

## 1 Noise reduction methods.

### 1.1 Random noise (chapter 6.2).

Generate a random noise signal 'rn1' of length 1000. The samples are generated from a normal probability density function  $N(m,\sigma)$ , where  $m$  is the mean-value and  $\sigma$  is the standard deviation.

```
%generate a noise signal rn1 of 1000 samples  
rn1=0.6 +sqrt(0.1)*randn(1,1000); %gaussian noise, m=0.6,  $\sigma^2=0.1$   
figure(1); subplot(3,1,1); plot(rn1); %show the noise-signal 'rn1'
```

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#### Question 1.

Verify that the generated signal *rn1* is generated from a normal probability density function  $N(0.6, \sqrt{0.1})$  by showing its histogram and by computing its mean-value

$$m = \frac{1}{N} \sum_{i=1}^N x_i \quad \text{and its variance } \sigma^2 = \frac{1}{N-1} \sum_{i=1}^N (x_i - m)^2 .$$

%Compute and show the histogram in 20 bins.

```
[y,x]=hist(rn1,20); %Y=the number of samples in each bin, x=the bin midpoint
```

```
figure(1); subplot(3,1,2); bar(x,y); %show histogram
```

```
%Print on the screen the values of y and x and compare these values with the showed  
%histogram in figure 1.
```

```
y
```

```
x
```

```
%Estimate  $m$  and  $\sigma^2$  of the random signal rn1, and print the values on the screen.
```

```
%Without semicolon the result is printed on the screen.
```

```
m=mean(rn1) %mean value
```

```
v=var(rn1) %variance
```

```
s=std(rn1) %standard deviation
```

---

If the histogram should be interpreted as a probability density function its area must be normalized to one.

The area of bin  $k$  is interpreted as the probability that a sample is contained in the bin-

interval  $x_k \pm \Delta x$  with a probability of  $\frac{y_k}{\sum_{k=1}^N y_k}$  where  $x_k$  is the centre of the bin-interval,  $\Delta x$

is the half-width of the bin,  $y_k$  is the number of samples in bin  $k$ , and  $N$  is the number of bins in the histogram.

```
%Normalize the histogram
```

```
ynorm=y/sum(y); %probability
```

```
figure(1);subplot(3,1,3);bar(x,ynorm); %probability function
```

---

### Question 2.

From the generated normalized histogram ( $x, y_{norm}$ ) select a bin ( $=x$ ) and note the probability ( $=y_{norm}$ ) that a sample is contained in the bin-interval .

Compute by hand the probability for the selected bin-interval by assuming a probability density function  $N(0.6, \sqrt{0.1})$  and by using table-values for a  $N(0,1)$  probability density function (the table is included in the lab manuscript).

Are the two probabilities equal?

Comment on your result!

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## 1.2 Averaging.

### 1.2.1 Ensemble averaging (repetitive measurement, chapter 6.5.7).

Generate a signal 's' as a sum of two cosine signals with different frequency using the following commands:

```
n=0:399; %number of samples  
f1=3000;  
f2=5000;  
fs=20*12000; %sample frequency  
s1=cos(2*pi*f1*n/fs);  
s2=sin(2*pi*f2*n/fs);  
s=s1+s2; %signal  
figure(2);subplot(4,1,1);plot(n,s);
```

Suppose we have 50 repetitive measurement of the signal 's' each added by random noise  $N(0, \sqrt{0.5})$ .

These 50 measurements are generated as:

```
S= repmat(s,50,1); %50 copies of the signal s  
RN=sqrt(0.5)*randn(50,400); %50 random noise signals of length 400 samples  
MS=S+RN; %add random noise to each signal s  
%Show two of the 50 measurements, number 17 and 32  
figure(2);subplot(4,1,2);plot(n,MS(17,:));  
figure(2);subplot(4,1,3);plot(n,MS(32,:));
```

Compute the average (ensemble averaging) of the first 9 measurements in MS.

```
MS9=MS(1:9,:); %select the first 9 measurements in MS  
y9=mean(MS9); %averaged signal  
%show the averaged signal  
figure(2);subplot(4,1,4);plot(n,y9);
```

---

### Question 3.

- Compute the ensemble- average of 49 measurements and show the averaged signal. Compare the plots of the two averaged signals  $y_9$  and  $y_{49}$  and comment the result.

