Understanding Digital Signal Processing

Third Edition

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Understanding Digital Signal Processing

Third Edition

Richard G. Lyons

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I dedicate this book to my daughters, Julie and Meredith—I wish I could go with you; to my mother, Ruth, for making me finish my homework; to my father, Grady, who didn't know what he started when he built that workbench in the basement; to my brother Ray for improving us all; to my brother Ken who succeeded where I failed; to my sister Nancy for running interference for us; and to the skilled folks on the USENET newsgroup comp.dsp. They ask the good questions and provide the best answers. Finally, to Sigi Pardula (Bat-girl): Without your keeping the place running, this book wouldn't exist.

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Contents

PREFACE xv ABOUT THE AUTHOR xxiii

1 DISCRETE SEQUENCES AND SYSTEMS 1

- 1.1 Discrete Sequences and Their Notation 2
- 1.2 Signal Amplitude, Magnitude, Power 8
- 1.3 Signal Processing Operational Symbols 10
- 1.4 Introduction to Discrete Linear Time-Invariant Systems 12
- 1.5 Discrete Linear Systems 12
- 1.6 Time-Invariant Systems 17
- 1.7 The Commutative Property of Linear Time-Invariant Systems 18
- 1.8 Analyzing Linear Time-Invariant Systems 19 References 21 Chapter 1 Problems 23

2 PERIODIC SAMPLING 33

- 2.1 Aliasing: Signal Ambiguity in the Frequency Domain 33
- 2.2 Sampling Lowpass Signals 38
- 2.3 Sampling Bandpass Signals 42
- 2.4 Practical Aspects of Bandpass Sampling 45 References 49 Chapter 2 Problems 50

3 THE DISCRETE FOURIER TRANSFORM 59

- 3.1 Understanding the DFT Equation 60
- 3.2 DFT Symmetry 73

- 3.3 DFT Linearity 75
- 3.4 DFT Magnitudes 75
- 3.5 DFT Frequency Axis 77
- 3.6 DFT Shifting Theorem 77
- 3.7 Inverse DFT 80
- 3.8 DFT Leakage 81
- 3.9 Windows 89
- 3.10 DFT Scalloping Loss 96
- 3.11 DFT Resolution, Zero Padding, and Frequency-Domain Sampling 98
- 3.12 DFT Processing Gain 102
- 3.13 The DFT of Rectangular Functions 105
- 3.14 Interpreting the DFT Using the Discrete-Time Fourier Transform 120 References 124 Chapter 3 Problems 125

4 THE FAST FOURIER TRANSFORM 135

- 4.1 Relationship of the FFT to the DFT 136
- 4.2 Hints on Using FFTs in Practice 137
- 4.3 Derivation of the Radix-2 FFT Algorithm 141
- 4.4 FFT Input/Output Data Index Bit Reversal 149
- 4.5 Radix-2 FFT Butterfly Structures 151
- 4.6 Alternate Single-Butterfly Structures 154 References 158 Chapter 4 Problems 160

5 FINITE IMPULSE RESPONSE FILTERS 169

- 5.1 An Introduction to Finite Impulse Response (FIR) Filters 170
- 5.2 Convolution in FIR Filters 175
- 5.3 Lowpass FIR Filter Design 186
- 5.4 Bandpass FIR Filter Design 201
- 5.5 Highpass FIR Filter Design 203
- 5.6 Parks-McClellan Exchange FIR Filter Design Method 204
- 5.7 Half-band FIR Filters 207
- 5.8 Phase Response of FIR Filters 209
- 5.9 A Generic Description of Discrete Convolution 214

Contents

5.10 Analyzing FIR Filters 226 References 235 Chapter 5 Problems 238

6 INFINITE IMPULSE RESPONSE FILTERS 253

- 6.1 An Introduction to Infinite Impulse Response Filters 254
- 6.2 The Laplace Transform 257
- 6.3 The *z*-Transform 270
- 6.4 Using the *z*-Transform to Analyze IIR Filters 274
- 6.5 Using Poles and Zeros to Analyze IIR Filters 282
- 6.6 Alternate IIR Filter Structures 289
- 6.7 Pitfalls in Building IIR Filters 292
- 6.8 Improving IIR Filters with Cascaded Structures 295
- 6.9 Scaling the Gain of IIR Filters 300
- 6.10 Impulse Invariance IIR Filter Design Method 303
- 6.11 Bilinear Transform IIR Filter Design Method 319
- 6.12 Optimized IIR Filter Design Method 330
- 6.13 A Brief Comparison of IIR and FIR Filters 332 References 333 Chapter 6 Problems 336

7 SPECIALIZED DIGITAL NETWORKS AND FILTERS 361

- 7.1 Differentiators 361
- 7.2 Integrators 370
- 7.3 Matched Filters 376
- 7.4 Interpolated Lowpass FIR Filters 381
- 7.5 Frequency Sampling Filters: The Lost Art 392 References 426 Chapter 7 Problems 429

8 QUADRATURE SIGNALS 439

- 8.1 Why Care about Quadrature Signals? 440
- 8.2 The Notation of Complex Numbers 440
- 8.3 Representing Real Signals Using Complex Phasors 446
- 8.4 A Few Thoughts on Negative Frequency 450

- 8.5 Quadrature Signals in the Frequency Domain 451
- 8.6 Bandpass Quadrature Signals in the Frequency Domain 454
- 8.7 Complex Down-Conversion 456
- 8.8 A Complex Down-Conversion Example 458
- 8.9 An Alternate Down-Conversion Method 462 References 464 Chapter 8 Problems 465

9 THE DISCRETE HILBERT TRANSFORM 479

| 9.1 | Hilbert Transform Definition | 480 |
|-----|------------------------------|-----|
|-----|------------------------------|-----|

- 9.2 Why Care about the Hilbert Transform? 482
- 9.3 Impulse Response of a Hilbert Transformer 487
- 9.4 Designing a Discrete Hilbert Transformer 489
- 9.5 Time-Domain Analytic Signal Generation 495
- 9.6 Comparing Analytical Signal Generation Methods 497 References 498 Chapter 9 Problems 499

10 SAMPLE RATE CONVERSION 507

| 10.1 Decimation 500 | 10.1 | Decimation | 508 |
|---------------------|------|------------|-----|
|---------------------|------|------------|-----|

- 10.2 Two-Stage Decimation 510
- 10.3 Properties of Downsampling 514
- 10.4 Interpolation 516
- 10.5 Properties of Interpolation 518
- 10.6 Combining Decimation and Interpolation 521
- 10.7 Polyphase Filters 522
- 10.8 Two-Stage Interpolation 528
- 10.9 z-Transform Analysis of Multirate Systems 533
- 10.10 Polyphase Filter Implementations 535
- 10.11 Sample Rate Conversion by Rational Factors 540
- 10.12 Sample Rate Conversion with Half-band Filters 543
- 10.13 Sample Rate Conversion with IFIR Filters 548
- 10.14 Cascaded Integrator-Comb Filters 550 References 566 Chapter 10 Problems 568

11 SIGNAL AVERAGING 589

- 11.1 Coherent Averaging 590
- 11.2 Incoherent Averaging 597
- 11.3 Averaging Multiple Fast Fourier Transforms 600
- 11.4 Averaging Phase Angles 603
- 11.5 Filtering Aspects of Time-Domain Averaging 604
- 11.6 Exponential Averaging 608 References 615 Chapter 11 Problems 617

12 DIGITAL DATA FORMATS AND THEIR EFFECTS 623

- 12.1 Fixed-Point Binary Formats 623
- 12.2 Binary Number Precision and Dynamic Range 632
- 12.3 Effects of Finite Fixed-Point Binary Word Length 634
- 12.4 Floating-Point Binary Formats 652
- 12.5 Block Floating-Point Binary Format 658 References 658 Chapter 12 Problems 661

13 DIGITAL SIGNAL PROCESSING TRICKS 671

- 13.1 Frequency Translation without Multiplication 671
- 13.2 High-Speed Vector Magnitude Approximation 679
- 13.3 Frequency-Domain Windowing 683
- 13.4 Fast Multiplication of Complex Numbers 686
- 13.5 Efficiently Performing the FFT of Real Sequences 687
- 13.6 Computing the Inverse FFT Using the Forward FFT 699
- 13.7 Simplified FIR Filter Structure 702
- 13.8 Reducing A/D Converter Quantization Noise 704
- 13.9 A/D Converter Testing Techniques 709
- 13.10 Fast FIR Filtering Using the FFT 716
- 13.11 Generating Normally Distributed Random Data 722
- 13.12 Zero-Phase Filtering 725
- 13.13 Sharpened FIR Filters 726
- 13.14 Interpolating a Bandpass Signal 728
- 13.15 Spectral Peak Location Algorithm 730

| 13.16 | Computing FFT Twiddle Factors 734 |
|-------|--|
| 13.17 | Single Tone Detection 737 |
| 13.18 | The Sliding DFT 741 |
| 13.19 | The Zoom FFT 749 |
| 13.20 | A Practical Spectrum Analyzer 753 |
| 13.21 | An Efficient Arctangent Approximation 756 |
| 13.22 | Frequency Demodulation Algorithms 758 |
| 13.23 | DC Removal 761 |
| 13.24 | Improving Traditional CIC Filters 765 |
| 13.25 | Smoothing Impulsive Noise 770 |
| 13.26 | Efficient Polynomial Evaluation 772 |
| 13.27 | Designing Very High-Order FIR Filters 775 |
| 13.28 | Time-Domain Interpolation Using the FFT 778 |
| 13.29 | Frequency Translation Using Decimation 781 |
| 13.30 | Automatic Gain Control (AGC) 783 |
| 13.31 | Approximate Envelope Detection 784 |
| 13.32 | A Quadrature Oscillator 786 |
| 13.33 | Specialized Exponential Averaging 789 |
| 13.34 | Filtering Narrowband Noise Using Filter Nulls 792 |
| 13.35 | Efficient Computation of Signal Variance 797 |
| 13.36 | Real-time Computation of Signal Averages and Variances 799 |
| 13.37 | Building Hilbert Transformers from Half-band Filters 802 |
| 13.38 | Complex Vector Rotation with Arctangents 805 |
| 13.39 | An Efficient Differentiating Network 810 |
| 13.40 | Linear-Phase DC-Removal Filter 812 |
| 13.41 | Avoiding Overflow in Magnitude Computations 815 |
| 13.42 | Efficient Linear Interpolation 815 |
| 13.43 | Alternate Complex Down-conversion Schemes 816 |
| 13.44 | Signal Transition Detection 820 |
| 13.45 | Spectral Flipping around Signal Center Frequency 821 |
| 13.46 | Computing Missing Signal Samples 823 |
| 13.47 | Computing Large DFTs Using Small FFTs 826 |
| 13.48 | Computing Filter Group Delay without Arctangents 830 |
| 13.49 | Computing a Forward and Inverse FFT Using a Single FFT 831 |
| 13.50 | Improved Narrowband Lowpass IIR Filters 833 |
| 13.51 | A Stable Goertzel Algorithm 838 |
| | References 840 |

