
Digital Signal Processing

Formulary

Author: Daniel Thiem - studium@daniel-thiem.de

Version 0.5.2 - 13.02.2013



TECHNISCHE
UNIVERSITÄT
DARMSTADT



Contents

1	Digital Processing of Continuous-Time Signals	5
1.1	Periodic Sampling	5
1.1.1	Reconstruction of Band-Limited Signals	5
1.1.2	Discrete-time Processing of Continuous-Time Signals	5
2	Digital Filter Design	6
2.1	Finite Impulse Response (FIR) filter	6
2.1.1	Properties of Filters	6
2.2	Linear Phase Filters	7
2.2.1	Generalized linear phase system	7
2.3	Linear Phase FIR filters	7
2.4	Linear Phase FIR filter Types	8
2.4.1	Type I FIR linear phase filter	8
2.4.2	Type II FIR linear phase filter	8
2.4.3	Type III FIR linear phase filter	9
2.4.4	Type IV FIR linear phase filter	9
2.5	FIR filter design	9
2.5.1	FIR filter type choice	9
2.5.2	FIR filter design by Windowing	10
2.5.3	Kaiser Window Filter Design	13
2.5.4	Optimal Filter Design	13
2.6	Infinite Impulse Response (IIR) filter	14
2.6.1	Properties of IIR filters	14
2.6.2	IIR filter design from an analog or continuous-time filter (Impulse Invariance Method)	14
2.6.3	The Butterworth filter	15
2.6.4	Bilinear Transformation	15
2.6.5	Implementation of IIR Filters	16
2.7	Filter Specification	17
2.7.1	Ripple and Attenuation calculation	18
3	Random Variables and Stochastic Processes	19

4	The Finite Fourier Transform	20
4.1	Definition	20
4.1.1	Properties	20
4.2	Discrete Finite Fourier Transform	20
4.3	Statistical Properties	21
4.3.1	White Gaussian Process	21
4.3.2	Real Stationary Random Process	21
4.4	Segmentation of the Finite Fourier Transform	21
4.5	Windowing of the process	22
4.5.1	Power of the windowed process	22
5	Digital Spectral Analysis	23
5.1	Consistency and Mean Square Error in terms of bias and variance . . .	23
5.2	Mean Estimation	23
5.3	The Periodogram	23
5.3.1	Distribution of the Periodogram	23
5.3.2	Mean of the Periodogram	24
5.3.3	Variance of the Periodogram	24
5.3.4	Averaging Periodograms (Barlett's method)	24
5.3.5	Welch's method	25
5.3.6	Smoothing the Periodogram	25
5.3.7	General Class of Spectral Estimates	25
5.4	The Log-Spectrum	26
5.5	The Blackman-Tuckey Method	26
5.6	Cross-Spectrum Estimation	26
5.6.1	The Cross-Periodogram	26
5.6.2	Segmented Cross-Periodogram	27
6	Parametric Spectrum Estimation	28
6.1	Auto-regressive (AR) Processes	28
6.1.1	Yule-Walker Equations	28
6.1.2	extended Yule-Walker equations	28
6.2	Moving Average (MA) Process	29
6.2.1	Solving	29
6.3	Auto-regressive Moving Average (ARMA) Process	30
6.4	Model order selection	30
6.4.1	Akaike's Information Criterion (AIC)	30
6.4.2	Minimum Description Length (MDL)	30

7	Miscellaneous	31
7.1	Useful mathematical equations	31
7.1.1	Geometric series	31
7.1.2	Conversion from Geometric series to trigonometric fraction . .	31

Preface

This formulary is based on the formulary of the course Stochastic Signals and Systems, which can be found here <https://github.com/Tyde/stosigsysfs/blob/master/document.pdf?raw=true>. If you find any errors or have any ideas for improvement, mail me at studium@daniel-thiem.de or file an issue at <https://github.com/Tyde/dspformulary/issues>. The \LaTeX source code is online on <https://github.com/Tyde/dspformulary> and can be improved and extended.

1 Digital Processing of Continous-Time Signals

1.1 Periodic Sampling

Basic principles of sampling and transforming signals can be found in the Stochastic Signals and Systems formulary

1.1.1 Reconstruction of Band-Limited Signals

Assume, that $H_r(j\Omega)$ and $h_r(t)$ are the frequency and time responses for an ideal low pass filter where $x(n)$ is the input signal. Then the output will be

$$x_r(t) = \sum_{n=-\infty}^{\infty} x(n)h_r(t - nT) \quad (1.1)$$

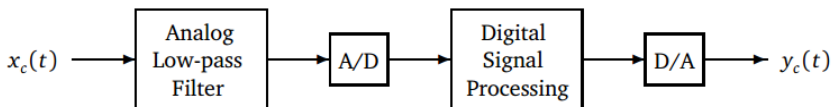
Because the filter is assumed to be ideal, its impulse response is given by:

$$h_r(t) = \frac{\sin(\pi t/T)}{\pi t/T} \quad (1.2)$$

where T is the sampling interval that should fulfil the Nyquist condition $\Omega_s > 2\Omega_B$

1.1.2 Discrete-time Processing of Continous-Time Signals

To process a continous-time signal $x_c(t)$ with digital signal processing techniques, the following setup is used:



