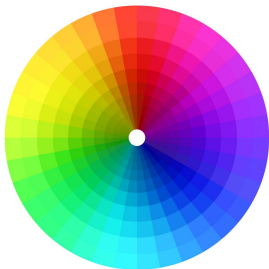




# Nonparametric methods: Improved periodogram methods



Per Mattsson

Systems and Control  
Department of Information Technology  
Uppsala University

2019-09-06

# Summary from last lecture

## Practical non-parametric methods

Periodogram:

$$\hat{\phi}_p(\omega) = \frac{1}{N} \left| \sum_{t=1}^N y(t) e^{-i\omega t} \right|^2$$

Correlogram:

$$\hat{\phi}_c(\omega) = \sum_{k=-(N-1)}^{N-1} \hat{r}(k) e^{-i\omega k}, \quad \hat{r}(k) = \frac{1}{N} \sum_{t=k+1}^N y(t) y^*(t-k)$$

- ▶ Periodogram and Correlogram
- ▶ Asymptotically Unbiased
- ▶ High variance (inconsistent)
- ▶ Resolution  $\omega \cong 2\pi/N$

**Today:** How can the periodogram be improved?

# What is the problem with the periodogram?

---

- ▶ **Bias:** Smearing and leakage. Goes to zero as  $N \rightarrow \infty$ .
- ▶ **Variance:** High even when  $N \rightarrow \infty$ .

# What is the problem with the periodogram?

---

- ▶ **Bias:** Smearing and leakage. Goes to zero as  $N \rightarrow \infty$ .
- ▶ **Variance:** High even when  $N \rightarrow \infty$ .

Some intuition:

- ▶ Large error in the estimate  $\hat{r}(k)$  for large  $|k|$ .

# What is the problem with the periodogram?

---

- ▶ **Bias:** Smearing and leakage. Goes to zero as  $N \rightarrow \infty$ .
- ▶ **Variance:** High even when  $N \rightarrow \infty$ .

Some intuition:

- ▶ Large error in the estimate  $\hat{r}(k)$  for large  $|k|$ .
- ▶ Adding up many errors.

# What is the problem with the periodogram?

---

- ▶ **Bias:** Smearing and leakage. Goes to zero as  $N \rightarrow \infty$ .
- ▶ **Variance:** High even when  $N \rightarrow \infty$ .

Some intuition:

- ▶ Large error in the estimate  $\hat{r}(k)$  for large  $|k|$ .
- ▶ Adding up many errors.

Idea:

- ▶ Why not just remove the terms with large  $|k|$ ?

# What is the problem with the periodogram?

- ▶ **Bias:** Smearing and leakage. Goes to zero as  $N \rightarrow \infty$ .
- ▶ **Variance:** High even when  $N \rightarrow \infty$ .

Some intuition:

- ▶ Large error in the estimate  $\hat{r}(k)$  for large  $|k|$ .
- ▶ Adding up many errors.

Idea:

- ▶ Why not just remove the terms with large  $|k|$ ? I.e., use

$$\hat{\phi}(\omega) = \sum_{k=-(M-1)}^{M-1} \hat{r}(k) e^{-i\omega k}, \quad M < N.$$

# What is the problem with the periodogram?

- ▶ **Bias:** Smearing and leakage. Goes to zero as  $N \rightarrow \infty$ .
- ▶ **Variance:** High even when  $N \rightarrow \infty$ .

Some intuition:

- ▶ Large error in the estimate  $\hat{r}(k)$  for large  $|k|$ .
- ▶ Adding up many errors.

Idea:

- ▶ Why not just remove the terms with large  $|k|$ ? I.e., use

$$\hat{\phi}(\omega) = \sum_{k=-(M-1)}^{M-1} \hat{r}(k) e^{-i\omega k}, \quad M < N.$$

- ▶ Smaller  $M$  should give less variance. But at what cost?



# What is the problem with the periodogram?

- ▶ **Bias:** Smearing and leakage. Goes to zero as  $N \rightarrow \infty$ .
- ▶ **Variance:** High even when  $N \rightarrow \infty$ .

Some intuition:

- ▶ Large error in the estimate  $\hat{r}(k)$  for large  $|k|$ .
- ▶ Adding up many errors.

Idea:

- ▶ Why not just remove the terms with large  $|k|$ ? I.e., use

$$\hat{\phi}(\omega) = \sum_{k=-(M-1)}^{M-1} \hat{r}(k) e^{-i\omega k}, \quad M < N.$$

- ▶ Smaller  $M$  should give less variance. But at what cost?
- ▶ More generally, we could give different weights to different lags  $|k|$ . Small  $|k|$  higher weight.