A THE ARITHMETIC OF COMPLEX NUMBERS 847

- A.1 Graphical Representation of Real and Complex Numbers 847
- A.2 Arithmetic Representation of Complex Numbers 848
- A.3 Arithmetic Operations of Complex Numbers 850
- A.4 Some Practical Implications of Using Complex Numbers 856

B CLOSED FORM OF A GEOMETRIC SERIES 859

C TIME REVERSAL AND THE DFT 863

D MEAN, VARIANCE, AND STANDARD DEVIATION 867

- D.1 Statistical Measures 867
- D.2 Statistics of Short Sequences 870
- D.3 Statistics of Summed Sequences 872
- D.4 Standard Deviation (RMS) of a Continuous Sinewave 874
- D.5 Estimating Signal-to-Noise Ratios 875
- D.6 The Mean and Variance of Random Functions 879
- D.7 The Normal Probability Density Function 882

E DECIBELS (DB AND DBM) 885

- E.1 Using Logarithms to Determine Relative Signal Power 885
- E.2 Some Useful Decibel Numbers 889
- E.3 Absolute Power Using Decibels 891

F DIGITAL FILTER TERMINOLOGY 893

G FREQUENCY SAMPLING FILTER DERIVATIONS 903

- G.1 Frequency Response of a Comb Filter 903
- G.2 Single Complex FSF Frequency Response 904
- G.3 Multisection Complex FSF Phase 905
- G.4 Multisection Complex FSF Frequency Response 906

- G.5 Real FSF Transfer Function 908
- G.6 Type-IV FSF Frequency Response 910

H FREQUENCY SAMPLING FILTER DESIGN TABLES 913

I COMPUTING CHEBYSHEV WINDOW SEQUENCES 927

- I.1 Chebyshev Windows for FIR Filter Design 927
- I.2 Chebyshev Windows for Spectrum Analysis 929

INDEX 931

Preface

This book is an expansion of previous editions of *Understanding Digital Signal Processing*. Like those earlier editions, its goals are (1) to help beginning students understand the theory of digital signal processing (DSP) and (2) to provide practical DSP information, not found in other books, to help working engineers/scientists design and test their signal processing systems. Each chapter of this book contains new information beyond that provided in earlier editions.

It's traditional at this point in the preface of a DSP textbook for the author to tell readers why they should learn DSP. I don't need to tell you how important DSP is in our modern engineering world. You already know that. I'll just say that the future of electronics is DSP, and with this book you will not be left behind.

FOR INSTRUCTORS

This third edition is appropriate as the text for a one- or two-semester undergraduate course in DSP. It follows the DSP material I cover in my corporate training activities and a signal processing course I taught at the University of California Santa Cruz Extension. To aid students in their efforts to learn DSP, this third edition provides additional explanations and examples to increase its tutorial value. To test a student's understanding of the material, homework problems have been included at the end of each chapter. (For qualified instructors, a Solutions Manual is available from Prentice Hall.)

FOR PRACTICING ENGINEERS

To help working DSP engineers, the changes in this third edition include, but are not limited to, the following:

- Practical guidance in building discrete differentiators, integrators, and matched filters
- Descriptions of statistical measures of signals, variance reduction by way of averaging, and techniques for computing real-world signal-to-noise ratios (SNRs)
- A significantly expanded chapter on sample rate conversion (multirate systems) and its associated filtering
- Implementing fast convolution (FIR filtering in the frequency domain)
- IIR filter scaling
- Enhanced material covering techniques for analyzing the behavior and performance of digital filters
- Expanded descriptions of industry-standard binary number formats used in modern processing systems
- Numerous additions to the popular "Digital Signal Processing Tricks" chapter

FOR STUDENTS

Learning the fundamentals, and how to speak the language, of digital signal processing does not require profound analytical skills or an extensive background in mathematics. All you need is a little experience with elementary algebra, knowledge of what a sinewave is, this book, and enthusiasm. This may sound hard to believe, particularly if you've just flipped through the pages of this book and seen figures and equations that look rather complicated. The content here, you say, looks suspiciously like material in technical journals and textbooks whose meaning has eluded you in the past. Well, this is not just another book on digital signal processing.

In this book I provide a gentle, but thorough, explanation of the theory and practice of DSP. The text is not written so that you *may* understand the material, but so that you *must* understand the material. I've attempted to avoid the traditional instructor–student relationship and have tried to make reading this book seem like talking to a friend while walking in the park. I've used just enough mathematics to help you develop a fundamental understanding of DSP theory and have illustrated that theory with practical examples.

I have designed the homework problems to be more than mere exercises that assign values to variables for the student to plug into some equation in order to compute a result. Instead, the homework problems are designed to be as educational as possible in the sense of expanding on and enabling further investigation of specific aspects of DSP topics covered in the text. Stated differently, the homework problems are not designed to induce "death by algebra," but rather to improve your understanding of DSP. Solving the problems helps you become proactive in your own DSP education instead of merely being an inactive recipient of DSP information.

THE JOURNEY

Learning digital signal processing is not something you accomplish; it's a journey you take. When you gain an understanding of one topic, questions arise that cause you to investigate some other facet of digital signal processing.[†] Armed with more knowledge, you're likely to begin exploring further aspects of digital signal processing much like those shown in the diagram on page xviii. This book is your tour guide during the first steps of your journey.

You don't need a computer to learn the material in this book, but it would certainly help. DSP simulation software allows the beginner to verify signal processing theory through the time-tested trial and error process.[‡] In particular, software routines that plot signal data, perform the fast Fourier transforms, and analyze digital filters would be very useful.

As you go through the material in this book, don't be discouraged if your understanding comes slowly. As the Greek mathematician Menaechmus curtly remarked to Alexander the Great, when asked for a quick explanation of mathematics, "There is no royal road to mathematics." Menaechmus was confident in telling Alexander the only way to learn mathematics is through careful study. The same applies to digital signal processing. Also, don't worry if you need to read some of the material twice. While the concepts in this book are not as complicated as quantum physics, as mysterious as the lyrics of the song "Louie Louie," or as puzzling as the assembly instructions of a metal shed, they can become a little involved. They deserve your thoughtful attention. So, go slowly and read the material twice if necessary; you'll be glad you did. If you show persistence, to quote Susan B. Anthony, "Failure is impossible."

⁺"You see I went on with this research just the way it led me. This is the only way I ever heard of research going. I asked a question, devised some method of getting an answer, and got—a fresh question. Was this possible, or that possible? You cannot imagine what this means to an investigator, what an intellectual passion grows upon him. You cannot imagine the strange colourless delight of these intellectual desires" (Dr. Moreau—infamous physician and vivisectionist from H.G. Wells' *Island of Dr. Moreau*, 1896).

[‡]"One must learn by doing the thing; for though you think you know it, you have no certainty until you try it" (Sophocles, 496–406 B.C.).



COMING ATTRACTIONS

Chapter 1 begins by establishing the notation used throughout the remainder of the book. In that chapter we introduce the concept of discrete signal sequences, show how they relate to continuous signals, and illustrate how those sequences can be depicted in both the time and frequency domains. In addition, Chapter 1 defines the operational symbols we'll use to build our signal processing system block diagrams. We conclude that chapter with a brief introduction to the idea of linear systems and see why linearity enables us to use a number of powerful mathematical tools in our analysis.

Chapter 2 introduces the most frequently misunderstood process in digital signal processing, periodic sampling. Although the concept of sampling a continuous signal is not complicated, there are mathematical subtleties in the process that require thoughtful attention. Beginning gradually with simple examples of lowpass sampling, we then proceed to the interesting subject of bandpass sampling. Chapter 2 explains and quantifies the frequency-domain ambiguity (aliasing) associated with these important topics.

Chapter 3 is devoted to one of the foremost topics in digital signal processing, the discrete Fourier transform (DFT) used for spectrum analysis. Coverage begins with detailed examples illustrating the important properties of the DFT and how to interpret DFT spectral results, progresses to the topic of windows used to reduce DFT leakage, and discusses the processing gain afforded by the DFT. The chapter concludes with a detailed discussion of the various forms of the transform of rectangular functions that the reader is likely to encounter in the literature.

Chapter 4 covers the innovation that made the most profound impact on the field of digital signal processing, the fast Fourier transform (FFT). There we show the relationship of the popular radix 2 FFT to the DFT, quantify the powerful processing advantages gained by using the FFT, demonstrate why the FFT functions as it does, and present various FFT implementation structures. Chapter 4 also includes a list of recommendations to help the reader use the FFT in practice.