2 Digital Filter Design

Let $x(n)$ and $y(n)$, $n = 0 \pm 1, \dots$ be the input and the output of the system. Linear time-invariant discrete-time systems can be characterized by linear constant coefficient difference equations of the following type, where $\max(N-1, M)$ is the order:

$$\sum_{k=0}^M a_k y(n-k) = \sum_{r=0}^{N-1} b_r x(n-r) \quad (2.1)$$

2.1 Finite Impulse Response (FIR) filter

If $M = 0$ then the impulse response of the filter is finite so that:

$$y(n) = \frac{1}{a_0} \sum_{k=-\infty}^{\infty} b_r x(n-k) \quad (2.2a)$$

comparison with the convolution sum yields

$$h(n) = \begin{cases} b_n/a_n, & n = 0, \dots, N-1 \\ 0, & \text{otherwise} \end{cases} \quad (2.2b)$$

2.1.1 Properties of Filters

With f_{SR} being the sample rate.

$$\text{Filter Order} = N - 1 \quad (2.3)$$

$$\Delta\omega = \frac{f_s - f_p}{f_{SR}} 2\pi \quad (2.4)$$

$$\text{Delay} = \frac{N-1}{2} \quad (2.5)$$

2.2 Linear Phase Filters

A digital filter can be described as linear phase filter if $H(e^{j\omega})$ can be expressed as:

$$H(e^{j\omega}) = H_M(e^{j\omega}) e^{-j\omega\alpha} \quad (2.6)$$

with $H_M(e^{j\omega})$ real and α (group delay) constant

2.2.1 Generalized linear phase system

A Linear phase system with:

$$H(e^{j\omega}) = H_M(e^{j\omega}) e^{-j\omega\alpha + j\beta} \quad (2.7)$$

has to meet the condition:

$$\sum_{n=-\infty}^{\infty} h(n) \sin[\omega(n - \alpha) + \beta] = 0 \quad \forall \omega \in \mathbb{R} \quad (2.8)$$

2.3 Linear Phase FIR filters

Applying the condition for generalized linear phase systems (2.2.1) to the FIR Filters yields two possible causal FIR Systems:

$$h(n) = \begin{cases} h(N-1-n) & , 0 \leq n \leq N-1 \\ 0 & , \text{otherwise} \end{cases} \quad (2.9a)$$

$$H(e^{j\omega}) = H_e(e^{j\omega}) e^{-j\omega(N-1)/2} \quad (2.9b)$$

and

$$h(n) = \begin{cases} -h(N-1-n) & , 0 \leq n \leq N-1 \\ 0 & , \text{otherwise} \end{cases} \quad (2.10a)$$

$$H(e^{j\omega}) = H_o(e^{j\omega}) e^{-j\omega(N-1)/2 + j\pi/2} \quad (2.10b)$$

2.4 Linear Phase FIR filter Types

The linear phase FIR filters have been classified into 4 Types:

- **Type I** symmetric impulse response and N is odd
- **Type II** symmetric impulse response and N is even
- **Type III** antisymmetric impulse response and N is odd
- **Type IV** antisymmetric impulse response and N is even

2.4.1 Type I FIR linear phase filter

N is odd and the impulse response is symmetric. $\beta = 0$

$$h(n) = h(N - 1 - n) \quad 0 \leq n \leq N - 1 \quad (2.11a)$$

$$H(e^{j\omega}) = e^{-j\omega \frac{N-1}{2}} \left[\sum_{k=0}^{(N-1)/2} a(k) \cos(\omega k) \right] \quad (2.11b)$$

where

$$a(0) = h\left(\frac{N-1}{2}\right) \text{ and } a(k) = 2h\left(\frac{N-1}{2} - k\right), \quad k = 1, 2, \dots, (N-1)/2$$

2.4.2 Type II FIR linear phase filter

N is even and the impulse response is symmetric. $\beta = 0$

$$h(n) = h(N - 1 - n) \quad 0 \leq n \leq N - 1 \quad (2.12a)$$

$$H(e^{j\omega}) = e^{-j\omega \frac{N-1}{2}} \left\{ \sum_{k=1}^{N/2} b(k) \cos \left[\omega \left(k - \frac{1}{2} \right) \right] \right\} \quad (2.12b)$$

where

$$b(k) = 2h[N/2 - k], \quad k = 1, 2, \dots, N/2$$

2.4.3 Type III FIR linear phase filter

N is odd and the impuls response is antisymmetric. $\beta = \pi/2$

$$h(n) = -h(N-1-n) \quad 0 \leq n \leq N-1 \quad (2.13a)$$

$$H(e^{j\omega}) = je^{-j\omega \frac{N-1}{2}} \left[\sum_{k=1}^{(N-1)/2} c(k) \sin(\omega k) \right] \quad (2.13b)$$

where

$$c(k) = 2h[(N-1)/2 - k], \quad k = 1, 2, \dots, (N-1)/2$$

2.4.4 Type IV FIR linear phase filter

N is even and the impuls response is antisymmetric. $\beta = \pi/2$

$$h(n) = -h(N-1-n) \quad 0 \leq n \leq N-1 \quad (2.14a)$$

$$H(e^{j\omega}) = je^{-j\omega \frac{N-1}{2}} \left\{ \sum_{k=1}^{N/2} d(k) \sin \left[\omega \left(k - \frac{1}{2} \right) \right] \right\} \quad (2.14b)$$

where

$$d(k) = 2h[N/2 - k], \quad k = 1, 2, \dots, N/2$$

2.5 FIR filter design

2.5.1 FIR filter type choice

Not every FIR filter type fits on every filter.