# The Blackman-Tukey method

# The Blackman-Tukey method

---

- The Blackman-Tukey PSD estimate:

$$\hat{\phi}_{\text{BT}}(\omega) = \sum_{k=-(M-1)}^{M-1} w(k) \hat{r}(k) e^{-i\omega k}$$

# The Blackman-Tukey method

---

- ▶ The Blackman-Tukey PSD estimate:

$$\hat{\phi}_{\text{BT}}(\omega) = \sum_{k=-(M-1)}^{M-1} w(k) \hat{r}(k) e^{-i\omega k}$$

- ▶  $w(k)$  is called a **lag window**.

# The Blackman-Tukey method

- ▶ The Blackman-Tukey PSD estimate:

$$\hat{\phi}_{\text{BT}}(\omega) = \sum_{k=-(M-1)}^{M-1} w(k) \hat{r}(k) e^{-i\omega k}$$

- ▶  $w(k)$  is called a **lag window**.
- ▶ **Rectangular window**:  $w(k) = 1$  for  $|k| < M \Rightarrow$  truncated sum.

# The Blackman-Tukey method

- ▶ The Blackman-Tukey PSD estimate:

$$\hat{\phi}_{\text{BT}}(\omega) = \sum_{k=-(M-1)}^{M-1} w(k) \hat{r}(k) e^{-i\omega k}$$

- ▶  $w(k)$  is called a **lag window**.
- ▶ **Rectangular window**:  $w(k) = 1$  for  $|k| < M \Rightarrow$  truncated sum.
- ▶ Generally:  $w(0) = 1$ ,  $w(-k) = w(k)$ .

# Alternative interpretation

---

- ▶ Let  $\hat{r}(k) = 0$  for  $|k| \geq N$  and  $w(k) = 0$  for  $|k| \geq M$ .

# Alternative interpretation

---

- ▶ Let  $\hat{r}(k) = 0$  for  $|k| \geq N$  and  $w(k) = 0$  for  $|k| \geq M$ .
- ▶ **Periodogram:**  $\hat{\phi}_p(\omega)$  is the DTFT of  $\hat{r}(k)$ .



# Alternative interpretation

---

- ▶ Let  $\hat{r}(k) = 0$  for  $|k| \geq N$  and  $w(k) = 0$  for  $|k| \geq M$ .
- ▶ **Periodogram:**  $\hat{\phi}_p(\omega)$  is the DTFT of  $\hat{r}(k)$ .
- ▶ **Blackman-Tukey:**  $\hat{\phi}_{\text{BT}}(\omega)$  is the DTFT of  $w(k)\hat{r}(k)$ .

# Alternative interpretation

---

- ▶ Let  $\hat{r}(k) = 0$  for  $|k| \geq N$  and  $w(k) = 0$  for  $|k| \geq M$ .
- ▶ **Periodogram:**  $\hat{\phi}_p(\omega)$  is the DTFT of  $\hat{r}(k)$ .
- ▶ **Blackman-Tukey:**  $\hat{\phi}_{BT}(\omega)$  is the DTFT of  $w(k)\hat{r}(k)$ .
- ▶ Expressed as a convolution:

$$\hat{\phi}_{BT}(\omega) = \frac{1}{2\pi} \int_{-\pi}^{\pi} \hat{\phi}_p(\zeta) W(\omega - \zeta) d\zeta,$$

# Alternative interpretation

- ▶ Let  $\hat{r}(k) = 0$  for  $|k| \geq N$  and  $w(k) = 0$  for  $|k| \geq M$ .
- ▶ **Periodogram:**  $\hat{\phi}_p(\omega)$  is the DTFT of  $\hat{r}(k)$ .
- ▶ **Blackman-Tukey:**  $\hat{\phi}_{BT}(\omega)$  is the DTFT of  $w(k)\hat{r}(k)$ .
- ▶ Expressed as a convolution:

$$\hat{\phi}_{BT}(\omega) = \frac{1}{2\pi} \int_{-\pi}^{\pi} \hat{\phi}_p(\zeta) W(\omega - \zeta) d\zeta,$$

where the **spectral window**  $W(\omega)$  is the DTFT of the **lag window**  $w(k)$ .

# Alternative interpretation

- ▶ Let  $\hat{r}(k) = 0$  for  $|k| \geq N$  and  $w(k) = 0$  for  $|k| \geq M$ .
- ▶ **Periodogram:**  $\hat{\phi}_p(\omega)$  is the DTFT of  $\hat{r}(k)$ .
- ▶ **Blackman-Tukey:**  $\hat{\phi}_{BT}(\omega)$  is the DTFT of  $w(k)\hat{r}(k)$ .
- ▶ Expressed as a convolution:

$$\hat{\phi}_{BT}(\omega) = \frac{1}{2\pi} \int_{-\pi}^{\pi} \hat{\phi}_p(\zeta) W(\omega - \zeta) d\zeta,$$

where the **spectral window**  $W(\omega)$  is the DTFT of the **lag window**  $w(k)$ .

