

# Time Series lecture 11

## Linear time-invariant filters

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# Lecture outline

1. Linear filters
2. Impulse response and transfer function
  - ▶ Impulse response
  - ▶ Transfer function
3. The spectral density function and linear filters

# Linear filters

# Digital filters

A digital filter maps some input sequence to another output sequence. In this lecture, these sequences will have the index set  $\mathbb{Z}$ . Other filters exist, but in this course, filter will mean digital filter.

- ▶ If a filter is given by  $L$ , then the filter of a sequence  $\{X_t\}$  will be another sequence, say  $\{Y_t\}$ , and we write

$$\{Y_t\} = L[\{X_t\}]. \quad (11.1)$$

- ▶ When we refer to an element of the output of a filter, we will write a subscript after the bracket, e.g.

$$Y_u = L[\{X_t\}]_u. \quad (11.2)$$

To be clear, the  $t$  in  $\{X_t\}$  is a dummy variable, whilst  $u \in \mathbb{Z}$  has meaning.

We have dropped the index set from the sequences for notational convenience, i.e. in this lecture  $\{X_t\} = \{X_t\}_{t \in \mathbb{Z}}$ .

## Linear time-invariant filters

Recall the backshift operator, denoted  $B$ . It has the property that

$$B[\{X_t\}]_u = X_{u-1} \quad (11.3)$$

for any  $u \in \mathbb{Z}$ .

### Definition 11.1

A digital filter  $L$  is called a linear time-invariant (LTI) filter if for any sequences  $\{X_t\}$ ,  $\{Y_t\}$  and any  $\alpha \in \mathbb{C}$  we have

#### 1. Linearity:

$$L[\{\alpha X_t + Y_t\}] = \alpha L[\{X_t\}] + L[\{Y_t\}]. \quad (11.4)$$

#### 2. Time invariance:

$$L[B[\{X_t\}]] = B[L[\{X_t\}]]. \quad (11.5)$$

## Some examples

### Example 11.2

The backshift operator is clearly a linear time-invariant filter.

### Example 11.3

Consider a filter  $L$  such that for any  $u \in \mathbb{Z}$

$$L[\{X_t\}]_u = X_u + \phi X_{u-1},$$

where  $\phi \in \mathbb{R}$ . This is linear because for any  $u \in \mathbb{Z}$

$$\begin{aligned} L[\{\alpha X_t + Y_t\}]_u &= \alpha(X_u + \phi X_{u-1}) + Y_u + \phi Y_{u-1} \\ &= \alpha L[\{X_t\}]_u + L[\{Y_t\}]_u. \end{aligned}$$

Time invariance is left to the interested reader, but is easily verified.

## Arbitrary time shifts

Say we want to shift by some arbitrary  $u \in \mathbb{Z}$ , then we need only apply  $B$   $u$  times, i.e. for any  $s \in \mathbb{Z}$

$$B^u [\{X_t\}]_s = X_{s-u}. \quad (11.6)$$

(If  $u < 0$ , this means applying the inverse operator,  $B^{-1}$ ,  $-u$  times).

If  $L$  is an LTI filter, then for any  $u \in \mathbb{Z}$ ,

$$L [B^u \{X_t\}] = B^u L [\{X_t\}]. \quad (11.7)$$

Often, (11.7) is stated as the condition for time-invariance (as this parallels the continuous-time version), however, one only needs to show the weaker condition given in (11.5).

## Linear combinations of linear filters

### Proposition 11.4

Consider two LTI filters  $L_1$  and  $L_2$ , and let  $\alpha \in \mathbb{C}$  then the filter

$$L = \alpha L_1 + L_2 \quad (11.8)$$

is also an LTI filter.

### Proposition 11.5

Consider two LTI filters  $L_1$  and  $L_2$ . The filter  $L = L_1 L_2$ , i.e. so that

$$L[\{X_t\}] = L_1[L_2[\{X_t\}]] \quad (11.9)$$

is also an LTI filter. (This is called a cascaded filter.)

- ▶ See the exercises for proofs of these two results.

