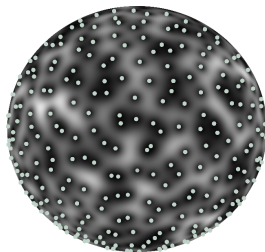
$$\Psi_{\vartheta, \varphi} = \sum_{n=0}^N \sqrt{\binom{N}{n}} \left( \cos \frac{\vartheta}{2} \right)^n \left( \sin \frac{\vartheta}{2} \right)^{N-n} e^{in\varphi} \mathbf{q}_n = \mathbf{R}_{\mathbf{u}(\vartheta, \varphi)} \Psi_{(0,0)},$$

# The Kravchuk transform: covariance under $SO(3)$

Coherent state interpretation      $\mathbf{y} \in \mathbb{C}^{N+1}$

$$T\mathbf{y}(\vartheta, \varphi) = \langle \mathbf{y}, \Psi_{(\vartheta, \varphi)} \rangle$$

$$\vartheta \in [0, \pi], \varphi \in [0, 2\pi]$$



$SO(3)$  **coherent states** (Gazeau, 2009)

$$\Psi_{\vartheta, \varphi} = \sum_{n=0}^N \sqrt{\binom{N}{n}} \left( \cos \frac{\vartheta}{2} \right)^n \left( \sin \frac{\vartheta}{2} \right)^{N-n} e^{in\varphi} \mathbf{q}_n = \mathbf{R}_{\mathbf{u}(\vartheta, \varphi)} \Psi_{(0,0)},$$

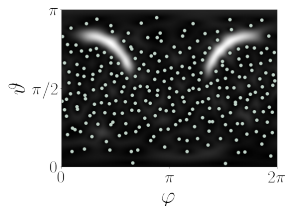
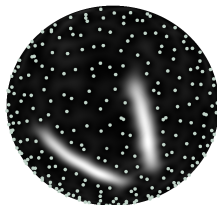
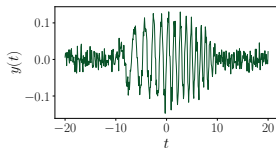
**Kravchuk transform**

$\{\mathbf{q}_n, n = 0, 1, \dots, N\}$  the *Kravchuk functions*

$$T\mathbf{y}(z) = \frac{1}{\sqrt{(1 + |z|^2)^N}} \sum_{n=0}^N \langle \mathbf{y}, \mathbf{q}_n \rangle \sqrt{\binom{N}{n}} z^n, \quad z = \cot(\vartheta/2) e^{i\varphi}$$

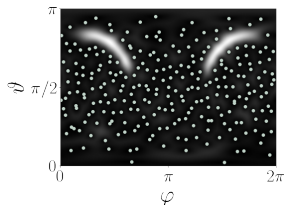
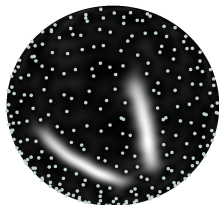
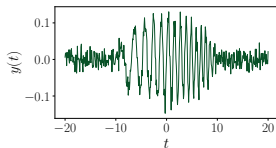
## Kravchuk transform

$$T\mathbf{y}(z) = \sqrt{(1+|z|^2)^{-N}} \sum_{n=0}^N \langle \mathbf{y}, \mathbf{q}_n \rangle \sqrt{\binom{N}{n}} z^n$$



## Kravchuk transform

$$T\mathbf{y}(z) = \sqrt{(1 + |z|^2)^{-N}} \sum_{n=0}^N \langle \mathbf{y}, \mathbf{q}_n \rangle \sqrt{\binom{N}{n}} z^n$$



### Theorem

$$T\xi(\vartheta, \varphi) = \sqrt{(1 + |z|^2)^{-N}} \text{GAF}_{\mathbb{S}}(z), \quad z = \cot(\vartheta/2)e^{i\varphi}$$

$$\text{GAF}_{\mathbb{S}}(z) = \sum_{n=0}^N \xi[n] \sqrt{\binom{N}{n}} z^n \text{ the spherical Gaussian Analytic Function}$$

(Pascal & Bardenet, 2022)