- ▶ Possible interpretation:





# Analysis

# Analysis of the Blackman-Tukey method

---

$$\hat{\phi}_{\text{BT}}(\omega) = \sum_{k=-(M-1)}^{M-1} w(k)\hat{r}(k)e^{-i\omega k} = \frac{1}{2\pi} \int_{-\pi}^{\pi} \hat{\phi}_p(\zeta)W(\omega - \zeta)d\zeta.$$

# Analysis of the Blackman-Tukey method

---

$$\hat{\phi}_{\text{BT}}(\omega) = \sum_{k=-(M-1)}^{M-1} w(k)\hat{r}(k)e^{-i\omega k} = \frac{1}{2\pi} \int_{-\pi}^{\pi} \hat{\phi}_p(\zeta)W(\omega - \zeta)d\zeta.$$

- “Smoothed periodogram”.

# Analysis of the Blackman-Tukey method

---

$$\hat{\phi}_{\text{BT}}(\omega) = \sum_{k=-(M-1)}^{M-1} w(k) \hat{r}(k) e^{-i\omega k} = \frac{1}{2\pi} \int_{-\pi}^{\pi} \hat{\phi}_p(\zeta) W(\omega - \zeta) d\zeta.$$

- ▶ “Smoothed periodogram”.
- ▶ **Reduces variance.** Smaller  $M$  gives smaller variance.



# Analysis of the Blackman-Tukey method

---

$$\hat{\phi}_{\text{BT}}(\omega) = \sum_{k=-(M-1)}^{M-1} w(k)\hat{r}(k)e^{-i\omega k} = \frac{1}{2\pi} \int_{-\pi}^{\pi} \hat{\phi}_p(\zeta)W(\omega - \zeta)d\zeta.$$

- ▶ “Smoothed periodogram”.
- ▶ **Reduces variance.** Smaller  $M$  gives smaller variance.
- ▶ **Slightly increases bias.** Smaller  $M$  gives higher bias, and worse resolution.

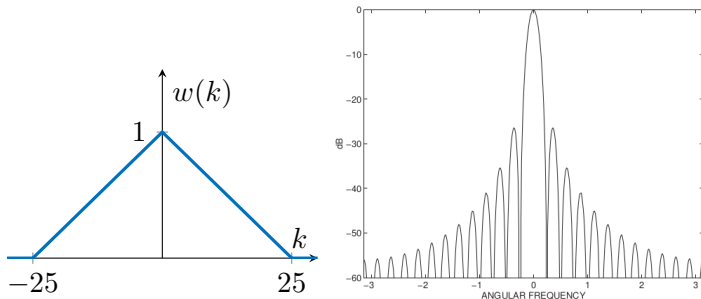
# Analysis of the Blackman-Tukey method

---

$$\hat{\phi}_{\text{BT}}(\omega) = \sum_{k=-(M-1)}^{M-1} w(k) \hat{r}(k) e^{-i\omega k} = \frac{1}{2\pi} \int_{-\pi}^{\pi} \hat{\phi}_p(\zeta) W(\omega - \zeta) d\zeta.$$

- ▶ “Smoothed periodogram”.
- ▶ **Reduces variance.** Smaller  $M$  gives smaller variance.
- ▶ **Slightly increases bias.** Smaller  $M$  gives higher bias, and worse resolution.
- ▶ If  $W(\omega) \geq 0$ , then  $\hat{\phi}_{\text{BT}}(\omega) \geq 0$ .

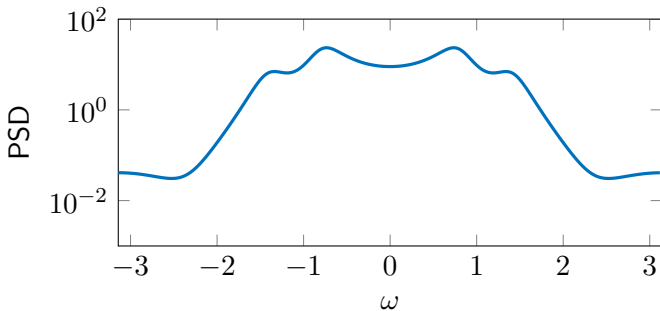
# Example: The Bartlett (triangular) window



The triangular window with  $M = 25$ .  
Main lobe 3db:  $2\pi/M$ .

# Example

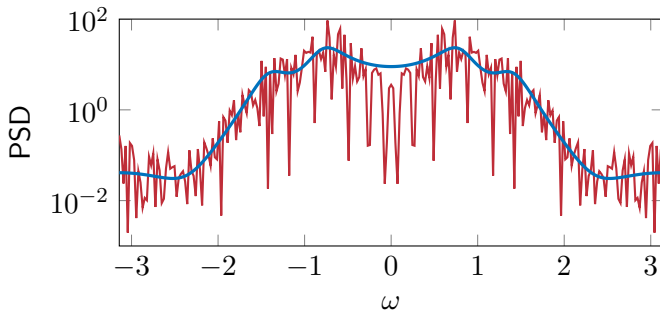
$$\hat{\phi}_{\text{BT}}(\omega) = \sum_{k=-(M-1)}^{M-1} w(k) \hat{r}(k) e^{-i\omega k}.$$



True spectrum estimated with  $N = 256$  samples.

