System Identification

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Contents

1 System Identification

2 Definitions

Definition 1. *A system is said to be **time invariant** if the response to a certain input is not depending on absolute time.*

Definition 2. *A system is said to be **linear** if its output response to a linear combination of inputs is the same as the linear combination of the output responses of the individual inputs.*

Definition 3. *A system is said to be **causal** if the output at a certain time depends on the input up to that time only.*

Definition 4. *A process is said to be **stationary** if it does not depend on time.*

3 Frequency Domain Methods

3.1 Sampling Operation

$$\boxed{y(k) = y(t)|_{t=kT, k=0,1,2,\ldots}}$$ Sampling with period T

3.2 Fourier Series of Periodic Signals

$$\boxed{X(e^{j\omega_m}) = \sum_{k=0}^{M-1} x(k)e^{-j\omega_m k}}$$

$$\omega_m = \frac{2\pi m}{M} = \omega_0$$

Non-negative frequencies are $m = 0$ to $m = M/s$.
They correspond to: $\omega_m = 0, \frac{2\pi}{M}, \frac{4\pi}{M}, \ldots, \frac{2\pi(M/2-1)}{M}, \pi$.

M	number of samples	
$\omega_0 = \frac{2\pi}{M}$	fundamental frequency $(y(k))$	[rad]
T	sampling time	[s]
$\tau_p = MT$	period	[s]
$\omega_0 = \frac{2\pi}{\tau_p}$	fundamental frequency $(y(t))$	[rad s^{-1}]

$$0, \quad \underbrace{\frac{2\pi}{\tau_p}}_{\substack{\text{Fundamental} \\ \text{frequency}}}, \underbrace{2\left(\frac{2\pi}{\tau_p}\right), \ldots, \frac{M}{2}\left(\frac{2\pi}{\tau_p}\right)}_{\text{Harmonics}}$$

Definition 5. *The highest frequency $\omega_u = \omega_{M/2} = \frac{\pi}{T}$ is called the **Nyquist frequency**.*
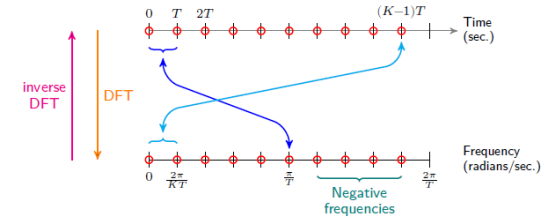

```
1  %Non negative frequency vector
2  omega = omega_n(N,'p0');
3  %Discrete Fourier Transform
4  fft(u); %Matlab
5  DFT(u); %Lecture
```

Note that the definition of the fft in the Matlab documentation does not describe the actual implementation perfectly. The index actually runs from 0 to $N-1$ as in the definition made in class.

4 Spectral Estimation
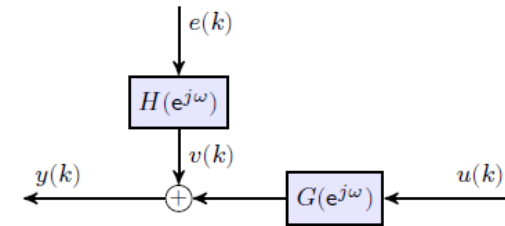
$$Y(j\omega) = G(j\omega)U(j\omega) \quad \text{Transfer function}$$

$$Y(e^{j\omega} = G(e^{j\omega}U(e^{j\omega}) \quad \text{Discrete time TF}$$

$$\frac{\omega_u}{2\pi} = \frac{r}{NT}$$

ω_u	input frequency	[rad s^{-1}]
N	calculation length	[ ]
T	experiment duration?	[s]
r	some integer	[ ]

$$u(k) = \alpha\cos(\omega_u k), \ k = 0,1,\ldots,K-1 \ \text{ with } K \geq N \quad \text{Input}$$

$$y(k) = \alpha\left|G(e^{j\omega_u})\right|\cos(\omega_u k + \theta(\omega_u)) + v(k) + \text{transient} \quad \text{Output}$$

where $\theta(\omega_u) = arg(G(e^{j\omega_u})$

Correlation functions:

$$I_c(N) = \frac{1}{N} \sum_{k=0}^{N-1} y(k) \cos(\omega_u k)$$

$$I_s(N) = \frac{1}{N} \sum_{k=0}^{N-1} y(k) \sin(\omega_u k)$$

To calculate those from the data:

$$I_c(N) = \frac{\alpha}{2} \left|G(e^{j\omega_u})\right| \cos(\theta(\omega_u) + \frac{\alpha}{2} \left|G(e^{j\omega_u})\right| \frac{1}{N} \sum_{k=0}^{N-1} \cos(2\omega_u k + \theta(\omega_u)) + \frac{1}{N} \sum_{k=0}^{N-1} v(k) \cos(\omega_u k)$$

If the noise, $v(k)$ is sufficiently uncorrelated then the variance satisfies,

$$\lim_{N \to \infty} \text{var} \left\{ \frac{1}{N} \sum_{k=0}^{N-1} v(k) \cos(\omega_u k) \right\} = 0$$

with a convergence rate of $1/N$.
Thus in the limit $N \to \infty$,

$$E\{I_c(N)\} \to \frac{\alpha}{2} \left|G(e^{j\omega_u})\right| \cos(\theta(\omega_u))$$

$$E\{I_s(N)\} \to -\frac{\alpha}{2} \left|G(e^{j\omega_u})\right| \sin(\theta(\omega_u))$$

and since $\lim_{N \to \infty} \text{var}\{I_c(N)\} = 0, \quad \lim_{N \to \infty} \text{var}\{I_s(N)\} = 0$
The transfer function can be estimated via:

$$\boxed{\hat{G}_N(e^{j\omega_u}) = \frac{I_c(N) - jI_s(N)}{\alpha/2}}$$

- Advantages
  - Energy is concentrated at the frequencies of interest.
  - Amplitude of $u(k)$ can easily be tuned as a function of frequency.
  - Easy to avoid saturation and tune signal/noise (S/N) ratio.

- Disadvantages
  - A large amount of data is required.
  - Significant amount of time required for experiments.
  - Some processes won't allow sinusoidal inputs.

5 FREQUENCY DOMAIN METHODS

$$x(k), \ k = -\infty, \ldots, \infty \quad \text{Discrete-time domain signal}$$

$$\boxed{X(e^{j\omega}) = \sum_{k=-\infty}^{\infty} x(k)e^{-j\omega k}} \quad \text{Fourier Transform}$$

- $X(e^{j\omega})$ is 2π periodic.

- If $\sum_{k=-\infty}^{\infty} |x(k)| < \infty$ then $X(e^{j\omega})$ converges.

$$\boxed{x(k) = \frac{1}{2\pi} \int_{-\pi}^{\pi} X(e^{j\omega})e^{j\omega k} d\omega} \quad \text{Inverse Fourier Transform}$$

where $k = -\infty, \ldots, \infty$

5.1 FINITE ENERGY SIGNAL
5.1.1 ENERGY SPECTRAL DENSITY (FINITE ENERGY SIGNAL)

If $x(k)$ is a finite energy signal,

$$||x(k)||_2^2 = \sum_{k=-\infty}^{\infty} |x(k)|^2 < \infty$$

$$\boxed{S_x(e^{j\omega}) = |X(e^{j\omega})|^2} \quad \text{Energy Spectral Density}$$

- For finite energy signals the energy spectral density is easily calculated, for signals of infinite length and thus infinite energy however, this is not possible. For that reason the **power** spectral density is calculated instead!

5.1.2 AUTOCORRELATION (FINITE ENERGY SIGNAL)

$$\boxed{R_x(\tau) = \sum_{k=-\infty}^{\infty} x(k)x(k-\tau), \quad \tau = -\infty, \ldots, 0, \ldots, \infty}$$

The spectral density is the Fourier Transform of the autocorrelation:

$$\sum_{\tau=-\infty}^{\infty} R_x(\tau)e^{-j\omega\tau} = S_x(e^{j\omega})$$

```
1  % autocorrelation for a non-periodic, finite energy signal
2  Correlation('finen',u); %Lecture
3  xcorr(u); %Matlab
4
5  % crosscorrelation for non-periodic, finite energy signals
6  Correlation('finen',u,y); %Lecture
7  xcorr(y,u); %Matlab
```

5.2 Discrete Periodic Signal

$$x(k) = x(k+M), \quad \forall \, k \in \{-\infty, \infty\} \quad \text{Periodic signal}$$

$$\omega_0 = \frac{2\pi}{M} \quad \text{Fundamental frequency}$$

- There are only M unique harmonics of the sinusoid $e^{j\omega_0}$.