Chapter 5 ushers in the subject of digital filtering. Beginning with a simple lowpass finite impulse response (FIR) filter example, we carefully progress through the analysis of that filter's frequency-domain magnitude and phase response. Next, we learn how window functions affect, and can be used to design, FIR filters. The methods for converting lowpass FIR filter designs to bandpass and highpass digital filters are presented, and the popular Parks-McClellan (Remez) Exchange FIR filter design technique is introduced and illustrated by example. In that chapter we acquaint the reader with, and take the mystery out of, the process called convolution. Proceeding through several simple convolution examples, we conclude Chapter 5 with a discussion of the powerful convolution theorem and show why it's so useful as a qualitative tool in understanding digital signal processing.

Chapter 6 is devoted to a second class of digital filters, infinite impulse response (IIR) filters. In discussing several methods for the design of IIR filters, the reader is introduced to the powerful digital signal processing analysis tool called the *z*-transform. Because the *z*-transform is so closely related to the continuous Laplace transform, Chapter 6 starts by gently guiding the reader from the origin, through the properties, and on to the utility of the Laplace transform in preparation for learning the *z*-transform. We'll see how IIR filters are designed and implemented, and why their performance is so different from that of FIR filters. To indicate under what conditions these filters should be used, the chapter concludes with a qualitative comparison of the key properties of FIR and IIR filters. Chapter 7 introduces specialized networks known as *digital differentiators, integrators,* and *matched filters.* In addition, this chapter covers two specialized digital filter types that have not received their deserved exposure in traditional DSP textbooks. Called *interpolated FIR* and *frequency sampling* filters, providing improved lowpass filtering computational efficiency, they belong in our arsenal of filter design techniques. Although these are FIR filters, their introduction is delayed to this chapter because familiarity with the *z*-transform (in Chapter 6) makes the properties of these filters easier to understand.

Chapter 8 presents a detailed description of quadrature signals (also called *complex* signals). Because quadrature signal theory has become so important in recent years, in both signal analysis and digital communications implementations, it deserves its own chapter. Using three-dimensional illustrations, this chapter gives solid physical meaning to the mathematical notation, processing advantages, and use of quadrature signals. Special emphasis is given to quadrature sampling (also called *complex down-conversion*).

Chapter 9 provides a mathematically gentle, but technically thorough, description of the Hilbert transform—a process used to generate a quadrature (complex) signal from a real signal. In this chapter we describe the properties, behavior, and design of practical Hilbert transformers.

Chapter 10 presents an introduction to the fascinating and useful process of sample rate conversion (changing the effective sample rate of discrete data sequences through decimation or interpolation). Sample rate conversion—so useful in improving the performance and reducing the computational complexity of many signal processing operations—is essentially an exercise in lowpass filter design. As such, polyphase and cascaded integrator-comb filters are described in detail in this chapter.

Chapter 11 covers the important topic of signal averaging. There we learn how averaging increases the accuracy of signal measurement schemes by reducing measurement background noise. This accuracy enhancement is called *processing gain*, and the chapter shows how to predict the processing gain associated with averaging signals in both the time and frequency domains. In addition, the key differences between coherent and incoherent averaging techniques are explained and demonstrated with examples. To complete that chapter the popular scheme known as *exponential averaging* is covered in some detail.

Chapter 12 presents an introduction to the various binary number formats the reader is likely to encounter in modern digital signal processing. We establish the precision and dynamic range afforded by these formats along with the inherent pitfalls associated with their use. Our exploration of the critical subject of binary data word width (in bits) naturally leads to a discussion of the numerical resolution limitations of analog-to-digital (A/D) converters and how to determine the optimum A/D converter word size for a given application. The problems of data value overflow roundoff errors are covered along with a statistical introduction to the two most popular remedies for overflow, truncation and rounding. We end that chapter by covering the interesting subject of floating-point binary formats that allow us to overcome most of the limitations induced by fixed-point binary formats, particularly in reducing the ill effects of data overflow.

Chapter 13 provides the literature's most comprehensive collection of *tricks of the trade* used by DSP professionals to make their processing algorithms more efficient. These techniques are compiled into a chapter at the end of the book for two reasons. First, it seems wise to keep our collection of tricks in one chapter so that we'll know where to find them in the future. Second, many of these clever schemes require an understanding of the material from the previous chapters, making the last chapter an appropriate place to keep our arsenal of clever tricks. Exploring these techniques in detail verifies and reiterates many of the important ideas covered in previous chapters.

The appendices include a number of topics to help the beginner understand the nature and mathematics of digital signal processing. A comprehensive description of the arithmetic of complex numbers is covered in Appendix A, and Appendix B derives the often used, but seldom explained, closed form of a geometric series. The subtle aspects and two forms of time reversal in discrete systems (of which zero-phase digital filtering is an application) are explained in Appendix C. The statistical concepts of mean, variance, and standard deviation are introduced and illustrated in Appendix D, and Appendix E provides a discussion of the origin and utility of the logarithmic decibel scale used to improve the magnitude resolution of spectral representations. Appendix F, in a slightly different vein, provides a glossary of the terminology used in the field of digital filters. Appendices G and H provide supplementary information for designing and analyzing specialized digital filters. Appendix I explains the computation of Chebyshev window sequences.

ACKNOWLEDGMENTS

Much of the new material in this edition is a result of what I've learned from those clever folk on the USENET newsgroup comp.dsp. (I could list a dozen names, but in doing so I'd make 12 friends and 500 enemies.) So, I say thanks to my DSP pals on comp.dsp for teaching me so much signal processing theory.

In addition to the reviewers of previous editions of this book, I thank Randy Yates, Clay Turner, and Ryan Groulx for their time and efforts to help me improve the content of this book. I am especially indebted to my eagleeyed mathematician friend Antoine Trux for his relentless hard work to both enhance this DSP material and create a homework Solutions Manual. As before, I thank my acquisitions editor, Bernard Goodwin, for his patience and guidance, and his skilled team of production people, project editor Elizabeth Ryan in particular, at Prentice Hall.

If you're still with me this far in this Preface, I end by saying I had a ball writing this book and sincerely hope you benefit from reading it. If you have any comments or suggestions regarding this material, or detect any errors no matter how trivial, please send them to me at R.Lyons@ieee.org. I promise I will reply to your e-mail.

About the Author



Richard Lyons is a consulting systems engineer and lecturer with Besser Associates in Mountain View, California. He has been the lead hardware engineer for numerous signal processing systems for both the National Security Agency (NSA) and Northrop Grumman Corp. Lyons has taught DSP at the University of California Santa Cruz Extension and authored numerous articles on DSP. As associate editor for the *IEEE Signal Processing Magazine* he created, edits, and contributes to the magazine's "DSP Tips & Tricks" column.

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CHAPTER ONE

Discrete Sequences and Systems



Digital signal processing has never been more prevalent or easier to perform. It wasn't that long ago when the fast Fourier transform (FFT), a topic we'll discuss in Chapter 4, was a mysterious mathematical process used only in industrial research centers and universities. Now, amazingly, the FFT is readily available to us all. It's even a built-in function provided by inexpensive spreadsheet software for home computers. The availability of more sophisticated commercial signal processing software now allows us to analyze and develop complicated signal processing applications rapidly and reliably. We can perform spectral analysis, design digital filters, develop voice recognition, data communication, and image compression processes using software that's interactive both in the way algorithms are defined and how the resulting data are graphically displayed. Since the mid-1980s the same integrated circuit technology that led to affordable home computers has produced powerful and inexpensive hardware development systems on which to implement our digital signal processing designs.[†] Regardless, though, of the ease with which these new digital signal processing development systems and software can be applied, we still need a solid foundation in understanding the basics of digital signal processing. The purpose of this book is to build that foundation.

In this chapter we'll set the stage for the topics we'll study throughout the remainder of this book by defining the terminology used in digital signal process-

⁺ During a television interview in the early 1990s, a leading computer scientist stated that had automobile technology made the same strides as the computer industry, we'd all have a car that would go a half million miles per hour and get a half million miles per gallon. The cost of that car would be so low that it would be cheaper to throw it away than pay for one day's parking in San Francisco.

ing, illustrating the various ways of graphically representing discrete signals, establishing the notation used to describe sequences of data values, presenting the symbols used to depict signal processing operations, and briefly introducing the concept of a linear discrete system.

1.1 DISCRETE SEQUENCES AND THEIR NOTATION

In general, the term *signal processing* refers to the science of analyzing timevarying physical processes. As such, signal processing is divided into two categories, analog signal processing and digital signal processing. The term analog is used to describe a waveform that's continuous in time and can take on a continuous range of amplitude values. An example of an analog signal is some voltage that can be applied to an oscilloscope, resulting in a continuous display as a function of time. Analog signals can also be applied to a conventional spectrum analyzer to determine their frequency content. The term analog appears to have stemmed from the analog computers used prior to 1980. These computers solved linear differential equations by means of connecting physical (electronic) differentiators and integrators using old-style telephone operator patch cords. That way, a continuous voltage or current in the actual circuit was analogous to some variable in a differential equation, such as speed, temperature, air pressure, etc. (Although the flexibility and speed of modern-day digital computers have since made analog computers obsolete, a good description of the short-lived utility of analog computers can be found in reference [1].) Because present-day signal processing of continuous radiotype signals using resistors, capacitors, operational amplifiers, etc., has nothing to do with analogies, the term *analog* is actually a misnomer. The more correct term is continuous signal processing for what is today so commonly called analog signal processing. As such, in this book we'll minimize the use of the term analog signals and substitute the phrase continuous signals whenever appropriate.

