

TIME-FREQUENCY ANALYSIS

M2 AI — SIGNAL PROCESSING

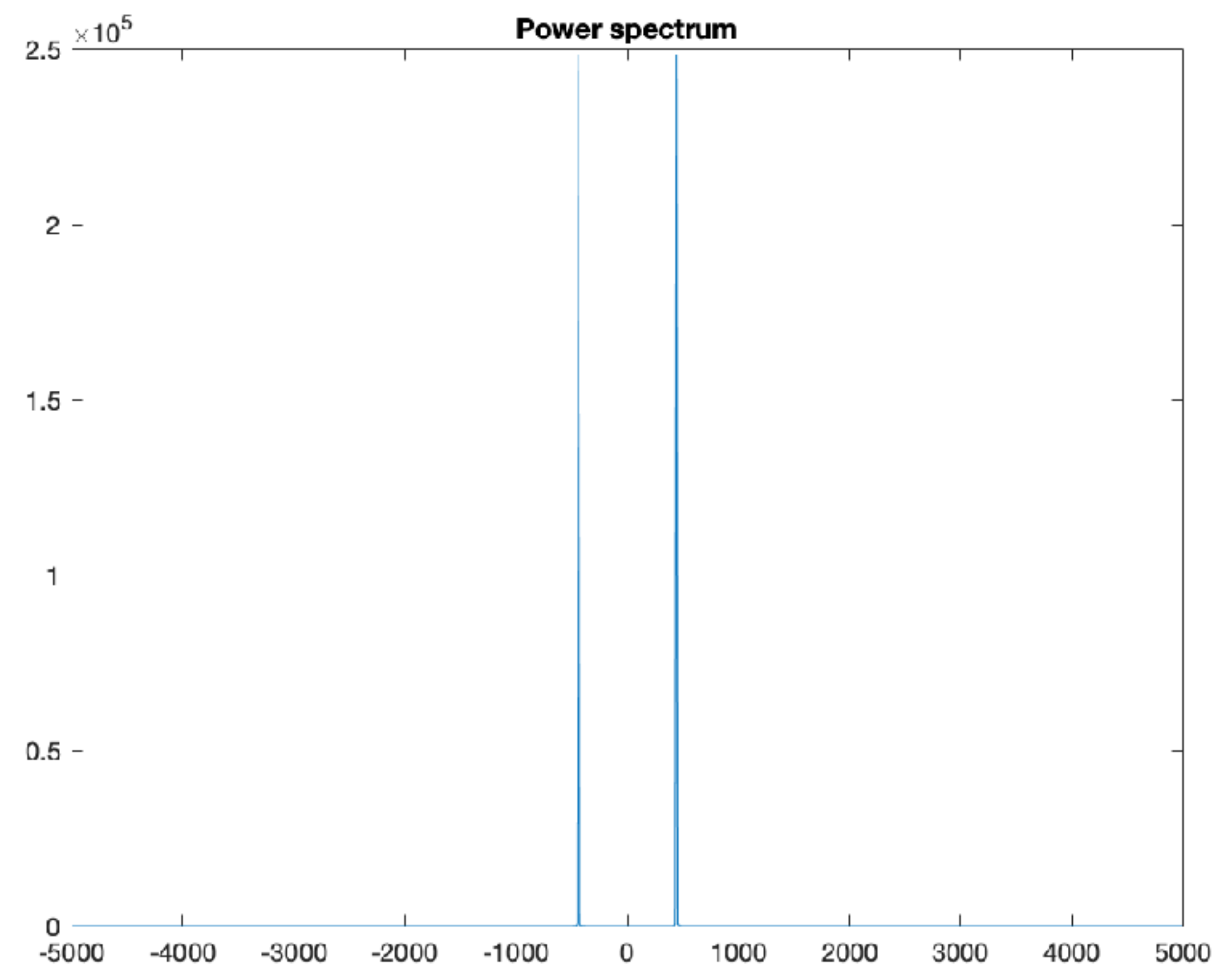
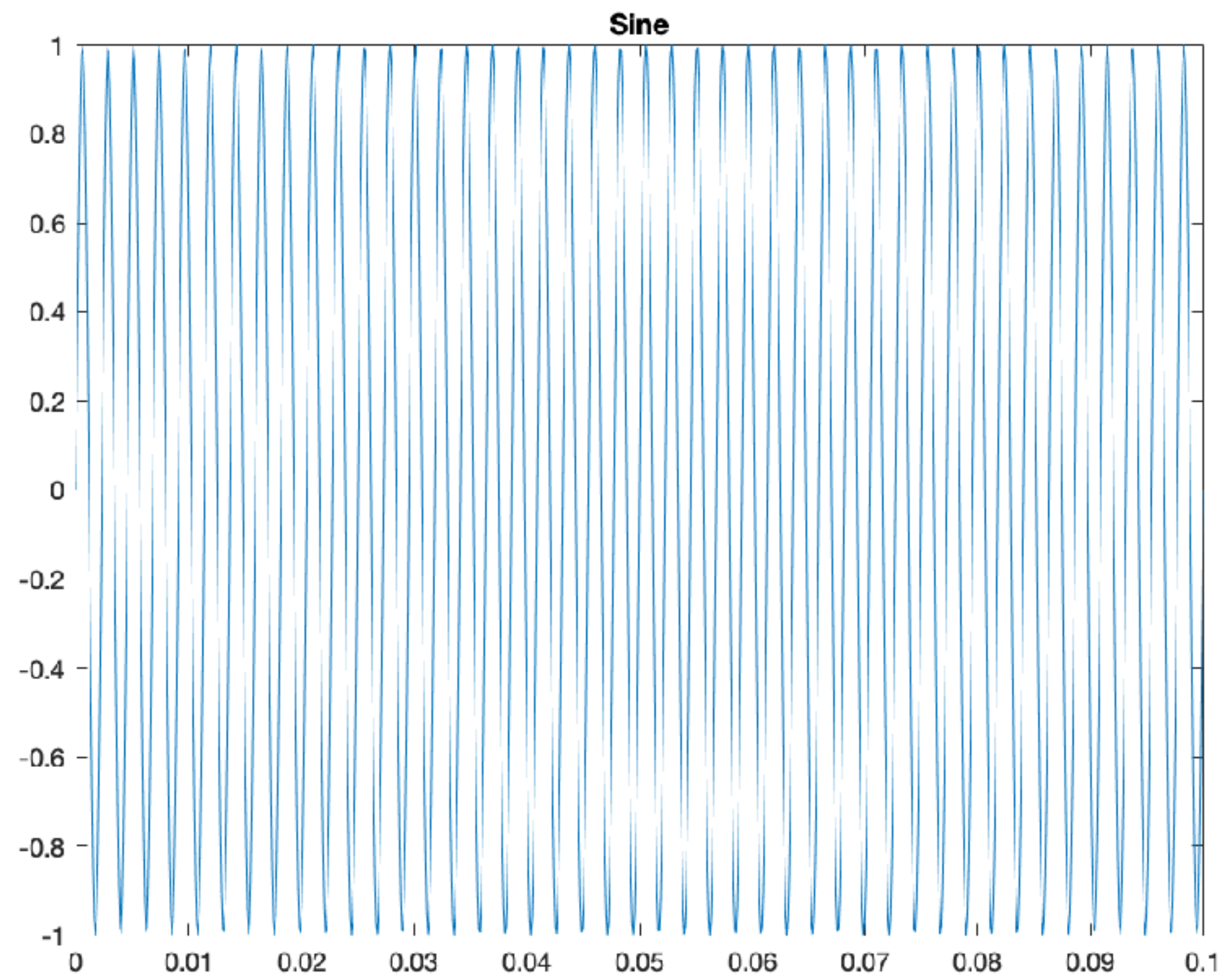
FOURIER REMINDER

- ▶ Spectral analysis: frequency content of a function (Think about musical notes!)
- ▶ Measure the similarity (correlation, angle) between pure (complex) sine and a signal
- ▶ Sines are eigen signals of time-invariant linear systems (filters)
- ▶ Fourier analysis computes the correlation between the signal $s(t)$ a pure sine at various frequencies ν