Type	Low Pass	High Pass	Band Pass	Band Stop
I				
II		Not suitable		Not suitable
III	Not suitable	Not suitable		Not suitable
IV	Not suitable			Not suitable

2.5.2 FIR filter design by Windowing

Most idealized systems are non causal and have infinite impulse responses. To achieve finite impulse responses and causality, truncating the ideal response is the most straightforward approach.

For the ideal impulse response

$$h_d(n) = \frac{1}{2\pi} \int_{-\pi}^{\pi} H_d(e^{j\omega}) e^{j\omega n} d\omega \quad (2.15)$$

the truncated response would be

$$h(n) = \begin{cases} h_d(n) & , 0 \leq n \leq N-1 \\ 0 & , \text{otherwise} \end{cases} \quad (2.16a)$$

or

$$h(n) = h_d(n) \cdot w(n) \quad (2.16b)$$

with

$$w(n) = \begin{cases} 1 & , 0 \leq n \leq N-1 \\ 0 & , \text{otherwise} \end{cases}$$

Properties of a rectangular Window

If the window-function is a rectangle, the frequency response of the filter has to be multiplied with the fourier transform of the rectangle:

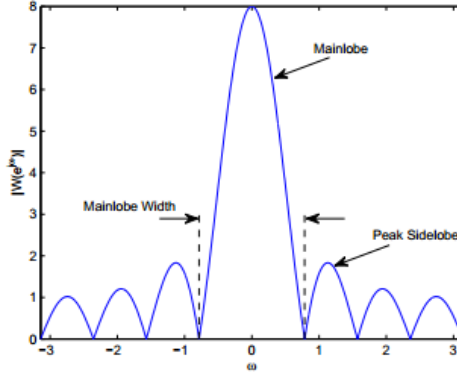
$$H(e^{j\omega}) = H_d(e^{j\omega}) \otimes W(e^{j\omega}) \quad (2.17a)$$

$$= H_d(e^{j\omega}) \otimes \left[e^{-j\omega \frac{N-1}{2}} \cdot \frac{\sin(\omega N/2)}{\omega/2} \right] \quad (2.17b)$$

This, if $H_d(e^{j\omega})$ should be closest to $H(e^{j\omega})$, N has to go to infinity

Main and Sidelobes

With increasing N , the 'main-lobe' width increases.



Peak approximation error (PAE)

$$PAE = \gamma \cdot \max_{\omega \in \mathbb{R}} |H_d(e^{j\omega}) - H(e^{j\omega})| \quad (2.18)$$

The PAE is also directly related to the maximum allowable specification tolerance. With ω_c as the discontinuity of $H_d(e^{j\omega})$:

$$\Delta H_d(e^{j\omega_c}) \cdot \gamma \leq \min(\alpha_1, \alpha_2) \quad (2.19)$$

Commonly used Windows

Rectangular

$$w(n) = \begin{cases} 1 & , 0 \leq n \leq N-1 \\ 0 & , \text{otherwise} \end{cases} \quad (2.20a)$$

Barlett

$$w(n) = \begin{cases} \frac{2n}{N-1} & , 0 \leq n \leq \frac{N-1}{2} \\ 2 - \frac{2n}{N-1} & , \frac{N-1}{2} \leq n \leq N-1 \end{cases} \quad (2.20b)$$

Hanning

$$w(n) = \frac{1}{2} \left[1 - \cos \left(\frac{2\pi n}{N-1} \right) \right] \quad 0 \leq n \leq N-1 \quad (2.20c)$$

Hamming

$$w(n) = 0.54 - 0.46 \cos \left(\frac{2\pi n}{N-1} \right) \quad 0 \leq n \leq N-1 \quad (2.20d)$$

Blackman

$$w(n) = 0.42 - 0.5 \cos \left(\frac{2\pi n}{N-1} \right) + 0.08 \cos \left(\frac{4\pi n}{N-1} \right) \quad 0 \leq n \leq N-1 \quad (2.20e)$$

These windows have different Properties:

Window Type	Peak Amplitude of Side-Lobe (dB) (relative)	Approximate Width (rad) of Main-Lobe $\Delta\omega$	Peak Approximation Error (dB) $20 \log_{10} \gamma$
Rectangular	-13	$4\pi/N$	-21
Bartlett	-25	$8\pi/(N-1)$	-25
Hanning	-31	$8\pi/(N-1)$	-44
Hamming	-41	$8\pi/(N-1)$	-53
Blackman	-57	$12\pi/(N-1)$	-74

2.5.3 Kaiser Window Filter Design

The Kaiser window function adapts to the specifications. Let $\alpha = \frac{N-1}{2}$ and I_0 be the zeroth order modified Bessel function of the first kind:

$$w(n) = \begin{cases} \frac{I_0 \left\{ \beta \left[1 - \left(\frac{n-\alpha}{\alpha} \right)^2 \right]^{\frac{1}{2}} \right\}}{I_0(\beta)} & , 0 \leq n \leq N-1 \\ 0 & , \text{otherwise} \end{cases} \quad (2.21)$$

Design a filter with Kaiser window

Assuming the transition region is $\Delta\omega = \omega_s - \omega_p$. With $A = -20 \log_{10} \min(\alpha_1, \alpha_2)$

$$\beta = \begin{cases} 0.1102(A-8.7) & A > 50 \\ 0.5842(A-21)^{0.4} + 0.07866(A-21) & 21 \leq A \leq 50 \\ 0 & A < 21 \end{cases} \quad (2.22)$$

and

$$N = \left\lceil \frac{A-8}{2.285\Delta\omega} + 1 \right\rceil \quad (2.23)$$

Integrated Square Error

To optimize a windowed filter, one has to attempt to minimize the integrated squared error

$$\epsilon^2 = \frac{1}{2\pi} \int_{-\pi}^{\pi} |H_d(e^{j\omega}) - H(e^{j\omega})|^2 d\omega \quad (2.24)$$