- The non-negative harmonic frequencies are,

$$e^{jn\omega_0}, \ n = 0, 1, \ldots, M/2$$

```
1  u_period = sqrt(variance)*randn(N,1)+bias;
2  u = repmat(u_period,periods,1);
```

5.2.1 Discrete Fourier Series (Discrete Periodic Signal)

$$X(e^{j\omega_n}) = \sum_{k=0}^{N-1} x(k)e^{-j\omega_n k}, \ \text{where } \omega_n = \frac{2\pi n}{N} = n\omega_0$$

$$x(k) = \frac{1}{N}\sum_{k=0}^{N-1} X(e^{j\omega_n})e^{j\omega_n k} \quad \text{Inverse Transform}$$

5.2.2 Autocorrelation (Discrete Periodic Signal)

$$R_x(\tau) = \frac{1}{N}\sum_{k=0}^{N-1} x(k)x(k-\tau)$$

The Fourier transform of $R_x(\tau)$ is now defined as the **power spectral density**, since it is normalized with the signal length.

$$\phi_x(e^{j\omega_n}) = \sum_{\tau=0}^{N-1} R_x(\tau)e^{-j\omega_n \tau} = \frac{1}{N}|X(e^{j\omega_n})|^2$$

The energy in a single period is:

$$\sum_{k=0}^{N-1} |x(k)|^2 = \sum_{n=0}^{N-1} \phi_x(e^{j\omega_n})$$

```
1  Correlation('periodic',u);
```

5.2.3 Cross-Correlation (Discrete Periodic Signal)

$$R_{yu}(\tau) = \frac{1}{N}\sum_{k=0}^{N-1} y(k)u(k-\tau)$$

The Fourier transform of $R_{yu}(\tau)$ is now defined as the **cross-spectral density**.

$$\phi_{yu}(e^{j\omega_n}) = \sum_{\tau=0}^{N-1} R_{yu}(\tau)e^{-j\omega_n \tau} = \frac{1}{N}Y(e^{j\omega_n})U^*(e^{j\omega_n})$$

```
1  Correlation('periodic',u,y);
```

5.3 Random Signal

Normally distributed noise:

$$e(k) \in \mathcal{N}(0, \lambda) \Rightarrow \begin{cases} \mathbb{E}\left[e(k)\right] = 0 \ \text{(zero mean)} \\ \mathbb{E}\left[|e(k)|^2\right] = \lambda \ \text{(variance)} \end{cases}$$

The $e(k)$ are independent and identically distributed (i.i.d.).

```
1  standard_deviation = 2;
2  variance = standard_deviation^2;
3  bias = 0;
4  N = 1024;
5  u = randn(N,1)*standard_deviation + bias;
```

5.3.1 Autocovariance (Random Signal)

$$\begin{aligned} R_x(\tau) &= \mathbb{E}\left[x(k)x(k-\tau)\right] \\ &= \mathbb{E}\left[x(k)x^*(k-\tau)\right] \ \text{(in the complex case)} \\ &= \mathbb{E}\left[x(k)x^*(x-\tau)\right] \ \text{(in the multivariable case)} \end{aligned}$$

General (non-stationary, non-zero mean) case:

$$\begin{aligned} R_x(s,t) &= \mathbb{E}\left[(x(s) - \mathbb{E}\left[x\right])(x(t) - \mathbb{E}\left[E\right])\right] \\ &= \mathbb{E}\left[x(s)x(t)\right] \ \text{(if zero mean)} \\ &= R_x(s-t) \ \text{(if stationary)} \end{aligned}$$

Further properties are

- $R_x(-\tau) = R_x^*(\tau)$

- $R_x(0) \geq |R_x(\tau)| \ \forall \tau > 0$

```
1  xcorr(u)/N; %Lecture 3.37
```

5.3.2 Power Spectral Density (Random Signal)

$$\phi_x(e^{j\omega}) := \sum_{\tau=-\infty}^{\infty} R_x(\tau)e^{-j\omega\tau} \text{ where } \omega \in [-\pi, \pi)$$

For a zero-mean random signal:

$$\lim_{N\to\infty} \frac{1}{N} \sum_{k=0}^{N-1} |x(k)|^2 = \text{Var}\,(x(k)) = \frac{1}{2\pi} \int_{-\pi}^{\pi} \phi_x(e^{j\omega})d\omega$$

Further properties are

- $\phi_x(e^{j\omega}) \in \mathbb{R}$

- $\phi_x(e^{j\omega}) \geq 0 \ \forall \ \omega$

- $\phi_x(e^{j\omega}) = \phi_x(e^{-j\omega})$ for all real-valued $x(k)$

```
1  fft(xcorr(u)/N)) %Lecture 3.37 (?)
```

5.3.3 Cross-Covariance (Random Signal)

$$R_{yu}(\tau) = \mathbb{E}\left[(y(k) - \mathbb{E}\left[y(k)\right])(u(k-\tau) - \mathbb{E}\left[u(k)\right]\right]$$

For zero mean signals:

$$R_{yu}(\tau) = \mathbb{E}\left[y(k)u(k-\tau)\right]$$

Joint stationarity is required to make the definition dependent on τ only.
If $R_{yu}(\tau) = 0$ for all τ then $y(k)$ and $u(k)$ are uncorrelated.

```
1  xcorr(u,y)/N; %Lecture 3.37 (?)
```

5.3.4 Cross Power Spectral Density (Random Signal)

$$\phi_{yu}(e^{j\omega}) = \sum_{\tau=-\infty}^{\infty} R_{yu}(\tau)e^{-j\omega\tau}, \ \omega \in [-\pi, \pi)$$

The inverse is,

$$R_{yu}(\tau) = \frac{1}{2\pi} \int_{-\pi}^{\pi} \phi_{yu}(e^{j\omega})e^{j\omega\tau}d\omega$$

```
1  fft(xcorr(y,u)/N); %Lecture 3.37 (?)
```

5.4 Finite Length Signal

5.4.1 Discrete-Fourier Transform (Finite Length Signal)

$$X_N(e^{j\omega_n}) = \sum_{k=0}^{N-1} x(k)e^{-j\omega_n k}, \text{ where } \omega_n = \frac{2\pi n}{N}$$

The inverse DFT is

$$x(k) = \frac{1}{N} \sum_{n=0}^{N-1} X_N(e^{j\omega_n})e^{j\omega_n k}, \quad k = 0, \ldots, N-1$$

5.4.2 Periodogram (Finite Length Signal)
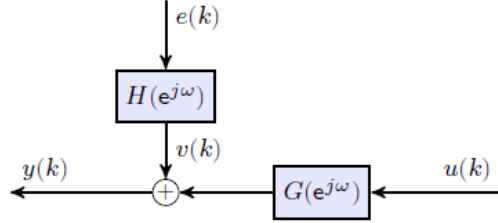
$$\frac{1}{N} \left| V_N(e^{j\omega}) \right|^2$$

An asymptotically unbiased estimator of the spectrum is

$$\lim_{N\to\infty} \mathbb{E}\left[\frac{1}{N}|V_N(e^{j\omega}|^2\right] = \phi_v(\omega)$$

This assumes that the autocorrelation decays quickly enough:

$$\lim_{N\to\infty} \frac{1}{N} \sum_{\tau=-N}^{N} |\tau R_v(\tau)| = 0$$

5

6 ETFE

Linear, time-invariant system, $g(l)$:

$$y(k) = \sum_{l=0}^{\infty} g(l)u(k-l) + v(k), \quad k = 0, 1, \ldots$$

Assumptions:

1. causal system: $g(l) = 0, \forall l < 0$

2. noise: $E\{v(k)\} = 0$, zero mean, stationary

Given $\{u(k), y(k)\}$ find an estimate $\hat{G}(e^{j\omega})$ such that it fits the $G(e^{j\omega})$.

$$\boxed{\text{Bias}(\hat{G})) G - E\{\hat{G}\}} \text{ Bias}$$

$$\boxed{\text{var}((\hat{G}) = E\left\{|\hat{G} - E\{\hat{G}\}|^2\right\}} \text{ Variance}$$

$$\boxed{\text{MSE}(\hat{G}) = E\left\{|G - \hat{G}|^2\right\}} \text{ Mean-square error}$$

Note that $\text{MSE}(\hat{G}) = \text{var}(\hat{G}) + \text{Bias}^2(\hat{G})$.

