REPORT

Zajęcia: Analog and digital electronic circuits Teacher: prof. dr hab. Vasyl Martsenyuk

Lab 4

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Topic: "Reaction of LTI systems on random signals"

Variant 1

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1. Problem statement:

Consider an LTI system with the DTFT transfer function

$$H(e^{j\Omega}) = \begin{cases} 1, & |\Omega| < \Omega_c \\ 0, & \Omega_c \le |\Omega| \le \pi \end{cases}$$
 (17)

for $\Omega_c > 0$ is excited by white noise x[k] that exhibits the input (auto)-PSD $\Phi_{xx}(e^{j\Omega}) = \Phi_0$. We assume that x[k] is drawn from a stationary, ergodic random process.

- 1. Calculate the ACF, the linear mean and the variance of the output signal y[k].
- 2. Calculate the PSD $\Phi_{yy}(e^{i\Omega})$ of the output signal y[k] = x[k] * h[k].
- 3. generate white noise signal x[k] drawn from gaussian PDF
 - create finite impulse response h[k] of a simple LTI system, i.e. a lowpass (in practice this would be unknown)
 - apply convolution y[k] = x[k] * h[k]
 - estimate the impulse response $\hat{h}[k]$ based on the concept of correlation functions.

2. Input data:

No	Ω_c	
1	$\pi/2$	
2	$\pi/3$	
3	$\pi/4$	
4	$\pi/5$	
5	$\pi/6$	
6	$\pi/7$	
7	$\pi/8$	
8	$\pi/9$	
9	$\pi/10$	
10	$\pi/11$	
11	$\pi/12$	
12	$\pi/13$	
13	$\pi/14$	
14	$\pi/15$	
15	$\pi/16$	