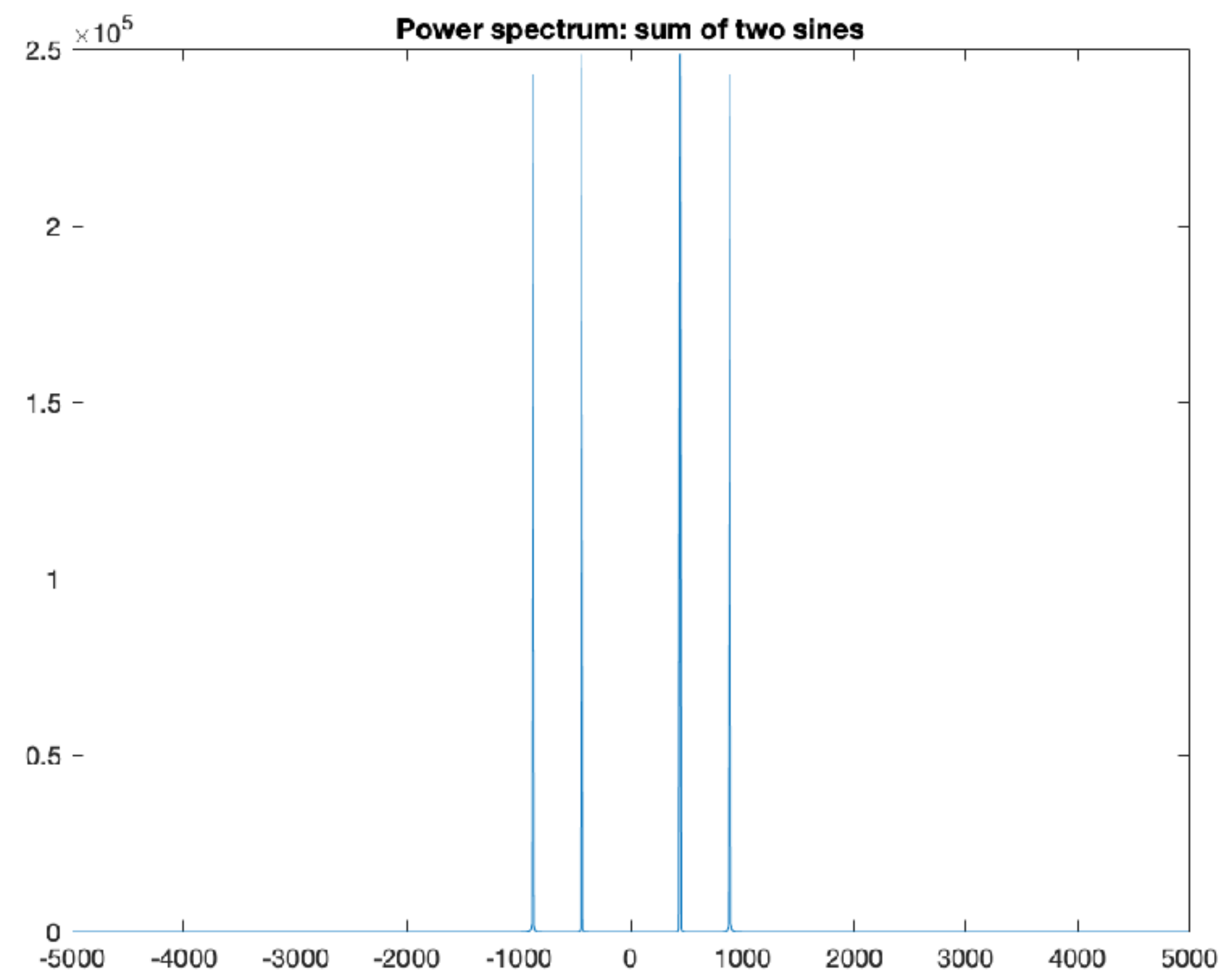
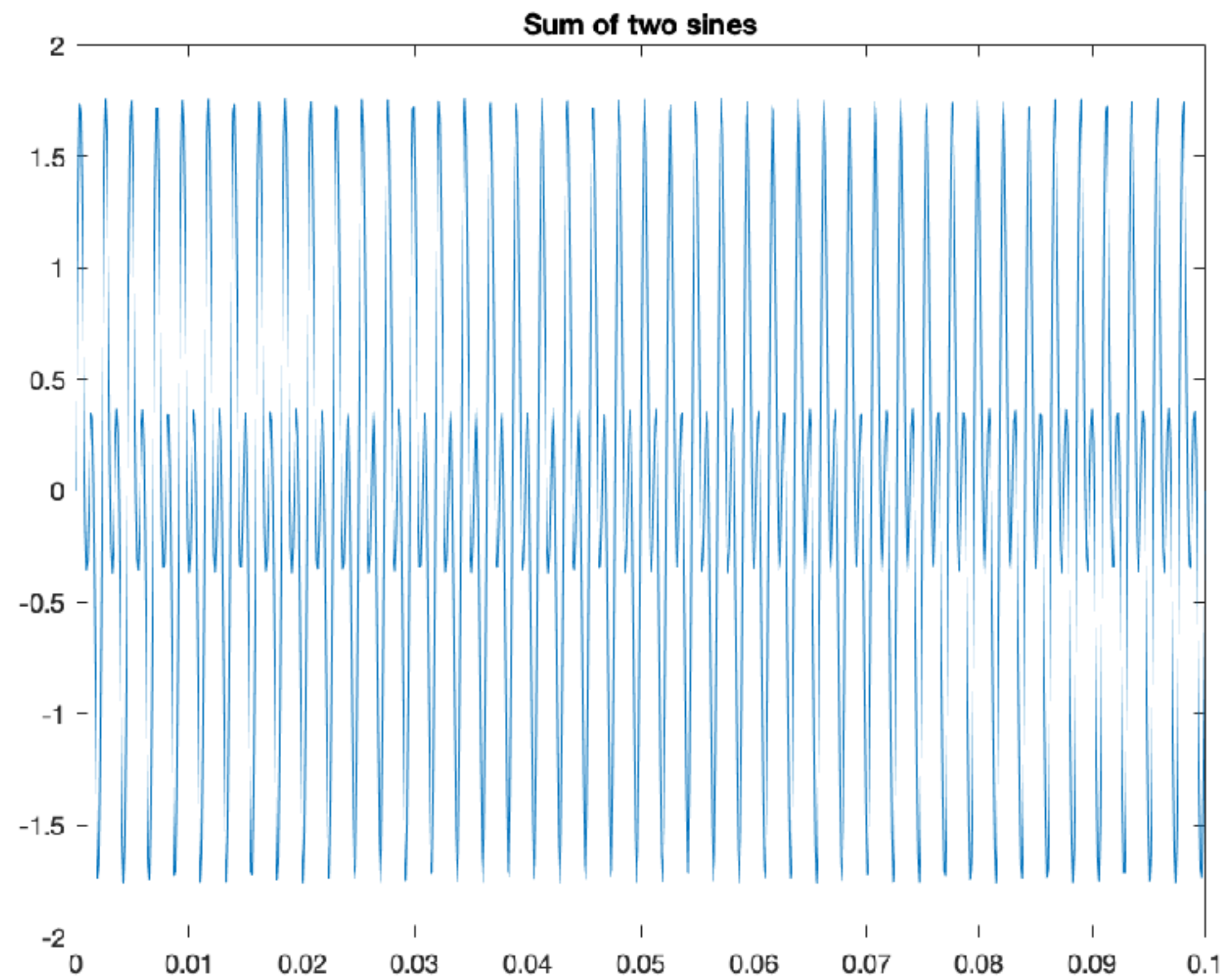
$$\hat{s}(\nu) = \langle s, e_\nu \rangle$$

- ▶ Limitation of Fourier analysis:
 - ▶ We obtain a pure frequency content from a pure temporal content
 - ▶ What is the difference between a sum of sine, and a succession of sines?