6.1 INPUT-OUTPUT RELATIONSHIP

For finite energy signals:

$$y(k) = \sum_{l=0}^{\infty} g(l)u(k-l) + v(k)$$

$$Y(e^{j\omega}) = G(e^{j\omega})U(e^{j\omega}) + V(e^{j\omega})$$

which in the idealized case leads to:

$$\boxed{\frac{Y(e^{j\omega})}{U(e^{j\omega})} = G(e^{j\omega}) + \frac{V(e^{j\omega})}{U(e^{j\omega})} \approx G(e^{j\omega})}$$

In reality we only have N samples:

$$\underbrace{Y_N(e^{j\omega_n})}_{\text{length-N DFT}} = \sum_{k=0}^{N-1} y(k)e^{-j\omega_n k} \approx \sum_{k=-\infty}^{\infty} y(k)e^{-j\omega_n k} = Y(e^{j\omega_n})$$

$$\underbrace{U_N(e^{j\omega_n})}_{\text{length-N DFT}} = \sum_{k=0}^{N-1} u(k)e^{-j\omega_n k} \approx \sum_{k=-\infty}^{\infty} u(k)e^{-j\omega_n k} = U(e^{j\omega_n})$$

$$\boxed{\hat{G}_N(e^{j\omega_n}) := \frac{Y_N(e^{j\omega_n})}{U_N(e^{j\omega_n})}} \text{ ETFE}$$

6.2 PERIODIC INPUT CASE

Period M inputs: $u(k) = u(k+M)$
If $sM = N$ for an integer s, the fourier series over N samples is equal to the real fourier series!

$$U_N(e^{j\omega_n}) = U(e^{j\omega_n}) \forall \omega_n = \frac{2\pi n}{N}, \ n = 0, \ldots, N-1$$

Then

$$Y_N(e^{j\omega_n}) = G(e^{j\omega_n})U_N(e^{j\omega_n}) + V_N(e^{j\omega_n})$$

$$\hat{G}_N(e^{j\omega_n}) = G(e^{j\omega_n}) + \frac{V_N(e^{j\omega_n})}{U_N(e^{j\omega_n})}$$

Bias:

$$E\{\hat{G}_N(e^{j\omega_n})\} = G(e^{j\omega_n}) + E\left\{\frac{V_N(e^{j\omega_n})}{U_N(e^{j\omega_n})}\right\} = G(e^{j\omega_n})$$

when assuming zero mean noise. Thus for periodic inputs with N being an integer number of periods, **the ETFE is unbiased**.
Variance:
For the unbiased case:

$$E\left\{|\hat{G}_N(e^{j\omega_n}) - G(e^{j\omega_n})|^2\right\} = \frac{\phi_v(e^{j\omega_n}) + \frac{2}{N}c}{\frac{1}{N}|U_N(e^{j\omega_n})|^2}$$

where $|c| \leq C = \sum_{\tau=1}^{\infty} |\tau R_v(\tau)|$ is assumed to be finite.
For estimates at different frequencies ($\omega_n \neq \omega_i$):

$$E\left\{(\hat{G}_N(e^{j\omega_n}) - G(e^{j\omega_n}))(\hat{G}_N(e^{-j\omega_i}) - G(e^{-j\omega_i}))\right\} = 0$$

Transient responses:
Initial transient corrupts the measurement

$$y(k) = G(u_{periodic}(k)W_{[0,N-1]}(k)) + v(k)$$

with the window function:

$$W_{[0,N-1]}(k) = \begin{cases} 1 & \text{if } 0 \leq 0 < N \\ 0 & \text{otherwise} \end{cases}$$

For all outputs up to time $k = N - 1$

$$y(k) = Gu_{periodic}(k) - \underbrace{G(u_{periodic}W_{(-\infty,-1)})}_{r(k)} + v(k)$$

$$Y_N(e^{j\omega_n}) = G(e^{j\omega_n})U_N(e^{j\omega_n}) + R_N(e^{j\omega_n}) + V_N(e^{j\omega_n})$$

The input in negative time, which is present in a ideal periodic input, and missing in a real periodic input, has an influence on positive time, which is described by $r(k)$.

When using a periodic signal multiple times the resulting DFT does not contain more information, since in a periodic signal there are only a certain number of frequencies contained, but the energy in those frequencies increases!

Transient bias error:

$$\hat{G}(e^{j\omega_n}) = \frac{Y_N(e^{j\omega_n})}{U_N(e^{j\omega_n})} = G(e^{j\omega_n}) + \frac{R_N(e^{j\omega_n})}{U_N(e^{j\omega_n})} + \frac{V_N(e^{j\omega_n})}{U_N(e^{j\omega_n})}$$

For periodic $u(k)$
As $N = mM, m \to \infty$

$$|U_N(e^{j\omega_n})| = m|U_M(e^{j\omega_n})|$$

For random $u(k)$
As $N \to \infty$

$$E\{|U_N(e^{j\omega_n})|\} \to \sqrt{N}\sqrt{\phi_u(e^{j\omega_n})}$$

Thus

$$\left|\frac{R_N(e^{j\omega_n})}{U_N(e^{j\omega_n})}\right| \to 0 \text{ with rate } \begin{cases} \frac{1}{N} & \text{for periodic input} \\ \frac{1}{\sqrt{N}} & \text{for random inputs} \end{cases}$$

A fix for getting rid of the influence of the transient response: Get rid of the first period.

```
1   r = 4;
2   N_split = N/r;
3   u_re = reshape(u(N_split+1:end),N_split,[]);
4   y_re = reshape(y(N_split+1:end),N_split,[]);
5
6   U_re = fft(u_re);
7   Y_re = fft(y_re);
8
9   G_re = Y_re./U_re;
10
11  G_avg = mean(G_re,2);
```

6.3 Spectral Transformations

If $v(k) = 0$

$$\phi_y(e^{j\omega_n}) = G(e^{j\omega_n})\phi_u(e^{j\omega_n})G^T(e^{j\omega_n})$$

where $G^T(e^{j\omega_n})$ is the complex conjugate of $G(e^{j\omega_n})$.
If $v(k) \neq 0$ and uncorrelated

$$\phi_y(e^{j\omega_n}) = |G(e^{j\omega_n})|^2\phi_u(e^{j\omega_n}) + |H(e^{j\omega_n})|^2$$

But this approach has no more phase information. For that reason use the cross spectrum:

$$\phi_{yu}(e^{j\omega_n}) = G(e^{j\omega_n})\phi_u(e^{j\omega_n}) + \phi_{uv}(e^{j\omega_n}) = G(e^{j\omega_n})\phi_u(e^{j\omega_n})$$

if $u(k)$ and $v(k)$ are uncorrelated.

$$\boxed{\hat{G}(e^{j\omega}) = \frac{\hat{\phi}_{yu}(e^{j\omega_n})}{\hat{\phi}_u(e^{j\omega_n})}} \text{ Spectral estimation methods}$$

where

$$\phi_y(e^{j\omega_n}) = |G(e^{j\omega_n})|^2\phi_u(e^{j\omega_n}) + \phi_v(e^{j\omega_n})$$

$$\phi_{yu}(e^{j\omega_n}) = G(e^{j\omega_n})\phi_u(e^{j\omega_n})$$

6.4 Approaches to spectral estimation

6.4.1 Spectral estimation (Periodogram)

The periodogram is an asymptotically unbiased estimator of the spectrum given
$$\lim_{n \to \infty} \frac{1}{N}\sum_{\tau=-N}^{N} |\tau R_v(\tau)| = 0$$

$$\frac{1}{N}|V_N(e^{j\omega_n})|^2 \quad \text{Periodogram}$$

$$\boxed{\lim_{N \to \infty} E\left\{\frac{1}{N}|V_N(e^{j\omega_n})|^2\right\} = \phi_v(e^{j\omega_n})}$$

which is under the assumption

$$\lim_{N \to \infty} \frac{1}{N}\sum_{\tau=-N}^{N} |\tau R_v(\tau)| = 0$$

6.4.2 Spectral estimation (via covariances)

The autocovariance of the noise for stochastic $v(k)$ is described as:

$$\hat{R}_v(\tau) = \begin{cases} \frac{1}{N-|\tau|} \sum\limits_{k=\tau}^{N_1} v(k)v(k-\tau), & \text{for } \tau \geq 0 \\ \frac{1}{N-|\tau|} \sum\limits_{k=0}^{N+\tau-1} v(k)v(k-\tau), & \text{for } \tau < 0 \end{cases}$$

This is an unbiased estimator of $R_v(\tau)$: $\mathrm{E}\left\{\hat{R}_v(\tau)\right\} = R_v(\tau)$

$$\boxed{\hat{\phi}_v(e^{j\omega_n}) = \sum_{\tau=-N+1}^{N-1} \hat{R}_v(\tau)e^{-j\omega\tau}}$$

```
1  xcorr(a-mean(a))-xcov(a) == 0 %true
```