# Outline of the presentation

- Time-frequency analysis: the Short-Time Fourier Transform
- 

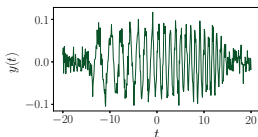
- Signal detection based on spectrogram zeros - I
  - Covariance principle and stationary point processes
- 

- The Kravchuk transform and its zeros
- Numerical implementation of the Kravchuk transform
- Signal detection based on spectrogram zeros - II

# Detection test: snr and relative duration of the signal

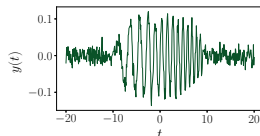
## Fixed observation window of 40 s

long time event



duration  $2\nu = 30$  s

short time event

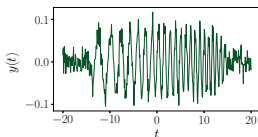


duration  $2\nu = 20$  s

# Detection test: snr and relative duration of the signal

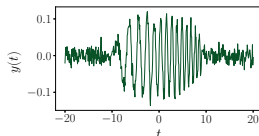
## Fixed observation window of 40 s

long time event



duration  $2\nu = 30$  s

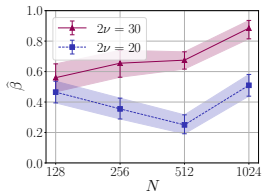
short time event



duration  $2\nu = 20$  s

## Robustness to small number of samples and short duration.

medium noise level

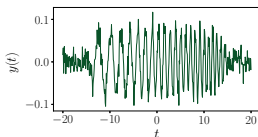


snr = 2

# Detection test: snr and relative duration of the signal

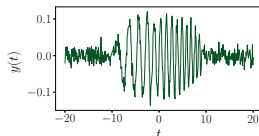
## Fixed observation window of 40 s

long time event



duration  $2\nu = 30$  s

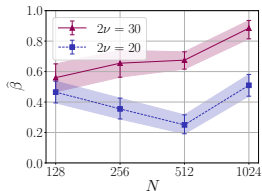
short time event



duration  $2\nu = 20$  s

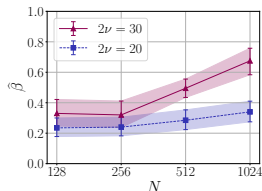
## Robustness to small number of samples and short duration.

medium noise level



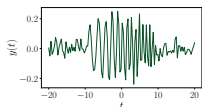
snr = 2

high noise level

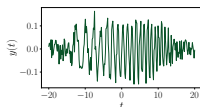


snr = 1.5

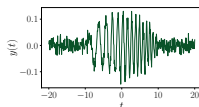
Detection of a noisy chirp of duration  $2\nu = 30$  s



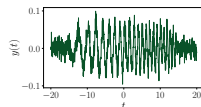
$N = 128$



$N = 256$

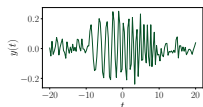


$N = 512$

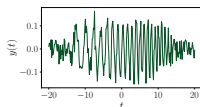


$N = 1024$

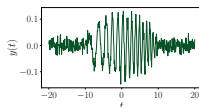
Detection of a noisy chirp of duration  $2\nu = 30$  s



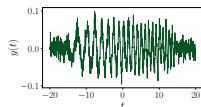
$N = 128$



$N = 256$

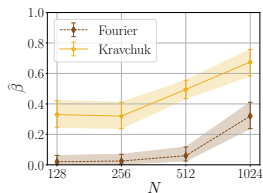


$N = 512$

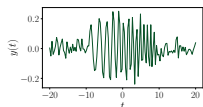


$N = 1024$

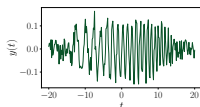
**Performance:** power of the test computed over 200 samples



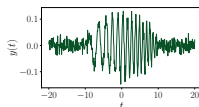
Detection of a noisy chirp of duration  $2\nu = 30$  s



