

# Stationary stochastic processes

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Lecture 10

October 2 2018

## The MA(q)-process

A Moving Average, an MA(q)-process, is given by

$$X_t = c_0 e_t + c_1 e_{t-1} + \dots + c_q e_{t-q},$$

where  $e_t$ ,  $0, \pm 1, \pm 2, \dots$ , is zero-mean white noise with variance  $\sigma^2$ . The expected value is  $E[X_t] = 0$  and the covariance function is given from

$$r_X(\tau) = C[X_t, X_{t+\tau}].$$

The spectral density is

$$R_X(f) = r_X(0) + 2 \sum_{\tau=1}^q r_X(\tau) \cos(2\pi f \tau) = |1 + c_1 e^{-i2\pi f} + \dots + c_q e^{-i2\pi f q}|^2 \sigma^2,$$

for  $-1/2 < f \leq 1/2$ . For an MA(q)-process we always have  $q$  zeros (possibly complex conjugated).

## The AR(p)-process

An Auto-Regressive, an AR(p)-process is given by

$$X_t + a_1 X_{t-1} + a_2 X_{t-2} + \dots + a_p X_{t-p} = e_t,$$

where,  $e_t$ ,  $t = 0, \pm 1, \pm 2, \dots$ , is zero-mean white noise with variance  $\sigma^2$ . The expected value is  $E[X_t] = 0$  and the covariance function is computed from the Yule-Walker equations defined as

$$r_X(\tau) + a_1 r_X(\tau - 1) + \dots + a_p r_X(\tau - p) = \begin{cases} \sigma^2 & \text{for } \tau = 0 \\ 0 & \text{for } \tau = 1, 2, \dots \end{cases}$$

The spectral density is

$$R_X(f) = \frac{\sigma^2}{|1 + a_1 e^{-i2\pi f} + \dots + a_p e^{-i2\pi fp}|^2}, \quad -1/2 < f \leq 1/2.$$

For an AR(p)-process we always have p poles (possibly complex conjugated).

# Computer exercise 3

More AR- and MA-processes in computer exercise 3!

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## News HT 2018

The registration system opens for Computer exercise 3, October 8 8.00.

Answer the questions in 1.1 of the tutorial of [Comp. exercise 3](#) and E-mail your answers to [FMSF10@matstat.lu.se](mailto:FMSF10@matstat.lu.se) at latest by **Thursday morning October 11 at 8.00.**

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### Comp. exercise 2:

- Tue Oct 2 13.15-15.00 (E:Hacke, E:Panter, E:Val)
- Wed Oct 3 10.15-12.00 (E:Satu, E:Uran)
- Fri Oct 5 15.15-17.00 (E:Elg, E:Elgkalv)

### Comp. exercise 3:

- Mon Oct 15 13.15-15.00 (E:Satu, E:Uran)
- Tue Oct 16 13.15-15.00 (E:Hacke, E:Panter, E:Val)
- Fri Oct 19 15.15-17.00 (E:Elg, E:Elgkalv)

## Schedule for today's lecture

- ▶ **Mean squared error optimal filter:** an example.
- ▶ **Wiener filter:** the optimal cleaning filter.
- ▶ **Matched filter:** the optimal detection filter.

## Example (old exam)

A discrete time process  $S_t$ ,  $t = 0, \pm 1, \pm 2, \dots$  is disturbed by noise  $N_t$ ,  $t = 0, \pm 1, \pm 2, \dots$ . To improve the measured signal,  $Z_t = S_t + N_t$  is filtered in a filter with frequency function

$$H(f) = a_0 + a_1 e^{-i2\pi f},$$

giving the output process  $Y_t$ . Determine the coefficients  $a_0$  and  $a_1$  so that the mean squared error,  $E[(Y_t - S_t)^2]$ , becomes as small as possible. The processes  $S_t$  and  $N_t$  are independent and have expected values,  $m_S = m_N = 0$ , and covariance functions  $r_S(\tau) = 0.5^{|\tau|}$  and  $r_N(\tau) = (-0.5)^{|\tau|}$ ,  $\tau = 0, \pm 1, \pm 2, \dots$

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## Exercise (old exam)

The output from the filter is

$$Y_t = a_0 Z_t + a_1 Z_{t-1},$$

and the mean squared error is

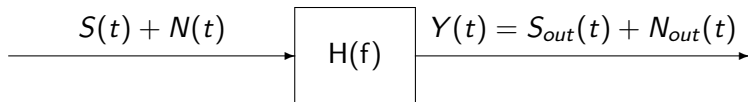
$$\begin{aligned} E [(a_0 Z_t + a_1 Z_{t-1} - S_t)^2] &= \\ E [(a_0 S_t + a_1 S_{t-1} - S_t + a_0 N_t + a_1 N_{t-1})^2] &= \\ a_0^2 V[S_t] + a_1^2 V[S_{t-1}] + a_0^2 V[N_t] + a_1^2 V[N_{t-1}] + V[S_t] + \\ 2a_0 a_1 C[S_t, S_{t-1}] + 2a_0 a_1 C[N_t, N_{t-1}] - 2a_0 V[S_t] - 2a_1 C[S_t, S_{t-1}] &= \\ 2a_0^2 + 2a_1^2 + 1 - 2a_0 - a_1 &= \epsilon. \end{aligned}$$