# Impulse response and transfer function

# Properties of a filter

In order to explore the properties of a given LTI filter, we will consider the effect of applying the filter to some test sequences. The sequences in question will be:

1. the impulse sequence,
2. a complex wave.

Formal definitions will be given on the following slides, however, informally they tell us about:

1. the effect of the filter if we input a single shock to the system at a given time,
2. the effect the filter has on a signal made up of one specific frequency.

# The impulse response sequence

For a given  $m \in \mathbb{Z}$ , define the impulse sequence  $\{\delta_{t,m}\}$  so that for  $t \in \mathbb{Z}$

$$\delta_{t,m} = \begin{cases} 1 & \text{if } m = t, \\ 0 & \text{otherwise.} \end{cases}$$

## Definition 11.6

For some LTI filter  $L$ , let the impulse response sequence be  $\{h_m\}$  such that for any  $m \in \mathbb{Z}$

$$h_m = L[\{\delta_{t,-m}\}]_0. \quad (11.10)$$

- ▶ Note: the zero here is the time index.

# Linear filters as a convolution

## Theorem 11.7

*A digital filter  $L$  is an LTI filter if and only if we can write the filter output as a convolution:*

$$L[\{X_t\}]_u = \sum_{m \in \mathbb{Z}} h_{u-m} X_m \quad (11.11)$$

*for any  $u \in \mathbb{Z}$ .*

- ▶ The  $\{h_m\}$  here is the same impulse response we defined on the previous slide.
- ▶ The proof of this result will be in the exercises.

# The transfer function

Recall, the second kind of test sequence of interest is a complex wave. For  $f \in \mathbb{R}$ , let  $\{\xi_{t,f}\}$  be such that for all  $t \in \mathbb{Z}$ ,

$$\xi_{t,f} = e^{2\pi i f t}.$$

## Definition 11.8

The transfer function of an LTI filter  $L$  is

$$H(f) = L[\{\xi_{t,f}\}]_0, \quad f \in \mathbb{R}. \quad (11.12)$$

- ▶ The transfer function is useful for understanding the frequency domain properties of a linear filter.

## Theorem 11.9

Consider an LTI filter  $L$ . The  $\{\xi_{t,f}\}$  sequences are the eigensequences and  $H(f)$  the eigenvalues of  $L$ . In other words,

$$L[\{\xi_{t,f}\}] = H(f) \{\xi_{t,f}\} \quad (11.13)$$

for any  $f \in \mathbb{R}$ .

- ▶ So we see that applying a linear filter to a complex wave just modifies its phase and amplitude, whilst retaining the same frequency.
- ▶ The shape of  $H(f)$  determines how this weighting occurs.

## Proof of Theorem 11.9.

For any  $u \in \mathbb{Z}$  and  $f \in \mathbb{R}$ , begin by noting that for any  $\tau \in \mathbb{Z}$

$$B^{-u} [\{\xi_{t,f}\}]_{\tau} = \xi_{\tau+u,f} = e^{2\pi i(\tau+u)f} = e^{2\pi iuf} \xi_{\tau,f},$$

and so

$$B^{-u} [\{\xi_{t,f}\}] = e^{2\pi iuf} \{\xi_{t,f}\}. \quad (11.14)$$

Therefore

$$\begin{aligned} L [\{\xi_{t,f}\}]_u &= B^u [L [B^{-u} [\{\xi_{t,f}\}]]]_u && \text{(time invariance)} \\ &= L \left[ e^{2\pi ifu} \{\xi_{t,f}\} \right]_0 && \text{(by (11.14))} \\ &= e^{2\pi ifu} L [\{\xi_{t,f}\}]_0 && \text{(linearity)} \\ &= \xi_{u,f} H(f). && \text{(by definition)} \end{aligned}$$

Therefore since this holds for any  $u \in \mathbb{Z}$ , the result holds. □

# Why did we do this?

If  $\{X_t\}$  is second order stationary, then we have two representations

$$X_t = \sum_{m \in \mathbb{Z}} X_m \delta_{m,t}, \quad (\text{sifting property})$$

$$X_t \stackrel{ms}{=} \mu + \int_{-1/2}^{1/2} e^{2\pi ift} dZ(f). \quad (\text{spectral representation})$$