- Theoretically how much do the signal-to-noise-ratio (SNR) increase when doing ensemble averaging using 9 respective 49 measurements?
  - Verify the increase of SNR when using 49 measurements  
(Hint: compute the ratio of the standard deviation of the original noise signal and the standard deviation of the ensemble-averaged noise signal).
- 

### 1.2.2 Time averaging by filtering (chapter 6.5.5 and 10.4.2).

Averaging is now done along the signal (=time averaging). This can be done by a digital low-pass filter.

Use a gaussian low-pass filter which is designed as:

```

sigma=1.4; %decide the cut-off frequency of the filter
M=2*round(4*sigma)+1; %the length of the filter (odd)
x=-(M-1)/2:(M-1)/2; %sample points
g=exp((-x.*x)/(2*sigma*sigma)); %the digital filter
g=g/sum(g); %the gain=1
G=fft(g,512); %the frequency response function
%Show the filter
figure(3); subplot(3,1,1);stem(x,g); %in the time domain
%In the frequency domain
figure(3);subplot(3,1,2);stem(-256:255,fftshift(abs(G))); %Amplitud function
figure(3);subplot(3,1,3);stem(-256:255,fftshift(angle(G))); %Phase function

```

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#### Question 4.

Generate a measurement  $sb=s+rn2$  where  $s$  is the signal you used before and  $rn2$  is a random noise signal  $N(0, \sqrt{0.5})$ . Do averaging by filtering the measurement  $sb$  and show the filtered signal  $y$ .

```

rn2=.....; %noise signal
sb=.....; %measurement
%Show the magnitude frequency response of the measurement and the filter.
SB=fft(sb,512); %frequency representation of the measurement
figure(4); subplot(2,1,1);stem(0:255,abs(G(1:256))); %filter
figure(4); subplot(2,1,2);stem(0:255,abs(SB(1:256))); %measurement
y=conv(sb,g); %filtering by convolution in the time domain
figure(5);subplot(3,1,1);plot(n,s); %signal
figure(5);subplot(3,1,2);plot(n,sb); %measurement
figure(5);subplot(3,1,3);plot(y); %filtered signal

```

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#### Question 5.

-Tune the filter, i.e. select a new sigma-value that fits the measurement by changing the cut-off frequency of the gaussian filter.

Hint: for help in the tuning, study the frequency representation of the measurement and the filter for different sigma-values.

- Use the tuned filter to filter the measurement sb (reuse the old code!) and comment on the result.

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### 1.3 The Fourier transform (chapter 10.4.2).

If the signal s has a narrow bandwidth and the noise has a wide bandwidth the SNR can be improved by doing a Fourier transform (FT) of the measurement sb.

```
SB=fft(sb,1024); %FT in 1024 points
%Show results
figure(6);subplot(4,1,1);plot(n,s); %signal
figure(6);subplot(4,1,2);plot(n,rn2); %noise
figure(6);subplot(4,1,3);plot(n,sb); %measurement
figure(6);subplot(4,1,4);plot(0:511,abs(SB(1:512))); %FT
```

---

#### Question 6.

- Identify the two signals s1 and s2 and also the noise rn2 in the Fourier-transform of the measurement sb.

- Check how much the SNR increase in the Fourier-transformed measurement SB compare to the SNR in the measurement sb.

Hint: estimate the SNR in the measurement sb and in the Fourier-transform of sb (=SB).

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### 1.4 Auto-correlation (chapter 6.2.5 and 6.5.8).

The autocorrelation can be used to reduce random noise in periodic signals.