Differentiation gives

$$\begin{aligned} \frac{\partial \epsilon}{\partial a_0} &= 4a_0 - 2 = 0 \rightarrow a_0 = \frac{1}{2} \\ \frac{\partial \epsilon}{\partial a_1} &= 4a_1 - 1 = 0 \rightarrow a_1 = \frac{1}{4} \end{aligned}$$

## The Wiener filter

A zero-mean stationary process with spectral density  $R_S(f)$  and a zero-mean stationary disturbance process with spectral density  $R_N(f)$  are independent.



The **Wiener filter** maximizes the Signal-to-Noise Ratio (SNR) defined as

$$\text{SNR} = \frac{\text{power for wanted signal}}{\text{power for not wanted signal}} = \frac{E[S(t)^2]}{E[(Y(t) - S(t))^2]}.$$



## The Wiener filter

The Wiener filter has the real-valued frequency function

$$H_{opt}(f) = \frac{R_S(f)}{R_S(f) + R_N(f)},$$

which is given by maximized SNR,

$$\text{SNR}_{opt} = \frac{E[S(t)^2]}{E[(Y(t) - S(t))^2]},$$

given by minimizing the mean squared error,

$$\epsilon^2 = E[(Y(t) - S(t))^2].$$

## The Wiener filter

We get,

$$\begin{aligned}\epsilon^2 &= E[(Y(t) - S(t))^2] = E[(S_{out}(t) + N_{out}(t) - S(t))^2] = \\ &E[(S_{out}(t) - S(t))^2] + E[(S_{out}(t) - S(t))N_{out}(t)] + E[N_{out}(t)^2] = \\ &E[(S_{out}(t) - S(t))^2] + E[N_{out}(t)^2] = \\ &V[(S_{out}(t) - S(t))] + V[N_{out}(t)].\end{aligned}$$

The variance of the filtered disturbance is,

$$V[N_{out}(t)] = \int |H(f)|^2 R_N(f) df.$$

## Wiener filter

$S_{out}(t)$  can be seen as the output from the filter with  $S(t)$  as input giving

$$\begin{aligned} V[S_{out}(t) - S(t)] &= V\left[\int h(u)S(t-u)du - \int \delta(u)S(t-u)du\right] = \\ &= V\left[\int h_1(u)S(t-u)du\right] = \int |H_1(f)|^2 R_S(f)df, \end{aligned}$$

where  $h_1(u) = h(u) - \delta(u)$  and  $H_1(f) = H(f) - 1$ . We find the following expression to be minimized,

$$\begin{aligned} \epsilon^2 &= E[(Y(t) - S(t))^2] = \\ &= E[(S_{out}(t) - S(t))^2] + E[N_{out}(t)^2] = \\ &= \int (|H(f) - 1|^2 R_S(f) + |H(f)|^2 R_N(f))df. \end{aligned}$$

## The Wiener filter

Omitting  $f$ ,

$$\begin{aligned} \min_H [(H - 1)(\bar{H} - 1)R_S + H\bar{H}R_N] &= \\ &= \min_H [H\bar{H}(R_S + R_N) - (H + \bar{H})R_S + R_S] = \\ &= \min_H [(\Re H^2 + \Im H^2)(R_S + R_N) - 2\Re HR_S + R_S]. \end{aligned}$$

If  $\Im H = 0$  the imaginary part of the expression is zero and we know that  $H$  is real-valued for all  $f$ .

Minimize

$$\min_H [H^2(R_S + R_N) - 2HR_S + R_S],$$

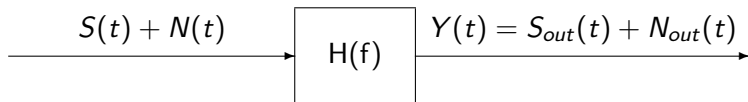
where the derivative with respect to  $H$  is

$$2H(R_S + R_N) - 2R_S = 0,$$

i.e.,

$$H_{opt} = \frac{R_S}{R_S + R_N}.$$

## The Wiener filter



The Wiener filter, which maximizes the Signal-to-Noise Ratio,

$$\text{SNR}_{opt} = \frac{E[S(t)^2]}{E[(Y(t) - S(t))^2]},$$

has the real-valued frequency function

$$H_{opt}(f) = \frac{R_S(f)}{R_S(f) + R_N(f)}.$$

## Exercise (old exam) modified

A stationary process  $S(t)$ ,  $t \in \mathbb{R}$  with spectral density

$$R_S(f) = |f|, \quad |f| < 2,$$

is disturbed by a stationary process,  $N(t)$ ,  $t \in \mathbb{R}$  with spectral density

$$R_N(f) = 1 - |f|, \quad |f| < 1.$$

The processes  $S(t)$  and  $N(t)$  are both zero-mean and independent.