The term *discrete-time signal* is used to describe a signal whose independent time variable is quantized so that we know only the value of the signal at discrete instants in time. Thus a discrete-time signal is not represented by a continuous waveform but, instead, a sequence of values. In addition to quantizing time, a discrete-time signal quantizes the signal amplitude. We can illustrate this concept with an example. Think of a continuous sinewave with a peak amplitude of 1 at a frequency f_0 described by the equation

$$x(t) = \sin(2\pi f_0 t). \tag{1-1}$$

The frequency f_0 is measured in hertz (Hz). (In physical systems, we usually measure frequency in units of hertz. One Hz is a single oscillation, or cycle, per second. One kilohertz (kHz) is a thousand Hz, and a megahertz (MHz) is



Figure 1-1 A time-domain sinewave: (a) continuous waveform representation; (b) discrete sample representation; (c) discrete samples with connecting lines.

one million Hz.[†]) With *t* in Eq. 1–1 representing time in seconds, the $f_0 t$ factor has dimensions of cycles, and the complete $2\pi f_0 t$ term is an angle measured in radians.

Plotting Eq. (1-1), we get the venerable continuous sinewave curve shown in Figure 1-1(a). If our continuous sinewave represents a physical volt-

⁺ The dimension for frequency used to be *cycles/second*; that's why the tuning dials of old radios indicate frequency as kilocycles/second (kcps) or megacycles/second (Mcps). In 1960 the scientific community adopted hertz as the unit of measure for frequency in honor of the German physicist Heinrich Hertz, who first demonstrated radio wave transmission and reception in 1887.

age, we could *sample* it once every t_s seconds using an analog-to-digital converter and represent the sinewave as a sequence of discrete values. Plotting those individual values as dots would give us the discrete waveform in Figure 1–1(b). We say that Figure 1–1(b) is the "discrete-time" version of the continuous signal in Figure 1–1(a). The independent variable t in Eq. (1–1) and Figure 1–1(a) is continuous. The independent *index* variable n in Figure 1–1(b) is discrete and can have only integer values. That is, index n is used to identify the individual elements of the discrete sequence in Figure 1–1(b).

Do not be tempted to draw lines between the dots in Figure 1–1(b). For some reason, people (particularly those engineers experienced in working with continuous signals) want to connect the dots with straight lines, or the stair-step lines shown in Figure 1–1(c). Don't fall into this innocent-looking trap. Connecting the dots can mislead the beginner into forgetting that the x(n) sequence is nothing more than a list of numbers. Remember, x(n) is a discrete-time sequence of individual values, and each value in that sequence plots as a single dot. It's not that we're ignorant of what lies between the dots of x(n); there *is* nothing between those dots.

We can reinforce this discrete-time sequence concept by listing those Figure 1–1(b) sampled values as follows:

| x(0) = 0 | (1st sequence value, index $n = 0$) | |
|-------------|--------------------------------------|-------|
| x(1) = 0.31 | (2nd sequence value, index $n = 1$) | |
| x(2) = 0.59 | (3rd sequence value, index $n = 2$) | |
| x(3) = 0.81 | (4th sequence value, index $n = 3$) | |
| | | |
| | and so on, | (1-2) |

where *n* represents the time index integer sequence 0, 1, 2, 3, etc., and t_s is some constant time period between samples. Those sample values can be represented collectively, and concisely, by the discrete-time expression

$$x(n) = \sin(2\pi f_0 n t_s). \tag{1-3}$$

(Here again, the $2\pi f_0 nt_s$ term is an angle measured in radians.) Notice that the index *n* in Eq. (1–2) started with a value of 0, instead of 1. There's nothing sacred about this; the first value of *n* could just as well have been 1, but we start the index *n* at zero out of habit because doing so allows us to describe the sinewave starting at time zero. The variable x(n) in Eq. (1–3) is read as "the sequence *x* of *n*." Equations (1–1) and (1–3) describe what are also referred to as *time-domain* signals because the independent variables, the continuous time *t* in Eq. (1–1), and the discrete-time nt_s values used in Eq. (1–3) are measures of time.

With this notion of a discrete-time signal in mind, let's say that a discrete system is a collection of hardware components, or software routines, that operate on a discrete-time signal sequence. For example, a discrete system could be a process that gives us a discrete output sequence y(0), y(1), y(2), etc., when a discrete input sequence of x(0), x(1), x(2), etc., is applied to the system input as shown in Figure 1–2(a). Again, to keep the notation concise and still keep track of individual elements of the input and output sequences, an abbreviated notation is used as shown in Figure 1–2(b) where *n* represents the integer sequence 0, 1, 2, 3, etc. Thus, x(n) and y(n) are general variables that represent two separate sequences of numbers. Figure 1–2(b) allows us to describe a system's output with a simple expression such as

$$y(n) = 2x(n) - 1. \tag{1-4}$$

Illustrating Eq. (1–4), if x(n) is the five-element sequence x(0) = 1, x(1) = 3, x(2) = 5, x(3) = 7, and x(4) = 9, then y(n) is the five-element sequence y(0) = 1, y(1) = 5, y(2) = 9, y(3) = 13, and y(4) = 17.

Equation (1–4) is formally called a *difference equation*. (In this book we won't be working with differential equations or partial differential equations. However, we will, now and then, work with partially difficult equations.)

The fundamental difference between the way time is represented in continuous and discrete systems leads to a very important difference in how we characterize frequency in continuous and discrete systems. To illustrate, let's reconsider the continuous sinewave in Figure 1–1(a). If it represented a voltage at the end of a cable, we could measure its frequency by applying it to an oscilloscope, a spectrum analyzer, or a frequency counter. We'd have a problem, however, if we were merely given the list of values from Eq. (1–2) and asked to determine the frequency of the waveform they represent. We'd graph those discrete values, and, sure enough, we'd recognize a single sinewave as in Figure 1–1(b). We can say that the sinewave repeats every 20 samples, but there's no way to determine the exact sinewave frequency from the discrete sequence values alone. You can probably see the point we're leading to here. If we knew the time between samples—the sample period t_s we'd be able to determine the absolute frequency of the discrete sinewave.



Figure 1-2 With an input applied, a discrete system provides an output: (a) the input and output are sequences of individual values; (b) input and output using the abbreviated notation of x(n) and y(n).

Given that the t_s sample period is, say, 0.05 milliseconds/sample, the period of the sinewave is

sinewave period =
$$\frac{20 \text{ samples}}{\text{period}} \cdot \frac{0.05 \text{ milliseconds}}{\text{sample}} = 1 \text{ millisecond.} \quad (1-5)$$

Because the frequency of a sinewave is the reciprocal of its period, we now know that the sinewave's absolute frequency is 1/(1 ms), or 1 kHz. On the other hand, if we found that the sample period was, in fact, 2 milliseconds, the discrete samples in Figure 1–1(b) would represent a sinewave whose period is 40 milliseconds and whose frequency is 25 Hz. The point here is that when dealing with discrete systems, absolute frequency determination in Hz is dependent on the sampling frequency

$$f_s = 1/t_s.$$
 (1–5')

We'll be reminded of this dependence throughout the remainder of this book.

In digital signal processing, we often find it necessary to characterize the frequency content of discrete time-domain signals. When we do so, this frequency representation takes place in what's called the *frequency domain*. By



Figure 1-3 Time- and frequency-domain graphical representations: (a) sinewave of frequency f_{o} ; (b) reduced amplitude sinewave of frequency $2f_{o}$; (c) sum of the two sinewaves.

way of example, let's say we have a discrete sinewave sequence $x_1(n)$ with an arbitrary frequency f_0 Hz as shown on the left side of Figure 1–3(a). We can also characterize $x_1(n)$ by showing its spectral content, the $X_1(m)$ sequence on the right side of Figure 1-3(a), indicating that it has a single spectral component, and no other frequency content. Although we won't dwell on it just now, notice that the frequency-domain representations in Figure 1–3 are themselves discrete.

To illustrate our time- and frequency-domain representations further, Figure 1–3(b) shows another discrete sinewave $x_2(n)$, whose peak amplitude is 0.4, with a frequency of $2f_0$. The discrete sample values of $x_2(n)$ are expressed by the equation

$$x_2(n) = 0.4 \cdot \sin(2\pi 2f_0 n t_s). \tag{1-6}$$

When the two sinewaves, $x_1(n)$ and $x_2(n)$, are added to produce a new waveform $x_{sum}(n)$, its time-domain equation is

$$x_{sum}(n) = x_1(n) + x_2(n) = \sin(2\pi f_0 n t_s) + 0.4 \cdot \sin(2\pi 2 f_0 n t_s), \quad (1-7)$$

and its time- and frequency-domain representations are those given in Figure 1–3(c). We interpret the $X_{sum}(m)$ frequency-domain depiction, the *spectrum*, in Figure 1–3(c) to indicate that $x_{sum}(n)$ has a frequency component of f_0 Hz and a reduced-amplitude frequency component of $2f_0$ Hz.