Thus  $L[\{X_t\}]$  is

$$L[\{X_t\}]_u = \sum_{m \in \mathbb{Z}} X_m L[\{\delta_{m,t}\}]_u,$$

$$\begin{aligned} L[\{X_t\}]_u &\stackrel{ms}{=} \mu + \int_{-1/2}^{1/2} L\left[\left\{e^{2\pi ift}\right\}\right]_u dZ(f) \\ &= \mu + \int_{-1/2}^{1/2} H(f) e^{2\pi ifu} dZ(f). \end{aligned}$$

# Relating the impulse response and transfer function

## Theorem 11.10

*The transfer function is the Fourier transform of the impulse response, in other words, assuming  $\{h_m\} \in \ell^1$ , for  $f \in \mathbb{R}$*

$$H(f) = \sum_{m \in \mathbb{Z}} h_m e^{-2\pi ifm}. \quad (11.15)$$

- ▶ This provides a convenient way to compute the transfer function.
- ▶ Notice that since the impulse response was a convolution, Theorem 11.9 is a consequence of the convolution theorem! (See exercises for details.)

## Proof.

We have for any  $f \in \mathbb{R}$

$$\begin{aligned} \sum_{m \in \mathbb{Z}} h_m e^{-2\pi ifm} &= \sum_{m \in \mathbb{Z}} L[\{\delta_{t,-m}\}]_0 e^{-2\pi ifm} \\ &= L \left[ \left\{ \sum_{m \in \mathbb{Z}} \delta_{t,-m} e^{-2\pi ifm} \right\} \right]_0 \quad (\text{linearity}) \\ &= L \left[ \left\{ e^{2\pi ift} \right\} \right]_0 \\ &= H(f). \end{aligned}$$

where the third line follows because  $\delta_{t,-m}$  is one if  $m = -t$  and zero otherwise. □

# The spectral density function and linear filters

# Spectra of the output process

In what follows, it will be convenient to augment our usual notation. For the stationary discrete-time time series  $\{X_t\}_{t \in \mathbb{Z}}$ , we will write

- ▶  $\mu_X$  for the mean,
- ▶  $\gamma_{\tau}^{(X)}$  for the autocovariance,
- ▶  $S_X(f)$  for the spectral density function.

## Theorem 11.11

Consider a stationary time series  $\{X_t\}_{t \in \mathbb{Z}}$ . If  $L$  is an LTI filter with impulse response  $h \in \ell^1$ , and

$$\{Y_t\} = L[\{X_t\}]$$

then  $\{Y_t\}$  is a stationary process.

## Proof.

From Theorem 11.7,  $Y = h * X$ . Thus for any  $t \in \mathbb{Z}$ , by Fubini's theorem

$$\mathbb{E}[Y_t] = \sum_{m \in \mathbb{Z}} h_m \mathbb{E}[X_{t-m}] = \mu_X \sum_{m \in \mathbb{Z}} h_m$$

which does not depend on  $t$ . Now for  $t, \tau \in \mathbb{Z}$  we have

$$\begin{aligned} \text{Cov}(Y_t, Y_{t+\tau}) &= \sum_{m \in \mathbb{Z}} \sum_{s \in \mathbb{Z}} h_m h_s \text{Cov}(X_{t-m}, X_{t+\tau-s}) && \text{(Fubini)} \\ &= \sum_{m \in \mathbb{Z}} \sum_{s \in \mathbb{Z}} h_m h_s \gamma_{\tau+m-s}^{(X)} && \text{(stationarity)} \end{aligned}$$

which does not depend on  $t$ . Finally by stationarity and  $h \in \ell^1$

$$\gamma_0^{(Y)} \leq \gamma_0^{(X)} \|h\|_1^2 < \infty.$$



## Theorem 11.12

Consider a stationary time series  $\{X_t\}_{t \in \mathbb{Z}}$ , with  $\gamma^{(X)} \in \ell^1$ . If  $L$  is an LTI filter with impulse response  $h \in \ell^1$ , and  $\{Y_t\} = L[\{X_t\}]$  then

$$S_Y(f) = |H(f)|^2 S_X(f) \quad (11.16)$$

where  $H$  is the transfer function of  $L$ .

