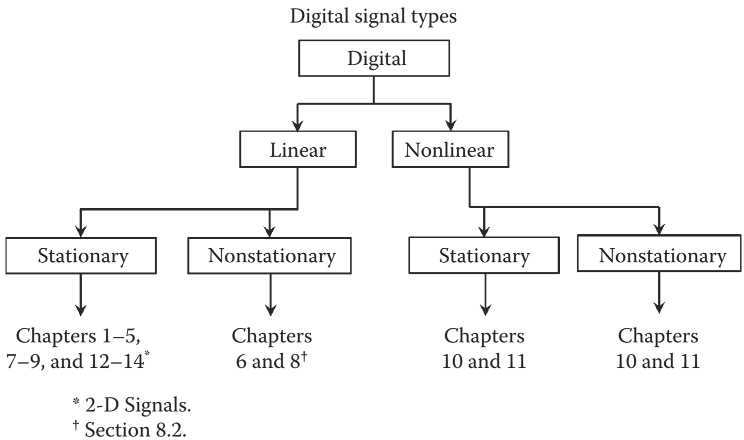

Figure 2.1 Classification of digital signals. The chapters that cover the different signal types are shown.

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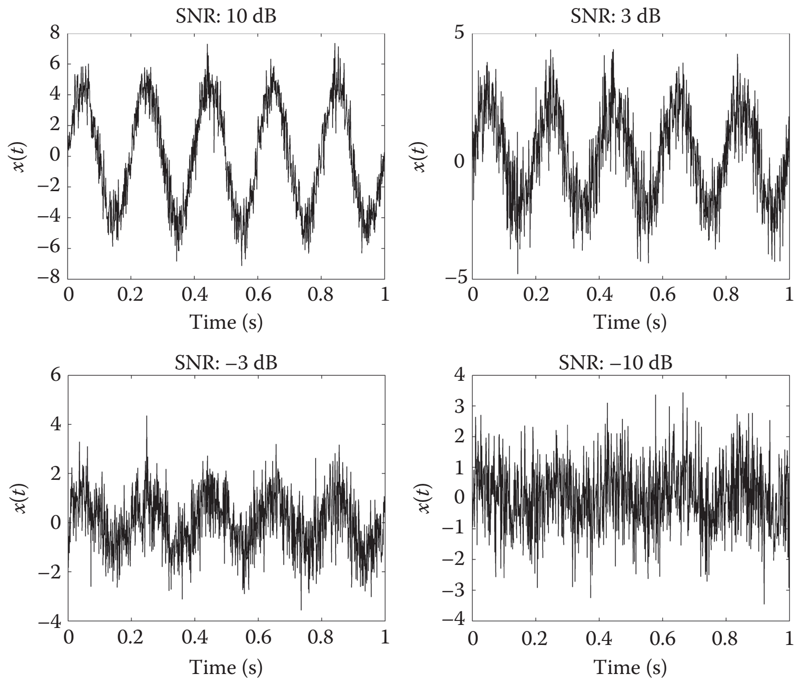

Figure 2.2 A 5-Hz sine wave with varying amounts of added noise. The sine wave is barely discernible when the SNR is –3 dB, and not visible when the SNR is –10 dB.

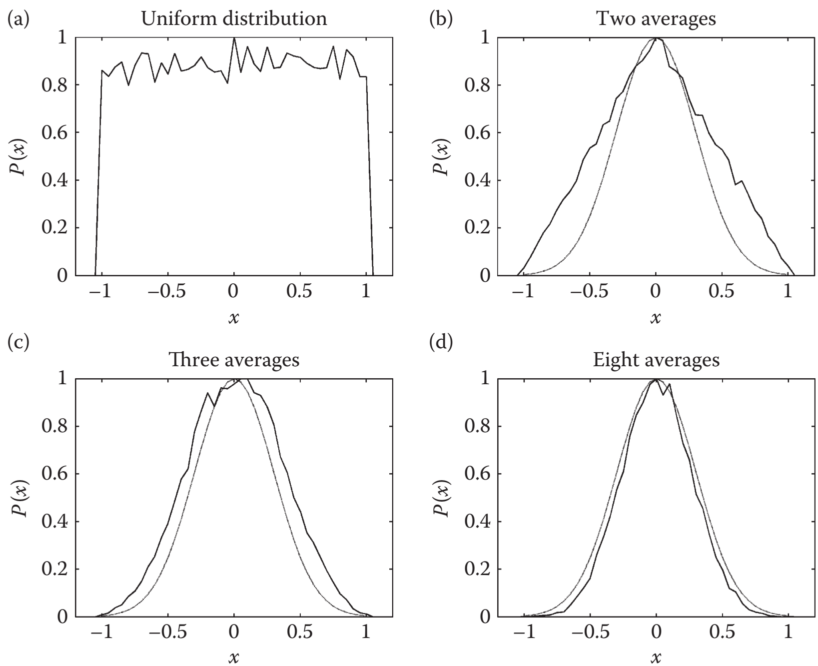

Figure 2.3 (a) The distribution of 20,000 uniformly distributed random numbers. The distribution function is approximately flat between 0 and 1. (b) The distribution of the same size data set where each number is the average of two uniformly distributed numbers. The dashed line is the Gaussian distribution. (c) Each number in the data set is the average of three uniformly distributed numbers. (d) When eight uniformly distributed numbers are averaged to produce one number in the data set, the distribution is very close to Gaussian.