# Example

$$\hat{\phi}_{\text{BT}}(\omega) = \sum_{k=-(M-1)}^{M-1} w(k) \hat{r}(k) e^{-i\omega k}.$$

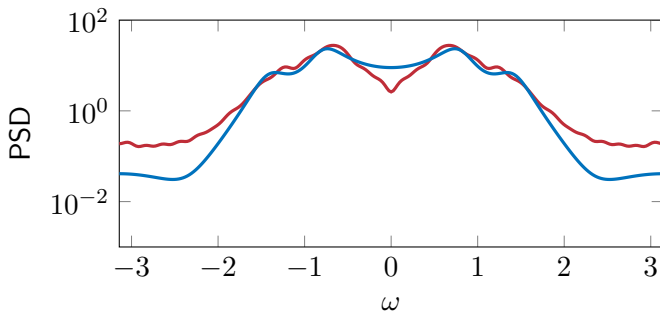


True spectrum estimated with  $N = 256$  samples.

Periodogram  $M = N = 256$  and  $w(k) = 1$

# Example

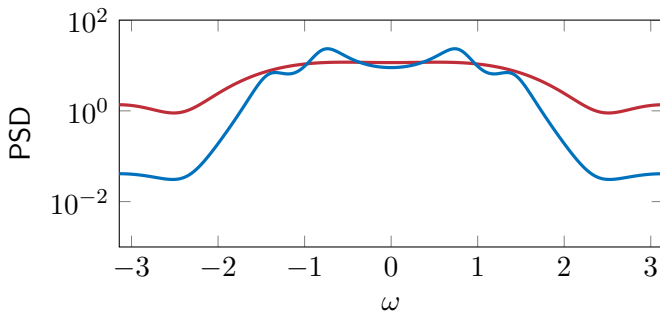
$$\hat{\phi}_{\text{BT}}(\omega) = \sum_{k=-(M-1)}^{M-1} w(k) \hat{r}(k) e^{-i\omega k}.$$



True spectrum estimated with  $N = 256$  samples.  
Blackman-Tukey with  $M = 32$ .

# Example

$$\hat{\phi}_{\text{BT}}(\omega) = \sum_{k=-(M-1)}^{M-1} w(k) \hat{r}(k) e^{-i\omega k}.$$



True spectrum estimated with  $N = 256$  samples.  
 Blackman-Tukey with  $M = 4$ .

# Time-Bandwidth product

---

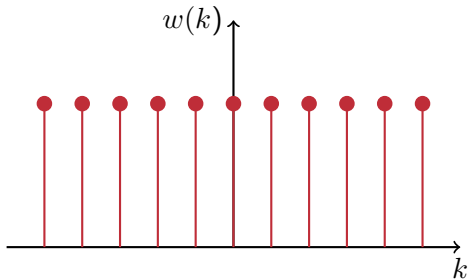
For the typical window functions, we can define

Equivalent time width: 
$$N_e = \frac{\sum_{k=-(M-1)}^{M-1} w(k)}{w(0)}$$

Equivalent bandwidth: 
$$\beta_e = \frac{\frac{1}{2\pi} \int_{-\pi}^{\pi} W(\omega) d\omega}{W(0)}$$

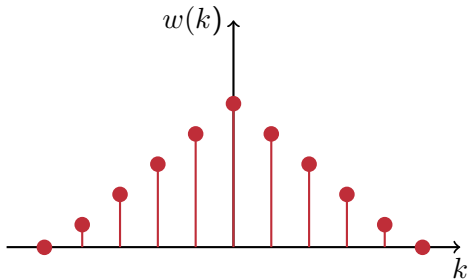


# Example: Rectangular window



$$N_e = \frac{\sum_{k=-(M-1)}^{M-1} w(k)}{w(0)} = 2M - 1$$

# Example: Triangular window



$$N_e = \frac{\sum_{k=-(M-1)}^{M-1} w(k)}{w(0)} = M$$

# Time-Bandwidth product

---

By the DTFT:

$$W(0) = \sum_{k=-(M-1)}^{M-1} w(k), \text{ and } w(0) = \frac{1}{2\pi} \int_{-\pi}^{\pi} W(\omega) d\omega$$

.