The functions above both calculate the zero-mean shifted autocorrelation of a signal which is **not** equivalent to the autocovariance of the signal! They lack the normalization by $N-|\tau|$!

```
1  Covariance('zero-mean',a);
2  Covariance('zero-mean',a,b);
```

6.4.3 Spectral estimation (periodic signals)

Periodic signal $x(k)$ with period M, $N = mM$ for some integer m

$$R_x(\tau) = \frac{1}{M} \sum_{k=0}^{M-1} x(k)x(k-\tau)$$

The power spectral density can be calculated and is equal to the periodogram:

$$\boxed{\phi_x(e^{j\omega_n}) = \sum_{\tau=0}^{M-1} R_x(\tau)e^{-j\omega_n\tau} = \frac{1}{M}\left|X_M(e^{j\omega_n})\right|^2}$$

```
1  Ru = Correlation('periodic',u);
```

6.4.4 Spectral estimation (more general case)

Alternative autocorrelation estimate:

$$\hat{R}_x(\tau) = \begin{cases} \frac{1}{N} \sum\limits_{k=\tau}^{N-1} x(k)x(k-\tau), & \text{for } \tau \geq 0 \\ \frac{1}{N} \sum\limits_{k=0}^{N+\tau-1} x(k)x(k-\tau), & \text{for } \tau < 0 \end{cases}$$

Periodic $x(k)$: unbiased (exact) if $N = mM$

Random $x(k)$ biased $\mathrm{E}\left\{\hat{R}_x(\tau)\right\} = \frac{N-|\tau|}{N} R_x(\tau)$.
asymptotically biased as $N \to \infty, \tau/N \to 0$

```
1  Ru = xcorr(u)/N;
```

- The bias when estimating R_x for a random signal has the form a triangular weighting across τ. A scaling of the signal would remove the bias, which is effectively done by the spectral estimation for via covariances 6.4.2.

7 Averaging and Smoothing

Multiple experiments $u_r(k), y_r(k), r = 1\ldots,R, k = 0,\ldots,K-1$

$$\hat{G}(e^{j\omega_n}) = \sum_{r=1}^{R} \alpha_r \hat{G}_r(e^{j\omega_n})$$

where $\sum\limits_{r=1}^{G} \alpha_r = 1$ and for calculating the average $\alpha_r = \frac{1}{R}$.

The averaging can be optimized by selecting α_r such that the variance $\sigma_r^2(e^{j\omega_n})$ is minimized.

$$\mathrm{Var}\left(\hat{G}(e^{j\omega_n})\right) = \mathrm{Var}\left(\sum_{r=1}^{R} \alpha_r(e^{j\omega_n})\hat{G}_r(e^{j\omega_n})\right) = \sum_{r=1}^{R} \alpha_r^2 \sigma_r^2(e^{j\omega_n})$$

This is minimized by

$$\boxed{\alpha_r(e^{j\omega_n}) = \frac{1/\sigma_r^2(e^{j\omega_n})}{\sum\limits_{r=1}^{T} 1/\sigma_r^2(e^{j\omega_n})}}$$

Thus the signal is weighted inversely proportional to the variance.

Thus if $\text{Var}\left(\hat{G}_r(e^{j\omega_n})\right) = \frac{\phi_v(e^{j\omega_n})}{\frac{1}{N}|U_r(e^{j\omega_n})|^2}$ then $\alpha_r(e^{j\omega_n}) = \frac{|U_r(e^{j\omega_n})|^2}{\frac{R}{\sum\limits_{r=1}} |U_r(e^{j\omega_n})|^2}$.

The best result is obtained if the input is the same for all r, which will lead to a reduction of the variance as follows:

$$\text{Var}\left(\hat{G}(e^{j\omega_n})\right) = \frac{\text{Var}\left(\hat{G}_r(e^{j\omega_n})\right)}{R}$$

Biased estimates will reduce the improvement in variance.

- Since we are adding complex numbers the magnitude of the average is not equal to the average of the magnitudes r_i.

7.1 Bias-variance trade-offs in data record splitting

Divide a data record into smaller parts for averaging:

$$\{u(k), y(k)\}, k = 0, \ldots, K-1$$

Choose R records and calculation length N, such that $NR \leq K$:

$$u_r(n) = u(rN + n)$$

And average the resulting estimates:

$$\boxed{\hat{G}(e^{j\omega_n}) = \frac{1}{R}\sum_{r=0}^{R-1} \hat{G}_r(e^{j\omega_n}) = \frac{1}{R}\sum_{r=0}^{R-1} \frac{\hat{Y}_r(e^{j\omega_n})}{\hat{U}_r(e^{j\omega_n})}}$$

As R increases:

- The number of points calculated, N decreases.

- The variance decreases (by up to $1/R$).

- The bias increases (due to non-periodicity transients).

Mean-square error

- Transient bias grows linearly with the number of data splits.

- Variance decays with a rate of up to $1/(\text{number of averages})$.

What if there is no option of running periodic input experiments? $\rightarrow$ exploit the assumed smoothness of the underlying system.

7.2 Smoothing the ETFE

Assume the true system to be close to constant for a range of frequencies: $G(e^{j\omega_{n+r}}) \approx G(e^{j\omega_n})$ for $r = 0, \pm 1, \ldots, \pm r$.

The minimum variance smoothed estimate is:

$$\tilde{G}_N(e^{j\omega_n}) = \frac{\sum\limits_{r=-R}^{R} \alpha_r \hat{G}_N(e^{j\omega_{n+r}})}{\sum\limits_{r=-R}^{R} \alpha_r}, \qquad \alpha_r = \frac{\frac{1}{N}|U_N(e^{j\omega_{r+n}})|^2}{\phi_v(e^{j\omega_{n+r}})}$$

The summation above can then be approximated by an integral:

$$\approx \frac{\int_{\omega_{n-r}}^{\omega_{n+r}} \alpha(e^{j\zeta})\hat{G}_N(e^{j\zeta})d\zeta}{\int_{\omega_{n-r}}^{\omega_{n+r}} \alpha(e^{j\zeta})d\zeta}, \qquad \text{with } \alpha(e^{j\zeta}) = \frac{\frac{1}{N}|U_N(e^{j\zeta})|^2}{\phi_v(e^{j\zeta})}$$

Which can be reformulated using a smoothing window:

$$\tilde{G}_N(e^{j\omega_n}) = \frac{\frac{1}{2\pi}\int_{-\pi}^{\pi} W_\gamma(e^{j(\zeta-\omega_n)})\alpha(e^{j\zeta})\hat{G}_N(e^{j\zeta})d\zeta}{\frac{1}{2\pi}\int_{-\pi}^{\pi} W_\gamma(e^{j(\zeta-\omega_n)})\alpha(e^{j\zeta})d\zeta} \qquad \text{with } \alpha(e^{j\zeta}) = \frac{\frac{1}{N}|U_N(e^{j\zeta})|^2}{\phi_v(e^{j\zeta})}$$

7.2.1 Assumptions on $\phi_v(e^{j\omega})$

Assume $\phi_v(e^{j\omega})$ is also a smooth function of frequency.

$$\frac{1}{2\pi}\int_{-\pi}^{\pi} W_\gamma(e^{j(\zeta-\omega_n)})\left|\frac{1}{\phi_v(e^{j\zeta})} - \frac{1}{\phi(e^{j\omega_n})}\right| d\zeta \approx 0$$

Then use,

$$\alpha(e^{j\zeta}) = \frac{\frac{1}{N}|U_N(e^{j\zeta})|^2}{\phi_v(e^{j\omega_n})}$$

to get

$$\boxed{\tilde{G}_N(e^{j\omega_n}) = \frac{\frac{1}{2\pi}\int_{-pi}^{\pi} W_\gamma(e^{-j(\zeta-\omega_n)})\frac{1}{N}|U_N(e^{j\zeta})|^2\hat{G}_N(e^{j\zeta})d\zeta}{\frac{1}{2\pi}\int_{-\pi}^{\pi} W_\gamma(e^{j(\zeta-\omega_n)})\frac{1}{N}|U_N(e^{j\zeta})^2 d\zeta}}$$

The wider the frequency window (decreasing γ)

- the more adjacent frequencies included in the smoothness estimate.

- the smoother the result.

- the lower the noise induced variance.