Notice three things in Figure 1–3. First, time sequences use lowercase variable names like the "x" in $x_1(n)$, and uppercase symbols for frequency-domain variables such as the "X" in $X_1(m)$. The term $X_1(m)$ is read as "the spectral sequence X sub one of m." Second, because the $X_1(m)$ frequency-domain representation of the $x_1(n)$ time sequence is itself a sequence (a list of numbers), we use the index "m" to keep track of individual elements in $X_1(m)$. We can list frequency-domain sequences just as we did with the time sequence in Eq. (1–2). For example, $X_{sum}(m)$ is listed as

$$\begin{array}{ll} X_{\mathrm{sum}}(0) = 0 & (1 \mathrm{st} \ X_{\mathrm{sum}} \ (m) \ \mathrm{value}, \ \mathrm{index} \ m = 0) \\ X_{\mathrm{sum}}(1) = 1.0 & (2 \mathrm{nd} \ X_{\mathrm{sum}}(m) \ \mathrm{value}, \ \mathrm{index} \ m = 1) \\ X_{\mathrm{sum}}(2) = 0.4 & (3 \mathrm{rd} \ X_{\mathrm{sum}} \ (m) \ \mathrm{value}, \ \mathrm{index} \ m = 2) \\ X_{\mathrm{sum}}(3) = 0 & (4 \mathrm{th} \ X_{\mathrm{sum}} \ (m) \ \mathrm{value}, \ \mathrm{index} \ m = 3) \\ & \cdots & & \cdots \\ & \text{and so on,} \end{array}$$

where the frequency index *m* is the integer sequence 0, 1, 2, 3, etc. Third, because the $x_1(n) + x_2(n)$ sinewaves have a phase shift of zero degrees relative to each other, we didn't really need to bother depicting this phase relationship in $X_{sum}(m)$ in Figure 1–3(c). In general, however, phase relationships in frequency-domain sequences are important, and we'll cover that subject in Chapters 3 and 5. A key point to keep in mind here is that we now know three equivalent ways to describe a discrete-time waveform. Mathematically, we can use a time-domain equation like Eq. (1–6). We can also represent a time-domain waveform graphically as we did on the left side of Figure 1–3, and we can depict its corresponding, discrete, frequency-domain equivalent as that on the right side of Figure 1–3.

As it turns out, the discrete time-domain signals we're concerned with are not only quantized in time; their amplitude values are also quantized. Because we represent all digital quantities with binary numbers, there's a limit to the resolution, or granularity, that we have in representing the values of discrete numbers. Although signal amplitude quantization can be an important consideration—we cover that particular topic in Chapter 12—we won't worry about it just now.

1.2 SIGNAL AMPLITUDE, MAGNITUDE, POWER

Let's define two important terms that we'll be using throughout this book: *amplitude* and *magnitude*. It's not surprising that, to the layman, these terms are typically used interchangeably. When we check our thesaurus, we find that they are synonymous.[†] In engineering, however, they mean two different things, and we must keep that difference clear in our discussions. The amplitude of a variable is the measure of how far, and in what direction, that variable differs from zero. Thus, signal amplitudes can be either positive or negative. The time-domain sequences in Figure 1–3 presented the sample value amplitudes of three different waveforms. Notice how some of the individual discrete amplitude values were positive and others were negative.



Figure 1-4 Magnitude samples, $|x_1(n)|$, of the time waveform in Figure 1–3(a).

⁺ Of course, laymen are "other people." To the engineer, the brain surgeon is the layman. To the brain surgeon, the engineer is the layman.



Figure 1-5 Frequency-domain amplitude and frequency-domain power of the $x_{sum}(n)$ time waveform in Figure 1–3(c).

The magnitude of a variable, on the other hand, is the measure of how far, regardless of direction, its quantity differs from zero. So magnitudes are always positive values. Figure 1–4 illustrates how the magnitude of the $x_1(n)$ time sequence in Figure 1–3(a) is equal to the amplitude, but with the sign always being positive for the magnitude. We use the modulus symbol (||) to represent the magnitude of $x_1(n)$. Occasionally, in the literature of digital signal processing, we'll find the term *magnitude* referred to as the *absolute value*.

When we examine signals in the frequency domain, we'll often be interested in the power level of those signals. The power of a signal is proportional to its amplitude (or magnitude) squared. If we assume that the proportionality constant is one, we can express the power of a sequence in the time or frequency domains as

$$x_{\text{pwr}}(n) = |x(n)|^2,$$
 (1-8)

or

$$X_{\rm pwr}(m) = |X(m)|^2.$$
(1-8')

Very often we'll want to know the difference in power levels of two signals in the frequency domain. Because of the squared nature of power, two signals with moderately different amplitudes will have a much larger difference in their relative powers. In Figure 1–3, for example, signal $x_1(n)$'s amplitude is 2.5 times the amplitude of signal $x_2(n)$, but its power level is 6.25 that of $x_2(n)$'s power level. This is illustrated in Figure 1–5 where both the amplitude and power of $X_{sum}(m)$ are shown.

Because of their squared nature, plots of power values often involve showing both very large and very small values on the same graph. To make these plots easier to generate and evaluate, practitioners usually employ the decibel scale as described in Appendix E.

1.3 SIGNAL PROCESSING OPERATIONAL SYMBOLS

We'll be using block diagrams to graphically depict the way digital signal processing operations are implemented. Those block diagrams will comprise an assortment of fundamental processing symbols, the most common of which are illustrated and mathematically defined in Figure 1–6.

Figure 1–6(a) shows the addition, element for element, of two discrete sequences to provide a new sequence. If our sequence index *n* begins at 0, we say that the first output sequence value is equal to the sum of the first element of the *b* sequence and the first element of the *c* sequence, or a(0) = b(0) + c(0). Likewise, the second output sequence value is equal to the sum of the second



Figure 1-6 Terminology and symbols used in digital signal processing block diagrams.

element of the *b* sequence and the second element of the *c* sequence, or a(1) = b(1) + c(1). Equation (1–7) is an example of adding two sequences. The subtraction process in Figure 1–6(b) generates an output sequence that's the element-for-element difference of the two input sequences. There are times when we must calculate a sequence whose elements are the sum of more than two values. This operation, illustrated in Figure 1–6(c), is called *summation* and is very common in digital signal processing. Notice how the lower and upper limits of the summation index *k* in the expression in Figure 1–6(c) tell us exactly which elements of the *b* sequence to sum to obtain a given a(n) value. Because we'll encounter summation operations so often, let's make sure we understand their notation. If we repeat the summation equation from Figure 1–6(c) here, we have

$$a(n) = \sum_{k=n}^{n+3} b(k).$$
(1-9)

This means that

when n = 0, index k goes from 0 to 3, so when n = 1, index k goes from 1 to 4, so when n = 2, index k goes from 2 to 5, so when n = 3, index k goes from 3 to 6, so a(0) = b(0) + b(1) + b(2) + b(3) a(1) = b(1) + b(2) + b(3) + b(4) a(2) = b(2) + b(3) + b(4) + b(5) (1–10) a(3) = b(3) + b(4) + b(5) + b(6)...

and so on.

We'll begin using summation operations in earnest when we discuss digital filters in Chapter 5.

The multiplication of two sequences is symbolized in Figure 1–6(d). Multiplication generates an output sequence that's the element-for-element product of two input sequences: a(0) = b(0)c(0), a(1) = b(1)c(1), and so on. The last fundamental operation that we'll be using is called the *unit delay* in Figure 1–6(e). While we don't need to appreciate its importance at this point, we'll merely state that the unit delay symbol signifies an operation where the output sequence a(n) is equal to a delayed version of the b(n) sequence. For example, a(5) = b(4), a(6) = b(5), a(7) = b(6), etc. As we'll see in Chapter 6, due to the mathematical techniques used to analyze digital filters, the unit delay is very often depicted using the term z^{-1} .

The symbols in Figure 1–6 remind us of two important aspects of digital signal processing. First, our processing operations are always performed on sequences of individual discrete values, and second, the elementary operations themselves are very simple. It's interesting that, regardless of how complicated they appear to be, the vast majority of digital signal processing algorithms can be performed using combinations of these simple operations. If we think of a digital signal processing algorithm as a recipe, then the symbols in Figure 1–6 are the ingredients.

1.4 INTRODUCTION TO DISCRETE LINEAR TIME-INVARIANT SYSTEMS

In keeping with tradition, we'll introduce the subject of linear time-invariant (LTI) systems at this early point in our text. Although an appreciation for LTI systems is not essential in studying the next three chapters of this book, when we begin exploring digital filters, we'll build on the strict definitions of linearity and time invariance. We need to recognize and understand the notions of linearity and time invariance not just because the vast majority of discrete systems used in practice are LTI systems, but because LTI systems are very accommodating when it comes to their analysis. That's good news for us because we can use straightforward methods to predict the performance of any digital signal processing scheme as long as it's linear and time invariant. Because linearity and time invariance are two important system characteristics having very special properties, we'll discuss them now.

1.5 DISCRETE LINEAR SYSTEMS

The term *linear* defines a special class of systems where the output is the superposition, or sum, of the individual outputs had the individual inputs been applied separately to the system. For example, we can say that the application of an input $x_1(n)$ to a system results in an output $y_1(n)$. We symbolize this situation with the following expression:

$$x_1(n) \xrightarrow{\text{results in}} y_1(n).$$
 (1–11)

Given a different input $x_2(n)$, the system has a $y_2(n)$ output as

$$x_2(n) \xrightarrow{\text{results in}} y_2(n).$$
 (1-12)

For the system to be linear, when its input is the sum $x_1(n) + x_2(n)$, its output must be the sum of the individual outputs so that

$$x_1(n) + x_2(n) \xrightarrow{\text{results in}} y_1(n) + y_2(n).$$
(1-13)

One way to paraphrase expression (1-13) is to state that a linear system's output is the sum of the outputs of its parts. Also, part of this description of linearity is a proportionality characteristic. This means that if the inputs are scaled by constant factors c_1 and c_2 , then the output sequence parts are also scaled by those factors as

$$c_1 x_1(n) + c_2 x_2(n) \xrightarrow{\text{results in}} c_1 y_1(n) + c_2 y_2(n).$$
 (1-14)

In the literature, this proportionality attribute of linear systems in expression (1–14) is sometimes called the *homogeneity property*. With these thoughts in mind, then, let's demonstrate the concept of system linearity.
1.5.1 Example of a Linear System