# Time-Bandwidth product

---

By the DTFT:

$$W(0) = \sum_{k=-(M-1)}^{M-1} w(k), \text{ and } w(0) = \frac{1}{2\pi} \int_{-\pi}^{\pi} W(\omega) d\omega$$

. Hence

$$N_e \beta_e = \frac{\sum_{k=-(M-1)}^{M-1} w(k)}{w(0)} \times \frac{\frac{1}{2\pi} \int_{-\pi}^{\pi} W(\omega) d\omega}{W(0)} =$$

# Time-Bandwidth product

---

By the DTFT:

$$W(0) = \sum_{k=-(M-1)}^{M-1} w(k), \text{ and } w(0) = \frac{1}{2\pi} \int_{-\pi}^{\pi} W(\omega) d\omega$$

. Hence

$$N_e \beta_e = \frac{\sum_{k=-(M-1)}^{M-1} w(k)}{w(0)} \times \frac{\frac{1}{2\pi} \int_{-\pi}^{\pi} W(\omega) d\omega}{W(0)} = 1.$$

# Time-Bandwidth product

---

By the DTFT:

$$W(0) = \sum_{k=-(M-1)}^{M-1} w(k), \text{ and } w(0) = \frac{1}{2\pi} \int_{-\pi}^{\pi} W(\omega) d\omega$$

. Hence

$$N_e \beta_e = \frac{\sum_{k=-(M-1)}^{M-1} w(k)}{w(0)} \times \frac{\frac{1}{2\pi} \int_{-\pi}^{\pi} W(\omega) d\omega}{W(0)} = 1.$$

► Equivalent time-bandwidth product:  $N_e \beta_e = 1$ .

# Time-Bandwidth product

---

By the DTFT:

$$W(0) = \sum_{k=-(M-1)}^{M-1} w(k), \text{ and } w(0) = \frac{1}{2\pi} \int_{-\pi}^{\pi} W(\omega) d\omega$$

. Hence

$$N_e \beta_e = \frac{\sum_{k=-(M-1)}^{M-1} w(k)}{w(0)} \times \frac{\frac{1}{2\pi} \int_{-\pi}^{\pi} W(\omega) d\omega}{W(0)} = 1.$$

- ▶ **Equivalent time-bandwidth product:**  $N_e \beta_e = 1$ .
- ▶ Window cannot be arbitrarily limited in both time and freq.

# Time-Bandwidth product

By the DTFT:

$$W(0) = \sum_{k=-(M-1)}^{M-1} w(k), \text{ and } w(0) = \frac{1}{2\pi} \int_{-\pi}^{\pi} W(\omega) d\omega$$

. Hence

$$N_e \beta_e = \frac{\sum_{k=-(M-1)}^{M-1} w(k)}{w(0)} \times \frac{\frac{1}{2\pi} \int_{-\pi}^{\pi} W(\omega) d\omega}{W(0)} = 1.$$

- ▶ **Equivalent time-bandwidth product:**  $N_e \beta_e = 1$ .
- ▶ Window cannot be arbitrarily limited in both time and freq.
- ▶  $N_e = \mathcal{O}(M)$ .



# Time-Bandwidth product

By the DTFT:

$$W(0) = \sum_{k=-(M-1)}^{M-1} w(k), \text{ and } w(0) = \frac{1}{2\pi} \int_{-\pi}^{\pi} W(\omega) d\omega$$

. Hence

$$N_e \beta_e = \frac{\sum_{k=-(M-1)}^{M-1} w(k)}{w(0)} \times \frac{\frac{1}{2\pi} \int_{-\pi}^{\pi} W(\omega) d\omega}{W(0)} = 1.$$

- ▶ **Equivalent time-bandwidth product:**  $N_e \beta_e = 1$ .
- ▶ Window cannot be arbitrarily limited in both time and freq.
- ▶  $N_e = \mathcal{O}(M)$ .
- ▶  $\beta_e = \mathcal{O}(1/M)$ .

# Summary of Blackman-Tukey

---

$$\hat{\phi}_{\text{BT}}(\omega) = \sum_{k=-(M-1)}^{M-1} w(k) \hat{r}(k) e^{-i\omega k}.$$

# Summary of Blackman-Tukey

---

$$\hat{\phi}_{\text{BT}}(\omega) = \sum_{k=-(M-1)}^{M-1} w(k) \hat{r}(k) e^{-i\omega k}.$$

► **Resolution:**  $\beta_e = 1/N_e = \mathcal{O}(1/M)$ .

# Summary of Blackman-Tukey

---

$$\hat{\phi}_{\text{BT}}(\omega) = \sum_{k=-(M-1)}^{M-1} w(k) \hat{r}(k) e^{-i\omega k}.$$

- ▶ **Resolution:**  $\beta_e = 1/N_e = \mathcal{O}(1/M)$ .
- ▶ **Variance:**  $\mathcal{O}(M/N)$ .

# Summary of Blackman-Tukey

---

$$\hat{\phi}_{\text{BT}}(\omega) = \sum_{k=-(M-1)}^{M-1} w(k) \hat{r}(k) e^{-i\omega k}.$$

- ▶ **Resolution:**  $\beta_e = 1/N_e = \mathcal{O}(1/M)$ .
- ▶ **Variance:**  $\mathcal{O}(M/N)$ .
- ▶ **Bias/variance:** Increasing  $M$  decreases bias but increases variance.