- ▶ From this result, we can conveniently compute the spectral density function of different processes.

## Proof.

Firstly from the proof of Theorem 11.11

$$\begin{aligned}
 \gamma_{\tau}^{(Y)} &= \sum_{m \in \mathbb{Z}} \sum_{s \in \mathbb{Z}} h_m h_s \gamma_{\tau+m-s}^{(X)} \\
 &= \sum_{m \in \mathbb{Z}} \sum_{u \in \mathbb{Z}} h_m h_{u+m} \gamma_{\tau-u}^{(x)} \quad (u = s - m) \\
 &= \sum_{u \in \mathbb{Z}} \sum_{m \in \mathbb{Z}} h_m h_{u+m} \gamma_{\tau-u}^{(x)} \quad (\text{Fubini}) \\
 &= \sum_{u \in \mathbb{Z}} w_u \gamma_{\tau-u}^{(x)}
 \end{aligned}$$

where

$$w_u = \sum_{m \in \mathbb{Z}} h_m h_{u+m}.$$

Therefore we can apply the convolution theorem, obtaining for  $f \in \mathbb{R}$

$$S_Y(f) = W(f)S_X(f).$$

All that remains is to find  $W$ , the Fourier transform of  $w$ . Letting  $\tilde{h}_t = h_{-t}$  for all  $t \in \mathbb{Z}$ , we see

$$\begin{aligned} w_u &= \sum_{m \in \mathbb{Z}} h_m h_{u+m} \\ &= \sum_{m' \in \mathbb{Z}} \tilde{h}_{m'} h_{u-m'} \quad (\text{setting } m' = -m) \end{aligned}$$

so  $w = \tilde{h} * h$  and thus applying the convolution theorem again

$$W(f) = \tilde{H}(f)H(f) = |H(f)|^2,$$

because  $\tilde{H}(f) = H(-f) = H(f)^*$ . This gives the required result. □

## Lemma 11.13

The filter given by  $\Phi(B)$  for some  $p^{\text{th}}$  order polynomial  $\Phi$  is an LTI filter with transfer function

$$H(f) = \Phi(e^{-2\pi if})$$

for  $f \in \mathbb{R}$ .

## Proof.

A linear combination of LTI filters is an LTI filter. The impulse response is

$$h_m = \begin{cases} \phi_m & \text{if } 0 \leq m \leq p, \\ 0 & \text{otherwise.} \end{cases}$$

So its transfer function is

$$H(f) = \sum_{m \in \mathbb{Z}} h_m e^{-2\pi ifm} = \sum_{j=0}^p \phi_j e^{-2\pi ifj} = \Phi(e^{-2\pi if}).$$

## Theorem 11.14

Consider a stationary ARMA( $p, q$ ) process

$$\Phi(B)X_t = \theta(B)\epsilon_t,$$

the spectral density function of  $X$  is given by

$$\begin{aligned} S_X(f) &= \sigma^2 \frac{|\Theta(e^{-2\pi if})|^2}{|\Phi(e^{-2\pi if})|^2} \\ &= \sigma^2 \left| \frac{\sum_{j=0}^q \theta_j e^{-2\pi ifj}}{\sum_{j=0}^p \phi_j e^{-2\pi ifj}} \right|^2 \end{aligned}$$

- We do not have a nice closed form for the autocovariance function of an ARMA process.
- But, we do have nice form for the spectral density function.

## Proof.

If we have a stationary ARMA process, then we can write

$$\Phi(B)[\{X_t\}] = \Theta(B)[\{\epsilon_t\}].$$

Therefore we have from Lemma 11.13

$$\left| \Phi(e^{-2\pi if}) \right|^2 S_X(f) = \left| \Theta(e^{-2\pi if}) \right|^2 S_\epsilon(f)$$

and so

$$S_X(f) = \sigma^2 \frac{\left| \Theta(e^{-2\pi if}) \right|^2}{\left| \Phi(e^{-2\pi if}) \right|^2}$$

because, by stationarity  $\Phi(e^{-2\pi if}) \neq 0$ .