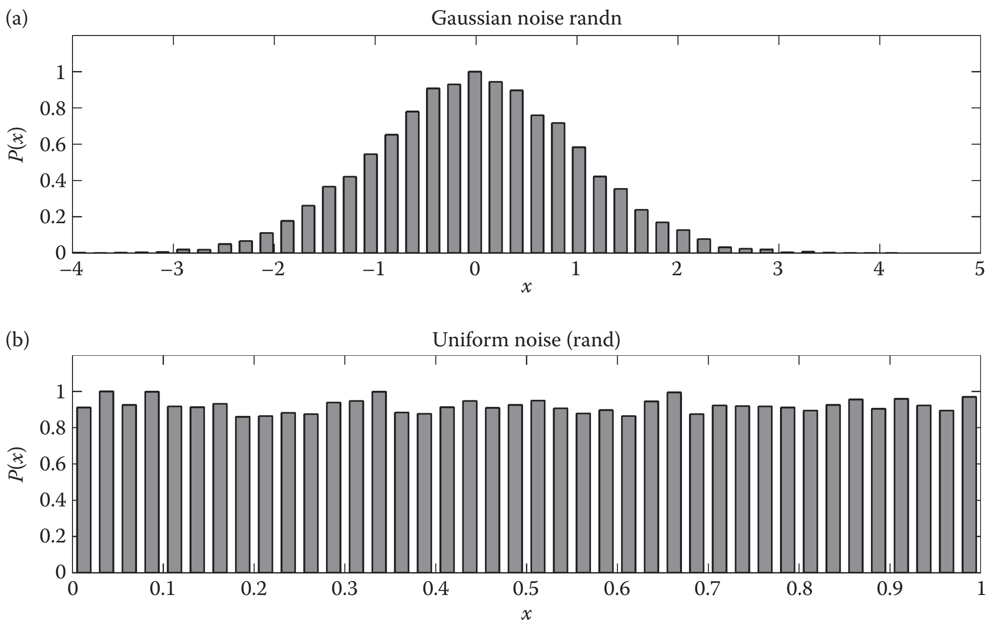

Figure 2.4 (a) The distribution of a 20,000-point data set produced by the MATLAB random number routine `randn`. As is seen here, the distribution is quite close to the theoretical Gaussian distribution. (b) The distribution of a 20,000-point data set produced by `rand`.

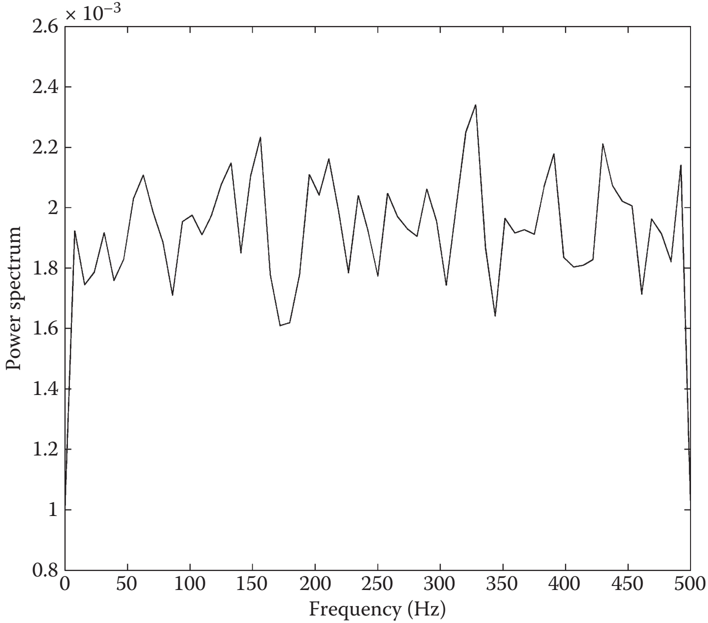

Figure 2.5 Power density (power spectrum) of white noise showing a fairly constant value over all frequencies. This constant energy feature is a property of both thermal and shot noise.

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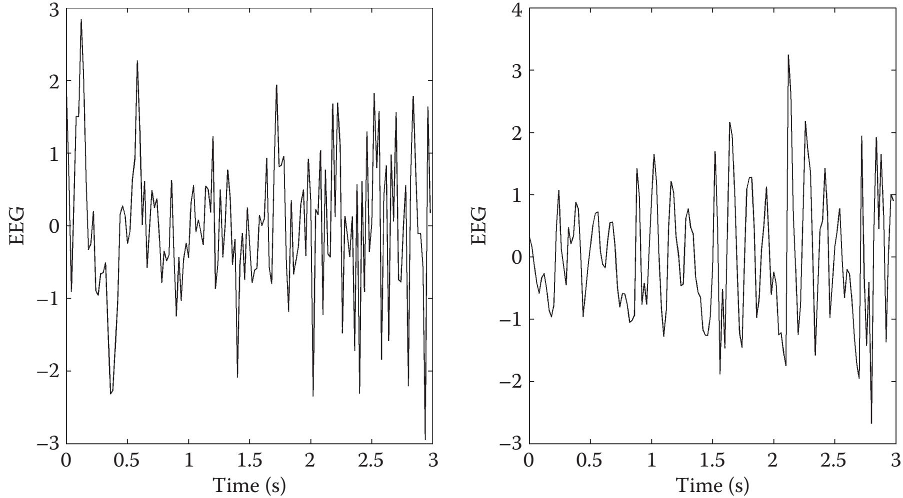

Figure 2.6 Two segments of an EEG signal with the same mean, RMS, and variance values, yet the signals are clearly different.

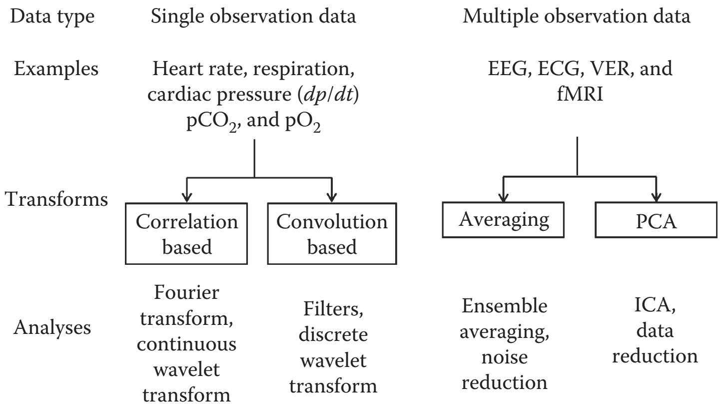

Figure 2.7 A summary of some of the analyses techniques covered in this book, the basic strategy used, and the related data type.