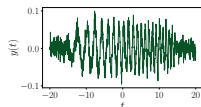
$N = 128$



$N = 256$

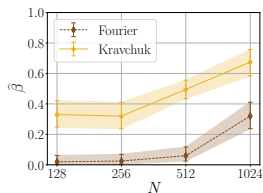


$N = 512$



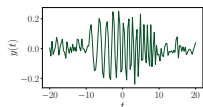
$N = 1024$

**Performance:** power of the test computed over 200 samples

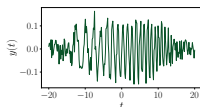


- ✓ higher detection power
- ✓ more robust to small  $N$
- ✗ no fast algorithm yet

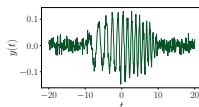
Detection of a noisy chirp of duration  $2\nu = 30$  s



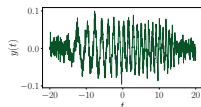
$N = 128$



$N = 256$

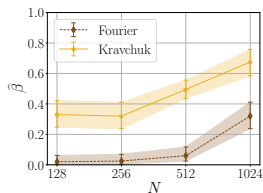


$N = 512$



$N = 1024$

**Performance:** power of the test computed over 200 samples



- ✓ higher detection power
- ✓ more robust to small  $N$
- ✗ no fast algorithm yet

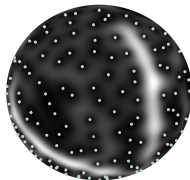
**Advantages of using Kravchuk vs. Fourier spectrogram**

- intrinsically encoded resolution: no need for prior knowledge
- compact phase space: no edge correction

- Novel covariant discrete Kravchuk transform

$$T\mathbf{y}(\vartheta, \varphi) = \frac{1}{\sqrt{(1 + |z|^2)^N}} \sum_{n=0}^N \langle \mathbf{y}, \mathbf{q}_n \rangle \sqrt{\binom{N}{n}} z^n, \quad z = \cot(\vartheta/2) e^{i\varphi}$$

- Interpreted as a coherent state decomposition  $\langle \mathbf{y}, \Psi_{(\vartheta, \varphi)} \rangle$
- Representation on a compact phase space  $S^2$
- Zeros of the Kravchuk spectrogram of white noise characterized *via*  $\text{GAF}_{\mathbb{S}}$



- Signal detection based on spectrogram zeros

- Robust to low snr and small  $N$
- Significant improvement using Kravchuk spectrogram

Pascal & Bardenet, 2022: [arxiv:2202.03835](https://arxiv.org/abs/2202.03835)

GitHub: [bpascal-fr/kravchuk-transform-and-its-zeros](https://github.com/bpascal-fr/kravchuk-transform-and-its-zeros)

- Interpretation of the action of  $\text{SO}(3)$  on  $\mathbb{C}^{N+1}$

$$\Psi_{\vartheta, \varphi} = \sum_{n=0}^N \sqrt{\binom{N}{n}} \left( \cos \frac{\vartheta}{2} \right)^n \left( \sin \frac{\vartheta}{2} \right)^{N-n} e^{in\varphi} \mathbf{q}_n = \mathbf{R}_{\mathbf{u}(\vartheta, \varphi)} \Psi_{(0,0)},$$

- Implementation of the inversion formula: denoising based on zeros

$$\mathbf{y} = (4\pi)^{-1} \int_{S^2} \overline{T\mathbf{y}(\vartheta, \varphi)} \Psi_{\vartheta, \varphi} d\mu(\vartheta, \varphi)$$

- Design of a Kravchuk FFT counterpart

$$T\mathbf{y}(z) = \frac{1}{\sqrt{(1+|z|^2)^N}} \sum_{\ell=0}^N \sqrt{\binom{N}{\ell}} \overline{\mathbf{y}[\ell]} \frac{(1-z)^\ell (1+z)^{N-\ell}}{\sqrt{2^N}}$$

- Convergence of Kravchuk toward the Fourier spectrogram as  $N \rightarrow \infty$

$$\mathbf{y}[\ell] = y(t_\ell), \quad t_\ell = T_0 + \frac{T_f - T_0}{N} \ell, \quad \ell = 0, 1, \dots, N$$

## Kravchuk transform

$\{\mathbf{q}_n, n = 0, 1, \dots, N\}$  the Kravchuk basis

$$T\mathbf{y}(z) = \frac{1}{\sqrt{(1 + |z|^2)^N}} \sum_{n=0}^N \langle \mathbf{y}, \mathbf{q}_n \rangle \sqrt{\binom{N}{n}} z^n, \quad z = \cot(\vartheta/2) e^{i\varphi}$$