- Calculate the SNR  $= E[S^2(t)]/E[(Y(t) - S(t))^2]$ , where  $Y(t)$  is the output from the filter  $H(f) = 1$ ,  $1 \leq |f| \leq 2$ , and the input is  $S(t) + N(t)$ .
- Calculate the Wiener filter and the corresponding SNR.

## Solution a)

The SNR is defined as

$$\text{SNR} = \frac{E[S(t)^2]}{E[(Y(t) - S(t))^2]},$$

where

$$E[S^2(t)] = V[S(t)] = 2 \int_0^2 R_S(f) df = 4,$$

and

$$\begin{aligned} E[(Y(t) - S(t))^2] &= E[(S_{out}(t) - S(t))^2] + E[N_{out}^2(t)] = \\ &= 2 \int_0^2 |H(f) - 1|^2 R_S(f) df + 0 = 2 \int_0^1 R_S(f) df = 1. \end{aligned}$$

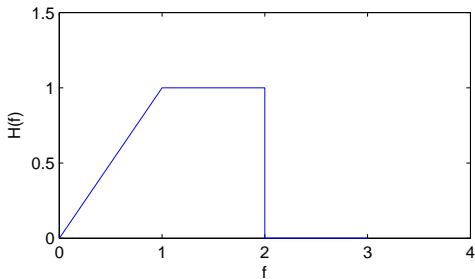
The resulting  $\text{SNR} = 4$ .

## Solution b)

The Wiener filter, given from

$$H_{opt}(f) = \frac{R_S(f)}{R_S(f) + R_N(f)},$$

is defined as





## Solution b)

The power of the wanted signal,

$$E[S^2(t)] = V[S(t)] = 2 \int_0^2 R_S(f) df = 4,$$

the same as in a). The power of the not wanted signal, is the sum of

$$E[(S_{out}(t) - S(t))^2] = 2 \int_0^2 |H(f) - 1|^2 R_S(f) df = 2 \int_0^1 (1-f)^2 f df = \frac{1}{6},$$

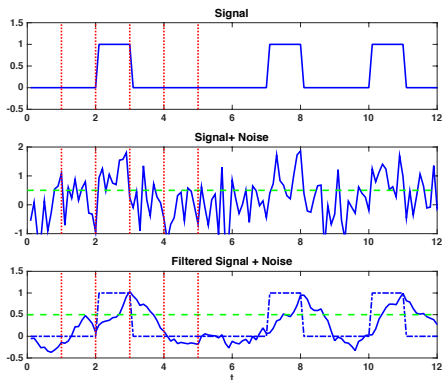
and

$$E[N_{out}^2(t)] = 2 \int_0^1 |H(f)|^2 R_N(f) df = 2 \int_0^1 f^2 (1-f) df = \frac{1}{6}.$$

The resulting  $\text{SNR}_{opt} = 4 / (\frac{1}{6} + \frac{1}{6}) = 12$ .

# The matched detector

In digital communication, a signal  $s(t) = 1, 0 \leq t \leq T$ , is either sent, i.e. is 'one', or not sent, i.e. is 'zero'. At the receiver, a matched detector should filter the signal to be correctly verified as a 'one' or a 'zero'.



## The matched detector

At the receiver we apply a causal filter,  $h(t)$ ,  $0 \leq t \leq T$ , which will give as output at  $t = T$ ,

$$s_{out}(T) + N_{out}(T) = \int_0^T h(u)s(T-u)du + \int_0^T h(u)N(T-u)du,$$

if signal is sent, and just

$$N_{out}(T) = \int_0^T h(u)N(T-u)du,$$

if no signal is sent. The disturbance is usually assumed to be stationary.