- the higher the bias.

$$W_\gamma(e^{j\omega}) = \frac{1}{\gamma}\left(\frac{\sin\gamma\omega/2}{\sin\omega/2}\right)^2 \text{ Bartlett}$$

$$W_\gamma(e^{j\omega}) = \frac{1}{2}D_\gamma(\omega) + \frac{1}{4}D_\gamma(\omega - \pi/\gamma) + \frac{1}{4}D_\gamma(\omega + \pi/\gamma) \text{ Hann}$$

where

$$D_\gamma(\omega) = \frac{\sin\omega(\gamma + 0.5)}{\sin\omega/2}$$

Properties of window functions:

- $\frac{1}{2\pi}\int_{-\pi}^{\pi} W_\gamma(e^{j\zeta})d\zeta = 1$

- $\int_{-\pi}^{\pi} \zeta W_\gamma(e^{j\zeta})d\zeta = 0$

- $M(\gamma) := \int_{-\pi}^{\pi} \zeta^2 W_\gamma(e^{j\zeta})d\zeta$

- $\bar{W}(\gamma) := 2\pi\int_{-\pi}^{\pi} W_\gamma^2(e^{j\zeta})d\zeta$

Bartlett $M(\gamma) = \frac{2.78}{\gamma}$, $\bar{W}(\gamma) \approx 0.67\gamma$ (for $\gamma > 5$)

Hamming $M(\gamma) = \frac{\pi^2}{2\gamma^2}$, $\bar{W}(\gamma) \approx 0.75\gamma$ (for $\gamma > 5$)

- $M(\gamma)$ gives an idea of the bias effect.

- $\bar{W}(\gamma)$ gives an idea of the variance effect.

$$\text{E}\left\{\tilde{G}(e^{j\omega_n}) - \text{E}\left\{G(e^{j\omega_n})\right\}\right\} = \text{E}\left\{\tilde{G}(e^{j\omega_n}) - G(e^{j\omega_n})\right\} =$$

$$M(\gamma)\left(\frac{1}{2}\underbrace{G''(e^{j\omega_n})}_{\text{curvature}} + \underbrace{G'(e^{j\omega_n})}_{\text{slope}}\frac{\phi_u'(e^{j\omega_n})}{\phi_u(e^{j\omega_n})}\right) + H.O.T.$$

Increasing γ

- makes the frequency window smaller.

- averages over fewer frequency values.

- makes $M(\gamma)$ smaller

- reduces the bias of the smoothed estimate $\tilde{G}(e^{j\omega_n})$

$$\text{E}\left\{(\tilde{G}(e^{j\omega_n}) - \text{E}\left\{\tilde{G}(e^{j\omega_n})\right\})^2\right\} = \frac{1}{N}\bar{W}(\gamma)\frac{\phi_v(e^{j\omega_n})}{\phi_u(e^{j\omega_n})} + H.O.T.$$

Increasing γ

- makes the frequency window narrower.

- averages over fewer frequency values.

- makes $\bar{W}_\gamma$ larger.

- increases the variance of the smoothed estimate $\tilde{G}(e^{j\omega_n})$.

$$\text{E}\left\{|\tilde{G}(e^{j\omega_n}) - G(e^{j\omega_n})|^2\right\} \approx M^2(\gamma)|F(e^{j\omega_n})|^2 + \frac{1}{N}\bar{W}(\gamma)\frac{\phi_v(e^{j\omega_n})}{\phi_u(e^{j\omega_n})}$$

where

$$F(e^{j\omega_n}) = \frac{1}{2}G''(e^{j\omega_n}) + G'(e^{j\omega_n})\frac{\phi_u'(e^{j\omega_n})}{\phi_u(e^{j\omega_n})}$$

If $M(\gamma) = M/\gamma^2$ and $\bar{W}(\gamma) = \bar{W}\gamma$ then MSE is minised by:

$$\gamma_{optimal} = \left(\frac{4M^2|F(e^{j\omega_n})|^2\phi_u(e^{j\omega_n})}{\bar{W}\phi_v(e^{j\omega_n})}\right)^{1/5} N^{1/5}$$

and

$$\text{MSE at } \gamma_{optimal} \approx CN^{-4/5}$$

8 Windowing and Input Signals

$$\phi_{yu}(e^{j\omega}) = G(e^{j\omega})\phi_u(e^{j\omega})$$

$$\hat{G}(e^{j\omega_n}) = \frac{\hat{\phi}_{yu}(e^{j\omega_n})}{\hat{\phi}_u(e^{j\omega_n})}$$

Recall that the smoothed ETFE is:

$$\tilde{G}_N(e^{j\omega_n}) = \frac{\frac{1}{2\pi}\int_{-\pi}^{\pi} W_\gamma(e^{j(\zeta-\omega_n)})\frac{1}{N}|U_N(e^{j\zeta})|^2\hat{G}_N(e^{j\zeta})d\zeta}{\frac{1}{2\pi}\int_{-\pi}^{\pi} W_\gamma(e^{j(\zeta-\omega_n)})\frac{1}{N}|U_n(e^{j\zeta})|^2 d\zeta}$$

The denominator term approaches $\frac{1}{2\pi}\int_{-\pi}^{\pi} W_\gamma(e^{j(\zeta-\omega_n)})\phi(e^{j\omega_n})d\zeta$ as $N \to \infty$.

If in addition $W_\gamma(e^{j\omega})$ is concentrated around $\zeta = 0$ (i.e. $\gamma/N \to 0$) then the denominator term approaches $\phi_u(e^{j\omega_n})$ as $N \to \infty$.

This motivates the smoothed spectral estimate:

$$\tilde{\phi}_u(e^{j\omega_n}) = \frac{1}{2\pi}\int_{-\pi}^{\pi} W_\gamma(e^{j(\zeta-\omega_n)})\frac{1}{N}|U_N(e^{j\omega})|^2 d\zeta$$

Similarly the numerator approaches ϕ_{yu} as $N \to \infty$:

$$\tilde{\phi}_{yu}(e^{j\omega_n}) = \frac{1}{2\pi}\int_{-\pi}^{\pi} W_\gamma(e^{j(\zeta-\omega_n)})\frac{1}{N}|U_N(e^{j\omega})|^2 \hat{G}_N(e^{j\omega}) d\zeta$$

For this reason the smoothed ETFE is equal to the smoothed spectral estimate for $N \to \infty$.

8.1 Frequency domain smoothing in matlab

```matlab
gamma = 80;
U = fft(u); Y = fft(y);
G_est = Y./U;
G_est_smooth = G_est*0;

[om,Wg] = WfHann(g,N);
%shift to start at zero
zidx = find(om == 0);
omega = [om(zidx:N);om(1:zidx-1)];
Wg = [Wg(zidx:N) Wg(1:zidx-1)];
%variance weighting
a = U.*conj(U);
```

```matlab
for wn = 1:N
  %reset normalization
  Wnorm = 0;
    for xi = 1:N
      %wrap window index
        widx = mod(xi-wn,N)+1;
        G_est_smooth(wn) = G_est_smooth(wn) +...
            Wg(widx)*G_est(xi)*a(xi);
        Wnorm = Wnorm + Wg(widx)*a(xi);
    end
    %weigh normalisation
    G_est_smooth(wn) = G_est_smooth(wn)/Wnorm;
end
```

8.2 Time domain windows

Define, via the inverse Fourier transform a time domain window:

$$\omega_\gamma(\tau) = \frac{1}{2\pi}\int_{-\pi}^{\pi} W_\gamma(e^{j\omega})e^{j\zeta\tau} d\zeta$$

Then the smoothed input spectral estimate $\tilde{\phi}_u(e^{j\omega_n})$ is:

$$\frac{1}{2\pi}\int_{-\pi}^{\pi} W_\gamma(e^{j(\zeta-\omega_n)})\frac{1}{N}|U_N(e^{j\omega})|^2 d\zeta \approx \sum_{\tau-\infty}^{\infty} \omega_\gamma(\tau)\hat{R}_u(\tau)e^{-j\tau\omega_n}$$

where

$$\omega_\gamma = \begin{cases} 0 & \text{for } \tau < -\gamma \\ > 0 & \text{for } -\gamma \leq \tau \leq \gamma \\ 0 & \text{for } \tau > \gamma \end{cases}$$

where often $\gamma << N$, which enables the faster calculated redefinition:

$$\frac{1}{2\pi}\int_{-\pi}^{\pi} W_\gamma(e^{j(\zeta-\omega_n)})\frac{1}{N}|U_N(e^{j\omega})|^2 d\zeta \approx \sum_{\tau-\gamma}^{\gamma} \omega_\gamma(\tau)\hat{R}_u(\tau)e^{-j\tau\omega_n}$$

The cross spectral estimate can also be formulated as a convolution in the frequency domain which leads to the analogous formulation to the spectral estimate of u:

$$\tilde{\phi}_u(e^{j\omega_n}) = \sum_{\tau=-\gamma}^{\gamma} \omega_\gamma(\tau)\hat{R}_u(\tau)e^{-j\tau\omega_n}$$

$$\tilde{\phi}_{yu}(e^{j\omega_n}) = \sum_{\tau=-\gamma}^{\gamma} \omega_\gamma(\tau)\hat{R}_{yu}(\tau)e^{-j\tau\omega_n}$$

8.2.1 Time domain smoothing in matlab

```matlab
gamma = 80;
[~,Wg] = WtHann(gamma,N);
R_u = xcorr(u,N/2)/N; %Lecture 3.37
R_yu = xcorr(y,u,N/2)/N;

omega = Omega_n(N);
phi_u = zeros(size(omega));
phi_yu = zeros(size(omega));

tau = -g:g;
ind = tau+N/2;
for i = 1:N
%Lecture 5.9 and 5.11
    phi_u(i) = sum(Wg(tau+N/2).*R_u(ind).*exp(-1j.*tau.'.*
        omega(i)));
    phi_yu(i) = sum(Wg(tau+N/2).*R_yu(ind).*exp(-1j*tau.'.*
        omega(i)));
end
G_est_smooth = phi_yu./phi_u;
```

8.2.2 WINDOW CHARACTERISTICS

Decreasing γ: narrower $\omega_\gamma(\tau)$, wider $W_\gamma(e^{j\omega})$

- the more frequencies, $\hat{G}(e^{j\omega_n})$ included in the smoothing.