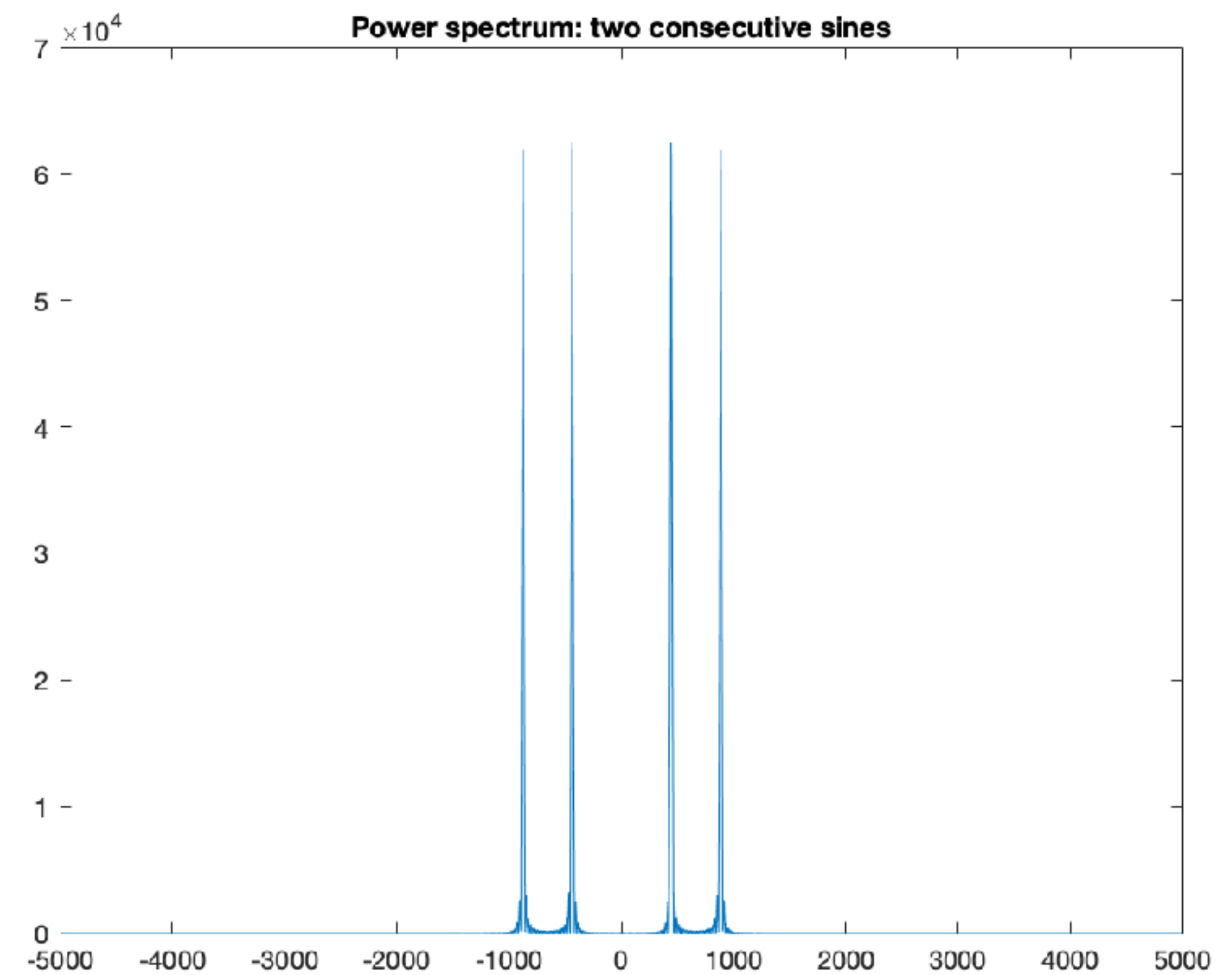
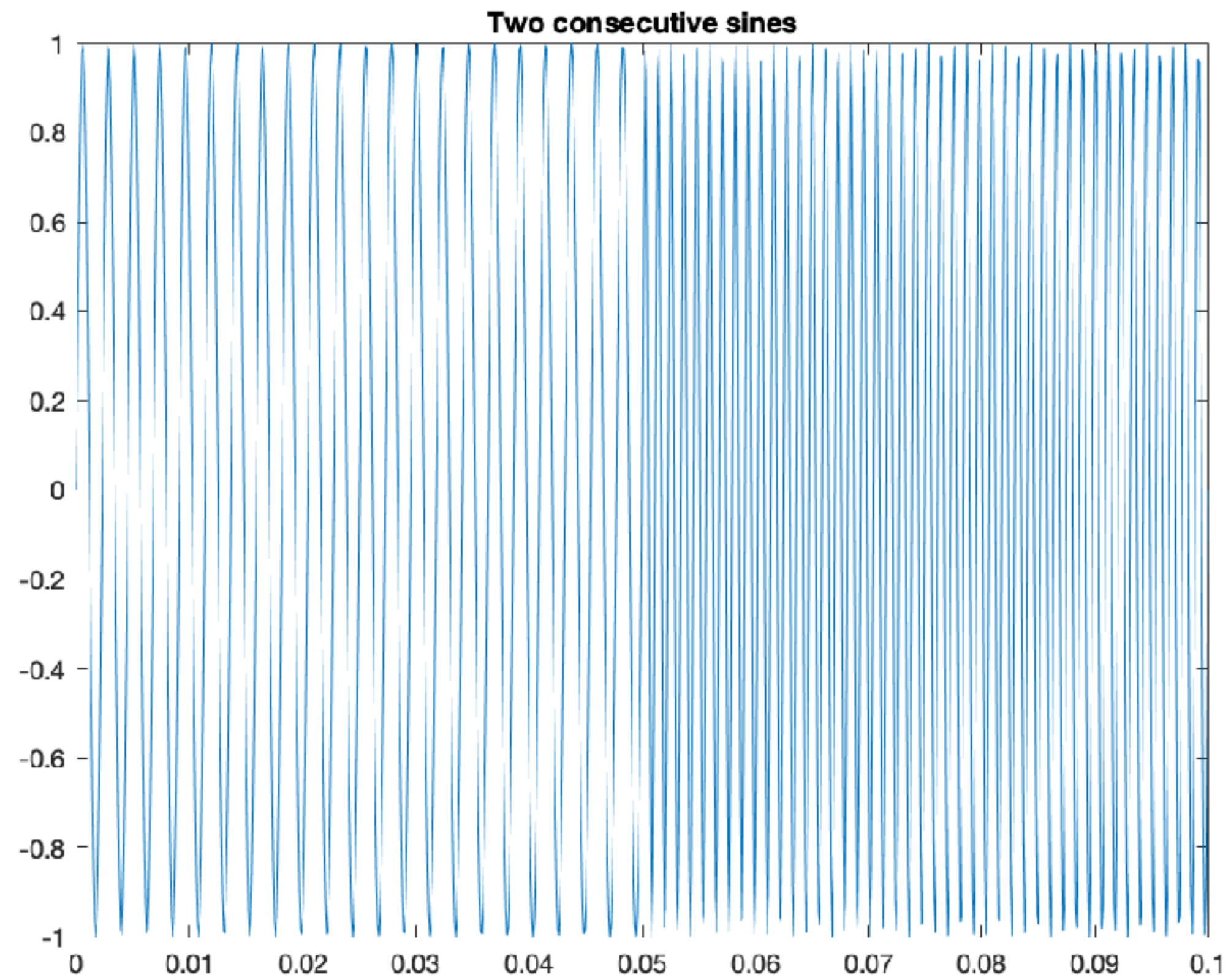
FOURIER EXAMPLE: 1 SINE



FOURIER EXAMPLE: SUM OF 2 SINES



FOURIER EXAMPLE: SUCCESSION OF 2 SINES



SHORT-TIME FOURIER TRANSFORM (STFT)