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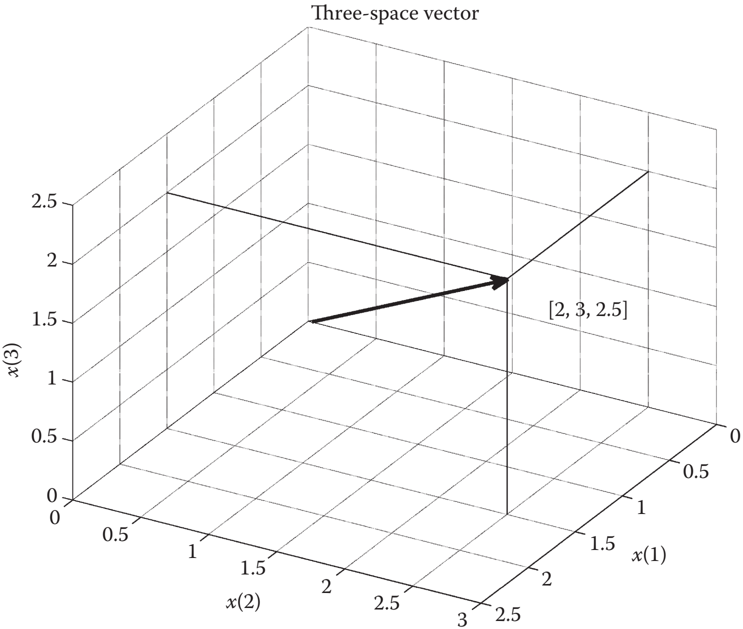

Figure 2.8 The data sequence $x[n] = [2, 3, 2.5]$ represented as a vector in 3-D space.

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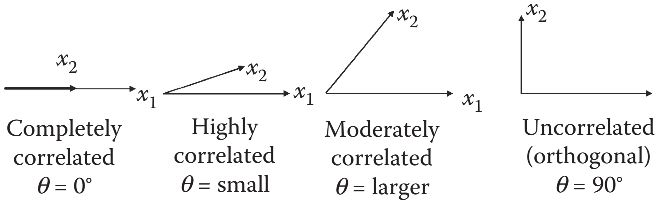

Figure 2.9 The correlation of two waveforms (or functions) can be viewed as a projection of one on the other when the signals are represented as vectors.

002x009.eps

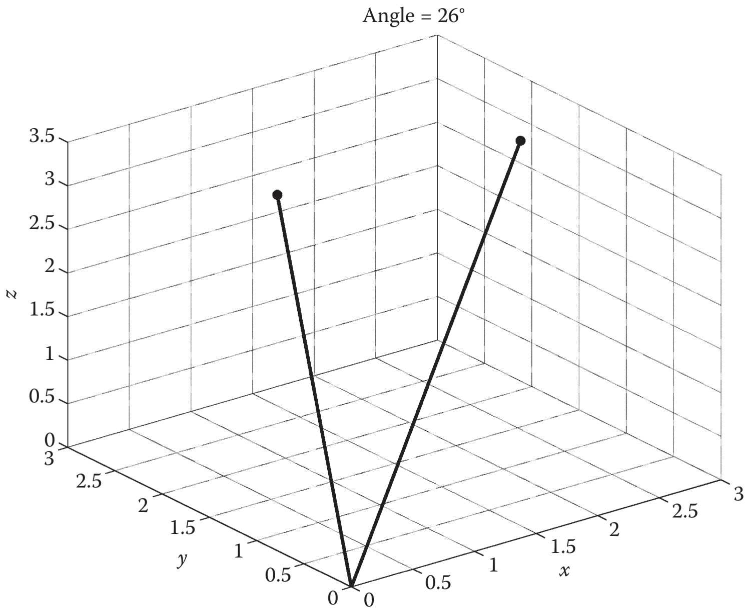

Figure 2.10 Two vectors used in Example 2.5. Using Equations 2.29, 2.32, and 2.33 the angle between these vectors is determined to be 26°. If these vectors represent signals (short signals to be sure), the small angle indicates some correlation between them.

002x010.eps

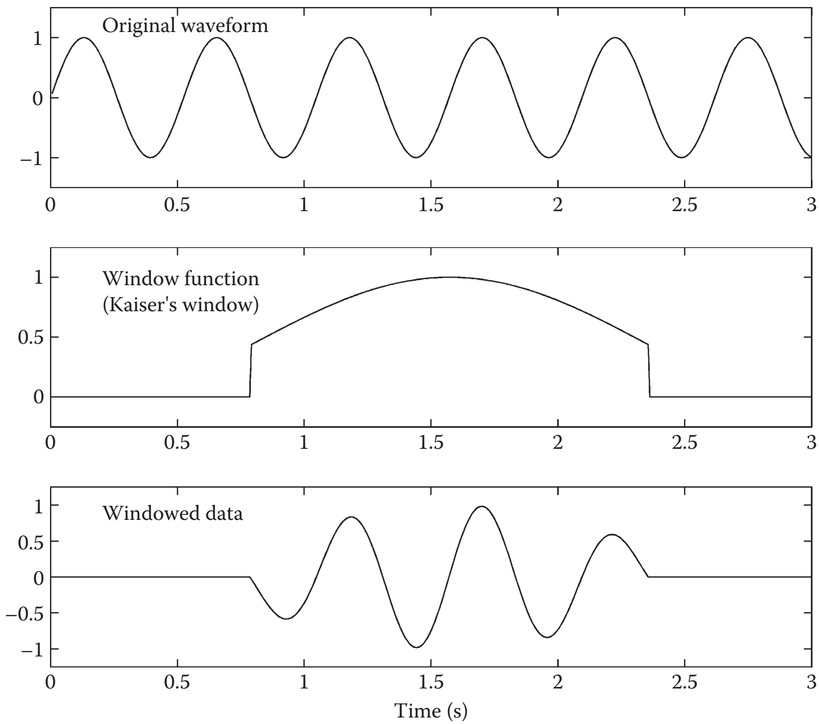

Figure 2.11 A waveform (upper plot) is multiplied by a window function (middle plot) to create a truncated version (lower plot) of the original waveform. The window function is shown in the middle plot. This particular window function is called the Kaiser window, one of many popular window functions described in Chapter 3.