- the fewer $\hat{R}(\tau)$ estimates included in the smoothing.

- the smoother the result.

- the lower the noise induced variance.
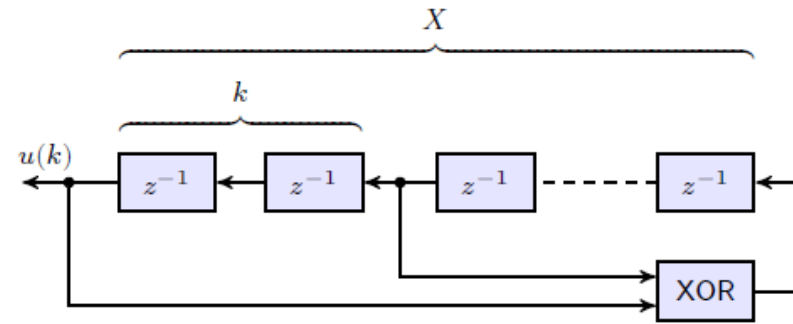
- the **higher the bias**.

8.3 INPUT SIGNALS

- Steps

- Doublet

- Sinusiods, Chirpts, Multi-Sines

- Filtered white noise

- Pseudo-Random Binary Signals (PRBS)

8.3.1 PRBS

$$u(k) = a \text{ or } -a$$

Shift-register generation

X	k
3	1 or 2
4	1 or 3
5	2 or 3
6	1 or 5
7	1 or 6
8	—
9	4 or 5
10	3 or 7

Periodicity

Periodic with period equal to at most $M = 2^X - 1$.

$$R_u(\tau) = \frac{1}{N} \sum_{k=0}^{N-1} u(k)u(k-\tau) = \begin{cases} a^2 & \text{if } \tau = 0 \\ \frac{-a^2}{2^X-1} & \text{if } \tau \neq 0 \end{cases}$$

Definition 6. ***Run length*** *defines how long the signal stays high.*

The run length distribution of $u(k)$ is then:

1/2 runs of length 1

1/4 runs of length 2

1/8 runs of length 3

$\vdots$

Other properties:

- Equal energy at all frequencies.

- The maximum period of a PRBS signal can be found based on the discrete time dynamic system that generates the signal:

$$A = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \quad C \qquad = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 2\gamma \end{bmatrix}$$

$$z = Ax(k)$$
$$x(k+1) = \mathrm{mod}_2(z(k))$$
$$y = Cx(k) - \gamma$$

where γ is the amplitude of the signal.

Now the maximum length period result from the idea that $x(k)$ and therefore the output $y(k)$ can only change so many times until it reaches a state it has already held before. From that point on, since the system is first order, the signal repeats. Thus in the longest case, all possible values contained in x are taken exactly once. Thus the maximum periodic length is equal to the number of possible binary numbers with 6 bits, where 6 is the order of the PRBS signal.

$$\boxed{2^6 - 1}$$ Maximum Length Period

8.3.2 PRBS in Matlab

```matlab
signal_order = 8;
singal_length = 2.^signal_order -1;
u = idinput(signal_length,'PRBS');
```

- Note that `idinput` only allows the choice of the total length of the signal and derives the fitting signal order such that the signal is at least of that chosen length. A warning is made if the chosen signal length is not equivalent to the run length.

8.3.3 Multi-sinusoidal signals

$$u(k) = \sum_{s=1}^{S} \sqrt{2\alpha_s} \cos(\omega_s kT + \phi_s)$$

where T is the sampling period, $\omega_s = \frac{2\pi}{T_P}$, $\frac{T_P}{T} = N$, $S \leq \frac{N}{2}$.

Choose N to be a power of 2 for efficient FFT calculations.

$$\sum_{s=1}^{S} \alpha_s = 1 \quad \text{Total signal power}$$

Schroeder phasing
Select the phases ϕ_s such that the minimize the peak amplitude:

$$\phi_s = 2\pi \sum_{j=1}^{s} j\alpha_s.$$

for equal power in each sinusoids:

$$\alpha_s = 1/S \text{ and } \phi_s = \frac{\pi(s^2+s)}{S}$$

9 Residual Spectra, Coherency, Aperiodicty, Offsets and Drifts

9.1 Residual Spectrum
9.1.1 Estimating $\phi_v(e^{j\omega_n})$

$$v(k) = y(k) - G(e^{j\omega})u(k)$$

$$\boxed{\tilde{\phi}_v(e^{j\omega_n}) \approx \frac{1}{N}\frac{1}{2\pi}\int_{-\pi}^{\pi} W_\gamma(e^{j(\zeta-\omega_n)}) \left| Y_N(e^{j\omega}) - \tilde{G}(e^{j\omega})U_N(e^{j\omega}) \right|^2 d\zeta \approx \tilde{\phi}_y(e^{j\omega_n}) - \frac{|\tilde{\phi}_{yu}(e^{j\omega_n})|^2}{\tilde{\phi}_u(e^{j\omega_n})}}$$

How much energy is accounted for by the model? How much by noise?

$$\phi_v(e^{j\omega_n}) = \phi_y(e^{j\omega_n})\left(1 - \frac{|\phi_{yu}((e^{j\omega_n}))|^2}{\phi_y(e^{j\omega_n})\phi_u(e^{j\omega_n})}\right)$$

$$\boxed{\hat{\kappa}_{yu}(e^{j\omega_n}) = \sqrt{\frac{|\hat{\phi}_{yu}(e^{j\omega_n})|^2}{\hat{\phi}_y(e^{j\omega_n})\hat{\phi}_u(e^{j\omega_n})}}} \quad \text{Coherency Spectrum}$$

- If all of the energy in the output is due to the model for a frequency ω_n then $\hat{\kappa}_{yu}(e^{j\omega_n}) = 1$.

- This can be used as a measure of effectiveness of the modelling at a particular frequency.

- Theoretically, $0 \leq \hat{\kappa}_{yu}(e^{j\omega_n}) \leq 1$. One should aim to keep the coherency spectrum as high as possible. It can be adjusted by adjusting the smoothing.

9.2 Time-domain data windowing

Putting a time domain window directly on the data.

$$U_w(e^{j\omega_n}) = \sum_{k=0}^{N-1} w_{data}(k)u(k)e^{-jk\omega_n}$$

often with $w_{data}(k) = w_\gamma(k - N/2)$ (shifted to middle). Typically $\gamma = N/2$ such that all of the data is used.
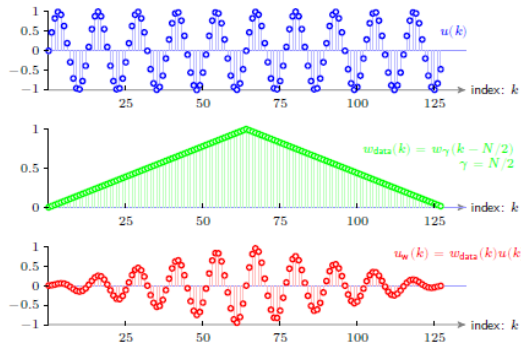
For an estimation of the periodogram **scaling is necessary!**

$$\boxed{\frac{1}{E_{scl}}\frac{1}{N}|U_w(e^{j\omega_n})|^2 \quad \text{where } E_{scl} = \frac{\sum\limits_{k=0}^{N-1}|w_{data}(k)u(k)|^2}{\sum\limits_{k=0}^{N-1}|u(k)|^2} \approx \frac{1}{N}\sum\limits_{k=0}^{N-1}|w_{data}(k)|^2} \quad \text{Periodogram}$$

- Transients influence the periodogram of a sequence, since by the application of the DFT, the signal is assumed to be periodic. Thus even if a sinusoid is sampled - if the periodic extension does not represent the same sinusoid - the DFT will show a range of frequencies, instead of a single distinct one.

