

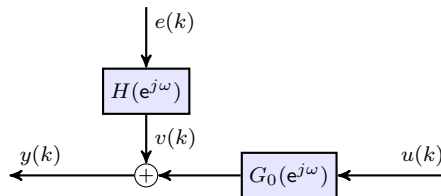
System Identification

Supplementary notes: lecture 5

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5 Frequency-domain identification

5.1 Input-output relationships: finite-energy signals



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

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

This serves as a motivation for the estimate of $G(e^{j\omega})$ as the ratio of Fourier Transform estimates.

$$\begin{aligned} Y(e^{j\omega}) &= \sum_{k=-\infty}^{\infty} y(k)e^{-j\omega k} = \sum_{k=-\infty}^{\infty} \sum_{l=0}^{\infty} g(l)u(k-l)e^{-j\omega k} + \sum_{k=-\infty}^{\infty} v(k)e^{-j\omega k} \\ &= \sum_{l=0}^{\infty} g(l)e^{-j\omega l} \sum_{k=-\infty}^{\infty} u(k-l)e^{-j\omega(k-l)} + V(e^{j\omega}), \\ &= \sum_{l=0}^{\infty} g(l)e^{-j\omega l} \sum_{m=-\infty}^{\infty} u(m)e^{-j\omega m} + V(e^{j\omega}) \quad (m = k-l) \\ &= G(e^{j\omega})U(e^{j\omega}) + V(e^{j\omega}). \end{aligned}$$

The result holds true for the Fourier Transforms in the expected value case:

$$E\{v(k)\} = 0 \implies E\{V(e^{j\omega})\} = 0 \quad (\text{via linearity of expectation operator})$$

So,

$$E\{Y(e^{j\omega})\} = G(e^{j\omega})E\{U(e^{j\omega})\}.$$

This is “idealised” in several senses:

1. The Fourier transform of $v(k)$ is assumed to exist. As noise is typically finite power, and not finite energy, this won't be satisfied. However we are more interested in the relationship between $U(e^{j\omega})$ and $Y(e^{j\omega})$ and so we will overlook this issue for the time being.
2. We can only estimate $Y(e^{j\omega})$ and $U(e^{j\omega})$. In practice we will only have finite data and so the infinite summations above can usually¹ only be approximated by finite truncations.
3. Even if $u(k)$ has a non-zero value on a finite range of values of k , the output, $y(k)$, will not share this property unless the impulse response, $g(l)$, also has finite support.

5.2 ETFE for periodic signals

In the periodic signal case it turns out that an exact input-output frequency domain relationship can be calculated from finite data.

The time domain response of the system is,

$$\begin{aligned} y(k) &= G(z)u(k) + v(k), \quad k = 0, \dots, N-1, \\ &= \sum_{i=0}^{\infty} g(i)u(k-i) + v(k) \\ &= \sum_{i=-\infty}^{\infty} g(i)u(k-i) + v(k). \end{aligned}$$

¹Periodic signals are an exception to this as only one period is needed to define the entire signal.

By taking the DFT of $y(k)$ we get,

$$\begin{aligned}
 Y_N(e^{j\omega_n}) &= \sum_{k=0}^{N-1} y(k)e^{-j\omega_n k} \\
 &= \sum_{k=0}^{N-1} \sum_{i=-\infty}^{\infty} g(i)u(k-i)e^{-j\omega_n k} + \sum_{k=0}^{N-1} v(k)e^{-j\omega_n k} \\
 &= \underbrace{\sum_{i=-\infty}^{\infty} g(i)e^{-j\omega_n i}}_{G(e^{j\omega_n})} \sum_{k=0}^{N-1} u(k-i)e^{-j\omega_n(k-i)} + V_N(e^{j\omega_n}) \\
 &= G(e^{j\omega_n}) \sum_{l=-i}^{N-1-i} u(l)e^{-j\omega_n l} + V_N(e^{j\omega_n}) \\
 &= G(e^{j\omega_n}) \underbrace{\left(\sum_{l=0}^{N-i-1} u(l)e^{-j\omega_n l} + \sum_{l=N-i}^{N-1} u(l+N)e^{-j\omega_n(l+N)} \right)}_{U_N(e^{j\omega_n})} + V_N(e^{j\omega_n})
 \end{aligned}$$

This argument assumes $l < N$. If this is not satisfied then shift the index by an appropriate multiple of N .

Note that the true plant, $G(e^{j\omega_n})$, appears in the relationship. So $G(e^{j\omega_n})$ is given by,

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

For periodic signals then, the ETFE gives an unbiased estimate of $G(e^{j\omega_n})$. There is no error arising from the truncation of finite data as periodic signals are completely defined by the data on a single period.

Note however that noise is still present and will give a variance error. The summation to $-\infty$ makes it clear that we need $u(k)$ and $y(k)$ to be periodic in negative time as well. In practice this is never exactly achieved.

5.3 Transients in ETFE methods

The average magnitude of $U_N(e^{j\omega_n})$ grows with a rate of N (periodic case) or \sqrt{N} (random case). As we are dividing by $U_N(e^{j\omega_n})$ the transient decays with a rate of $1/N$ in the periodic input case, or $1/\sqrt{N}$ in the random input case.

To see this note that the total energy in the time and frequency domains is the same. Consider the periodic and the random cases.

Periodic $u(k)$ case:

The DFT for a single length M period of a signal is,

$$U_M(e^{j\omega_n}) = \sum_{k=0}^{M-1} u(k)e^{jk\omega_n}, \quad m = n, \dots, M.$$

Now consider increasing the experiment length to $N = mM$ where m is an integer. This adds $m - 1$ more periods to the experiment. Then,

$$\begin{aligned} U_N(e^{j\omega_n}) &= U_{mM}(e^{j\omega_n}) = \sum_{k=0}^{mN-1} u(k)e^{jk\omega_n} = \sum_{r=1}^m \sum_{s=0}^{M-1} u(s+rM)e^{j(s+rM)\omega_n} \\ &= \sum_{r=1}^m \sum_{s=0}^{M-1} u(s)e^{js\omega_n} \underbrace{e^{jrM\omega_n}}_{=1} = m \sum_{s=0}^{M-1} u(s)e^{js\omega_n} = mU_N(e^{j\omega_n}) \end{aligned}$$

as $M\omega_n = 2\pi$

So we see that the magnitude of the DFT frequencies are scaled by m . It is important to note that there are still only M frequencies that can be calculated. The energy at the other frequencies is zero.

This implies that, for periodic $u(k)$,

$$\lim_{m \rightarrow \infty} \frac{R_{mM}(e^{j\omega_n})}{U_M(e^{j\omega_n})} = 0 \quad \text{with rate } 1/m.$$

Random $u(k)$ case:

This result for random $u(k)$ can be seen from the proof of convergence of the periodogram to the spectrum². From this proof we have,

$$\begin{aligned} E \left\{ |U_N(e^{j\omega_n})|^2 \right\} &= E \left\{ U_N(e^{j\omega_n}) U_N(e^{-j\omega_n}) \right\} \\ &= N\phi_u(e^{j\omega_n}) + 2c, \end{aligned}$$

where

$$|c| \leq C = \sum_{\tau=1}^{\infty} |\tau R_u(\tau)|.$$

As the power spectral density of $u(k)$ is constant, this immediately gives the random result.

References

- [1] L. Ljung, *System Identification: Theory for the User*, 2nd ed. Prentice-Hall, 1999.

²See Ljung [1] for details.