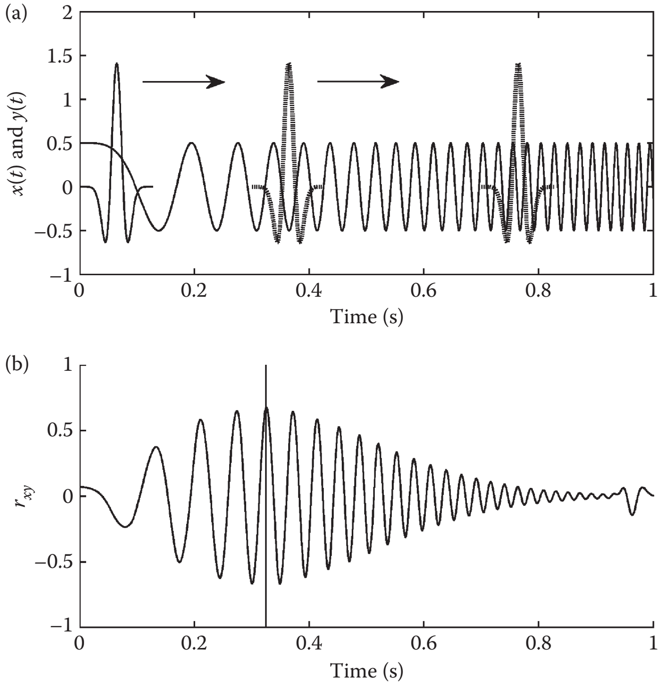

Figure 2.12 (a) The probing function slides over the signal and at each position the correlation between probe and signal is calculated using Equation 2.39. In this example, the probing function is one member of the *Mexican Hat* family (see Chapter 7) and the signal is a sinusoid that increases its frequency linearly over time known as a *chirp*. (b) The result shows the correlation between the waveform and the probing function as it slides across the waveform. Note that this correlation varies sinusoidally as the phase between the two functions varies, but reaches a maximum around 2.5 s, the time when the signal is most like the probing function.

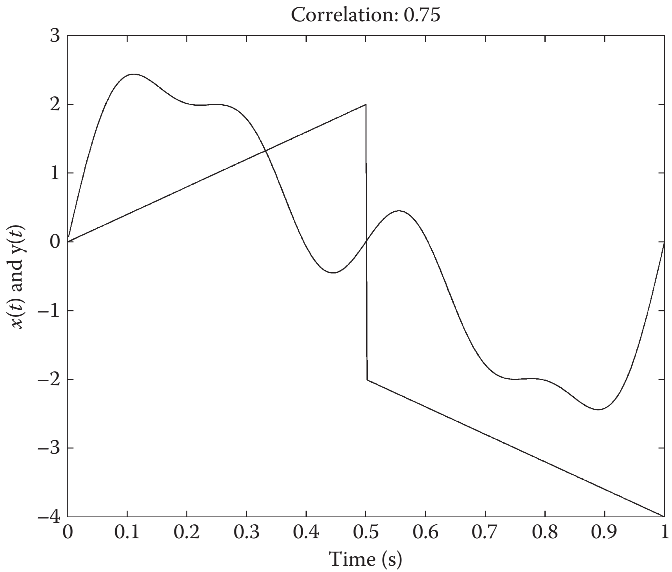

Figure 2.13 Two waveforms used in Example 2.7. The Pearson correlation was found to be 0.75, reflecting the similarity between the two waveforms.

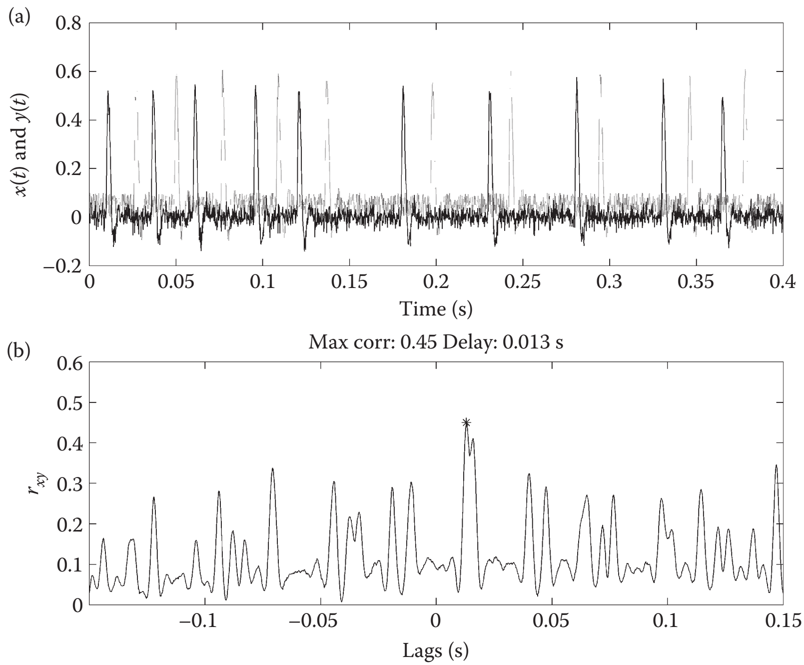

Figure 2.14 (a) Signals recorded from two different neurons (light and dark traces) used in Example 2.9. (b) To determine if they are related, the cross-correlation is taken and the delay (lag) at which the maximum correlation occurs is determined. The maximum correlation found by the `max` operator is indicated.