- ▶ Idea: perform a local spectral analysis of the signal thanks to a sliding window
- ▶ Let $w(t)$ be a smooth window localized around $t = 0$. Let the time-frequency atom

$$\varphi_{\tau,\nu}(t) = w(t - \tau)e^{i2\pi\nu t}$$

- ▶ The time-frequency transform of a signal x computes its correlation with the time-frequency atom $\varphi_{\tau,\nu}(t)$:

$$X(\tau, \nu) = \langle x, \varphi_{\tau,\nu} \rangle = \int_{-\infty}^{+\infty} x(t)w(t - \tau)e^{i2\pi\nu t} dt$$

- ▶ It corresponds to the Fourier transform of the windowed signal $x(t)w(t - \tau)$
- ▶ Parameters of the STFT:
 - ▶ The length (and shape) of the window
 - ▶ The redundancy in time (hop size between two windows)
 - ▶ The redundancy in frequency (length of the frequency transform inside one window)

DISCRETE STFT (GABOR TRANSFORM)

- ▶ Let $x \in \mathbb{R}^T$ be a digital signal and let $w \in \mathbb{R}^L$ be a window. The discrete STFT is given by

$$X[\tau, \nu] = \sum_{t=0}^{N-1} x[t]w[t - a\tau]e^{i\frac{2\pi\nu}{M}t}$$

- ▶ $a \geq 1$ control the redundancy in time (the hop size, in samples, between two windows)
- ▶ $M \geq N$ control the redundancy in frequency (usually $M = L$ or $M = 2L$)
- ▶ Using the matrix notation, all the time-frequency coefficients $X[\tau, \nu]$ can be computed by the analysis operator Φ : $X = \Phi^*x$
- ▶ Each column of Φ is one time-frequency atom.
- ▶ The number $K > T$ of columns depends on the time-frequency redundancy,

DISCRETE INVERSE STFT

- ▶ We do not have in general:

$$x[t] = \sum_{\tau, \nu} X[\tau, \nu] w[t - a\tau] e^{i\frac{2\pi\nu}{M}t}$$

- ▶ With matrix notation:

$$x \neq \Phi\Phi^*x$$

- ▶ The invert of a Gabor dictionary Φ is obtained by the canonical dual $\tilde{\Phi}$, which is also a Gabor transform constructed using a dual window \tilde{w}

$$x[t] = \sum_{\tau, \nu} X[\tau, \nu] \tilde{w}[t - a\tau] e^{i\frac{2\pi\nu}{M}t}$$

- ▶ With matrix notation:

$$x = \tilde{\Phi}\Phi^*x = \Phi\tilde{\Phi}^*x$$

- ▶ If the Gabor dictionary is a Parseval Frame (or a normalized tight frame), then $\tilde{\Phi} = \Phi$ and $\|x\|^2 = \|X\|^2$

SYNTHESIS OPERATION

- ▶ We have

$$x[t] = \sum_{\tau, \nu} \tilde{X}[\tau, \nu] w[t - a\tau] e^{i\frac{2\pi\nu}{M}t}$$