2.5.4 Optimal Filter Design

Optimal filter design does not use the integrated square error but instead the maximum error, which occurs at the discontinuities of $H_d(e^{j\omega})$. This error gets distributed equally across the frequency band. Please use the script pages 33-36 for information about optimal filter design. ,

2.6 Infinite Impulse Response (IIR) filter

IIR filters are systems, which follow the following Restrictions:

$h(n)$ is

- real
- causal
- satisfies stability

$h(n)$ possesses a rational z-transform with $a_0 = 1$, i.e.

$$H(z) = \frac{\sum_{k=0}^{N-1} b_k z^{-k}}{1 - \sum_{k=0}^{N-1} a_k z^{-k}} \quad (2.25)$$

2.6.1 Properties of IIR filters

- **Stability**
All poles of $H(z)$ must lie inside the unit disk
- **Linear Phase**
IIR filters do not have linear phase. Only the magnitude response is specified.

2.6.2 IIR filter design from an analog or continuous-time filter (Impulse Invariance Method)

Steps to design:

- **Step 1:** Specification of the digital filter
- **Step 2:** Translation to a continuous-time filter specification
- **Step 3:** Determination of the continuous-time filter system function $H_c(s)$
- **Step 4:** Transformation of $H_c(s)$ to a digital filter system function $H(z)$

Step 1

Filter parameters like $\alpha_1, \alpha_2, \omega_p, \omega_s$ and T_d have to be set.

Step 2

If a Filter $H_c(\Omega)$ is given, applying the relation $\Omega = \omega/T_d$ leads to the continuous-time filter specifications, where T_d is the design sampling interval. Then the filter has to be checked to fulfil the Specifications given in Step 1

Step 4

Steps for the transformation of $H_c(s)$ to $H(z)$

1. From $H_c(s)$ and $H_c(j\Omega)$, we determine $h_c(t)$
2. Obtain the digital sequence by $h(n) = T_d \cdot h_c(nT_d)$ where T_d is the design sampling interval
3. $H(z)$ is obtained from $h(n)$

2.6.3 The Butterworth filter

With Ω_c being the 3dB cut-off frequency

$$|H(e^{j\omega})|^2 = \frac{1}{1 + \left(\frac{\Omega}{\Omega_c}\right)^2} \quad (2.26)$$

2.6.4 Bilinear Transformation

The bilinear transformation is used to map the imaginary axis of the s -plane to the unit circle. Now let

$$s = \frac{2}{T_d} \left[\frac{1 - z^{-1}}{1 + z^{-1}} \right] \quad (2.27a)$$

which leads to

$$H(z) = H_c \left[\frac{2}{T_d} \left(\frac{1 - z^{-1}}{1 + z^{-1}} \right) \right] \quad (2.27b)$$

with $z = e^{j\omega}$:

$$s = \frac{2}{T_d} \left[\frac{1 - e^{-j\omega}}{1 + e^{-j\omega}} \right] = j \frac{2}{T_d} \tan(\omega/2) \quad (2.27c)$$

with $s = \sigma + j\Omega$ follows:

$$\Omega = \frac{2}{T_d} \tan(\omega/2) \text{ and } \sigma = 0 \quad (2.27d)$$

Remarks on the bilinear transformation

- The frequency deformation $\Omega = \frac{2}{T_d} \tan(\omega/2)$ comes to a deviation in the detailed shape of $H_c(j\Omega)$
- The delay time is also modified: $\tau_d = \tau_c [1 + ((\omega_c T_d)/2)^2]$
- The bilinear transformation has no aliasing problems.
- This transformation is the most used in practise

2.6.5 Implementation of IIR Filters

The output of the filter can be described as

$$y(n) = \sum_{k=1}^M a_k y(n-k) + \sum_{r=0}^{N-1} b_r x(n-r) \quad (2.28)$$

Direct Form I

A Signal flow graph can be seen at Figure 5.8 on page 47 in the DSP script.

$$H(z) = H_2(z)H_1(z) = \left(\frac{1}{\sum_{k=1}^M a_k z^{-k}} \right) \left(\sum_{r=0}^{N-1} b_r z^{-r} \right) \quad (2.29)$$

Direct Form II

The direct form II can change the order of $H_1(z)$ and $H_2(z)$. A Signal flow graph can be seen at Figure 5.9 on page 48 in the DSP script.

$$H_1(z)H_2(z) = H(z) = H_2(z)H_1(z) \quad (2.30)$$

Cascade Form

A Signal flow graph can be seen at Figure 5.10 on page 48 in the DSP script.

$$H(z) = \frac{\sum_{r=0}^{N-1} b_r z^{-r}}{1 - \sum_{k=1}^M a_k z^{-k}} = A \prod_k H_k(z) \quad (2.31a)$$