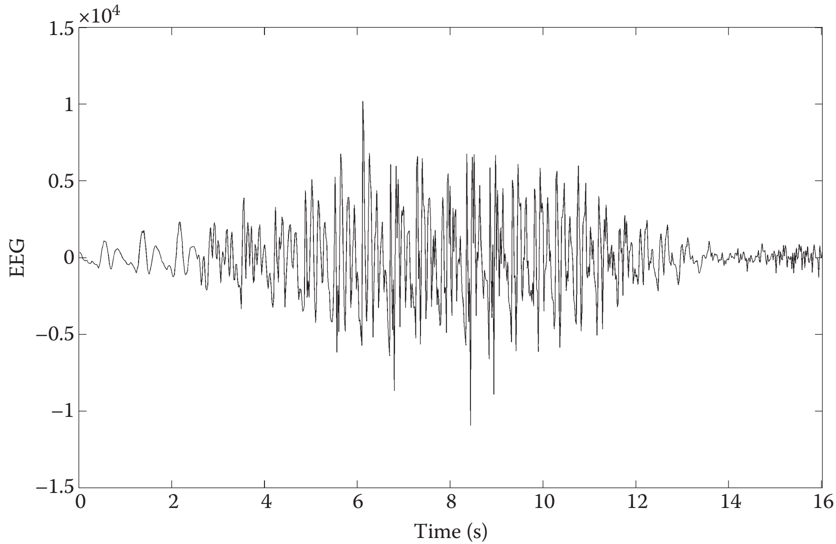

Figure 2.15 An EEG signal that is compared with sinusoids at different frequencies in Example 2.10.

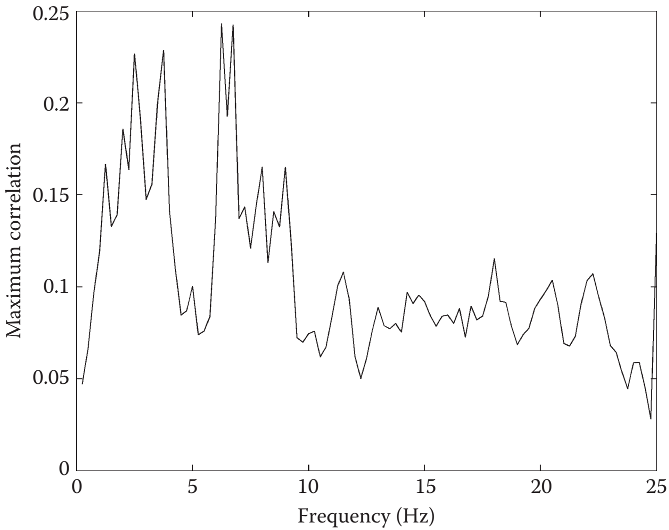

Figure 2.16 The maximum correlation between the EEG signal in Figure 2.15 and a sinusoid plotted as a function of the frequency of the sinusoid.

002x016.eps

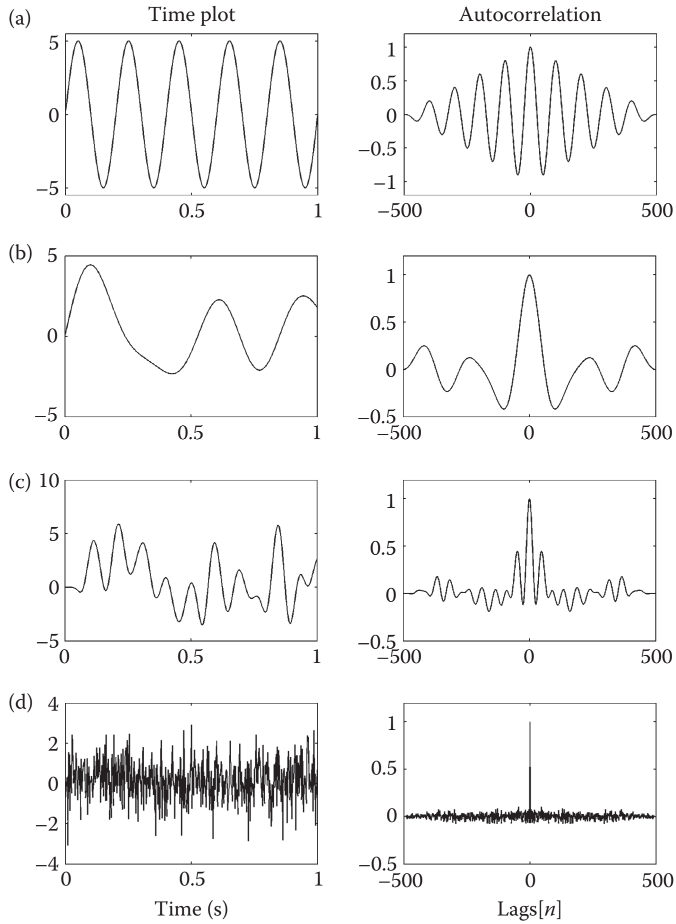

Figure 2.17 Four different signals (left side) and their autocorrelation functions (right side): (a) A truncated sinusoid. The reduction in amplitude is due to the finite length of the signal. A true (i.e., infinite) sinusoid would have a nondiminishing cosine wave as its autocorrelation function; (b) A slowly varying signal; (c) A rapidly varying signal; (d) A random signal (Gaussian's noise). Signal samples are all uncorrelated with one another.

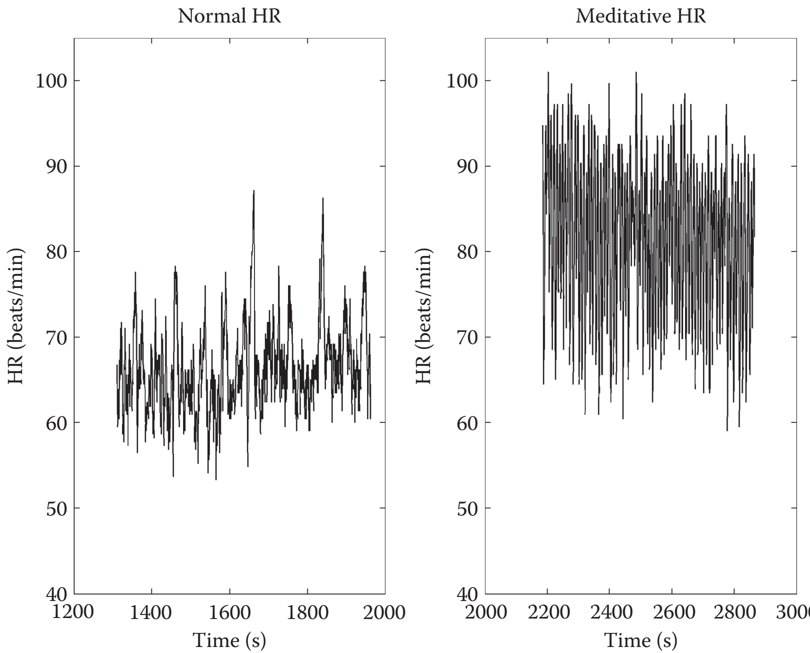

Figure 2.18 Approximately 10 min of instantaneous heart rate data taken from a normal subject and one who is meditating. The meditating subject shows a higher overall heart rate and much greater beat-to-beat fluctuations.