# Summary of Blackman-Tukey

---

$$\hat{\phi}_{\text{BT}}(\omega) = \sum_{k=-(M-1)}^{M-1} w(k) \hat{r}(k) e^{-i\omega k}.$$

- ▶ **Resolution:**  $\beta_e = 1/N_e = \mathcal{O}(1/M)$ .
- ▶ **Variance:**  $\mathcal{O}(M/N)$ .
- ▶ **Bias/variance:** Increasing  $M$  decreases bias but increases variance.
- ▶ Once  $M$  is chosen, the window shape controls mainlobe vs sidelobes (smearing vs leakage).

# Summary of Blackman-Tukey

---

$$\hat{\phi}_{\text{BT}}(\omega) = \sum_{k=-(M-1)}^{M-1} w(k) \hat{r}(k) e^{-i\omega k}.$$

- ▶ **Resolution:**  $\beta_e = 1/N_e = \mathcal{O}(1/M)$ .
- ▶ **Variance:**  $\mathcal{O}(M/N)$ .
- ▶ **Bias/variance:** Increasing  $M$  decreases bias but increases variance.
- ▶ Once  $M$  is chosen, the window shape controls mainlobe vs sidelobes (smearing vs leakage).
- ▶ No “correct” way to choose  $M$ , depends on application. But important to know how choice of  $M$  affects estimate.

# Summary of Blackman-Tukey

---

$$\hat{\phi}_{\text{BT}}(\omega) = \sum_{k=-(M-1)}^{M-1} w(k) \hat{r}(k) e^{-i\omega k}.$$

- ▶ **Resolution:**  $\beta_e = 1/N_e = \mathcal{O}(1/M)$ .
- ▶ **Variance:**  $\mathcal{O}(M/N)$ .
- ▶ **Bias/variance:** Increasing  $M$  decreases bias but increases variance.
- ▶ Once  $M$  is chosen, the window shape controls mainlobe vs sidelobes (smearing vs leakage).
- ▶ No “correct” way to choose  $M$ , depends on application. But important to know how choice of  $M$  affects estimate.
- ▶ **Rule of thumb:**  $M \leq N/10$ .



# Fixed window functions

**TABLE 2.1: Some Common Windows and their Properties**

The windows satisfy  $w(k) \equiv 0$  for  $|k| \geq M$ , and  $w(k) = w(-k)$ ; the defining equations below are valid for  $0 \leq k \leq (M-1)$ .

| Window Name | Defining Equation  | Approx. Main Lobe Width (radians) | Sidelobe Level (dB) |
|-------------|--|-----------------------------------|---------------------|
| Rectangular | $w(k) = 1$   | $2\pi/M$                          | -13                 |
| Bartlett    | $w(k) = \frac{M-k}{M}$   | $4\pi/M$                          | -25                 |
| Hanning     | $w(k) = 0.5 + 0.5 \cos\left(\frac{\pi k}{M}\right)$  | $4\pi/M$                          | -31                 |
| Hamming     | $w(k) = 0.54 + 0.46 \cos\left(\frac{\pi k}{M-1}\right)$  | $4\pi/M$                          | -41                 |
| Blackman    | $w(k) = 0.42 + 0.5 \cos\left(\frac{\pi k}{M-1}\right) + 0.08 \cos\left(\frac{\pi k}{M-1}\right)$ | $6\pi/M$                          | -57                 |

# Window design

---

Windows with design parameter:

- ▶ Chebyshev (constant peak sidelobe ripples)
- ▶ Kaiser (main lobe/sidelobe trade-off.  $\gamma = 0 \implies \text{rect.}$ )

$$w(k) = \frac{I_0(\gamma \sqrt{1 - [k/(M-1)]^2})}{I_0(\gamma)}, \quad |k| \leq M-1$$

# Window design

Windows with design parameter:

- ▶ Chebyshev (constant peak sidelobe ripples)
- ▶ Kaiser (main lobe/sidelobe trade-off.  $\gamma = 0 \implies \text{rect.}$ )

$$w(k) = \frac{I_0(\gamma \sqrt{1 - [k/(M-1)]^2})}{I_0(\gamma)}, \quad |k| \leq M-1$$

## Optimal design

E.g. Minimize the relative energy in the sidelobes, or equivalently, maximizing the relative energy in the main lobe

# Window design

Windows with design parameter:

- ▶ Chebyshev (constant peak sidelobe ripples)
- ▶ Kaiser (main lobe/sidelobe trade-off.  $\gamma = 0 \implies \text{rect.}$ )