→ first: basis change, i.e., computation of  $\langle \mathbf{y}, \mathbf{q}_n \rangle = \sum_{\ell=0}^N \overline{\mathbf{y}[\ell]} q_n(\ell; N)$

## Kravchuk transform

$\{\mathbf{q}_n, n = 0, 1, \dots, N\}$  the Kravchuk basis

$$T\mathbf{y}(z) = \frac{1}{\sqrt{(1+|z|^2)^N}} \sum_{n=0}^N \langle \mathbf{y}, \mathbf{q}_n \rangle \sqrt{\binom{N}{n}} z^n, \quad z = \cot(\vartheta/2) e^{i\varphi}$$

→ first: basis change, i.e., computation of  $\langle \mathbf{y}, \mathbf{q}_n \rangle = \sum_{\ell=0}^N \mathbf{y}[\ell] \overline{q_n(\ell; N)}$

**Evaluation of Kravchuk functions**  $q_n(\ell; N) = \frac{1}{\sqrt{2^N}} \sqrt{\binom{N}{n}} Q_n(\ell; N) \sqrt{\binom{N}{\ell}}$

$$(N-n)Q_{n+1}(t; N) = (N-2t)Q_n(t; N) - nQ_{n-1}(t; N),$$

$\{Q_n(t; N), n = 0, 1, \dots, N\}$  orthogonal family of Kravchuk polynomials

$$\sum_{\ell=0}^N \binom{N}{\ell} Q_n(\ell; N) Q_{n'}(\ell; N) = 2^N \binom{N}{n}^{-1} \delta_{n,n'}$$

## Evaluation of Kravchuk functions

(i) recursion to compute the Kravchuk polynomials

$$(N - n)Q_{n+1}(t; N) = (N - 2t)Q_n(t; N) - nQ_{n-1}(t; N),$$

(ii) multiplication by the binomial coefficients

$$q_n(\ell; N) = \frac{1}{\sqrt{2^N}} \sqrt{\binom{N}{n}} Q_n(\ell; N) \sqrt{\binom{N}{\ell}}$$

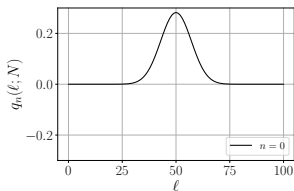
## Evaluation of Kravchuk functions

(i) recursion to compute the Kravchuk polynomials

$$(N - n)Q_{n+1}(t; N) = (N - 2t)Q_n(t; N) - nQ_{n-1}(t; N),$$

(ii) multiplication by the binomial coefficients

$$q_n(\ell; N) = \frac{1}{\sqrt{2^N}} \sqrt{\binom{N}{n}} Q_n(\ell; N) \sqrt{\binom{N}{\ell}}$$



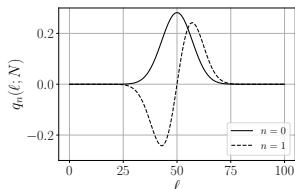
## Evaluation of Kravchuk functions

(i) recursion to compute the Kravchuk polynomials

$$(N - n)Q_{n+1}(t; N) = (N - 2t)Q_n(t; N) - nQ_{n-1}(t; N),$$

(ii) multiplication by the binomial coefficients

$$q_n(\ell; N) = \frac{1}{\sqrt{2^N}} \sqrt{\binom{N}{n}} Q_n(\ell; N) \sqrt{\binom{N}{\ell}}$$



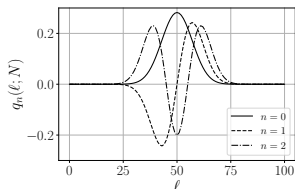
## Evaluation of Kravchuk functions

(i) recursion to compute the Kravchuk polynomials

$$(N - n)Q_{n+1}(t; N) = (N - 2t)Q_n(t; N) - nQ_{n-1}(t; N),$$

(ii) multiplication by the binomial coefficients

$$q_n(\ell; N) = \frac{1}{\sqrt{2^N}} \sqrt{\binom{N}{n}} Q_n(\ell; N) \sqrt{\binom{N}{\ell}}$$