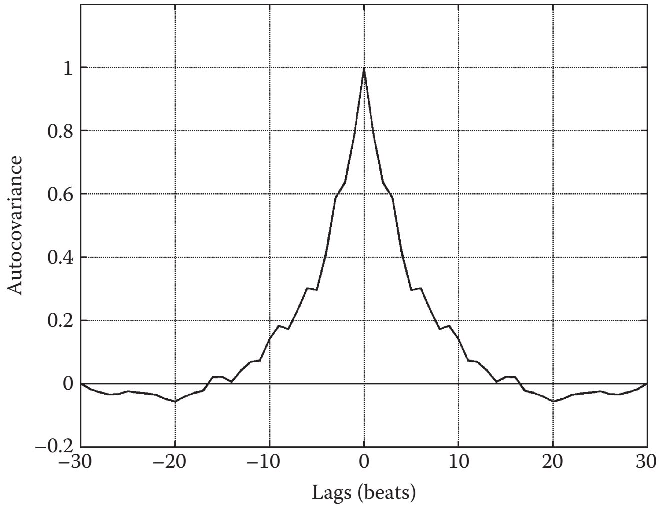

Figure 2.19 Autocovariance function of the heart rate under normal resting conditions (solid line). Some correlation is observed in the normal conditions over approximately 10 successive heartbeats.

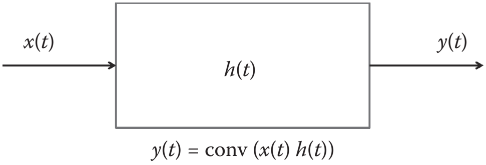

Figure 2.20 The operation of convolution is used in linear systems theory to calculate the output of an LTI system to any input signal.

002x020.eps

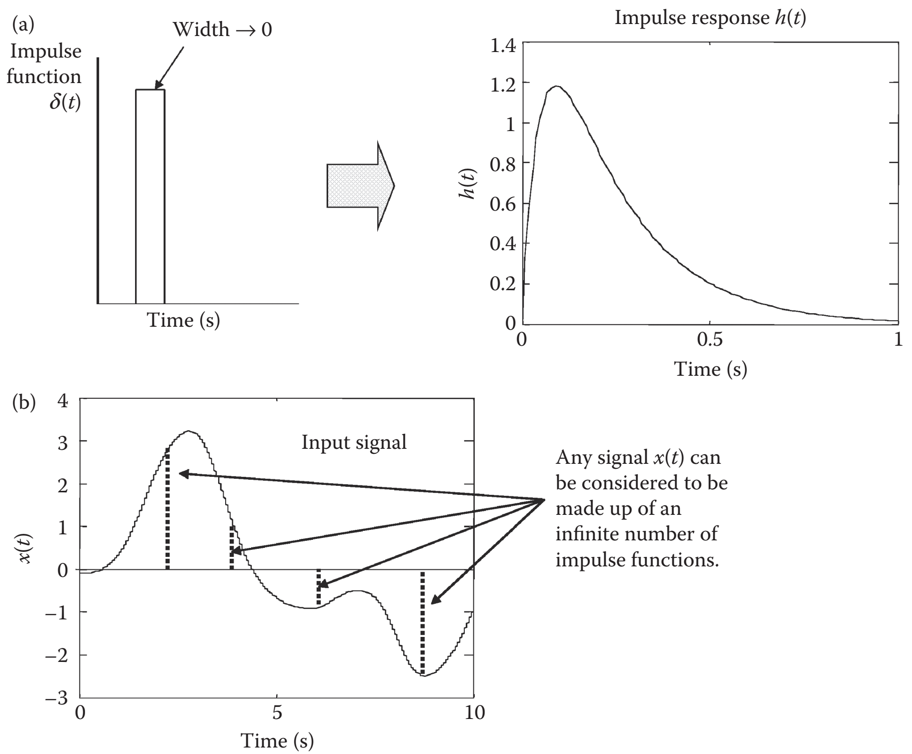

Figure 2.21 (a) If the input to a system is a short pulse (left side), then the output is termed the impulse response (right side). (b) Every signal can be thought of as composed of short pulses.

002x021.eps

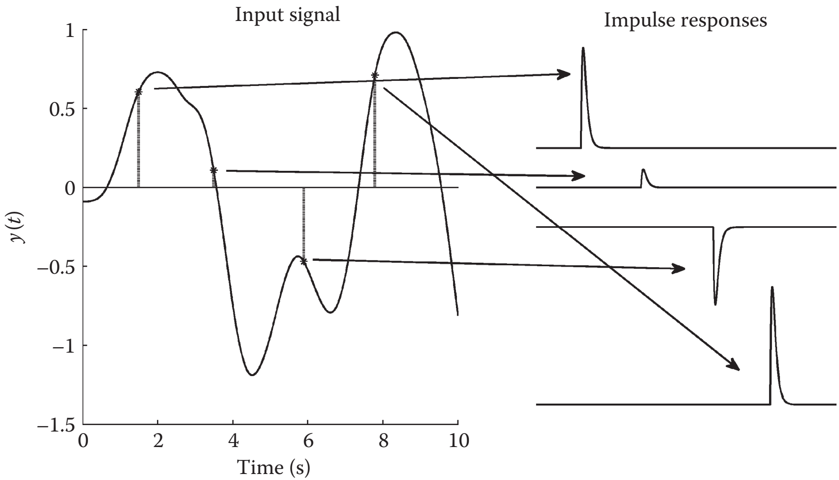

Figure 2.22 Each segment of an input signal can be represented by an impulse, and each produces its own impulse response. The amplitude and position of the impulse response is determined by the amplitude and position of the associated input segment.