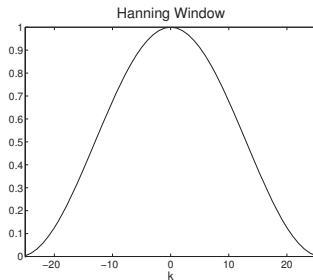
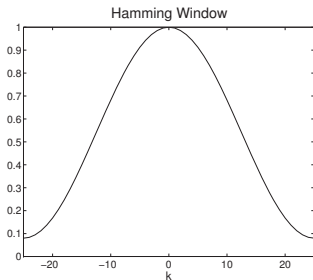
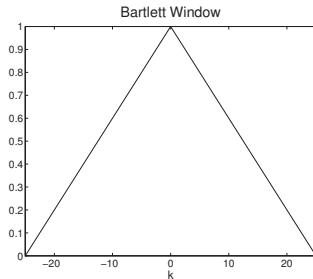
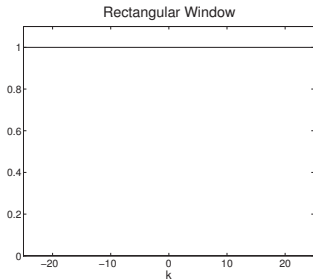
$$w(k) = \frac{I_0(\gamma \sqrt{1 - [k/(M-1)]^2})}{I_0(\gamma)}, \quad |k| \leq M-1$$

## Optimal design

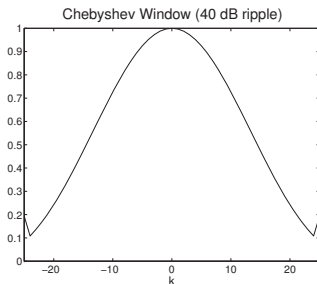
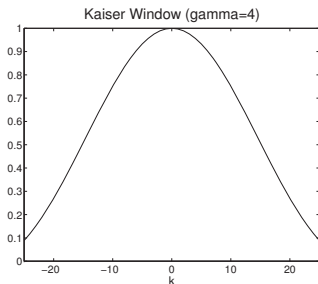
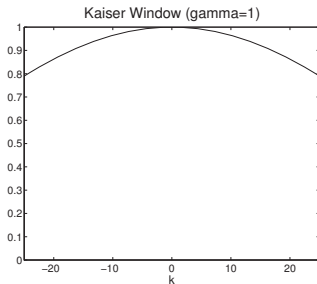
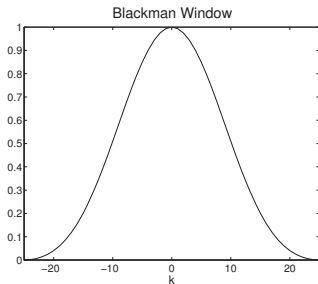
E.g. Minimize the relative energy in the sidelobes, or equivalently, maximizing the relative energy in the main lobe

- ▶ Temporal lag windows (for the Periodogram) can also be designed
- ▶ One can relate the lag windows to temporal windows
- ▶ These windowed Periodograms have the same *average* behavior as the corresponding windowed Correlograms

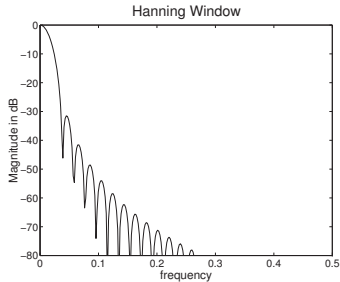
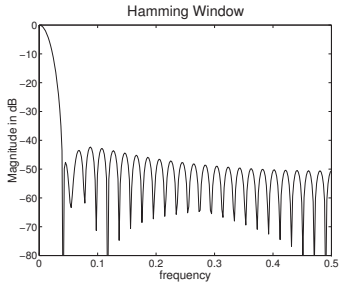
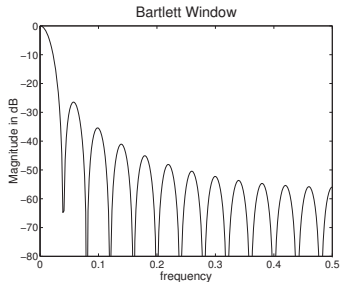
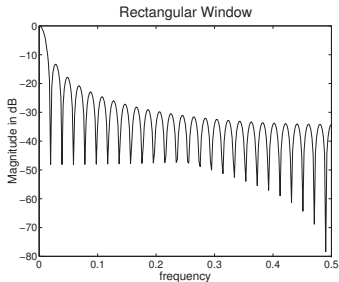
# Windows (1)



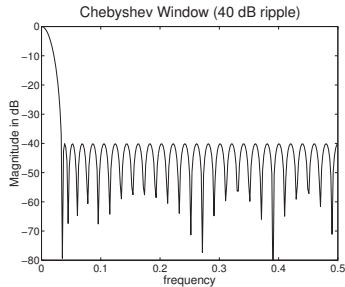
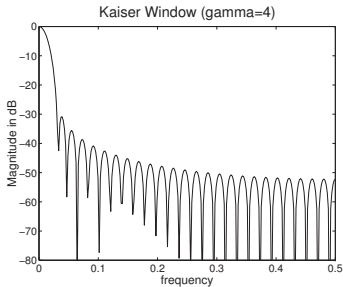
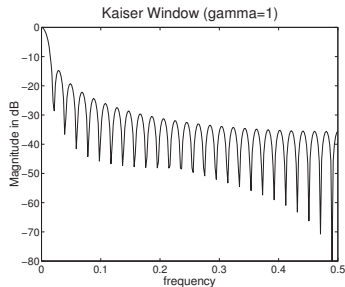
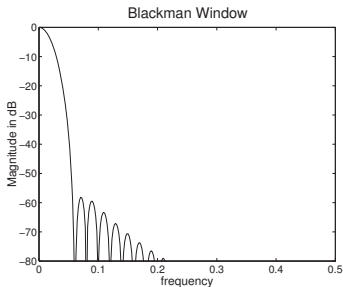
# Windows (2)