- ▶ With $\tilde{X} = \tilde{\Phi}^* x$, that is

$$x = \Phi \tilde{X}$$

- ▶ However, it exists an infinity of synthesis coefficients α such that

$$x = \Phi \alpha$$

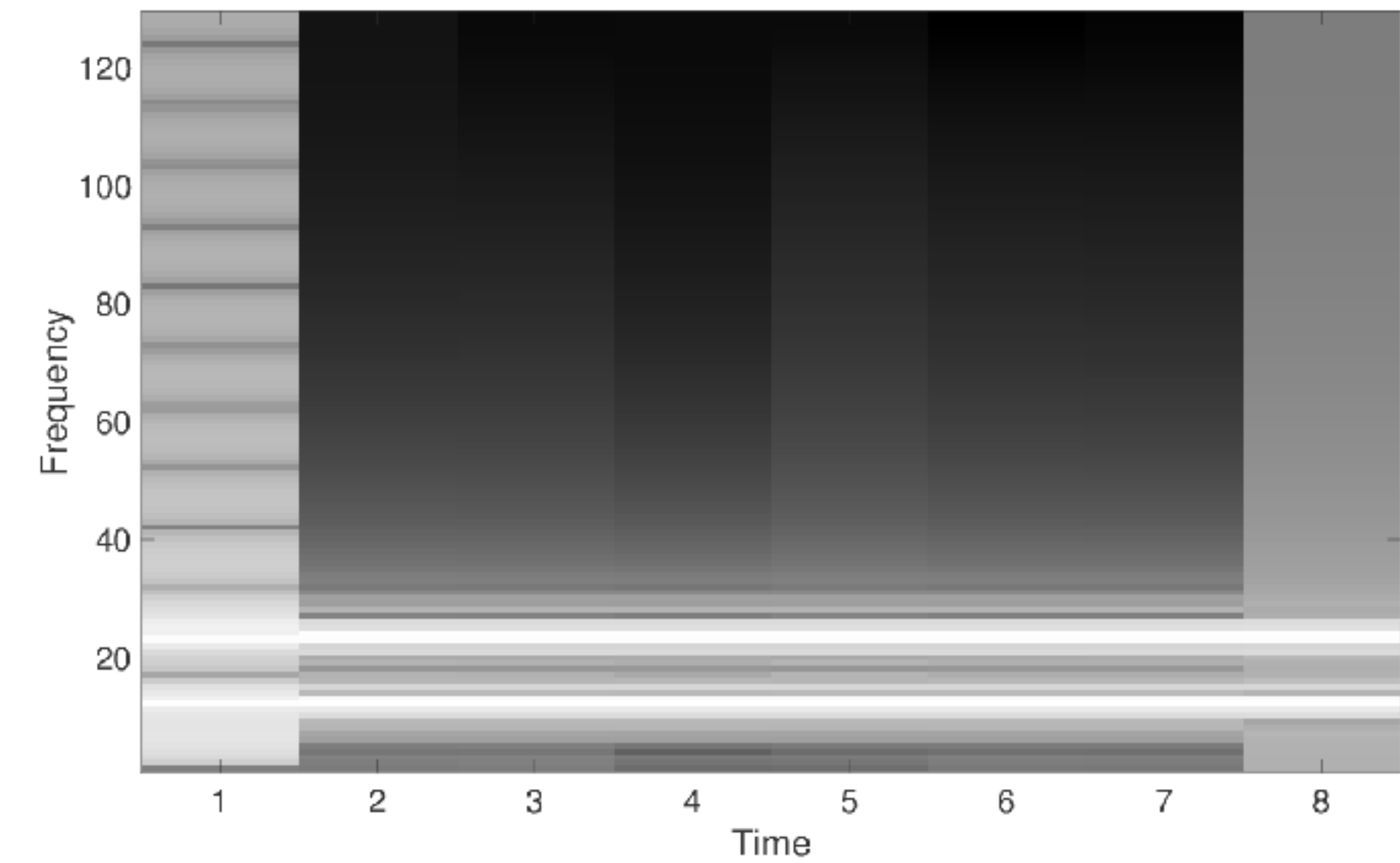
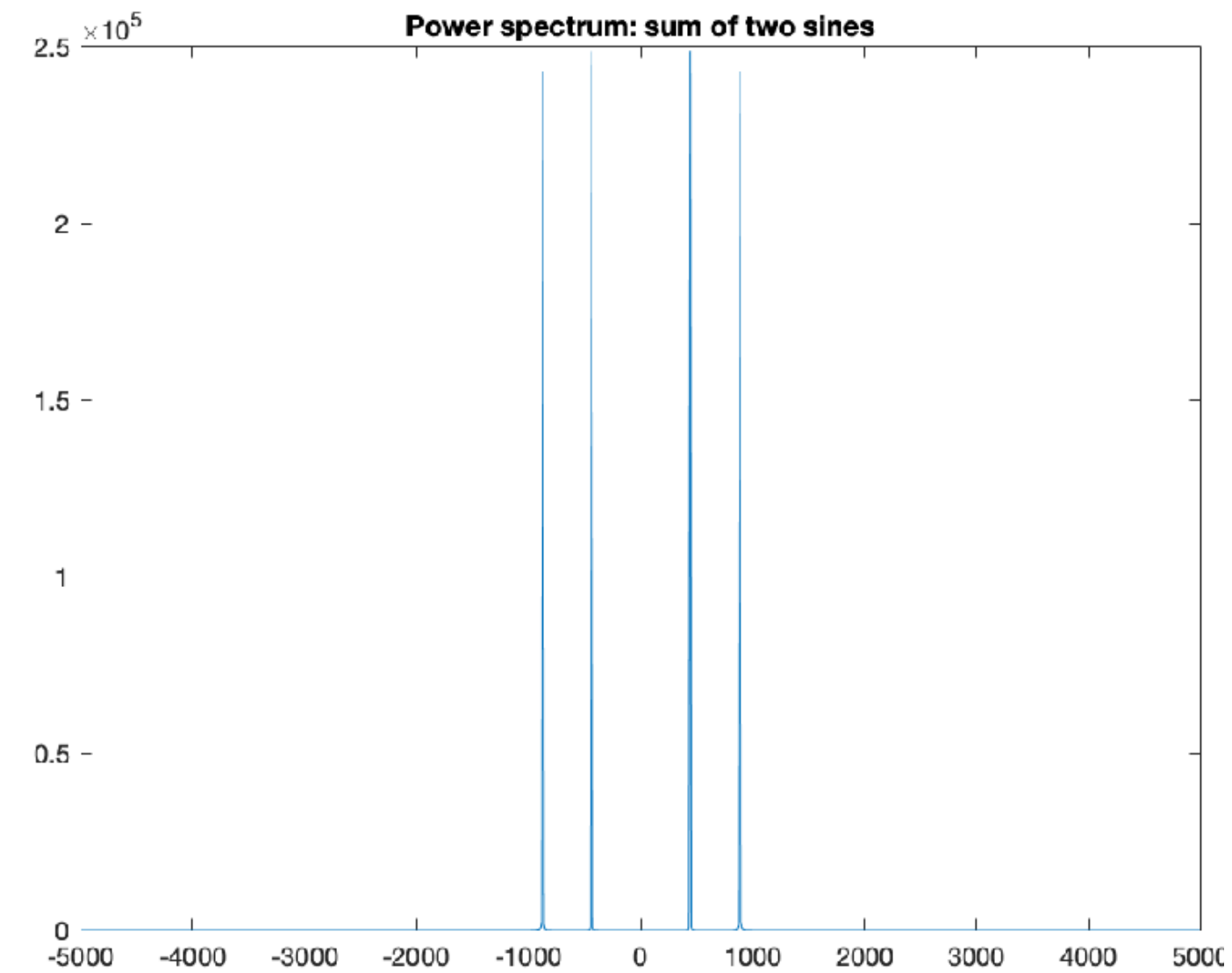
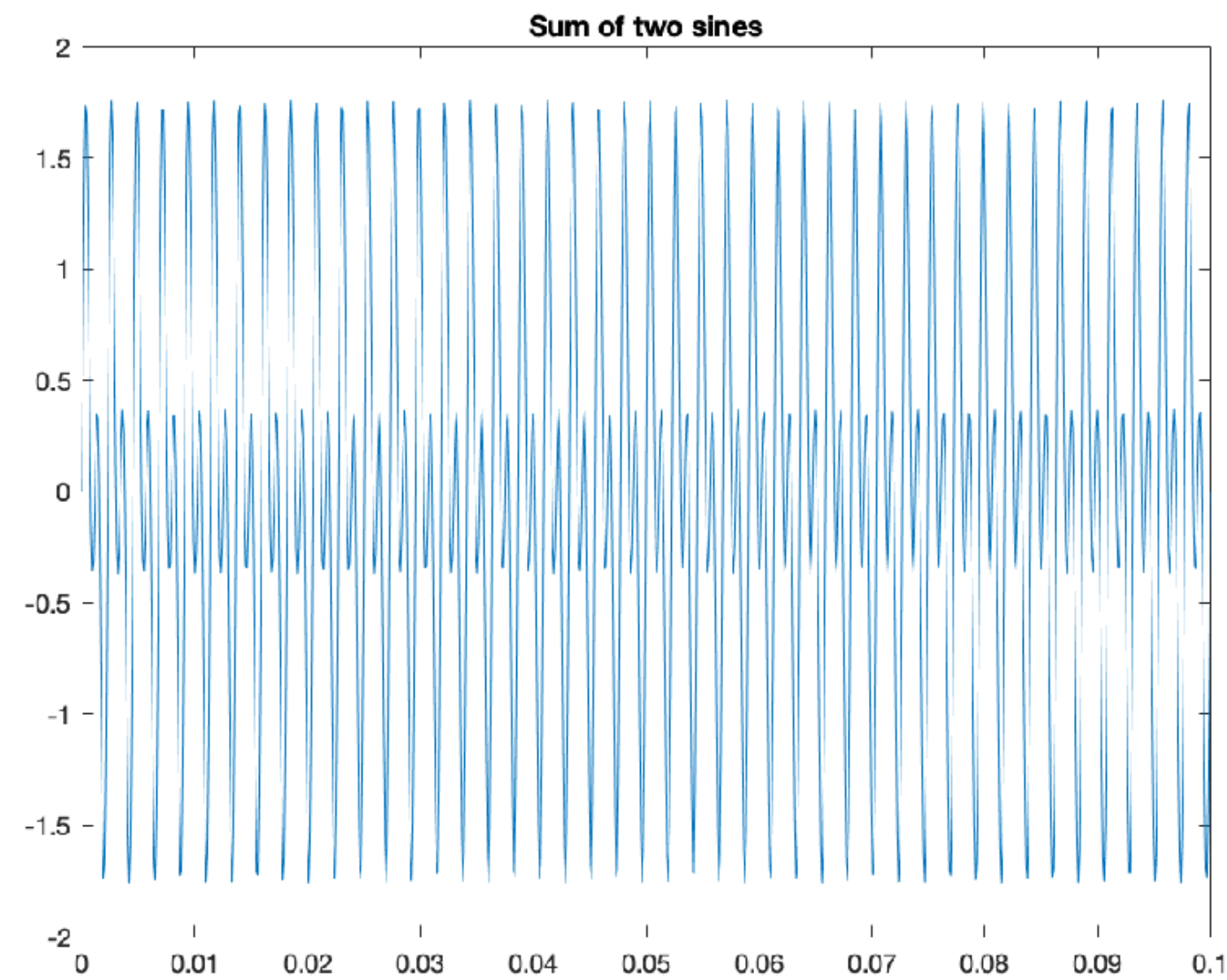
- ▶ Beware:

- ▶ In some implementations, the "invert" operator is the "synthesis" operation and must be performed with the appropriate dual window
- ▶ It is more useful to have access to the "synthesis" operator rather than the actual invert operator

