

Time-Domain Windowing

Let $\{x(n)\}$ denote a sequence to be analyzed. Let's limit the duration of $\{x(n)\}$ to *L* samples:

$$\hat{x}(n) = x(n)w(n)$$

where w(n) is a rectangular window and is defined as

$$w(n) = \begin{cases} 1, & 0 \le n \le L-1 \\ 0, & otherwise \end{cases}$$

The Fourier transform of w(n) is given by:

 $W(\omega) = \frac{\sin(\omega(L/2))}{\sin(\omega/2)}e^{-j\omega((L-1)/2)}$

The transform of $\hat{x}(n)$ is given by:

$$\hat{X}(\omega) = \frac{1}{2} [W(\omega - \omega_o) + W(\omega + \omega_o)].$$

This introduces frequency domain aliasing (the so-called picket fence effect):



Time/Frequency Properties of Windows



Fig. 6. A frame-based overlapping analysis is depicted. In this case, a 33% overlap is shown. One-third of the data used in each analysis frame is shared with the previous frame. Note that only one-third of the data are unique to the current frame—the remaining two-thirds are shared between adjacent frames.

$$\% Overlap = \frac{(T_w - T_f)}{T_w} \times 100\%$$







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$$Popular Windows$$
1. Rectangular:

$$w(k) = \begin{cases} 1, & |k| \le N \\ 0, & otherwise \end{cases}$$
2. Generalized Hanning:

$$w_{H}(k) = w(k) \Big[\alpha + (1 - \alpha) \cos \Big(\frac{2\pi}{N} k \Big) \Big] \qquad 0 < \alpha < 1$$

$$\alpha = 0.54, \qquad Hamming window$$

$$\alpha = 0.50, \qquad Hanning window$$
3. Bartlett

$$w_{B}(k) = w(k) \Big[1 - \frac{|k|}{N+1} \Big]$$
4. Kaiser

$$w_{K}(k) = w(k) I_{0} \Big(\alpha \sqrt{1 - \frac{K^{2}}{N}} \Big) / I_{0}(\alpha)$$
5. Chebyshev:

$$w_{N}(k) = 2(x_{0}^{2} - 1)w_{N-1}(k) + x_{0}^{2}[w_{N-1}(k - 1) + w_{N-1}(k + 1)] - w_{N-2}(k)$$
6. Gaussian

$$w_{G}(k) = \begin{cases} \exp \Big[-\frac{1}{2}k^{2} \tan^{2} \Big(\frac{\theta_{0}}{2} \Big) \Big] & |k| < N \\ w_{G}(N-1) / \Big[2N \sin^{2} \Big(\frac{\theta_{0}}{2} \Big) \Big] & |k| < N \end{cases}$$

There are many others. The most important characteristics are the width of the main lobe and the attenuation in the stop-band (height of highest sidelobe). The Hamming window is used quite extensively.

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|k| > N

Recursive-in-Time Approaches

Define the short-term estimate of the power as:

$$P(n) = \frac{1}{N_s} \sum_{m=0}^{N_s - 1} \left(w(m)s(n - \frac{N_s}{2} + m) \right)^2$$

We can view the above operation as a moving-average filter applied to the sequence $s^{2}(n)$.

This can be computed recursively using a linear constant-coefficient difference equation:

$$P(n) = -\sum_{i=1}^{N_a} a_{pw}(i)P(n-i) + \sum_{j=1}^{N_b} b_{pw}(j)s^2(n-j)$$

Common forms of this general equation are:

 $P(n) = \alpha P(n-1) + s^2(n)$ (Leaky Integrator)

 $P(n) = \alpha P(n-1) + (1-\alpha)s^2(n)$

(First-order weighted average)

 $P(n) = \alpha P(n-1) + \beta P(n-2) + s^{2}(n) + \gamma s^{2}(n-1)$ (2nd-order Integrator)

Of course, these are nothing more than various types of low-pass filters, or adaptive controllers. How do we compute the constants for these equations?

In what other applications have we seen such filters?



Relationship to Control Systems

The first-order systems can be related to physical quantities by observing that the system consists of one real pole:

$$H(z) = \frac{1}{1 - \alpha z^{-1}}$$

 α can be defined in terms of the bandwidth of the pole.

For second-order systems, we have a number of alternatives. Recall that a second-order system can consist of at most one zero and one pole and their complex conjugates. Classical filter design algorithms can be used to design the filter in terms of a bandwidth and an attenuation.

An alternate approach is to design the system in terms of its unit-step response:



There are many forms of such controllers (often known as servo-controllers). One very interesting family of such systems are those that correct to the velocity and acceleration of the input. All such systems can be implemented as a digital filter.