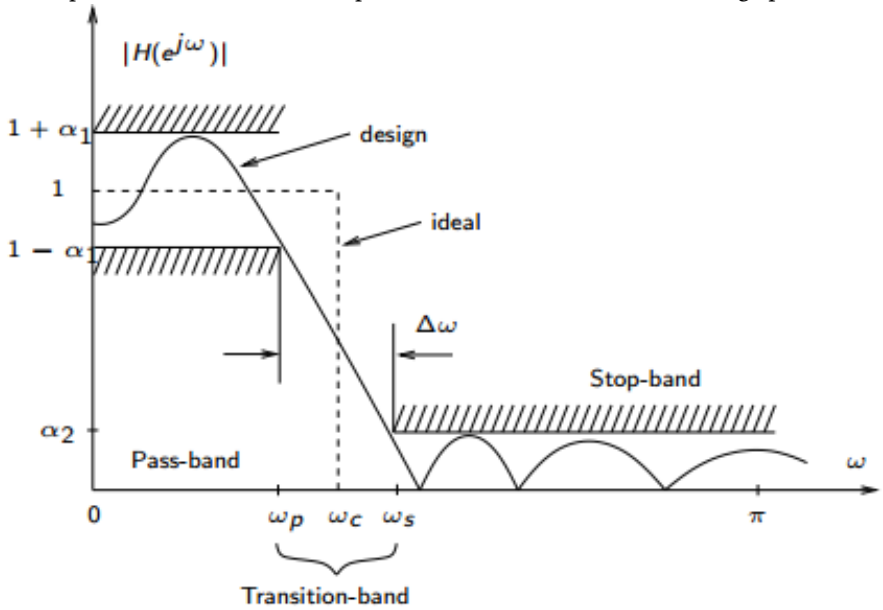
with

$$H_k(z) = \frac{1 + \beta_{1k} z^{-1} + \beta_{2k} z^{-2}}{1 - \alpha_{1k} z^{-1} - \alpha_{2k} z^{-2}} \quad (2.31b)$$

2.7 Filter Specifaion

Non-ideal Filters have one or more pass-bands(ω_p), transition-bands(between ω_p and ω_s) and stop-bands(ω_s). For the pass- and the stop- band, a tolerance α_i has

to be specified. Therefore a low-pass filter would have the following specification:



2.7.1 Ripple and Attenuation calculation

Given the pass-band attenuation ATT_p and the stop-band attenuation ATT_s

$$\alpha_1 = 1 - 10^{-ATT_p/20} \quad (2.32a)$$

$$\alpha_2 = 10^{-ATT_s/20} \quad (2.32b)$$

Given the pass-band ripple R_p and the stop-band ripple R_s

$$\alpha_1 = 10^{R_p/20} - 1 \quad (2.32c)$$

$$\alpha_2 = 10^{-R_s/20} \quad (2.32d)$$

3 Random Variables and Stochastic Processes

This is a revision of the Stochastic Signals and Systems course, which has an own Formulary which can be found at: <https://github.com/Tyde/stosigsysfs/blob/master/document.pdf?raw=true>

4 The Finite Fourier Transform

4.1 Definition

Let $x(0), \dots, x(N-1)$ be realisations of a stationary random process $X(n), n = 0, 1, 2, \dots, N-1$

$$X_N(e^{j\omega}) = \sum_{n=0}^{N-1} X(n)e^{-j\omega n}, \quad -\infty < \omega < \infty \quad (4.1)$$

and inverse:

$$X(n) = \frac{1}{2\pi} \int_{-\pi}^{\pi} X_N(e^{j\omega}) e^{j\omega n} d\omega, \quad n = 0, 1, \dots, N-1 \quad (4.2)$$

4.1.1 Properties

- **Periodicity** $X_N(e^{j(\omega+k2\pi)}) = X_N(e^{j\omega}) \quad \forall k \in \mathbb{N}$
- **Symmetry** $X_N(e^{-j\omega}) = X_N(e^{j\omega})^* \quad \forall X(n) \in \mathbb{R}$
- **Linearity** $\mathcal{F}\{aX(n) + bY(n)\} = aX_N(e^{j\omega}) + bY_N(e^{j\omega})$

4.2 Discrete Finite Fourier Transform

With $\omega_k = 2\pi k/N, k = 0, \dots, N-1$

$$X_N(e^{j\frac{2\pi k}{N}}) = \sum_{n=0}^{N-1} X(n)e^{-j2\pi kn/N}, \quad k = 0, 1, \dots, N-1 \quad (4.3)$$

4.3 Statistical Properties

4.3.1 White Gaussian Process

Let $X(0), \dots, X(N-1)$ be real valued random variables with $X(n) \sim \mathcal{N}(0, 1)$ and $N = 2^r$ with $r \in \mathbb{N}$ Then:

$$\Re\{X_N(e^{j2\pi k/N})\} = \sum_{n=0}^{N-1} X(n) \cos(2\pi kn/N) \quad (4.4a)$$

$$\Im\{X_N(e^{j2\pi k/N})\} = -\sum_{n=0}^{N-1} X(n) \sin(2\pi kn/N) \quad (4.4b)$$

The Mean and Variance can be determined to:

$$\begin{bmatrix} \Re\{X_N(e^{j2\pi k/N})\} \\ \Im\{X_N(e^{j2\pi k/N})\} \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \frac{N}{2} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}\right) \quad (4.4c)$$

4.3.2 Real Stationary Random Process

If the process has an arbitrary $\mu_x, c_{XX}(\kappa)$ and $C_{XX}(e^{j\omega})$ for $N \rightarrow \infty$ the asymptotic distribution is:

$$\begin{bmatrix} \Re\{X_N(e^{j\omega})\} \\ \Im\{X_N(e^{j\omega})\} \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \frac{N}{2} C_{XX}(e^{j\omega}) \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}\right) \quad \omega \in (0, \pi) \quad (4.5a)$$