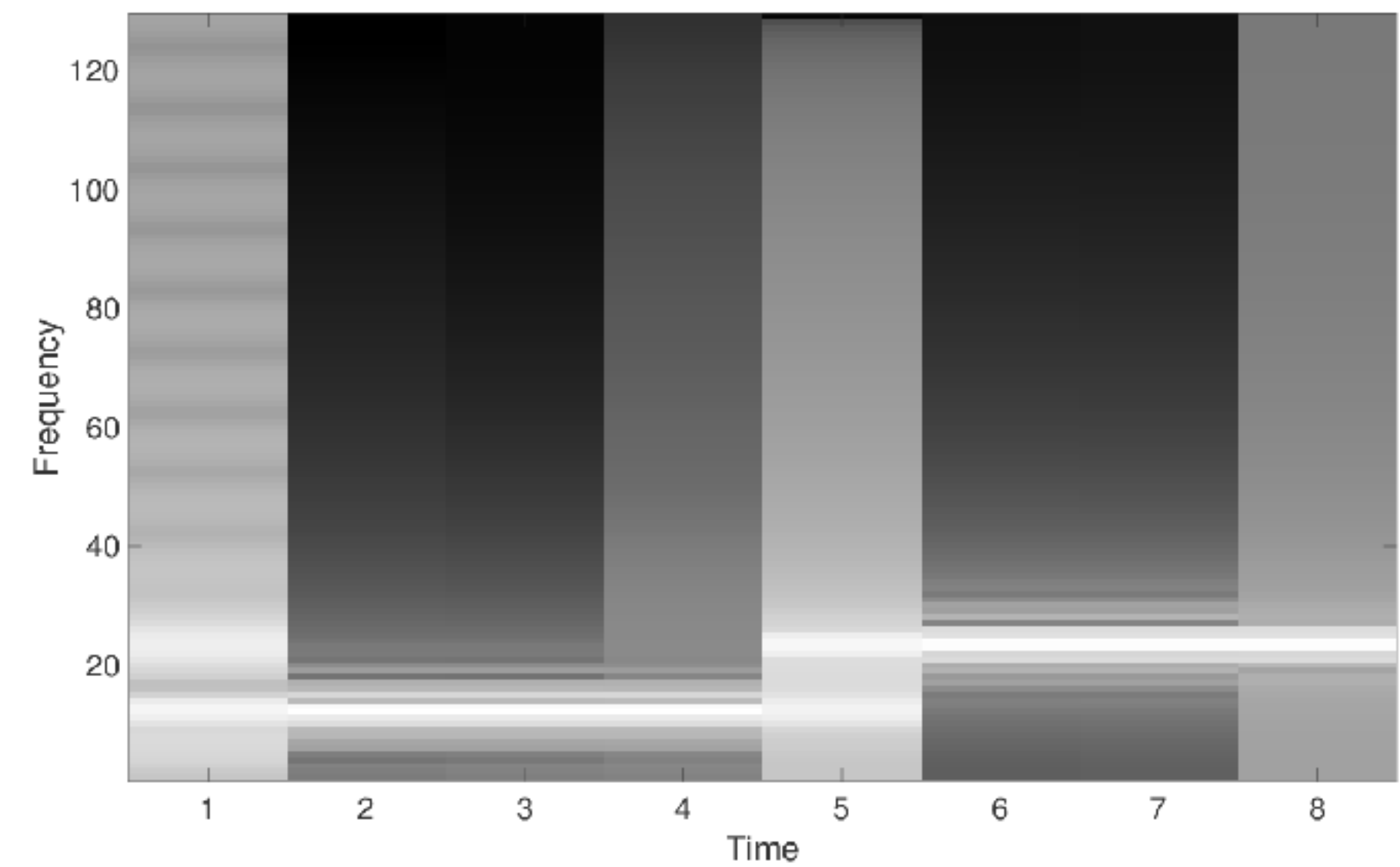
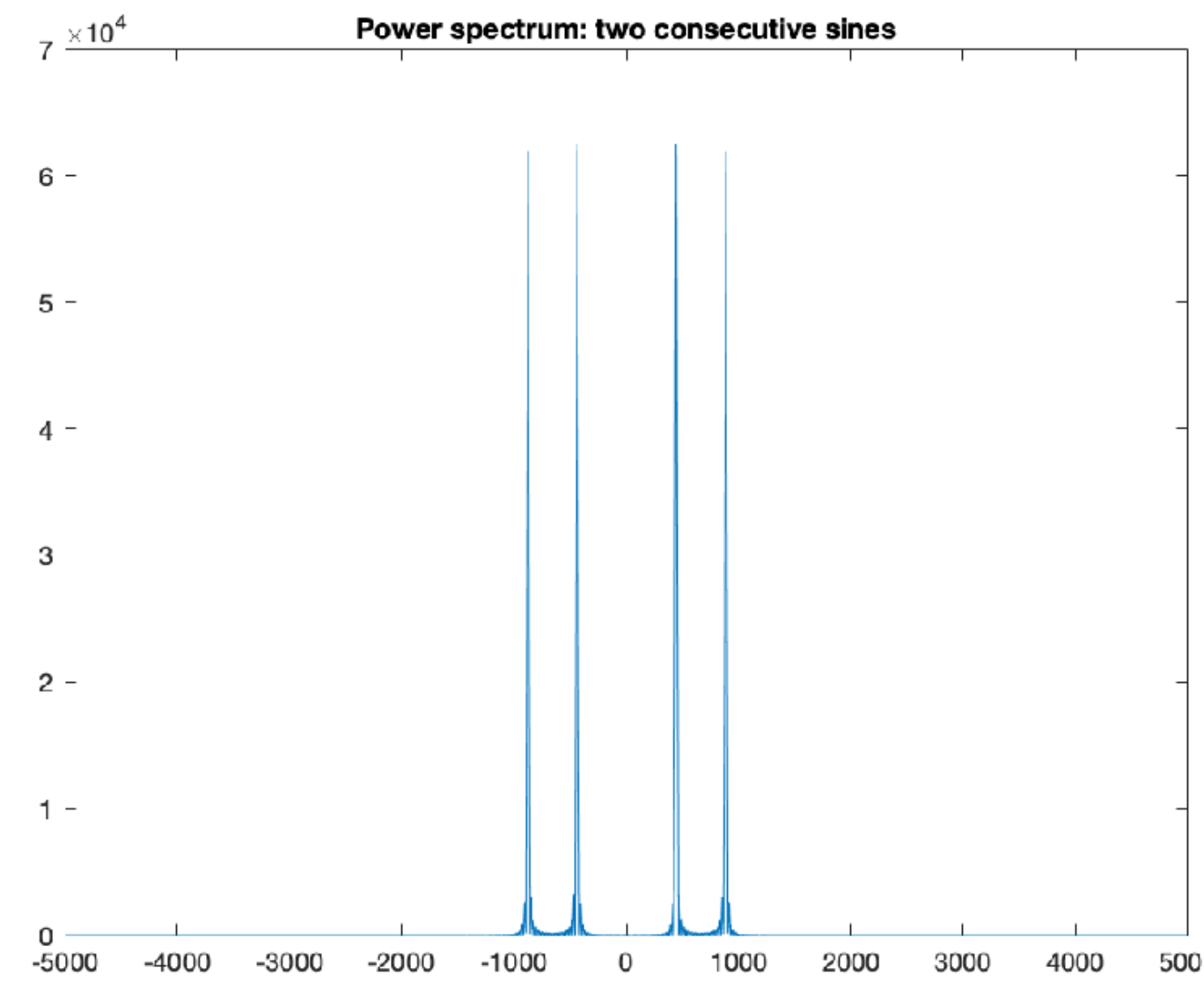
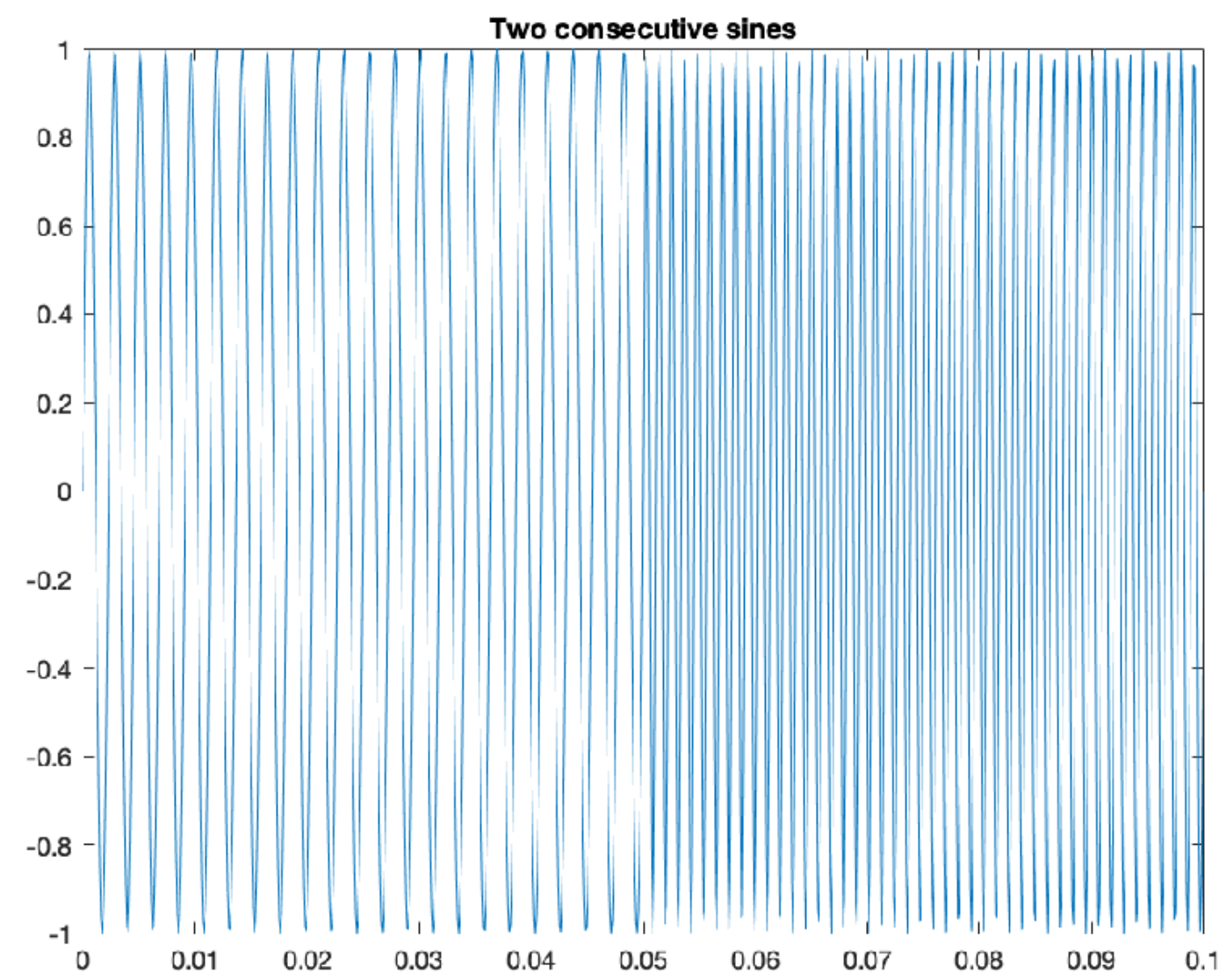
HOW TO CHOOSE THE PARAMETERS