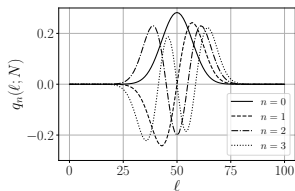
## Evaluation of Kravchuk functions

(i) recursion to compute the Kravchuk polynomials

$$(N - n)Q_{n+1}(t; N) = (N - 2t)Q_n(t; N) - nQ_{n-1}(t; N),$$

(ii) multiplication by the binomial coefficients

$$q_n(\ell; N) = \frac{1}{\sqrt{2^N}} \sqrt{\binom{N}{n}} Q_n(\ell; N) \sqrt{\binom{N}{\ell}}$$



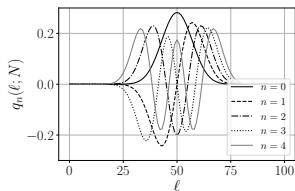
## Evaluation of Kravchuk functions

(i) recursion to compute the Kravchuk polynomials

$$(N - n)Q_{n+1}(t; N) = (N - 2t)Q_n(t; N) - nQ_{n-1}(t; N),$$

(ii) multiplication by the binomial coefficients

$$q_n(\ell; N) = \frac{1}{\sqrt{2^N}} \sqrt{\binom{N}{n}} Q_n(\ell; N) \sqrt{\binom{N}{\ell}}$$



# Instability of the computation of Kravchuk polynomials

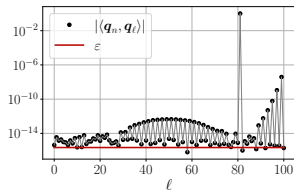
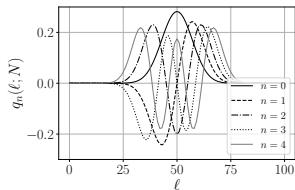
## Evaluation of Kravchuk functions

(i) recursion to compute the Kravchuk polynomials

$$(N - n)Q_{n+1}(t; N) = (N - 2t)Q_n(t; N) - nQ_{n-1}(t; N),$$

(ii) multiplication by the binomial coefficients

$$q_n(\ell; N) = \frac{1}{\sqrt{2^N}} \sqrt{\binom{N}{n}} Q_n(\ell; N) \sqrt{\binom{N}{\ell}}$$



# Instability of the computation of Kravchuk polynomials

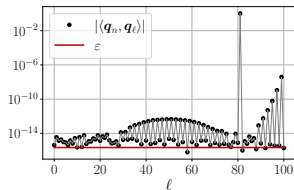
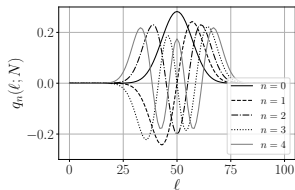
## Evaluation of Kravchuk functions

(i) recursion to compute the Kravchuk polynomials

$$(N - n)Q_{n+1}(t; N) = (N - 2t)Q_n(t; N) - nQ_{n-1}(t; N),$$

(ii) multiplication by the binomial coefficients

$$q_n(\ell; N) = \frac{1}{\sqrt{2^N}} \sqrt{\binom{N}{n}} Q_n(\ell; N) \sqrt{\binom{N}{\ell}}$$



→ estimated basis is **not orthogonal!** Not possible to compute  $\langle \mathbf{y}, \mathbf{q}_n \rangle$ .

# Rewriting of the Kravchuk transform

## Kravchuk transform

$\{q_n, n = 0, 1, \dots, N\}$  the Kravchuk basis

$$T\mathbf{y}(z) = \frac{1}{\sqrt{(1+|z|^2)^N}} \sum_{n=0}^N \left( \sum_{\ell=0}^N \overline{\mathbf{y}[\ell]} q_n(\ell; N) \right) \sqrt{\binom{N}{n}} z^n \rightarrow \text{intractable}$$