If s1 and rn2 are uncorrelated, the autocorrelation of the measurement sb1=s1+rn2 is the sum of the autocorrelation of s1 and rn2, i.e.  $R_{sb1sb1}(\tau)=R_{s1s1}(\tau)+R_{rn2rn2}(\tau)$ .

```
sb1=s1+rn2;
auto=xcorr(sb1,'unbiased'); %compute the autocorrelation
%Show results
figure(7);subplot(3,1,1);plot(n,s1);
figure(7);subplot(3,1,2);plot(n,sb1);
figure(7);subplot(3,1,3);plot(-200:200,auto(400-200:400+200)); %autocorrelation
```

---

#### Question 7.

- How do you interpret the "x-scale" in the autocorrelation signal?

- At which x-value in the autocorrelation do you see the influence of the noise?

Explain by computing according to the formula:  $R_{sb1sb1}(\tau)=R_{s1s1}(\tau)+R_{rn2rn2}(\tau)$  and show all three autocorrelations in one figure.

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#### Question 8.

- Combine the two noise reduction methods autocorrelation and Fourier-transform.

Check it by computing the Fourier-transform of the autocorrelation of the measurement sb and show your result.

- Did you get a higher SNR-value compare to only doing Fourier-transform?

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## 2. Detection using cross-correlation (matched filter technique).

Cross-correlation can be used to detect a “known signal” in a measurement. The known signal is often shorter in length (a transient signal) compare to the measurement. The result of the detection should be: the known signal is present in the measurement and at which position.

The detection can be implemented by a technique called “matched filter”, where the matched filter is a folded version of the known signal, and the computation is done by convolution (=filtering). It can be interpreted as a “local match” of the known signal and the measurement for each position.

### 2.1 A simple example.

Create a measurement as a square signal, the known signal as one period of the measurement, and do the detection using the matched filter technique.

```
%Generate the measurement and the known signal.
%The measurement is a square signal of 400 samples.
%The known signal is one period of the measurement, 20 sample in length.
transient=ones(1,20);
transient(11:20)=-ones(1,10);
square= repmat(transient,1,20);
%Show signals
exptr=[transient, zeros(1,400-length(transient))];
figure(8);subplot(3,1,1);stem(0:399,exptr);
figure(8);subplot(3,1,2);stem(0:399,square);

%Do the detection by the matched filter technique.
mfilter=fliplr(transient); %folded transient, mfilter(-n)
y_square=conv(square,mfilter); %crosscorrelation by convolution
figure(8);subplot(3,1,3);stem(0:399,y_square(length(mfilter):length(y_square)));
```

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### Question 9.

*Explain the position of the transient when the detection takes its highest and its lowest value.*

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### 2.2 Electrocardiograph (ecg) signal.

The known signal (the transient) to detect is taken from the ecg-measurement at a special position and of a certain length.

```
%Measurement
load ecg1; %ecg-signal, column vector
```

```

ecg1=ecg1'; %row vector
%Transient is taken from measurement at position 1270 and 146 samples long
tr_ecg=ecg1(1270:1415); %transient
%Design of the matched filter
mfilt_ecg=fliplr(tr_ecg); %folded transient; length=M
%Generate a measurement 'pos_ecg' with the transient at position 343
pos_ecg=zeros(1,1000);
pos_ecg(343:343+length(tr_ecg)-1)=tr_ecg;

%Detect the transient by matched filtering
y_ecg1=conv(pos_ecg,mfilt_ecg); %crosscorr by convolution
[d1,pos1]=find(y_ecg1==max(y_ecg1)); %search for maximum
%Compute the position of the transient
det_pos=pos1-(length(mfilt_ecg)-1); %add -(M-1)

%Show results
det_pos %detected position, should be 343
exptr_ecg=[tr_ecg, zeros(1,1000-length(tr_ecg))]; %expanded transient
figure(9);
subplot(3,1,1);plot(0:length(exptr_ecg)-1,exptr_ecg); %transient
subplot(3,1,2);plot(0:length(pos_ecg)-1,pos_ecg); %measurement
%crosscorrelation
subplot(3,1,3);plot(0:length(pos_ecg)-1,y_ecg1(length(mfilt_ecg):length(y_ecg1)));

```

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Question 10.