- ▶ Heisenberg's uncertainty principle
 - ▶ A signal cannot be both well localized in time and in frequency.
 - ▶ Consequence: short windows are more adapted to "transient", and long windows to "tonal", "stationary", parts of the signal
- ▶ Common choices for a high-fidelity audio signal with a sampling frequency of 44.1 kHz with a window of size L
 - ▶ Shape of the window: Hann, Hamming, Gaussian
 - ▶ Length of the window: between 256 samples to 4096 samples. Common choice: 1024 samples
 - ▶ Redundancy in time: overlap of 50% or 75% between two consecutive window
 - ▶ Redundancy in frequency: FFT of size L or $2L$

STFT EXAMPLE: SUM OF 2 SINES

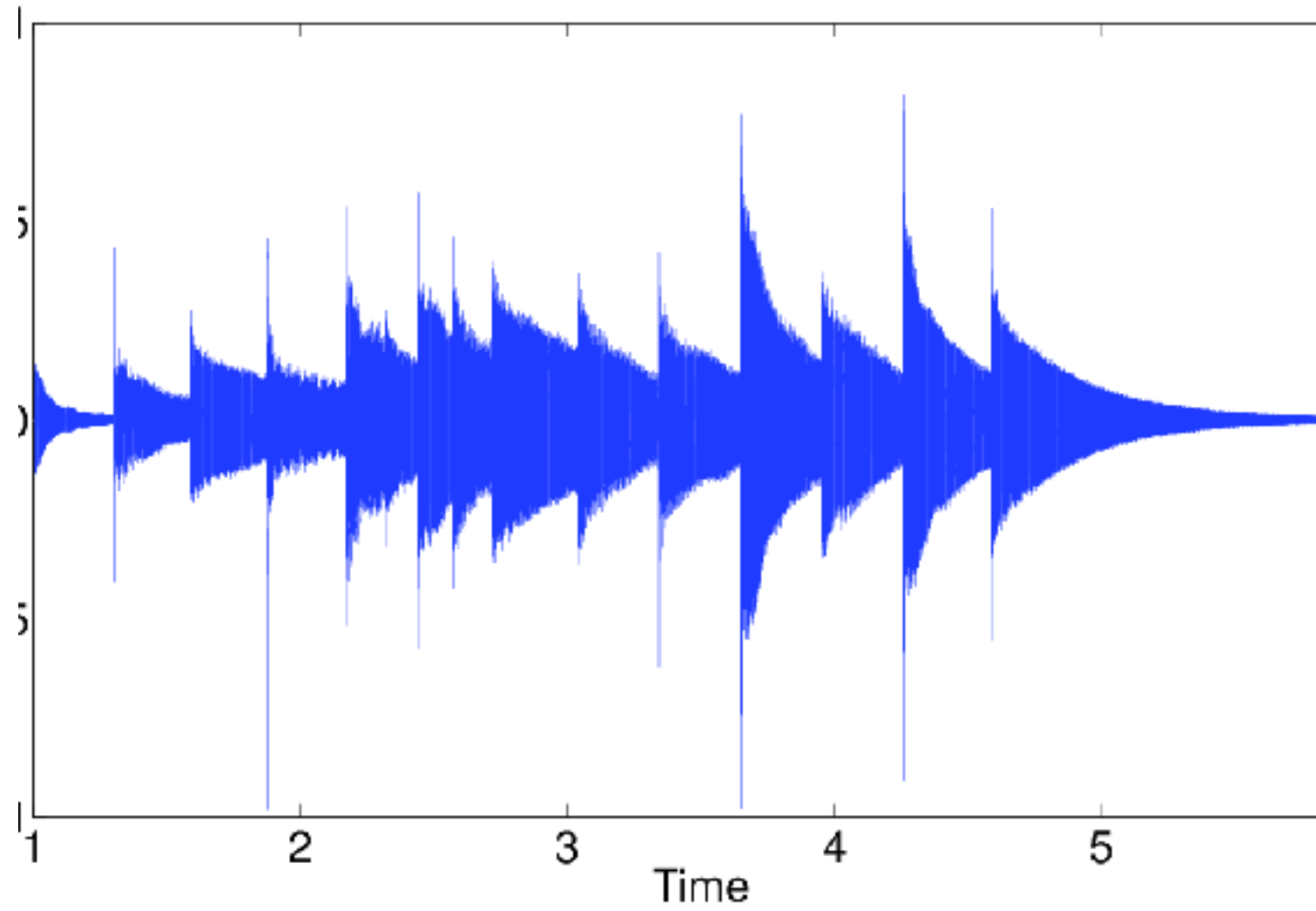
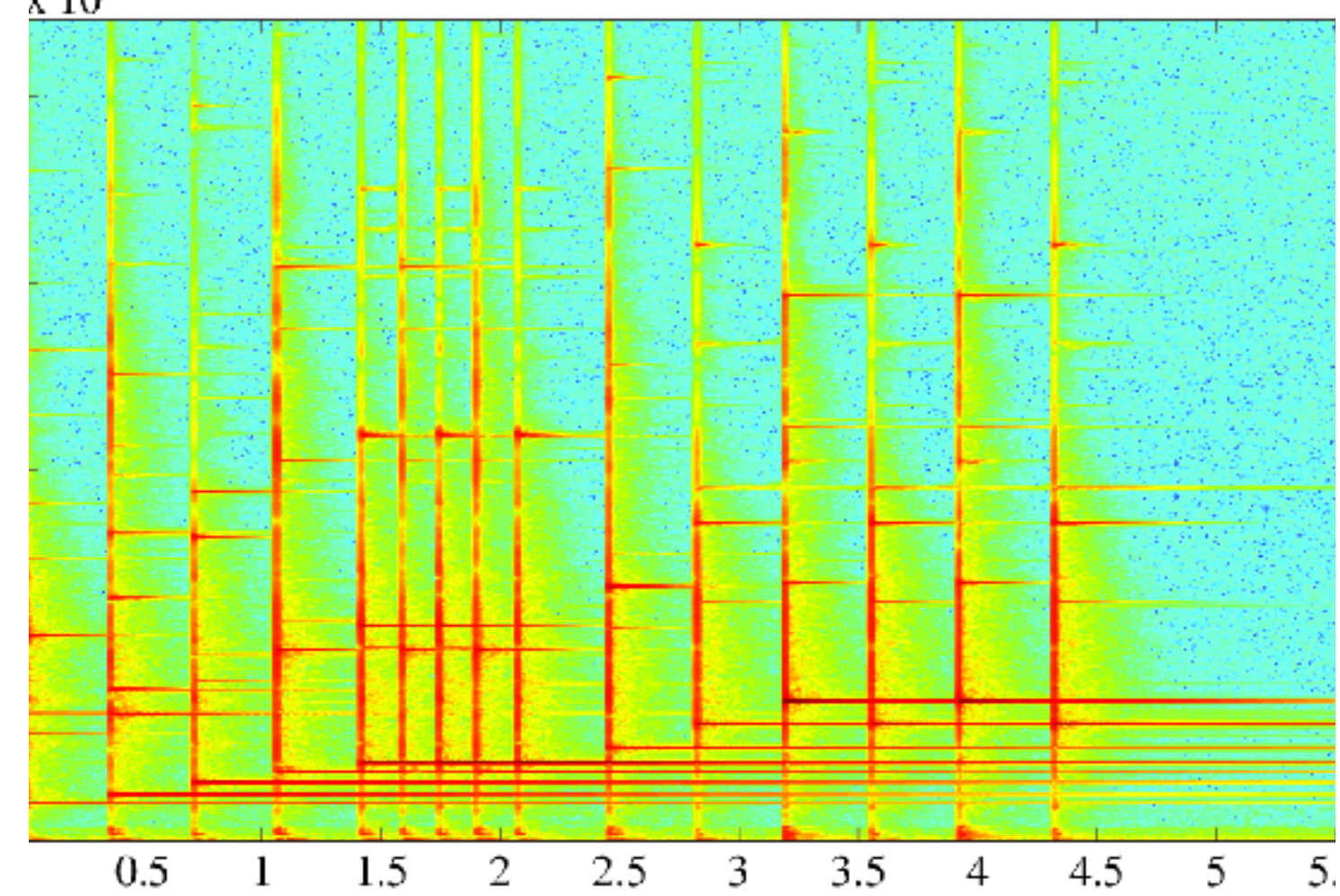