- Time-domain data windowing can help reducing the influence of transients.

9.2.1 Welch's Method
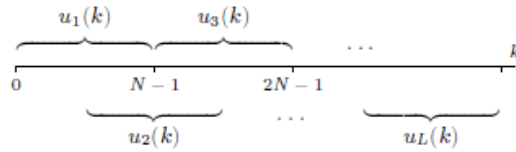
1. Split the data record into L overlapping segments of length N.

2. $U_l(e^{j\omega_n}) = \sum\limits_{k=0}^{N-1} w_{data}(k)u_l(k)e^{j\omega_n k}$

3. $\tilde{\phi}_u(e^{j\omega_n}) = \frac{1}{NLE_{scl}}\sum\limits_{l=1}^{L}\left|U_l(e^{j\omega_n})\right|^2$

+ Windowing can reduce transient response effects.

+ Noise reduction from averaging and windowing.

+ Variance error can be reduced.

- Windowing can cause energy leakage to adjacent frequencies.

- Frequency resolution deteriorates.

- Bias error can be increased.

- Noise on $u_l(k)$ and u_{l+1} is not uncorrelated.

- Do not use `welch()`, since it does not fit the definition here.

9.2.2 Drifts and Offsets

- Time domain windowing when an offset is present can lead to the introduction of additional frequencies close to zero, which is undesirable.

- Time domain windowing when a drift is present can lead to the introduction of additional frequencies close to the peak of the sampled sinusoid, which is undesirable as well.

- A possible solution is **preprocessing** the data via the assumption
$$u_d(k) = u(k) - (alphak + \beta)$$
where $\alpha k + \beta$ is the best linear fit to $u(k)$.

```
1  detrend(u);
```

+ `detrend` can completely remove the effect of drifts and offsets.

- It must be applied carefully, since if no drift/offset is present or if it is detected wrongly, large errors can be introduced.

10 Frequency Domain Subspace ID

$$x(k+1) = Ax(k) + Bu(k) \qquad A \in \mathbb{R}^{n_x \times n_x}$$
$$y(k) = Cx(k) + Du(k) \qquad D \in \mathbb{R}^{n_y \times n_u}$$

$$g(k) = \begin{cases} 0 & k = 0 \\ D & k = 0 \\ CA^{k-1} & k > 0 \end{cases} \quad \text{Pulse response coefficients}$$

$$G(e^{j\omega_n}) = \sum\limits_{k=0}^{\infty} g(k)e^{-j\omega k} \quad 0 \le \omega \le \pi$$

Given

$$G(n) = G(e^{j\omega_n}) + V(e^{j\omega_n}), \quad n = 0, \dots, N/2$$

Find

$$\hat{G}(e^{j\omega_n}) = \hat{C}\left(e^{j\omega}I - \hat{A}\right)^{-1}\hat{B} + \hat{D}$$

such that

$$\lim_{N\to\infty} ||\hat{G}(e^{j\omega_n}) - G(e^{j\omega_n})||_\infty = 0$$

$$\boxed{\mathcal{O} = \begin{bmatrix} C \\ CA \\ \vdots \\ CA^{q-1} \end{bmatrix} \in \mathbb{R}^{n_y q \times n_x}} \text{ Extended observability}$$

$\text{rank}(\mathcal{O}) = n_x$ for all $n_y q \geq n_x$

$$\boxed{\mathcal{C} = \begin{bmatrix} B & AB & \cdots & A^{r-1}B \end{bmatrix} \in \mathbb{R}^{n_x \times n_u r}} \text{ Extended controllability}$$

$\text{rank}(\mathcal{C}) = n_x$ for all $n_u r \geq n_x$

The ETFE matches the true transfer function only of there is no noise. In that case the inverse Fourier transform results in the time-aliased impulse response of the system h_k:

$$\boxed{h_k = \frac{1}{N}\sum_{n=0}^{N-1} G(e^{j\omega_n})e^{j2\pi kn/N} = CA^{k-1}\left(\sum_{l=0}^{\infty} A^{Nl}\right)B = CA^{k-1}\left(I - A^N\right)^{-1}B}$$

- We do not get the exact impulse response $g(k)$ since we do not have all the data until $N \to \infty$.

Now the **Hankel matrix** is formulated with the ultimate goal to extract estimates of the state space matrices.

$$H = \begin{bmatrix} h_1 & h_2 & h_3 & \cdots & h_r \\ h_2 & h_3 & \ddots & \ddots & h_{r+1} \\ h_3 & \ddots & \ddots & \ddots & \\ & \ddots & \ddots & & \vdots \\ h_q & h_{q+1} & & \cdots & h_{q+r-1} \end{bmatrix} \quad \text{choose } q > n_x, r > n_x \text{ and } q+r-1 \leq N-1$$

which leads to:

$$\boxed{H = \begin{bmatrix} C \\ CA \\ \vdots \\ CA^{q-1} \end{bmatrix} \left(I - A^N\right)^{-1} \begin{bmatrix} B & AB & \cdots & A^{r-1}B \end{bmatrix}}$$

Next singular value decomposition can be used to decompose the Hankel matrix, which allows to calculate the **rank** of the state space, as the dimension of Σ_1.

$$H = U\Sigma V^T = \begin{bmatrix} U_1 & U_2 \end{bmatrix} \begin{bmatrix} \Sigma_1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} V_1^T \\ V_2^T \end{bmatrix}, \quad \Sigma_1 \in \mathbb{R}^{n_x \times n_x}$$

Since U_2 is multiplied with $\mathbf{0}$ the $\text{range}(H) = \text{range}(U_1) = \mathcal{O}$. Which directly leads to $\text{span}(\{U_1\}) = \text{span}(\mathcal{O})$, which means that the observability matrix is some linear transform of U_1. Or differently said, for some choice of A they are equal. probably not correct!?

Next an estimate of $\hat{A}$ is made using the observability matrix, for which the selection matrix J is introduced:

$$J_1 \begin{bmatrix} C \\ CA \\ \vdots \\ CA^{q-1} \end{bmatrix} = \begin{bmatrix} C \\ CA \\ \vdots \\ CA^{q-2} \end{bmatrix} \text{ and } J_2 \begin{bmatrix} C \\ CA \\ \vdots \\ CA^{q-1} \end{bmatrix} = \begin{bmatrix} CA \\ \vdots \\ CA^{q-1} \end{bmatrix}$$

Then $j_1\mathcal{O}A = J_2\mathcal{O}$
So $\hat{A}$ is the least squares solution to $J_1\hat{U}_1\hat{A} = J_2\hat{U}_1$.

And $\hat{C}$ can be found as: $J_e\mathcal{O} = C \implies J_3\hat{U}_1 = \hat{C}$.
Next, using the initial formulation:

$$\hat{G}(e^{j\omega_n}) = \hat{C}\left(e^{j\omega}I - \hat{A}\right)^{-1}\hat{B} + \hat{D}$$

$\hat{B}$ and $\hat{D}$ can be found as the solution to the minimization:

$$\boxed{\hat{B}, \hat{D} = \underset{B,D}{\text{argmin}} \sum_{n=0}^{N} ||G(e^{j\omega_n}) - D - \hat{C}(e^{j\omega_n}I - \hat{A})^{-1}B||_F^2}$$

10.1 SUMMARIZING THE SUBSPACE IDENTIFICATION ALGORITHM

Uniform data spacing case:

$$G(n), \quad \omega_n = \frac{\pi n}{N}, \quad n = 0, \ldots, N/2$$

1. Extend data to negative frequencies

$$G(n) = \bar{G}(N-n), \quad n = N/2+1, \ldots, N-1$$

2. Calculate inverse DFT to obtain the time-aliased pulse response

$$\hat{h}_k = \frac{1}{N}\sum_{n=0}^{N-1} G(n)e^{j2\pi kn/N}, \quad k = 0, \ldots, N-1$$

3. Form a block-Hakel matrix:

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$$\hat{H} = \begin{bmatrix} \hat{h}_1 & \hat{h}_2 & \hat{h}_3 & \cdots \hat{h}_r \\ \hat{h}_2 & \hat{h}_3 & \ddots & \ddots & \hat{h}_{r+1} \\ \hat{h}_3 & \ddots & \ddots & \ddots & \\ & \ddots & \ddots & & \vdots \\ \hat{h}_q & \hat{h}_{q+1} & & \cdots & \hat{h}_{q+r+1} \end{bmatrix} \in \mathbb{R}^{n_y q \times \nu_r}$$