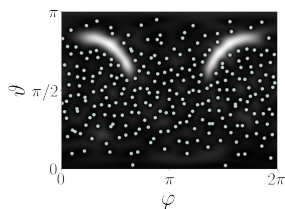
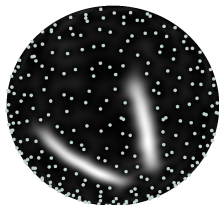
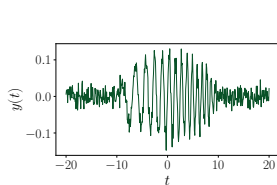
## A generative function for Kravchuk polynomials

$$\begin{aligned} \sum_{n=0}^N \binom{N}{n} Q_n(\ell; N) z^n &= (1-z)^\ell (1+z)^{N-\ell} \\ \Rightarrow \sum_{n=0}^N \sqrt{\binom{N}{n}} q_n(\ell; N) z^n &= \sqrt{\binom{N}{\ell}} \frac{(1-z)^\ell (1+z)^{N-\ell}}{\sqrt{2^N}} \end{aligned}$$

$$T\mathbf{y}(z) = \frac{1}{\sqrt{(1+|z|^2)^N}} \sum_{\ell=0}^N \sqrt{\binom{N}{\ell}} \overline{\mathbf{y}[\ell]} \frac{(1-z)^\ell (1+z)^{N-\ell}}{\sqrt{2^N}}$$

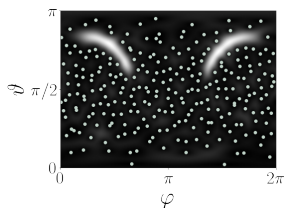
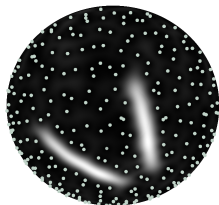
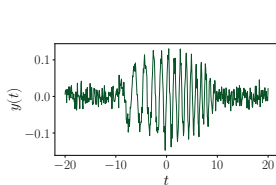
✗ no more Fast Fourier Transform algorithm using  $z^n = \cot(\vartheta/2)^n e^{in\varphi}$

# Detection of the zeros of the Kravchuk spectrogram $|T\mathbf{y}(z_i)|^2 = 0$

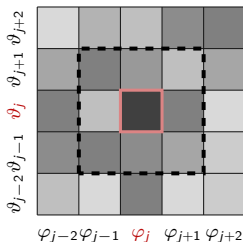


**Advantage compared to Fourier:** can tune the resolution of phase space.

# Detection of the zeros of the Kravchuk spectrogram $|Ty(z_i)|^2 = 0$

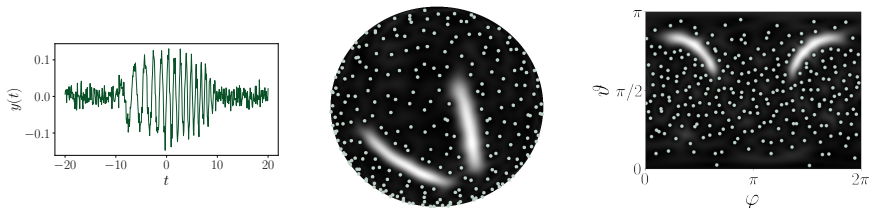


**Advantage compared to Fourier:** can tune the resolution of phase space.

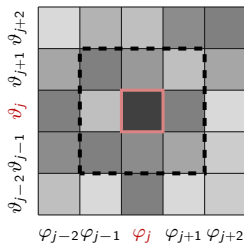


Minimal Grid Neighbors

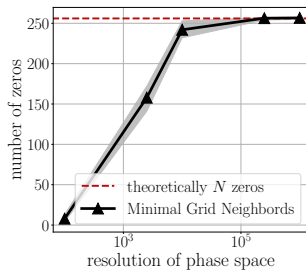
# Detection of the zeros of the Kravchuk spectrogram $|Ty(z_i)|^2 = 0$



**Advantage compared to Fourier:** can tune the resolution of phase space.

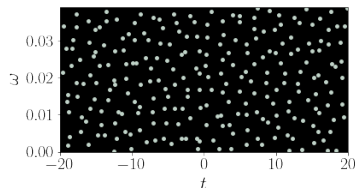


Minimal Grid Neighbors

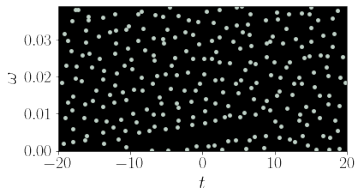


**In progress:** demonstrate that all local minima of  $|Ty(z)|^2$  are zeros.

# Unorthodox path: zeros of Gaussian Analytic Functions



$\text{snr} = 0$



$\text{snr} > 0$

The signal creates **holes** in the zeros pattern: **second order** statistics.