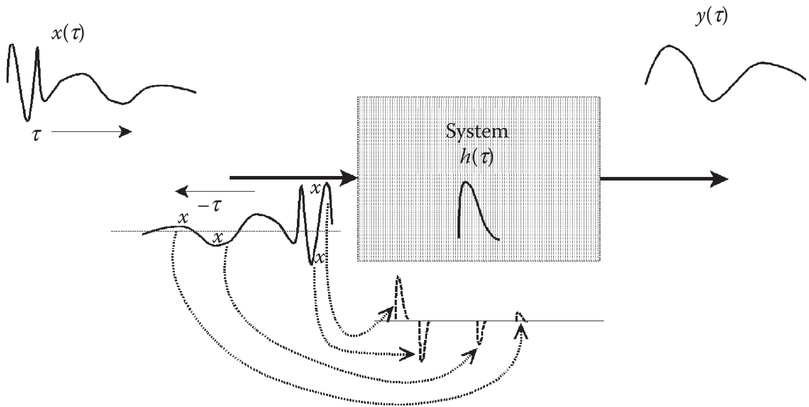

Figure 2.23 An input signal first enters the target system at the lowest (or most negative) time value. So the first impulse response generated by the input is from the left-most signal segment. As it proceeds in time through the system backwards, it generates a series of impulse responses scaled and shifted by the associated signal segment.

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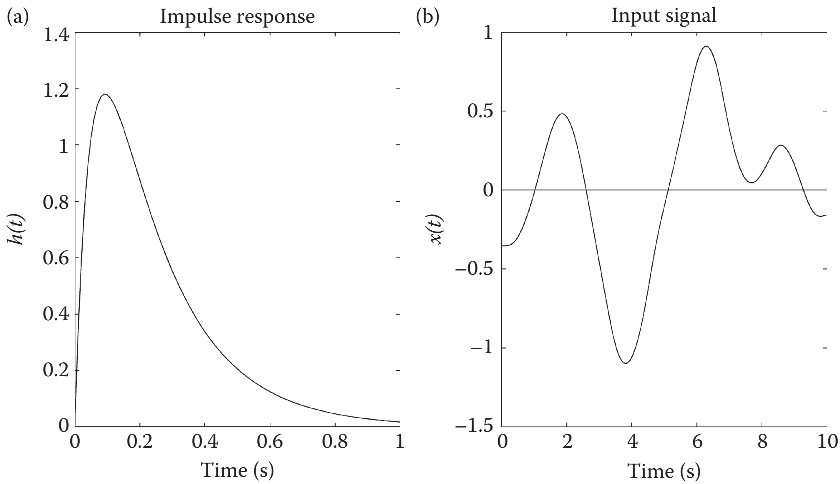

Figure 2.24 (a) The impulse response to a hypothetical system used to illustrate convolution. (b) The input signal to the hypothetical system. The impulse response is much shorter than the input signal (note the 1.0 versus 10 s time scales) as is usually the case.

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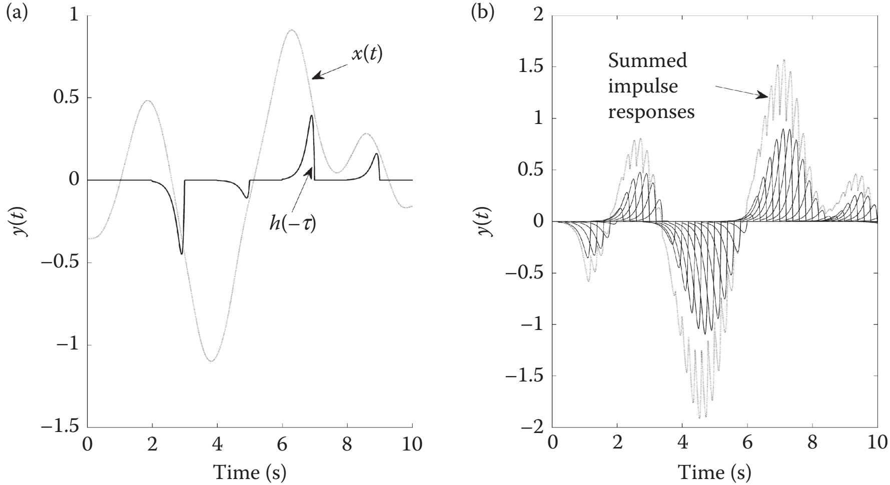

Figure 2.25 (a) Four impulse responses to instantaneous segments of the input signal ($x(t)$ in Figure 2.24a) at 2, 4, 6, and 8 s. (b) Impulse responses from 50 evenly spaced segments of $x(t)$ along with their summation. The summation begins to look like the actual output response.

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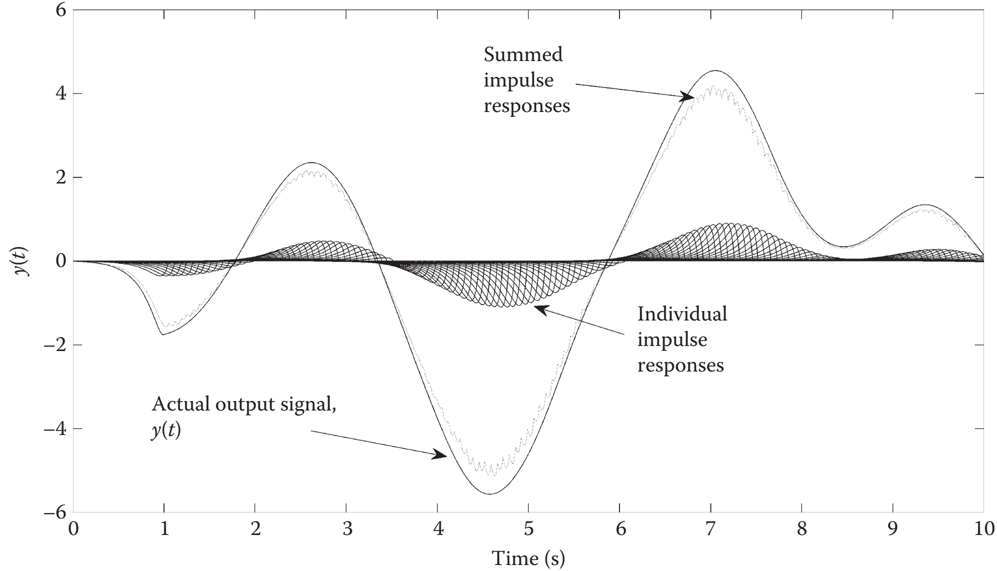

Figure 2.26 The reversed impulse responses of 150 evenly spaced segments of $x(t)$ along with the summation and the actual output signal.