For $\omega = 0$ and $\omega = \pi$ The Finite Fourier Transform is purely real:

$$\Re\{X_N(e^{j\omega})\} \sim \mathcal{N}(N\mu_x\delta(\omega), NC_{XX}(e^{j\omega})) \quad (4.5b)$$

For fixed frequencies $0 \leq \omega_{(1)} < \dots < \omega_{(M)} \leq \pi$ the random variables $X_N(e^{j\omega_{(1)}}), X_N(e^{j\omega_{(2)}}), \dots, X_N(e^{j\omega_{(M)}})$ are asymptotically for $N \rightarrow \infty$ **independently distributed**

4.4 Segmentation of the Finite Fourier Transform

Division of random process $X(n), n = 0, \dots, N-1$ into L segments of length M with $N = ML$ will yield a finite fourier transform for each segment l which has the same asymptotic distribution as for the non-segmented process

$$X_M(e^{j\omega}, l) = \sum_{n=0}^{M-1} X(n - (l-1)M) e^{-j\omega n}, \quad l = 1, \dots, L \quad (4.6)$$

The random variables $X_M(e^{j\omega}, l)$ are for $l = 1, \dots, L$ asymptotically as $N \rightarrow \infty$ independently distributed

4.5 Windowing of the process

Let $w(n) = 0$ for $n = 0, \dots, N-1$ be a window that is applied to the random process.

$$X_{n,\omega}(e^{j\omega}) = \sum_{n=0}^{N-1} w(n)X(n)e^{-j\omega n} \quad (4.7)$$

The window has the effect that the variance is multiplied by the factor $\sum_{n=0}^{N-1} w(n)^2$ and the mean at $\omega = 0$ is multiplied by the factor $\sum_{n=0}^{N-1} w(n)$

4.5.1 Power of the windowed process

The average power of $X(n)$ is defined by

$$P_{XX} = \lim_{N \rightarrow \infty} \frac{1}{N} \sum_{n=0}^{N-1} E[X(n)^2] = \lim_{N \rightarrow \infty} \frac{1}{2\pi} \int_{-\pi}^{\pi} \frac{1}{N} E[|X_N(e^{j\omega})|^2] d\omega \quad (4.8)$$

5 Digital Spectral Analysis

5.1 Consistency and Mean Square Error in terms of bias and variance

The MSE can be rewritten as follows:

$$\text{MSE}(\hat{\mu}_X) = \text{Var} [\hat{\mu}_X] + \text{bias}(\hat{\mu}_X)^2 \quad (5.1)$$

The Estimator $\hat{\mu}_X$ is called consistent if:

$$\lim_{N \rightarrow \infty} \text{MSE}(\hat{\mu}_X) = 0 \quad (5.2)$$

5.2 Mean Estimation

The mean of $X(0), \dots, X(N-1)$ which are each distributed as $\mathcal{N}(\mu_X, \sigma_X^2)$, can be estimated by:

$$\hat{\mu}_X = \frac{1}{N} \sum_{n=0}^{N-1} X(n) \quad (5.3)$$

5.3 The Periodogram

A candidate estimator for $C_{XX}(e^{j\omega})$ is the periodogram:

$$I_{XX}^N(e^{j\omega}) = \frac{1}{N} |X_N(e^{j\omega})|^2 = \frac{1}{N} \left| \sum_{n=0}^{N-1} X(n)e^{-j\omega n} \right|^2 \quad (5.4)$$

5.3.1 Distribution of the Periodogram

The periodogram for data values $X(N)$ is independently distributed as:

$$I_{XX}^N \sim \begin{cases} \frac{C_{XX}(e^{j\omega})}{2} \chi_2^2 & , \omega \neq \pi k \\ C_{XX}(e^{j\omega}) \chi_1^2 & , \omega = \pi k \end{cases} \quad (5.5)$$

5.3.2 Mean of the Periodogram

With the use of (7.1.2)

$$E [I_{XX}^N(e^{j\omega})] = \frac{|\Delta^N(e^{j\omega})|}{N} \oplus C_{XX}(e^{j\omega}) + \frac{|\Delta^N(e^{j\omega})|}{N} \cdot |\mu_x|^2 \quad (5.6a)$$

where

$$\Delta^N(e^{j\omega}) = \sum_{n=0}^{N-1} e^{-j\omega n} = e^{-j\omega \frac{N-1}{2}} \cdot \frac{\sin(\frac{\omega N}{2})}{\sin(\frac{\omega}{2})} \quad (5.6b)$$

Thus for a zero mean stationary process $X(n)$, $E [I_{XX}^N(e^{j\omega})]$ for $N \rightarrow \infty$

$$\lim_{N \rightarrow \infty} E [I_{XX}^N] = C_{XX}(e^{j\omega}) \quad \omega \neq 2k\pi \quad (5.7a)$$

$$\lim_{N \rightarrow \infty} E [I_{X-\mu_X, X-\mu_X}^N] = C_{XX}(e^{j\omega}) \quad \forall \omega \quad (5.7b)$$

5.3.3 Variance of the Periodogram

Let $X(n)$ be a real white Gaussian Process with σ^2 and $\omega, \lambda \neq 0$

$$\text{Var} [I_{XX}(e^{j\omega})] \approx C_{XX}(e^{j\omega})^2 \cdot \frac{1}{N^2} (|\Delta^N(e^{j2\omega})|^2 + N^2) \quad (5.8)$$