*In which signal did you analyse if the transient was present?*

*Change the position of the transient in the measurement and do the detection once more.*

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Now detect the transient in the ecg-measurement.

```

y_ecg2=conv(ecg1,mfilt_ecg); %crosscorr by convolution
%Show results
figure(10);
subplot(3,1,1);plot(0:length(ecg1)-1,ecg1); %ecg-measurement
%crosscorrelation
subplot(3,1,2);plot(0:length(ecg1)-1,y_ecg2(length(mfilt_ecg):length(y_ecg2)));

```

Add random noise to the ecg-measurement and do the detection of the transient.

%add random noise of low amplitude,  $N(0, \sqrt{0.01})$

```

rn3=sqrt(0.01)*randn(1,length(ecg1));
ecg_rn3=ecg1+rn3; %noisy ecg-signal
y_rn3=conv(ecg_rn3,mfilt_ecg); %crosscorr by convolution
%Show results
figure(11);
subplot(4,1,1);plot(0:length(ecg1)-1,ecg1); %ecg-signal

```

```

subplot(4,1,2);plot(0:length(ecg_rn3)-1,ecg_rn3); %noisy ecg-signal
%crosscorrelation noisy ecg-signal
subplot(4,1,3);plot(0:length(ecg_rn3)-1,y_rn3(length(mfilt_ecg):length(y_rn3)));

%crosscorrelation no noise
subplot(4,1,4);plot(0:length(ecg_rn3)-1,y_ecg2(length(mfilt_ecg):length(y_ecg2)));

```

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Question 11.

*Increase the amplitude of the noise by changing its variance in step of 0.01 and do the detection.*

*Note the variance of the noise when the detection goes wrong.*

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**More questions:**

**Capture a signal via a microphone.**

Listen to the original signal and a filtered version of it.

Useful commands:

```

%Set up the recording and check it.
%Sampling frequency=22050, number of bits=8, one channel
r=audiorecorder(22050,8,1); %set up the recording
record(r,1); %record in 1 second; talk into the microphone now!
play(r); %listen to the record sample

```

```

voice_sample=getaudiodata(r); %save the record sample
sound(voice_sample,22050); %listen to the saved sample
figure(27);stem(voice_sample); %show the voice signal

```

```

y_voice=conv(voice_sample,g); %do filtering by filter g
sound(y_voice,22050); %listen to the filtered version

```

**Capture an image via a web-camera.**

Do filtering of the captured image and do cross-correlation (matched filter) of subimages in the original image.

Useful commands :

```

%Set up image capturing and test it.
vid=videoinput('winvideo',1); %set up for image capturing
preview(vid); %test the set up
closepreview(vid); %close the capturing

```

```

I=getsnapshot(vid); %capture an rgb-image
face=double(I(:, :, 1)); %make to gray-scale

```

```

%Show the captured image
figure(1);
imagesc(face);colormap(gray); truesize;

y_face=filter2(g',filter2(g,face)); filter the image by the a 2D filter  $g * g'$ 

impixelinfo; %by the curser find the midpoint (c,r) of the subimage

%Compute a normalized scalar product (=one value in the normalized cross-correlation)
%between two subimages of equal size
Lefteye=face(65:85,90:110); %subimag1 with midpoint (c,r)=(100,75)
Righteye=face(65:85,140:160); %subimage2 with midpointn (c,r)=(150,75)

L1=sqrt(sum(sum(Lefteye.*Lefteye))); %length of subimage1
L2=sqrt(sum(sum(Righteye.*Righteye))); %length of subimage2

SProd=sum(sum(Lefteye.*Righteye)); %scalar product of two subimages
SC=SProd/(L1*L2); %normalized scalar product; [0, 1]

```