002x026.eps

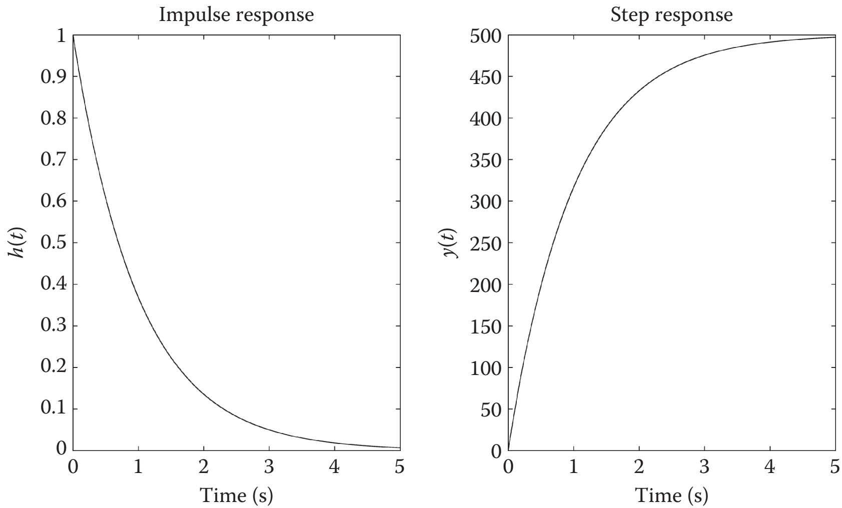

Figure 2.27 The impulse response of a first-order system and the output of this system to a step input. These plots are produced by the code in Example 2.12.

002x027.eps

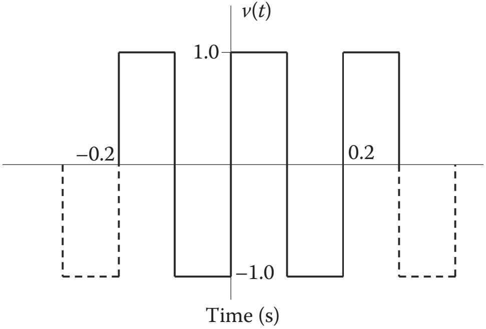

Figure P2.3 Square wave used in Problem 2.3.

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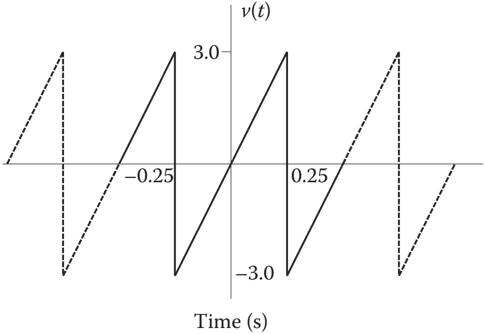

Figure P2.5 Waveform used in Problem 2.5.

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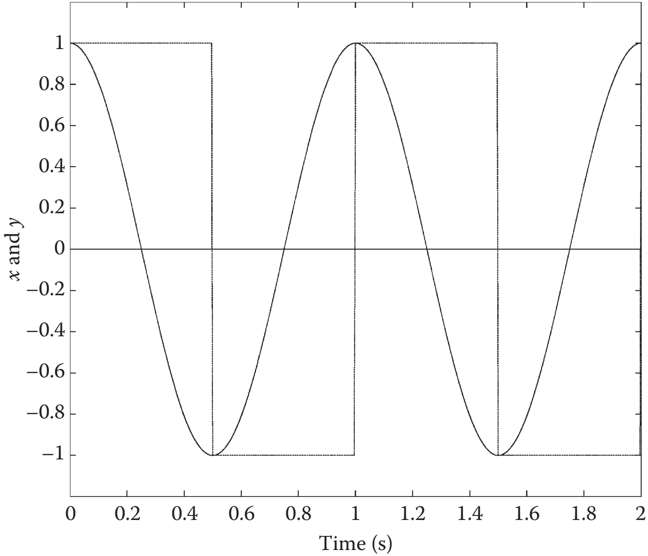

Figure P2.25 Waveforms wave used in Problem 2.25.

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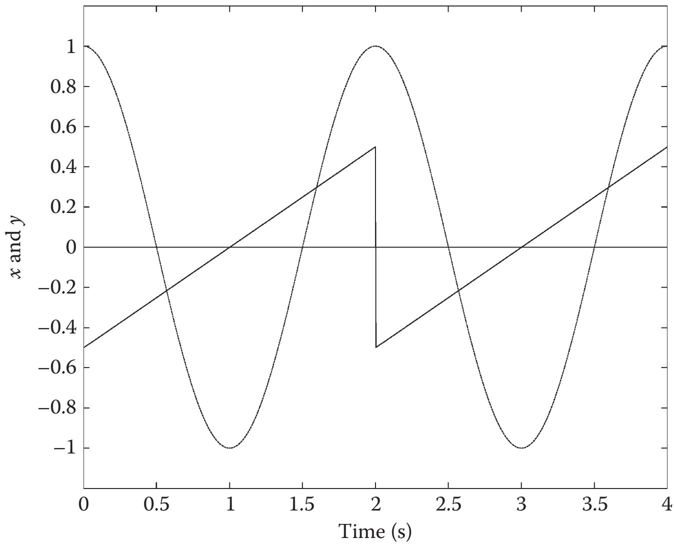

Figure P2.26 Waveforms wave used in Problem 2.26

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