STFT EXAMPLE: SUCCESSION OF 2 SINES

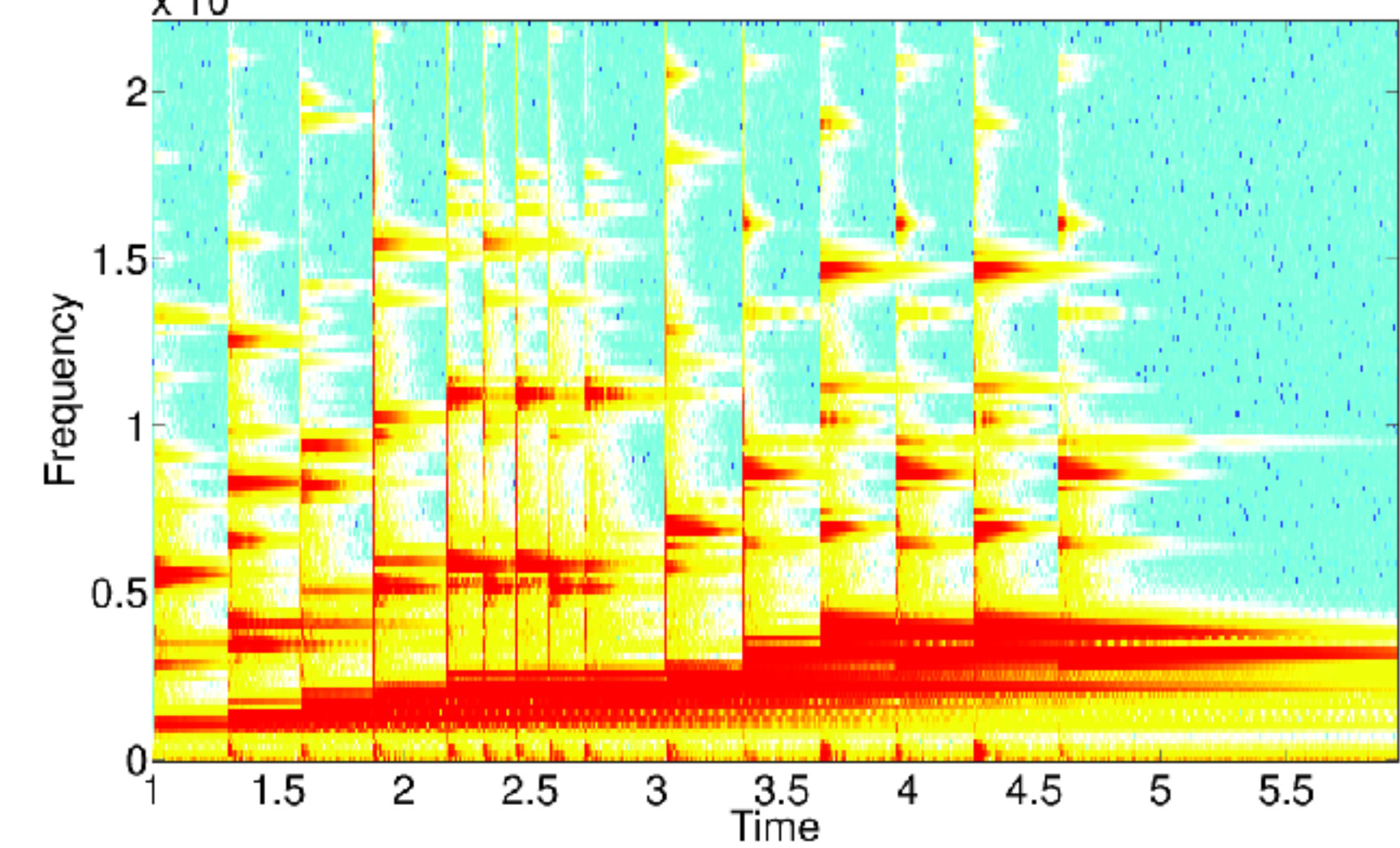


STFT EXAMPLE: GLOCKENSPIEL

Clean signal

 $\times 10^4$ 

Gabor Short Window

 $\times 10^4$ 

DENOISING IN THE TIME-FREQUENCY DOMAIN

- ▶ Let y be a noisy measure of a "clean" signal x corrupted by some additive noise n :

$$y = x + n$$

- ▶ In the STFT domain, we have

$$Y[\tau, \nu] = X[\tau, \nu] + N[\tau, \nu]$$
$$\mathbb{E} \left\{ |Y[\tau, \nu]|^2 \right\} = |X[\tau, \nu]|^2 + S_n[\nu]$$

- ▶ Proposed estimator
 - ▶ Hard Thresholding

$$X(\tau, \nu) = \begin{cases} Y(\tau, \nu) & \text{if } |Y(\tau, \nu)| > \lambda |S_n(\nu)| \\ 0 & \text{if } |Y(\tau, \nu)| \leq \lambda |S_n(\nu)| \end{cases}$$

- ▶ Spectral subtraction

$$X(\tau, \nu) = Y(\tau, \nu) \left(1 - \frac{\lambda^2 |S_n(\nu)|^2}{|Y(\tau, \nu)|^2} \right)^+$$

TO DO: DENOISING IN THE STFT DOMAIN

- ▶ Data
 - ▶ The 3 noises of the random chapter
 - ▶ “Clean” music signal
- ▶ Todo
 - ▶ Simulate a noisy version of the music using the noises at various SNR Level
 - ▶ Implement the denoising by hard thresholding and spectral subtraction
 - ▶ Denoise the different given noisy version of the clean signal
 - ▶ Discuss the parameters