To illustrate system linearity, let's say we have the discrete system shown in Figure 1-7(a) whose output is defined as

$$y(n) = \frac{-x(n)}{2},$$
 (1–15)

that is, the output sequence is equal to the negative of the input sequence with the amplitude reduced by a factor of two. If we apply an $x_1(n)$ input sequence representing a 1 Hz sinewave sampled at a rate of 32 samples per cycle, we'll have a $y_1(n)$ output as shown in the center of Figure 1–7(b). The frequency-domain spectral amplitude of the $y_1(n)$ output is the plot on the



Figure 1-7 Linear system input-to-output relationships: (a) system block diagram where y(n) = -x(n)/2; (b) system input and output with a 1 Hz sinewave applied; (c) with a 3 Hz sinewave applied; (d) with the sum of 1 Hz and 3 Hz sinewaves applied.

right side of Figure 1–7(b), indicating that the output comprises a single tone of peak amplitude equal to -0.5 whose frequency is 1 Hz. Next, applying an $x_2(n)$ input sequence representing a 3 Hz sinewave, the system provides a $y_2(n)$ output sequence, as shown in the center of Figure 1–7(c). The spectrum of the $y_2(n)$ output, $Y_2(m)$, confirming a single 3 Hz sinewave output is shown on the right side of Figure 1–7(c). Finally—here's where the linearity comes in—if we apply an $x_3(n)$ input sequence that's the sum of a 1 Hz sinewave and a 3 Hz sinewave, the $y_3(n)$ output is as shown in the center of Figure 1–7(d). Notice how $y_3(n)$ is the sample-for-sample sum of $y_1(n)$ and $y_2(n)$. Figure 1–7(d) also shows that the output spectrum $Y_3(m)$ is the sum of $Y_1(m)$ and $Y_2(m)$. That's linearity.

1.5.2 Example of a Nonlinear System

It's easy to demonstrate how a nonlinear system yields an output that is not equal to the sum of $y_1(n)$ and $y_2(n)$ when its input is $x_1(n) + x_2(n)$. A simple example of a nonlinear discrete system is that in Figure 1–8(a) where the output is the square of the input described by

$$y(n) = [x(n)]^2.$$
(1–16)

We'll use a well-known trigonometric identity and a little algebra to predict the output of this nonlinear system when the input comprises simple sinewaves. Following the form of Eq. (1–3), let's describe a sinusoidal sequence, whose frequency $f_0 = 1$ Hz, by

$$x_1(n) = \sin(2\pi f_o n t_s) = \sin(2\pi \cdot 1 \cdot n t_s).$$
(1-17)

Equation (1–17) describes the $x_1(n)$ sequence on the left side of Figure 1–8(b). Given this $x_1(n)$ input sequence, the $y_1(n)$ output of the nonlinear system is the square of a 1 Hz sinewave, or

$$y_1(n) = [x_1(n)]^2 = \sin(2\pi \cdot 1 \cdot nt_s) \cdot \sin(2\pi \cdot 1 \cdot nt_s).$$
(1-18)

We can simplify our expression for $y_1(n)$ in Eq. (1–18) by using the following trigonometric identity:

2

$$\sin(\alpha) \cdot \sin(\beta) = \frac{\cos(\alpha - \beta)}{2} - \frac{\cos(\alpha + \beta)}{2}.$$
 (1-19)

2

Using Eq. (1–19), we can express $y_1(n)$ as

2

$$y_{1}(n) = \frac{\cos(2\pi \cdot 1 \cdot nt_{s} - 2\pi \cdot 1 \cdot nt_{s})}{2} - \frac{\cos(2\pi \cdot 1 \cdot nt_{s} + 2\pi \cdot 1 \cdot nt_{s})}{2}$$

$$= \frac{\cos(0)}{2} - \frac{\cos(4\pi \cdot 1 \cdot nt_{s})}{2} = \frac{1}{2} - \frac{\cos(2\pi \cdot 2 \cdot nt_{s})}{2},$$
(1-20)

2

14



Figure 1-8 Nonlinear system input-to-output relationships: (a) system block diagram where $y(n) = (x(n))^2$; (b) system input and output with a 1 Hz sinewave applied; (c) with a 3 Hz sinewave applied; (d) with the sum of 1 Hz and 3 Hz sinewaves applied.

which is shown as the all-positive sequence in the center of Figure 1–8(b). Because Eq. (1–19) results in a frequency sum ($\alpha + \beta$) and frequency difference ($\alpha - \beta$) effect when multiplying two sinusoids, the $y_1(n)$ output sequence will be a cosine wave of 2 Hz and a peak amplitude of –0.5, added to a constant value of 1/2. The constant value of 1/2 in Eq. (1–20) is interpreted as a zero Hz frequency component, as shown in the $Y_1(m)$ spectrum in Figure 1–8(b). We could go through the same algebraic exercise to determine that when a 3 Hz sinewave $x_2(n)$ sequence is applied to this nonlinear system, the output $y_2(n)$ would contain a zero Hz component and a 6 Hz component, as shown in Figure 1–8(c).

System nonlinearity is evident if we apply an $x_3(n)$ sequence comprising the sum of a 1 Hz and a 3 Hz sinewave as shown in Figure 1–8(d). We can

predict the frequency content of the $y_3(n)$ output sequence by using the algebraic relationship

$$(a+b)^2 = a^2 + 2ab + b^2, (1-21)$$

where *a* and *b* represent the 1 Hz and 3 Hz sinewaves, respectively. From Eq. (1–19), the a^2 term in Eq. (1–21) generates the zero Hz and 2 Hz output sinusoids in Figure 1–8(b). Likewise, the b^2 term produces in $y_3(n)$ another zero Hz and the 6 Hz sinusoid in Figure 1–8(c). However, the 2*ab* term yields additional 2 Hz and 4 Hz sinusoids in $y_3(n)$. We can show this algebraically by using Eq. (1–19) and expressing the 2*ab* term in Eq. (1–21) as

$$2ab = 2 \cdot \sin(2\pi \cdot 1 \cdot nt_s) \cdot \sin(2\pi \cdot 3 \cdot nt_s)$$

$$=\frac{2\cos(2\pi\cdot1\cdot nt_s-2\pi\cdot3\cdot nt_s)}{2}-\frac{2\cos(2\pi\cdot1\cdot nt_s+2\pi\cdot3\cdot nt_s)}{2} \qquad (1-22)$$

$$=\cos(2\pi\cdot 2\cdot nt_s)-\cos(2\pi\cdot 4\cdot nt_s)$$
.[†]

Equation (1–22) tells us that two additional sinusoidal components will be present in $y_3(n)$ because of the system's nonlinearity, a 2 Hz cosine wave whose amplitude is +1 and a 4 Hz cosine wave having an amplitude of –1. These spectral components are illustrated in $Y_3(m)$ on the right side of Figure 1–8(d).

Notice that when the sum of the two sinewaves is applied to the nonlinear system, the output contained sinusoids, Eq. (1–22), that were not present in either of the outputs when the individual sinewaves alone were applied. Those extra sinusoids were generated by an interaction of the two input sinusoids due to the squaring operation. That's nonlinearity; expression (1–13) was not satisfied. (Electrical engineers recognize this effect of internally generated sinusoids as *intermodulation distortion*.) Although nonlinear systems are usually difficult to analyze, they are occasionally used in practice. References [2], [3], and [4], for example, describe their application in nonlinear digital filters. Again, expressions (1–13) and (1–14) state that a linear system's output resulting from a sum of individual inputs is the superposition (sum) of the individual outputs. They also stipulate that the output sequence $y_1(n)$ depends only on $x_1(n)$ combined with the system characteristics, and not on the other input $x_2(n)$; i.e., there's no interaction between inputs $x_1(n)$ and $x_2(n)$ at the output of a linear system.

⁺ The first term in Eq. (1–22) is $\cos(2\pi \cdot nt_s - 6\pi \cdot nt_s) = \cos(-4\pi \cdot nt_s) = \cos(-2\pi \cdot 2 \cdot nt_s)$. However, because the cosine function is even, $\cos(-\alpha) = \cos(\alpha)$, we can express that first term as $\cos(2\pi \cdot 2 \cdot nt_s)$.

1.6 Time-Invariant Systems

1.6 TIME-INVARIANT SYSTEMS

A time-invariant system is one where a time delay (or shift) in the input sequence causes an equivalent time delay in the system's output sequence. Keeping in mind that n is just an indexing variable we use to keep track of our input and output samples, let's say a system provides an output y(n) given an input of x(n), or

$$x(n) \xrightarrow{\text{results in}} y(n). \tag{1-23}$$

For a system to be time invariant, with a shifted version of the original x(n) input applied, x'(n), the following applies:

$$x'(n) = x(n+k) \xrightarrow{\text{results in}} y'(n) = y(n+k), \qquad (1-24)$$

where k is some integer representing k sample period time delays. For a system to be time invariant, Eq. (1–24) must hold true for any integer value of k and any input sequence.

1.6.1 Example of a Time-Invariant System

Let's look at a simple example of time invariance illustrated in Figure 1–9. Assume that our initial x(n) input is a unity-amplitude 1 Hz sinewave sequence with a y(n) output, as shown in Figure 1–9(b). Consider a different input sequence x'(n), where

$$x'(n) = x(n-4).$$
 (1–25)

Equation (1–25) tells us that the input sequence x'(n) is equal to sequence x(n) shifted to the right by k = -4 samples. That is, x'(4) = x(0), x'(5) = x(1), x'(6) = x(2), and so on as shown in Figure 1–9(c). The discrete system is time invariant because the y'(n) output sequence is equal to the y(n) sequence shifted to the right by four samples, or y'(n) = y(n-4). We can see that y'(4) = y(0), y'(5) = y(1), y'(6) = y(2), and so on as shown in Figure 1–9(c). For time-invariant systems, the time shifts in x'(n) and y'(n) are equal. Take careful notice of the minus sign in Eq. (1–25). In later chapters, that is the notation we'll use to algebraically describe a time-delayed discrete sequence.