# Windows (3)



# Windows (4)







# Other methods

# The Bartlett method

---

- ▶ Split up available sample into  $L = N/M$  subsamples
- ▶ Average the Periodograms obtained from each

That is,  $y_j(t) = y((j-1)M + t)$ ,  $t = 1, \dots, M$ ,  $j = 1, \dots, L$

$$\hat{\phi}_j(\omega) = \frac{1}{M} \left| \sum_{t=1}^M y_j(t) e^{-i\omega t} \right|^2$$

$$\hat{\phi}_B(\omega) = \frac{1}{L} \sum_{j=1}^L \hat{\phi}_j(\omega)$$

- ▶ Reduces the variance of the estimate
- ▶ Reduces the resolution (fewer samples)
- ▶ Similar to  $\hat{\phi}_{BT}(\omega)$  with a rectangular window.

# The Welch method

- ▶ Refines the Bartlett method in two ways:
  - ▶ Overlapping subsamples  $\rightarrow$  more averaging (but correlated)
  - ▶ Windowing the data (reduce correlation)
- ▶  $S$  subsamples,  $1 - K/M$  overlap,  $P$  window power

$$y_j(t) = y((j-1)K + t), \quad t = 1, \dots, M, \quad j = 1, \dots, S$$

$$\hat{\phi}_j(\omega) = \frac{1}{MP} \left| \sum_{t=1}^M v(t) y_j(t) e^{-i\omega t} \right|^2$$

$$\hat{\phi}_W(\omega) = \frac{1}{S} \sum_{j=1}^S \hat{\phi}_j(\omega)$$

- ▶  $K = M \implies$  no overlap, as in Bartlett's
- ▶ Commonly used:  $K = M/2$

# Wrapping up

---

- ▶ There are many variations of the Periodogram/Correlogram
- ▶ Reduce variance at the cost of resolution (bias)
- ▶ Smoothing or averaging the spectrum
- ▶ All can essentially be expressed as Blackman-Tukey estimators
- ▶ All special cases of the Filter bank approach (Lecture 8)

# Wrapping up

---

- ▶ There are many variations of the Periodogram/Correlogram
- ▶ Reduce variance at the cost of resolution (bias)
- ▶ Smoothing or averaging the spectrum
- ▶ All can essentially be expressed as Blackman-Tukey estimators
- ▶ All special cases of the Filter bank approach (Lecture 8)

## Twist

The refined methods are needed for estimating continuous PSDs, but the *unmodified* Periodogram can be shown to be a satisfactory estimator for discrete (or line) spectra corresponding to sinusoidal signals.

# Summary

---

- ▶ How can we improve the periodogram?
- ▶ The Blackman-Tukey method
- ▶ Different window functions and design
- ▶ Time-Bandwidth product
- ▶ The Bartlett method
- ▶ The Welch method

# Summary

---

- ▶ How can we improve the periodogram?
- ▶ The Blackman-Tukey method
- ▶ Different window functions and design
- ▶ Time-Bandwidth product
- ▶ The Bartlett method
- ▶ The Welch method

**Lab next week!** Discuss your results with lab assistant to pass.

# Summary

---

- ▶ How can we improve the periodogram?
- ▶ The Blackman-Tukey method
- ▶ Different window functions and design
- ▶ Time-Bandwidth product
- ▶ The Bartlett method
- ▶ The Welch method

**Lab next week!** Discuss your results with lab assistant to pass.

**Exercise session next week!**



# Summary

---

- ▶ How can we improve the periodogram?
- ▶ The Blackman-Tukey method
- ▶ Different window functions and design
- ▶ Time-Bandwidth product
- ▶ The Bartlett method
- ▶ The Welch method

**Lab next week!** Discuss your results with lab assistant to pass.

**Exercise session next week!**

**Next lecture:**

- ▶ Parametric Methods for Rational Spectra

**Exercises:**

- ▶ Exercise 1.5, 1.7, 1.10, 2.3, 2.6, 2.10

# MATLAB

---

Useful functions:

- ▶ `btse()`

Try the following:

- ▶ Implement the BT estimator using the FFT (how?)

Remember:

- ▶ The MATLAB built-in functions might not be directly compatible with the provided code!
- ▶ Window functions in MATLAB are defined differently, use the definitions in the book to compute the window vectors directly!