Table 1: Variants

3. Commands used (or GUI):

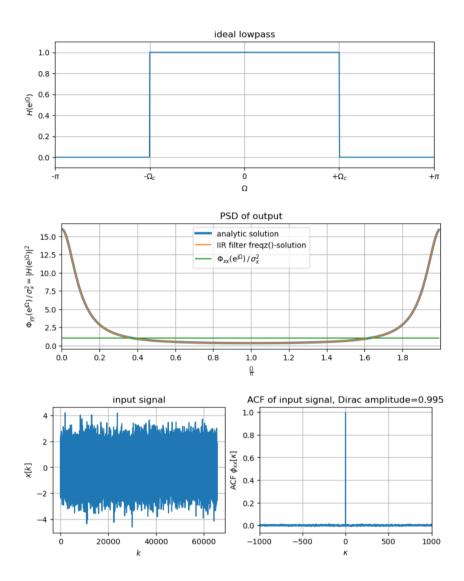
```
In [1]: import numpy as np
import matplotlib as mpl
import matplotlib.pyplot as plt
from scipy import signal
              def my_xcorr2(x, y, scaleopt='none'):
    N = len(x)
    M = len(y)
                     N = LETI(Y)
kappa = np.arange(0, N+M-1) - (M-1)
ccf = signal.correlate(x, y, mode='full', method='auto')
if N == M:
                          if scaleopt == 'none' or scaleopt == 'raw':
                           ccf /= 1
elif scaleopt == 'biased' or scaleopt == 'bias':
                           elif scaleopt == 'blased' or scaleopt == 'blas':
    ccf /= N
elif scaleopt == 'unbiased' or scaleopt == 'unbias':
    ccf /= (N - np.abs(kappa))
elif scaleopt == 'coeff' or scaleopt == 'normalized':
    ccf /= np.sqrt(np.sum(x**2) * np.sum(y**2))
                    print('scaleopt unknown: we leave output unnormalized')
return kappa, ccf
In [2]: \underset{N = 2**10}{\mathsf{Omegac}} = \underset{N = 2**10}{\mathsf{np.pi/2}} \text{ # arbitrary choice, must be <pi}
              Omega = np.arange(N) * 2*np.pi/N - np.pi # [-pi...pi)
              H = np.ones(N)
              H = np.ones(N)
H[Omegac < np.abs(Omega)] = 0
plt.figure(figsize=(9, 3))
              plt.grid(True)
In [3]: N = 2**8
              Omega = np.arange(N) * 2*np.pi/N

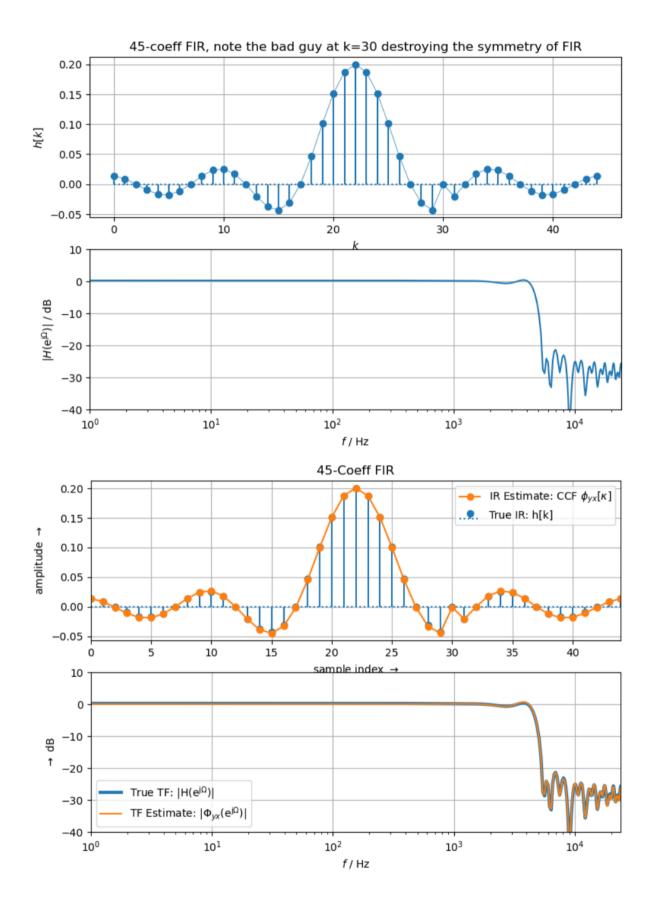
H2 = 2 / (25/8 - 3*np.cos(Omega)) # analytic

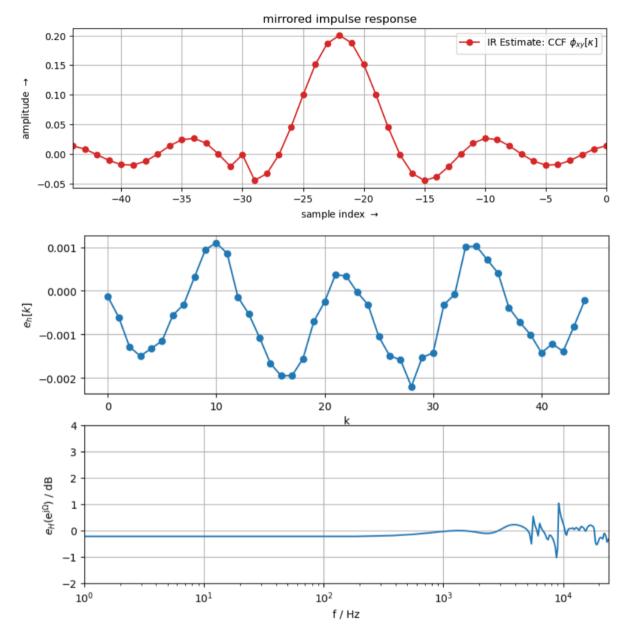
Omega, H_IIR = signal.freqz(b=(1), a=(1, -3/4), worN=Omega) # numeric
              plt.ylabel(
    r'$\Phi_{yy}(\mathrm{e}^{\mathbb{j}\Omega})\,/\,\sigma_x^2 = |H(\mathrm{e}^{\mathbb{j}\Omega})|^2$')
plt.title('PSD of output')
              plt.xlim(0, 2)
              plt.xticks(np.arange(0, 20, 2)/10)
              plt.legend()
plt.grid(True)
In [4]: np.random.seed(4) # arbitrary choice
Nx = 2**16
k = np.arange(Nx)
x = np.random.randn(Nx)
              kappa, phixx = my_xcorn2(x, x, 'biased') # we use biased here, i.e. 1/N normalization idx = np.where(kappa==0)[0][0]
              plt.figure(figsize=(9, 3))
              plt.tigure(figsize=(9, 3))
plt.subplot(1, 2, 1)
plt.plot(k, x)
plt.xlabel('$k$')
plt.ylabel('$k$')
plt.title('input signal')
plt.grid(True)
plt.subplot(1, 2, 2)
              plt.subplot(x, 2, 2)
plt.plot(kappa, phixx)
plt.xlim(-1000, +1000)
plt.xlabel('$\kappa$')
plt.ylabel('ACF $\phi_{xx}[\kappa]$')
plt.title('ACF of input signal, Dirac amplitude=%4.3f' % phixx[idx])
plt.grid(True)
```

```
In [5]: fs = 48000 # sampling frequency in Hz
fc = 4800 # cut frequency in Hz
number_fir_coeff = 45 # FIR taps
h = signal.firls(numtaps=number_fir_coeff, # example for demo
bands=(0, fc, fc+1, fs//2),
desired=(1, 1, 0, 0),
fc-fc
                                                                            fs=fs)
                        k = np.arange(Nh)