Some authors succumb to the urge to define a time-invariant system as one whose parameters do not change with time. That definition is incomplete and can get us in trouble if we're not careful. We'll just stick with the formal definition that a time-invariant system is one where a time shift in an input sequence results in an equal time shift in the output sequence. By the way, timeinvariant systems in the literature are often called *shift-invariant* systems.[†]

⁺ An example of a discrete process that's not time invariant is the downsampling, or decimation, process described in Chapter 10.



Figure 1-9 Time-invariant system input/output relationships: (a) system block diagram, y(n) = -x(n)/2; (b) system input/output with a sinewave input; (c) input/output when a sinewave, delayed by four samples, is the input.

1.7 THE COMMUTATIVE PROPERTY OF LINEAR TIME-INVARIANT SYSTEMS

Although we don't substantiate this fact until we reach Section 6.11, it's not too early to realize that LTI systems have a useful commutative property by which their sequential order can be rearranged with no change in their final output. This situation is shown in Figure 1–10 where two different LTI systems are configured in series. Swapping the order of two cascaded systems does not alter the final output. Although the intermediate data sequences f(n) and g(n) will usually not be equal, the two pairs of LTI systems will have iden-



Figure 1-10 Linear time-invariant (LTI) systems in series: (a) block diagram of two LTI systems; (b) swapping the order of the two systems does not change the resultant output *y*(*n*).

tical y(n) output sequences. This commutative characteristic comes in handy for designers of digital filters, as we'll see in Chapters 5 and 6.

1.8 ANALYZING LINEAR TIME-INVARIANT SYSTEMS

As previously stated, LTI systems can be analyzed to predict their performance. Specifically, if we know the *unit impulse response* of an LTI system, we can calculate everything there is to know about the system; that is, the system's unit impulse response completely characterizes the system. By "unit impulse response" we mean the system's time-domain output sequence when the input is a single unity-valued sample (unit impulse) preceded and followed by zero-valued samples as shown in Figure 1–11(b).

Knowing the (unit) impulse response of an LTI system, we can determine the system's output sequence for any input sequence because the output is equal to the *convolution* of the input sequence and the system's impulse response. Moreover, given an LTI system's time-domain impulse response, we can find the system's *frequency response* by taking the Fourier transform in the form of a *discrete Fourier transform* of that impulse response[5]. The concepts in the two previous sentences are among the most important principles in all of digital signal processing!

Don't be alarmed if you're not exactly sure what is meant by convolution, frequency response, or the discrete Fourier transform. We'll introduce these subjects and define them slowly and carefully as we need them in later chapters. The point to keep in mind here is that LTI systems can be designed and analyzed using a number of straightforward and powerful analysis techniques. These techniques will become tools that we'll add to



Figure 1-11 LTI system unit impulse response sequences: (a) system block diagram; (b) impulse input sequence x(n) and impulse response output sequence y(n).

our signal processing toolboxes as we journey through the subject of digital signal processing.

In the testing (analyzing) of continuous linear systems, engineers often use a narrow-in-time impulsive signal as an input signal to their systems. Mechanical engineers give their systems a little whack with a hammer, and electrical engineers working with analog-voltage systems generate a very narrow voltage spike as an impulsive input. Audio engineers, who need an impulsive acoustic test signal, sometimes generate an audio impulse by firing a starter pistol.

In the world of DSP, an impulse sequence called a *unit impulse* takes the form

$$x(n) = \dots 0, 0, 0, 0, 0, A, 0, 0, 0, 0, 0, \dots$$
(1–26)

The value *A* is often set equal to one. The leading sequence of zero-valued samples, before the *A*-valued sample, must be a bit longer than the length of the transient response of the system under test in order to initialize the system to its zero state. The trailing sequence of zero-valued samples, following the *A*-valued sample, must be a bit longer than the transient response of the system under test in order to capture the system's entire y(n) impulse response output sequence.

Let's further explore this notion of impulse response testing to determine the frequency response of a discrete system (and take an opportunity to start using the operational symbols introduced in Section 1.3). Consider the block diagram of a 4-point moving averager shown in Figure 1–12(a). As the x(n) input samples march their way through the system, at each time index nfour successive input samples are averaged to compute a single y(n) output. As we'll learn in subsequent chapters, a *moving averager* behaves like a digital lowpass filter. However, we can quickly illustrate that fact now.

If we apply an impulse input sequence to the system, we'll obtain its y(n) impulse response output shown in Figure 1–12(b). The y(n) output is computed using the following difference equation:

$$y(n) = \frac{1}{4} [x(n) + x(n-1) + x(n-2) + x(n-3)] = \frac{1}{4} \sum_{k=n-3}^{n} x(k).$$
(1-27)

If we then perform a discrete Fourier transform (a process we cover in much detail in Chapter 3) on y(n), we obtain the Y(m) frequency-domain information, allowing us to plot the frequency magnitude response of the 4-point moving averager as shown in Figure 1–12(c). So we see that a moving averager indeed has the characteristic of a lowpass filter. That is, the averager attenuates (reduces the amplitude of) high-frequency signal content applied to its input.



Figure 1-12 Analyzing a moving averager: (a) averager block diagram; (b) impulse input and impulse response; (c) averager frequency magnitude response.

OK, this concludes our brief introduction to discrete sequences and systems. In later chapters we'll learn the details of discrete Fourier transforms, discrete system impulse responses, and digital filters.

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CHAPTER 1 PROBLEMS

1.1 This problem gives us practice in thinking about sequences of numbers. For centuries mathematicians have developed clever ways of computing π . In 1671 the Scottish mathematician James Gregory proposed the following very simple series for calculating π :

$$\pi \approx 4 \cdot \left(1 - \frac{1}{3} + \frac{1}{5} - \frac{1}{7} + \frac{1}{9} - \frac{1}{11} \dots \right).$$

Thinking of the terms inside the parentheses as a sequence indexed by the variable n, where n = 0, 1, 2, 3, ..., 100, write Gregory's algorithm in the form

$$\pi \approx 4 \cdot \sum_{n=0}^{100} (-1)^{?} \cdot ?$$

replacing the "?" characters with expressions in terms of index *n*.

- 1.2 One of the ways to obtain discrete sequences, for follow-on processing, is to digitize a continuous (analog) signal with an analog-to-digital (A/D) converter. A 6-bit A/D converter's output words (6-bit binary words) can only represent 2^{6} =64 different numbers. (We cover this digitization, *sampling*, and A/D converters in detail in upcoming chapters.) Thus we say the A/D converter's "digital" output can only represent a finite number of amplitude values. Can you think of a continuous time-domain electrical signal that only has a finite number of amplitude values? If so, draw a graph of that continuous time signal.
- **1.3** On the Internet, the author once encountered the following line of C-language code

$$PI = 2*asin(1.0);$$

whose purpose was to define the constant π . In standard mathematical notation, that line of code can be described by

$$\pi = 2 \cdot \sin^{-1}(1).$$

Under what assumption does the above expression correctly define the constant π ?

1.4 Many times in the literature of signal processing you will encounter the identity

 $x^0 = 1.$

That is, *x* raised to the zero power is equal to one. Using the Laws of Exponents, prove the above expression to be true.

- **1.5** Recall that for discrete sequences the t_s sample period (the time period between samples) is the reciprocal of the sample frequency f_s . Write the equations, as we did in the text's Eq. (1–3), describing time-domain sequences for unity-amplitude cosine waves whose f_0 frequencies are
 - (a) $f_o = f_s/2$, one-half the sample rate, (b) $f_o = f_s/4$, one-fourth the sample rate, (c) $f_o = 0$ (zero) Hz.
- **1.6** Draw the three time-domain cosine wave sequences, where a sample value is represented by a dot, described in Problem 1.5. The correct solution to Part (a) of this problem is a useful sequence used to convert some lowpass digital filters into highpass filters. (Chapter 5 discusses that topic.) The correct solution to Part (b) of this problem is an important discrete sequence used for *frequency translation* (both for signal *down-conversion* and *up-conversion*) in modern-day wireless communications systems. The correct solution to Part (c) of this problem should convince us that it's perfectly valid to describe a cosine sequence whose frequency is zero Hz.
- **1.7** Draw the three time-domain sequences of unity-amplitude sinewaves (not cosine waves) whose frequencies are
 - (a) $f_o = f_s/2$, one-half the sample rate, (b) $f_o = f_s/4$, one-fourth the sample rate, (c) $f_o = 0$ (zero) Hz.

The correct solutions to Parts (a) and (c) show us that the two frequencies, 0 Hz and $f_s/2$ Hz, are special frequencies in the world of discrete signal processing. What is *special* about the sinewave sequences obtained from the above Parts (a) and (c)?

1.8 Consider the infinite-length time-domain sequence x(n) in Figure P1–8. Draw the first eight samples of a shifted time sequence defined by

$$x_{\text{shift}}(n) = x(n+1).$$

24



Figure P1-8

1.9 Assume, during your reading of the literature of DSP, you encounter the process shown in Figure P1–9. The x(n) input sequence, whose f_s sample rate is 2500 Hz, is multiplied by a sinusoidal m(n) sequence to produce the y(n) output sequence. What is the frequency, measured in Hz, of the sinusoidal m(n) sequence?



Figure P1-9

1.10 There is a process in DSP called an "*N*-point running sum" (a kind of digital lowpass filter, actually) that is described by the following equation:

$$y(n) = \sum_{p=0}^{N-1} x(n-p).$$

Write out, giving the indices of all the x() terms, the algebraic expression that describes the computations needed to compute y(9) when N=6.