## Functional statistics:

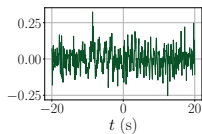
- the empty space function

$$F(r) = \mathbb{P} \left( \inf_{z_i \in Z} d(z_0, z_i) < r \right) : \text{probability to find a zero at less than } r$$

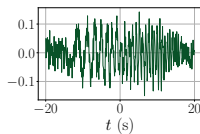
- Ripley's  $K$ -function

$$K(r) = 2\pi \int_0^r s g_0(s) ds : \text{expected \# of pairs at distance less than } r$$

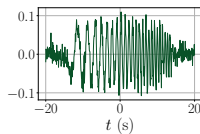
# Detection test: choice of the functional statistic



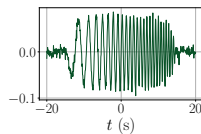
$\text{snr} = 0.5$



$\text{snr} = 1$

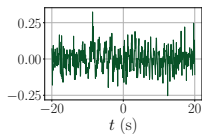


$\text{snr} = 2$

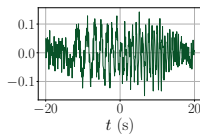


$\text{snr} = 5$

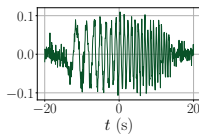
## Detection test: choice of the functional statistic



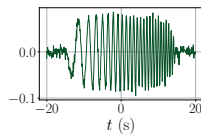
$\text{snr} = 0.5$



$\text{snr} = 1$

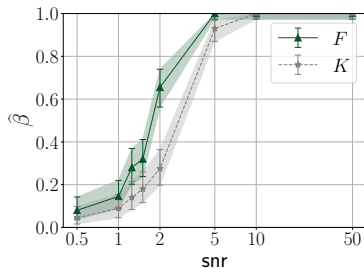


$\text{snr} = 2$

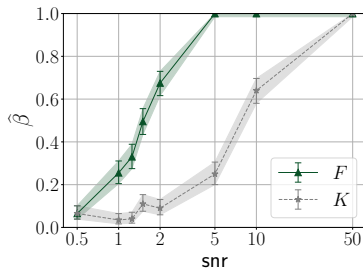


$\text{snr} = 5$

## Ripley's $K$ functional vs. empty space functional $F$

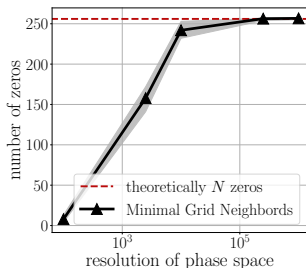


$N + 1 = 257$  points



$N + 1 = 513$  points

# Opening: can the Kravchuk spectrogram have multiple zeros?



## Spherical Gaussian Analytic Function

$$\text{GAF}_{\mathbb{S}}(z) = \sum_{n=0}^N \xi[n] \sqrt{\binom{N}{n}} z^n$$

with  $\xi[n] \sim \mathcal{N}_{\mathbb{C}}(0, 1)$  i.i.d.

→ only **simple** zeros

**General case**  $T\mathbf{y}(z) = \sqrt{(1 + |z|^2)}^{-N} \sum_{n=0}^N \sqrt{\binom{N}{n}} (\mathbf{Q}\mathbf{y})[n] z^n$

If  $\mathbf{y}$  deterministic, such that  $(\mathbf{Q}\mathbf{y})[n] = \sqrt{\binom{N}{n}} a^{N-n} b^n$ ,  $a \in \mathbb{C}$ ,  $b \in \mathbb{C}^*$ ,

$$\sqrt{(1 + |z|^2)}^{-N} \sum_{n=0}^N \sqrt{\binom{N}{n}} (\mathbf{Q}\mathbf{y})[n] z^n = (a + bz)^N$$

→  $-a/b$  multiple root of order of degeneracy  $N$