# make the IR unsymmetric by arbitray choice for demonstration purpose
                          idx = 30
                         h[idx] = 0 # then FIR is not Longer linear-phase, see the spike in the plot
                         print('h[0]={0:4.3f}, DC={1:4.3f} dB'.format(h[0], 20*np.log10(np.sum(h))))
                        Omega = np.arange(0, N) * 2*np.pi/N
_, H = signal.freqz(b=h, a=1, worN=Omega)
                        plt.figure(figsize=(9, 6))
plt.subplot(2, 1, 1)
plt.stem(k, h, basefmt='C0:')
plt.plot(k, h, 'C0-', lw=0.5)
plt.xlabel(r'$\fs(\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{1}{2}\frac{
                          plt.title(str(Nh)+'-coeff FIR, note the bad guy at k=%d destroying the symmetry of FIR' % idx)
                        plt.title(str(Nh)+'-coeff FIR, note the bad guy at k=%d desti
plt.grid(True)
plt.subplot(2, 1, 2)
plt.semilogx(Omega / (2*np.pi) * fs, 20*np.log10(np.abs(H)))
plt.xlabel(r'$f$ / Hz')
plt.ylabel(r'$fH(\mathrm{e}^{{\mathbf{b}^{mthrm}{j} Omega}})|$ / dB')
plt.xlim(1, fs//2)
plt.xlim(1, 40, 10)
plt.grid(True)
 In [6]: y = np.convolve(x, h, mode='full') # signal x through system h returns output y
 In [7]: kappa, phiyx = my_xcorr2(y, x, 'biased') # get cross correlation in order y,x
                        # find the index for kappa=0, the IR starts here
idx = np.where(kappa == 0)[0][0]
# cut out the IR, since we know the numtaps this is easy to decide here
h_est = phiyx[idx:idx+Nh] / len(y)
# get DTFT estimate of PSD
                         _, Phiyx = signal.freqz(b=h_est, a=1, worN=Omega)
                        plt.xlabel(r'sample index $\rightarrow$')
plt.ylabel(r'amplitude $\rightarrow$')
plt.title(str(Nh)+'-Coeff FIR')
plt.legend()
                       plt.grid(True)
 In [8]: kappa, phixy = my_xcorr2(x, y, 'biased') # get cross correlation x,y
                         plt.xlim(-(Nh-1), 0)
plt.xlabel(r'sample index $\rightarrow$')
plt.ylabel(r'amplitude $\rightarrow$')
plt.title('mirrored impulse response')
                        plt.legend()
plt.grid(True)
In [9]: plt.figure(figsize=(9, 6))
    plt.subplot(2, 1, 1)
    plt.plot(h est - h, 'o-')
    plt.xlabel('k')
    plt.ylabel(r'$e_h[k]$')
                        plt.xlim(1, fs//2)
plt.ylim(-2, 4)
                          plt.grid(True)
```

4. Outcomes:







5. Conclusions:

In this laboratory exercise exploring the impact of random signals on linearly time invariant (LTI) systems, I delved into the complex dynamics of signal processing and its applications. Through a hands-on exploration of basic concepts such as cross-correlation, cross-power spectral density and auto-correlation, I gained a deep understanding of signal interactions within LTI. Moreover, the practical implementation of generating white noise signals, constructing finite impulse responses and performing splicing provided invaluable insight into real-world signal processing scenarios.