Therefore the Periodogram is not a consistent estimator

5.3.4 Averaging Periodograms (Barlett's method)

To improve the consistency of the Periodogram, it is possible to average the estimates of multiple independent measurements. With $X_l(n) = X(n + (l-1) \cdot M)$ and $n = 0, \dots, M-1$

$$I_{XX}^M(e^{j\omega}, l) = \frac{1}{M} \left| \sum_{n=0}^{M-1} X_l(n) e^{-j\omega n} \right|^2 \quad = 1, \dots, L \quad (5.9)$$

And estimate with:

$$\hat{C}_{XX}^B(e^{j\omega}) = \frac{1}{L} \sum_{l=1}^L I_{XX}^M(e^{j\omega}, l) \quad (5.10)$$

The variance of Barlett's estimator decreases when L increases

5.3.5 Welch's method

Welch's method is similar to Barlett's method but the data segments are multiplied by a window $w_M(n)$ of length M and the segments may overlap. With $X_l(n) = X(n + (l-1) \cdot D)$

$$\hat{C}_{XX}^W(e^{j\omega}) = \frac{1}{L} \sum_{l=1}^L I_{w_M, w_M}^M(e^{j\omega}, l) \quad (5.11a)$$

and

$$I_{w_M, w_M}^M(e^{j\omega}, l) = \frac{1}{MA} \left| \sum_{n=0}^{M-1} w_M(n) \cdot X_l(n) e^{-j\omega n} \right|^2 \quad (5.11b)$$

Where A is a factor to get an asymptotic unbiased estimation, which can be found using Parseval's theorem:

$$\frac{1}{2\pi} \int_{-\pi}^{\pi} |W_M(e^{j\lambda})|^2 d\lambda = \sum_{n=0}^{M-1} |w_M(n)|^2 = MA \quad (5.11c)$$

5.3.6 Smoothing the Periodogram

With $\omega_k \neq \omega_l$, thus $X_N(e^{j\omega_k})$ and $X_N(e^{j\omega_l})$ are asymptotically independent and $I_{XX}^N(e^{j\omega_k})$ and $I_{XX}^N(e^{j\omega_l})$ are also independent:

$$\hat{C}_{XX}^S(e^{j\omega}) = \frac{1}{2m+1} \sum_{k=-m}^m I_{XX}^N(e^{j2\pi(k(\omega)+k)/N}) \quad (5.12)$$

5.3.7 General Class of Spectral Estimates

With $A = \frac{1}{2m+1} \sum_{k=-m}^m W_k$ a general class of estimators can be defined analogously to the smoothed periodogram

$$\hat{C}_{XX}^{SW}(e^{j\omega}) = \frac{1}{(2m+1)A} \sum_{k=-m}^m W_k I_{XX}^N(e^{j2\pi(k(\omega)+k)/N}) \quad (5.13)$$

5.4 The Log-Spectrum

Estimating $10 \log C_{XX}(e^{j\omega})$ from $10 \log \hat{C}_{XX}(e^{j\omega})$ instead of the spectrum

5.5 The Blackman-Tuckey Method

This Method estimates the sample covariance function and windows it with $w_{2M-1}(\kappa)$

$$w_{2M-1}(\kappa) = \begin{cases} w_{2M-1}(-\kappa) & , \text{for } |\kappa| \leq M-1, \text{ with } M \ll N \\ 0 & , \text{otherwise} \end{cases} \quad (5.14a)$$

$$\hat{C}_{XX}^{BT}(e^{j\omega}) = \sum_{\kappa=-M+1}^{M-1} \hat{c}_{XX}(\kappa) \cdot w_{2M-1}(\kappa) \cdot e^{-j\omega\kappa} \quad (5.14b)$$

This is the same as

$$\hat{C}_{XX}^{BT}(e^{j\omega}) = \frac{1}{2\pi} \int_{-\pi}^{\pi} I_{X-\bar{X}, X-\bar{X}}^N(e^{j\lambda}) \cdot W_{2M-1}(e^{j(\omega-\lambda)}) d\lambda \quad (5.14c)$$

This has the following constraint for the window:

$$W_{2M-1}(e^{j\omega}) \geq 0 \quad \forall \omega \quad (5.14d)$$

The Blackman-Tukey estimator is unbiased for $N \rightarrow \infty$ and its variance tends to zero if the window function has finite energy.

5.6 Cross-Spectrum Estimation

5.6.1 The Cross-Periodogram

For $X(0), \dots, X(N-1), Y(0), \dots, Y(N-1)$ the objective is to estimate the cross-spectrum $C_{YX}(e^{j\omega})$ for $-\pi < \omega < \pi$

$$I_{YX}^N(e^{j\omega}) = \frac{1}{N} Y_N(e^{j\omega}) X_N(e^{j\omega})^* \quad (5.15)$$

This has the bias $C_{YX}(e^{j\omega})$ and the variance $C_{YY}(e^{j\omega}) C_{XX}(e^{j\omega})$

5.6.2 Segmented Cross-Periodogram

For different Segments $l = 1, \dots, L$ with length M

$$\hat{C}_{YX}^B(e^{j\omega}) = \frac{1}{L} \sum_{l=1}^L \frac{1}{M} Y_M(e^{j\omega}, l) X_M(e^{j\omega}, l)^* \quad (5.16a)$$

with

$$Y_N(e^{j\omega}, l) = \sum_{n=0}^{M-1} Y(n - (l-1)M) e^{j\omega n} \quad (5.16b)$$

$$X_N(e^{j\omega}, l) = \sum_{n=0}^{M-1} X(n - (l-1)M) e^{j\omega n} \quad (5.16c)$$