4. Calculate a singular value decomposition:

$$\hat{H} = \hat{U}\hat{\Sigma}\hat{V}^T$$

5. Select a model order, $\hat{n}_x$ and partition the SVD:

$$\hat{U}\hat{\Sigma}\hat{V}^T = \begin{bmatrix} \hat{U}_1 & \hat{U}_2 \end{bmatrix} \begin{bmatrix} \hat{\Sigma}_1 & 0 \\ 0 & \hat{\Sigma}_2 \end{bmatrix} \begin{bmatrix} \hat{V}_1^T \\ \hat{V}_2^T \end{bmatrix}, \quad \hat{\Sigma} \in \mathbb{R}^{\hat{n}_x \times \hat{n}_x}$$

6. Estimate $\hat{A}$ via:

$$J_1 = \begin{bmatrix} I_{n_y(q-1)} & O_{n_y(q-1) \times n_y} \end{bmatrix}$$
$$J_2 = \begin{bmatrix} 0_{n_q(q-1)} \times n_y & I_{n_y(q-1)} \end{bmatrix}$$

Solve for $\hat{A}$ via LS:

$$\boxed{J_1 \hat{U}_1 \hat{A} = J_2 \hat{U}_1}$$

7. Estimate $\hat{C}$ via

$$J_3 = \begin{bmatrix} I_{n_y} & 0_{n_y \times n_y(q_1)} \end{bmatrix}$$

$$\boxed{\hat{C} = J_3 \hat{U}_1}$$

8. Find $\hat{B}$ and $\hat{D}$ via least squares:

$$\boxed{\hat{B}, \hat{D} = \underset{B,D}{\text{argmin}} \sum_{n=0}^{N} ||G(e^{j\omega_n}) - D - \hat{C}(e^{j\omega_n}I - \hat{A})^{-1}B||_F^2}$$

9. Form the estimate

$$\boxed{\hat{G}(z) = \hat{D} + \hat{C}(zI - \hat{A})^{-1}\hat{B}}$$

• To get real valued B and D:

$$\begin{bmatrix} \text{real}\left((\hat{C}((e^{j\omega_n})I - \hat{A})^{-1}\right) & I \\ \text{imag}\left((\hat{C}((e^{j\omega_n})I - \hat{A})^{-1}\right) & 0 \end{bmatrix} \begin{bmatrix} B \\ D \end{bmatrix} = \begin{bmatrix} \text{real}(G(n)) \\ \text{imag}(G(n)) \end{bmatrix}$$

10.1.1 Properties

• Asymptotic convergence

$$\lim_{N \to \infty} ||\hat{G}(e^{j\omega_n}) - G(e^{j\omega_n})||_\infty = 0, \quad n = 0, \dots, N-1 \text{ w.p. } 1$$

• The algorithm is „correct". If $V(e^{j\omega_n}) = 0$ then there exists a data length $N_0 < \infty$ such that:

$$||\hat{G}_N(e^{j\omega}) - G(e^{j\omega})||_\infty = 0 \text{ for all } N > N_0$$

+ Time- and frequency-domain versions available. $N4SID$, etc

+ Many variants which depend on weighting for noise.

+ gives a state-space model directly.

+ Can be effective in determining system order.

+ Works equally well for MIMO systems.

- Unusual noise weighting in frequency-domain case.

- Truncated SVD reconstructions are not Hankel.

- $\hat{U}_1$ does not have the „shift"structure.

- Least-squares noise assumptions are not correct.

- Can give unstable models for stable systems.

10.2 Nonuniformly spaced frequencies

Time domain

$$x(k+1) = Ax(k) + Bu(k)$$
$$y(k) = Cx(k) + Du(k)$$

Frequency domain

$$e^{j\omega}X(\omega) = AX(\omega) + BU(\omega)$$
$$Y(\omega) = CX(\omega) + BU(\omega)$$

For a specific frequency ω on each channel

$$U_i(\omega) = e_i \quad i = 1, \dots n_u$$

Resulting system equations

$$e^{j\omega}X_i(\omega) = AX_i(\omega) + BU_i(\omega)$$
$$Y_i(\omega) = CX_i(\omega) + DU_i(\omega)$$

Defining

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$$X_c(\omega) = \begin{bmatrix} X_1(\omega) & \cdots & X_{n_u}(\omega) \end{bmatrix}$$

and stacking the equations column-wise gives:

$$e^{j\omega} X_c(\omega) = A X_c(\omega) + B$$
$$G(\omega) = C X_c(\omega) + D$$

Multiplying by $e^{j\omega}$ and substituting, repeating and stacking row-wise:

$$\begin{bmatrix} G(e^{j\omega}) \\ e^{j\omega} G(e^{j\omega}) \\ \vdots \\ e^{j(q-1)\omega} G(e^{j\omega}) \end{bmatrix} = \begin{bmatrix} C \\ CA \\ \vdots \\ CA^{q-1} \end{bmatrix} X_c(\omega) + \Gamma \begin{bmatrix} I_{n_u} \\ e^{j\omega} I_{n_u} \\ \vdots \\ e^{j(q-1)\omega} I_{n_u} \end{bmatrix}$$

where

$$\Gamma = \begin{bmatrix} D & & & \\ CB & D & 0 & 0 \\ CAB & \ddots & \ddots & \\ \vdots & & \ddots & \\ CA^{q-2}B & \cdots & CB & D \end{bmatrix}$$

Repeat for all frequencies ω_i:

$$\mathcal{G} = \frac{1}{\sqrt{N}} \begin{bmatrix} G(e^{j\omega_1}) & \cdots & G(e^{j\omega_N}) \\ e^{j\omega_1} G(e^{j\omega_1}) & & e^{j\omega_N} G(e^{j\omega_N}) \\ \vdots & & \vdots \\ e^{j(q-1)\omega_1} G(e^{j\omega_1}) & \cdots & e^{j(q-1)\omega_N} G(e^{j\omega_N}) \end{bmatrix}$$

$$\mathcal{W} = \frac{1}{\sqrt{N}} \begin{bmatrix} I & \cdots & I \\ e^{j\omega_1} & & e^{j\omega_N} I \\ \vdots & & \vdots \\ e^{j(q-1)\omega_1} & \cdots & e^{j(q-1)\omega_N} I \end{bmatrix}$$

$$\mathcal{X}_c = \frac{1}{\sqrt{N}} \begin{bmatrix} X_c(\omega_1) \cdots & X_c(\omega_N) \end{bmatrix}$$

$$\boxed{g = \mathcal{O}\mathcal{X}_c + \Gamma\mathcal{W}}$$

Now as $\mathcal{O}$ and Γ are real valued

$$\underbrace{\begin{bmatrix} \text{real}(\mathcal{G}) & \text{imag}(\mathcal{G}) \end{bmatrix}}_{\mathcal{G}_r} = \mathcal{O} \underbrace{\begin{bmatrix} \text{real}(\mathcal{X}_c) & \text{imag}(\mathcal{X}_c) \end{bmatrix}}_{\mathcal{X}_{cr}} + \Gamma \underbrace{\begin{bmatrix} \text{real}(\mathcal{W}) & \text{imag}(\mathcal{W}) \end{bmatrix}}_{\mathcal{W}_r}$$

If $n_y q < n_u r$ then $\exists \mathcal{W}_r^\perp$ such that $\mathcal{W}_r \mathcal{W}_r^\perp$.

$$\mathcal{G}_r \mathcal{W}_r^\perp = (\mathcal{O}\mathcal{X}_{rc} + \Gamma\mathcal{W}_r)\mathcal{W}_r^\perp = \mathcal{O}\mathcal{X}_{cr}\mathcal{W}_r^\perp$$

$$\text{range}\left(\mathcal{G}_r \mathcal{W}_r^\perp\right) = \text{range}(\mathcal{O})$$

```matlab
%To solve linear least squares problem: Ax = b
x = A\b;
```

11 Closed-Loop ID

12 Time-Domain Correlation Method

13 Prediction Error Methods

14 Parameter estimation statistics

15 Nomenclature

$y(k) = Gu(k)$	output signal	[ ]
$u(k)$	input signal	[ ]
G	plant	[ ]
$\hat{G} = \frac{y}{u}$	estimated plant	[ ]
$Y(e^{j\omega})$	output spectrum	[ ]
$U(e^{j\omega})$	input spectrum	[ ]
ZOH	zero order hold	
DAC	digital analog converter	
ADC	analog digital converter	

16 OVERVIEWS

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akjf ej fajef ajef
aöal-
skjdöfalkjsdölfkjaöslkdjf
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