## The matched detector

The SNR at  $t = T$  should be maximized, i.e.

$$\max SNR = \frac{s_{out}^2(T)}{V[N_{out}(T)]}$$

For the case of white noise disturbance, with input variance  $\sigma_N^2$ , the SNR is

$$SNR = \frac{(\int_0^T h(u)s(T-u)du)^2}{\sigma_N^2 \int_0^T h^2(u)du}.$$

The maximum is reached for the [matched filter](#)

$$h_{opt}(t) = s(T-t), \quad 0 \leq t \leq T,$$

and the optimal SNR is

$$SNR_{max} = \frac{\int_0^T s^2(T-u)du}{\sigma_N^2}.$$

## Statistical decision test

We formulate a statistical decision problem with the matched filter as a hypothesis test with Gaussian distributions:

$$H_0 : Y(T) = N_{out}(T), \in N(0, \sigma_{N_{out}}^2),$$

$$H_1 : Y(T) = s_{out}(T) + N_{out}(T), \in N(s_{out}(T), \sigma_{N_{out}}^2),$$

### MATCHED FILTER

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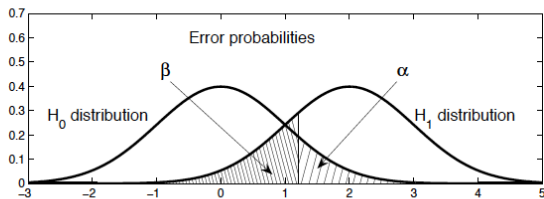


Figure 8.7: Filter output distributions under two hypotheses.

## Equal probability for error decisions

The probability for error decisions are,

$$\alpha = P(Y(T) > k | Y(T) \in N(0, \sigma_{Nout}^2)) = 1 - \Phi\left(\frac{k}{\sigma_{Nout}}\right) = \Phi\left(\frac{-k}{\sigma_{Nout}}\right),$$
$$\beta = P(Y(T) < k | Y(T) \in N(s_{out}(T), \sigma_{Nout}^2)) = \Phi\left(\frac{k - s_{out}(T)}{\sigma_{Nout}}\right).$$

If the errors should be equal,  $\alpha = \beta$ , then  $k - s_{out}(T) = -k$ , i.e. the **decision level** is

$$k = s_{out}(T)/2,$$

yielding the **probability of errors**,

$$\alpha = \beta = 1 - \Phi\left(\frac{s_{out}(T)}{2\sigma_{Nout}}\right).$$

## Example

We would like to detect the sent signal,  $s_t = 1$ ,  $t = 0, 1, 2$ , where the zero-mean Gaussian disturbance is  $N_t$ .

- a) Determine the decision level and the probability of errors, using the causal matched filter for white noise disturbance with variance  $\sigma_N^2 = 1$ .
- b) Calculate the causal matched filter, the decision level and probability of errors, when the noise covariance function is  $r_N(0) = 1$ ,  $r_N(\pm 1) = 0.5$ .

The decision level should, in both cases, be decided so the two error probabilities are equal.

## Solution a)

We get for  $t = T = 2$ :

$$s_{out_2} = \sum_{u=0}^2 h(u)s_{2-u} = \sum_{u=0}^2 s_{2-u}^2 = 3.$$

Choose decision level  $k = \frac{s_{out_2}}{2} = 1.5$  for equal errors. We get

$$\sigma_{Nout}^2 = \sigma_N^2 \sum_{u=0}^2 h^2(u) = 3.$$

Then

$$P(Y(2) > 1.5 | Y(2) \in N(0, 3)) = 1 - \Phi\left(\frac{1.5}{\sqrt{3}}\right) = 0.196,$$

$$P(Y(2) < 1.5 | Y(2) \in N(3, 3)) = \Phi\left(\frac{1.5 - 3}{\sqrt{3}}\right) = 0.196.$$



## Summary matched filter: coloured noise

Theorem 8.6: The causal matched filter for detection of  $s(t)$ ,  $0 \leq t \leq T$ , disturbed by zero-mean coloured noise with covariance function  $r_N(\tau)$ , has the impulse response  $h(t)$ ,  $0 \leq t \leq T$ , found from the solution of

$$s(T - t) = \int_0^T h(u)r_N(t - u)du.$$

Proof, see pages 217-218.

## Solution b)

The optimal causal filter fulfills the equation system for  $T = 2$ ,

$$s_{2-t} = \sum_{u=0}^2 h(u)r_N(t-u),$$

which has the solution  $h(0) = h(2) = 1, h(1) = 0$ . We get  $\sigma_{Nout}^2 = \sum_{u=0}^2 h(u)s_{2-u} = 2$ . Choose decision level  $k = \frac{\sigma_{Nout}^2}{2} = 1$  for equal errors. We get

$$\sigma_{Nout}^2 = \sum_{u=0}^2 \sum_{v=0}^2 h(u)h(v)r_N(u-v) = 2,$$

and

$$P(Y(2) > 1 | Y(2) \in N(0, 2)) = 1 - \Phi\left(\frac{1}{\sqrt{2}}\right) = 0.239,$$

$$P(Y(2) < 1 | Y(2) \in N(2, 2)) = \Phi\left(\frac{1-2}{\sqrt{2}}\right) = 0.239.$$