Now for $N \rightarrow \infty$ the bias is $C_{YX}(e^{j\omega})$ and the variance is $\frac{1}{L} C_{YY}(e^{j\omega}) C_{XX}(e^{j\omega})$

6 Parametric Spectrum Estimation

6.1 Auto-regressive (AR) Processes

With

$$C_{XX}(e^{j\omega}) = \frac{\sigma_Z^2}{|1 + \sum_{k=1}^p a_k e^{-k\omega}|^2} \quad (6.1)$$

The objective is to estimate the parameter a_1, \dots, a_p which will be used to estimate the spectrum $C_{XX}(e^{j\omega})$

6.1.1 Yule-Walker Equations

$$c_{XX}(l) + \sum_{k=1}^p a_k c_{XX}(l-k) = \begin{cases} \sigma_Z^2 & , l = 0 \\ 0 & , l = 1, \dots, p \end{cases} \quad (6.2)$$

Using $\hat{c}_{XX}(0), \dots, \hat{c}_{XX}(p)$ leads to a unique solution for a_1, \dots, a_p

6.1.2 extended Yule-Walker equations

$Z(n)$ and $V(n)$ are uncorrelated white noise processes with variances σ_Z^2 and σ_V^2 . With the difference equation of the system $Y(n) + aY(n-1) = Z(n) + V(n) + aV(n-1)$

$$c_{YY}(l) + \sum_{k=1}^p a_k c_{YY}(l-k) = \begin{cases} \sigma_Z^2 + \sigma_V^2 & , l = 0 \\ a_l \sigma_V^2 & , l = 1, \dots, p \\ 0 & , l > p \end{cases} \quad (6.3)$$

6.2 Moving Average (MA) Process

Consider a transversal filter $h(n)$ with input real-valued $Z(n)$ and real-valued output $X(n)$

$$X(n) = \sum_{k=0}^q h(k)Z(n-k) \quad (6.4)$$

If $Z(n)$ is a white noise process, $X(n)$ is a **Moving average (MA) process** with

$$C_{XX} = |H(e^{j\omega})|^2 C_{ZZ}(e^{j\omega}) = |H(e^{j\omega})|^2 \sigma_Z^2 \quad (6.5)$$

With $b(m) = \sigma_Z h(m)$ and $m = 0, \dots, q$ and $h(0) = 1$ we get

$$c_{XX}(l) = \sum_{m=0}^{q-|l|} b(m)b(m+|l|) \quad \text{for } 0 \leq |l| \leq q \quad (6.6)$$

$$\text{and} \quad (6.7)$$

$$C_{XX} = B(e^{j\omega})B(e^{-j\omega}) \quad (6.8)$$

6.2.1 Solving

1. substitute $e^{j\omega}$
2. Calculate $P(z) = z^q C_{XX}(z)$
3. Assign all roots z_i of $P(z)$ inside the unit circle to $B(z)$
 $B(z) = b(0) \prod_{i=1}^q (1 - z_i z^{-1})$ with $b(0) > 0$ and $|z_i| \leq 1$
4. Calculate $h(m) = b(m)/b(0)$ for $m = 1, \dots, q$
With $b(0)^2 = \sigma_Z^2 = \frac{c_{XX}(0)}{1 + \sum_{m=1}^q h(m)^2}$ and replacing $c_{XX}(l)$ with $\hat{c}_{XX}(l)$

The Spectrum can be obtained by the relationship

$$\hat{C}_{XX}(e^{j\omega}) = \left| \sum_{n=0}^q \hat{b}(n)e^{-j\omega n} \right|^2 \quad (6.9)$$

6.3 Auto-regressive Moving Average (ARMA) Process

The difference equation of an ARMA process, called $ARMA(p, q)$, is given by

$$X(n) + \sum_{k=1}^p a_k X(n-k) = Z(n) + \sum_{k=1}^q b_k z(n-k) \quad (6.10)$$

The modified Yule-Walker equations can be found:

$$c_{XX}(l) + \sum_{k=1}^p a_k c_{XX}(l-k) = \begin{cases} \sigma_z^2 \sum_{k=1}^q b_k h(k-l) & , l = 0, \dots, q \\ 0 & , l > q \end{cases} \quad (6.11)$$

To solve for a_1, \dots, a_p , the equations can be employed with $l = q+1, \dots, q+p$. Then to determine b_1, \dots, b_q , $l = 1, \dots, q$ are used with (6.2.1)

6.4 Model order selection

6.4.1 Akaike's Information Criterion (AIC)

$$AIC(m) = \log \sigma_{Z,m}^2 + m \frac{2}{N} \quad m = 1, \dots, M \quad (6.12)$$

6.4.2 Minimum Description Length (MDL)

$$MDL(m) = \log \sigma_{Z,m}^2 + m \frac{\log N}{N} \quad m = 1, \dots, M \quad (6.13)$$

7 Miscellaneous

7.1 Useful mathematical equations

7.1.1 Geometric series

$$\sum_{n=0}^{N-1} q^n = \frac{1-q^N}{1-q} \quad \text{for } |q| < 1 \quad (7.1)$$

7.1.2 Conversion from Geometric series to trigonometric fraction

Let $\frac{1-q^N}{1-q}$ be with $q = e^{-j\omega}$

$$\frac{1 - e^{-jN\omega}}{1 - e^{-j\omega}} = e^{-j\omega \frac{N-1}{2}} \frac{\sin\left(\frac{N}{2}\omega\right)}{\sin\left(\frac{\omega}{2}\right)} \quad (7.2)$$