1.11 A 5-point *moving averager* can be described by the following difference equation:

$$y(n) = \frac{1}{5} [x(n) + x(n-1) + x(n-2) + x(n-3) + x(n-4)] = \frac{1}{5} \sum_{k=n-4}^{n} x(k).$$
(P1-1)

The averager's signal-flow block diagram is shown in Figure P1–11, where the x(n) input samples flow through the averager from left to right.



Figure P1-11

Equation (P1–1) is equivalent to

$$y(n) = \frac{x(n)}{5} + \frac{x(n-1)}{5} + \frac{x(n-2)}{5} + \frac{x(n-3)}{5} + \frac{x(n-4)}{5}$$

$$= \sum_{k=n-4}^{n} \frac{x(k)}{5}.$$
(P1-2)

- (a) Draw the block diagram of the discrete system described by Eq. (P1–2).
- **(b)** The *moving average* processes described by Eqs. (P1–1) and (P1–2) have identical impulse responses. Draw that impulse response.
- (c) If you had to implement (using programmable hardware or assembling discrete hardware components) either Eq. (P1–1) or Eq. (P1–2), which would you choose? Explain why.
- **1.12** In this book we will look at many two-dimensional drawings showing the value of one variable (y) plotted as a function of another variable (x). Stated in different words, we'll graphically display what are the values of a y axis variable for various values of an x axis variable. For example, Figure P1–12(a) plots the weight of a male child as a function of the child's age. The dimension of the x axis is years



Figure P1-12

and the dimension of the *y* axis is kilograms. What are the dimensions of the *x* and *y* axes of the familiar two-dimensional plot given in Figure P1–12(b)?

1.13 Let's say you are writing software code to generate an x(n) test sequence composed of the sum of two equal-amplitude discrete cosine waves, as

$$x(n) = \cos(2\pi f_0 n t_s + \phi) + \cos(2\pi f_0 n t_s)$$

where t_s is the time between your x(n) samples, and ϕ is a constant phase shift measured in radians. An example x(n) when $\phi = \pi/2$ is shown in Figure P1–13 where the x(n) sequence, represented by the circular dots, is a single sinusoid whose frequency is f_0 Hz.





Using the trigonometric identity $\cos(\alpha+\beta) + \cos(\alpha-\beta) = 2\cos(\alpha)\cos(\beta)$, derive an equation for x(n) that is of the form

$$x(n) = 2\cos(\alpha)\cos(\beta)$$

where variables α and β are in terms of $2\pi f_0 nt_s$ and ϕ .

1.14 In your engineering education you'll often read in some mathematical derivation, or hear someone say, "For small α , $\sin(\alpha) = \alpha$." (In fact, you'll encounter that statement a few times in this book.) Draw two curves defined by

$$x = \alpha$$
, and $y = \sin(\alpha)$

over the range of $\alpha = -\pi/2$ to $\alpha = \pi/2$, and discuss why that venerable "For small α , sin(α) = α " statement is valid.

- **1.15** Considering two continuous (analog) sinusoids, having initial phase angles of α radians at time t = 0, replace the following "?" characters with the correct angle arguments:
 - (a) $\sin(2\pi f_0 t + \alpha) = \cos(?)$.
 - **(b)** $\cos(2\pi f_0 t + \alpha) = \sin(?).$

- **1.16** National Instruments Corp. manufactures an A/D converter, Model #NI USB-5133, that is capable of sampling an analog signal at an f_s sample rate of 100 megasamples per second (100 MHz). The A/D converter has internal memory that can store up to 4×10^6 discrete samples. What is the maximum number of cycles of a 25 MHz analog sinewave that can be stored in the A/D converter's memory? Show your work.
- **1.17** In the first part of the text's Section 1.5 we stated that for a process (or system) to be *linear* it must satisfy a scaling property that we called the *proportionality* characteristic in the text's Eq. (1–14). Determine if the following processes have that proportionality characteristic:

(a) $y_a(n) = x(n-1)/6$, (b) $y_b(n) = 3 + x(n)$, (c) $y_c(n) = \sin[x(n)]$.

This problem is *not* "busy work." Knowing if a process (or system) is linear tells us what signal processing principles, and algorithms, can be applied in the analysis of that process (or system).

1.18 There is an often-used process in DSP called *decimation*, and in that process we retain some samples of an x(n) input sequence and discard other x(n) samples. Decimation by a factor of two can be described algebraically by

$$y(m) = x(2n) \tag{P1-3}$$

where index m=0,1,2,3,. . . The decimation defined by Eq. (P1–3) means that y(m) is equal to alternate samples (every other sample) of x(n). For example:

$$y(0) = x(0), y(1) = x(2), y(2) = x(4), y(3) = x(6), \dots$$

and so on. Here is the question: Is that decimation process time invariant? Illustrate your answer by decimating a simple sinusoidal x(n) time-domain sequence by a factor of two to obtain y(m). Next, create a shifted-by-one-sample version of x(n) and call it $x_{shift}(n)$. That new sequence is defined by

$$x_{\text{shift}}(n) = x(n+1).$$
 (P1-4)

Finally, decimate $x_{\text{shift}}(n)$ according to Eq. (P1–3) to obtain $y_{\text{shift}}(m)$. The decimation process is time invariant if $y_{\text{shift}}(m)$ is equal to a time-shifted version of y(m). That is, decimation is time invariant if

$$y_{\text{shift}}(m) = y(m+1).$$

1.19 In Section 1.7 of the text we discussed the commutative property of linear time-invariant systems. The two networks in Figure P1–19 exhibit that prop-

erty. Prove this to be true by showing that, given the same x(n) input sequence, outputs $y_1(n)$ and $y_2(n)$ will be equal.



Figure P1-19

- **1.20** Here we investigate several simple discrete processes that turn out to be useful in a number of DSP applications. Draw the block diagrams, showing their inputs as x(n), of the processes described by the following difference equations:
 - (a) a 4th-order comb filter: $y_{C}(n) = x(n) x(n-4)$,
 - **(b)** an *integrator*: $y_{I}(n) = x(n) + y_{I}(n-1)$,
 - (c) a *leaky integrator*: $y_{LI}(n) = Ax(n) + (1-A)y_{LI}(n-1)$ [the scalar value *A* is a real-valued constant in the range 0 < A < 1],
 - (d) a differentiator: $y_{D}(n) = 0.5x(n) 0.5x(n-2)$.
- **1.21** Draw the unit impulse responses (the output sequences when the input is a unit sample impulse applied at time n=0) of the four processes listed in Problem 1.20. Let A = 0.5 for the leaky integrator. Assume that all sample values within the systems are zero at time n = 0.
- **1.22** DSP engineers involved in building control systems often need to know what is the *step response* of a discrete system. The step response, $y_{step}(n)$, can be defined in two equivalent ways. One way is to say that $y_{step}(n)$ is a system's response to an input sequence of all unity-valued samples. A second definition is that $y_{step}(n)$ is the cumulative sum (the accumulation, discrete integration) of that system's unit impulse response $y_{imp}(n)$. Algebraically, this second definition of step response is expressed as

$$y_{\text{step}}(n) = \sum_{k=-\infty}^{n} y_{\text{imp}}(k).$$

In words, the above $y_{step}(n)$ expression tells us: "The step response at time index *n* is equal to the sum of all the previous impulse response samples up to and including $y_{imp}(n)$." With that said, what are the step responses of the

four processes listed in Problem 1.20? (Let A = 0.5 for the leaky integrator.) Assume that all sample values within the system are zero at time n=0.

1.23 Thinking about the spectra of signals, the *ideal* continuous (analog) squarewave s(t) in Figure P1–23, whose fundamental frequency is f_0 Hz, is equal to the sum of an f_0 Hz sinewave and all sinewaves whose frequencies are odd multiples of f_0 Hz. We call s(t) "ideal" because we assume the amplitude transitions from plus and minus *A* occur instantaneously (zero seconds!). Continuous Fourier analysis of the s(t) squarewave allows us to describe this sum of frequencies as the following infinite sum:

$$s(t) = \frac{4A}{\pi} \left[\sin(2\pi f_0 t) + \frac{\sin(6\pi f_0 t)}{3} + \frac{\sin(10\pi f_0 t)}{5} + \frac{\sin(14\pi f_0 t)}{7} + \dots \right]$$



Figure P1-23

Using a summation symbol, we can express squarewave s(t) algebraically as

$$s(t) = \frac{4A}{\pi} \sum_{n=1}^{\infty} \sin(2\pi n f_0 t) / n,$$

for n = odd integers only, showing s(t) to be an infinite sum of sinusoids.

- (a) Imagine applying *s*(*t*) to a filter that completely removes *s*(*t*)'s lowest-frequency spectral component. Draw the time-domain waveform at the output of such a filter.
- (b) Assume s(t) represents a voltage whose f_0 fundamental frequency is 1 Hz, and we wish to amplify that voltage to peak amplitudes of ±2*A*. Over what frequency range must an amplifier operate (that is, what must be the amplifier's *passband width*) in order to exactly double the ideal 1 Hz squarewave's peak-peak amplitude?
- **1.24** This interesting problem illustrates an *illegal* mathematical operation that we must learn to avoid in our future algebraic activities. The following claims to

be a mathematical proof that 4 = 5. Which of the following steps is illegal? Explain why.

Proof that 4 = 5:

Step 1: 16 - 36 = 25 - 45Step 2: $4^2 - 9 \cdot 4 = 5^2 - 9 \cdot 5$ Step 3: $4^2 - 9 \cdot 4 + 81/4 = 5^2 - 9 \cdot 5 + 81/4$ Step 4: $(4 - 9/2)^2 = (5 - 9/2)^2$ Step 5: 4 - 9/2 = 5 - 9/2Step 6: 4 = 5 This page intentionally left blank

Index

A

Absolute value, 9. *See also* Magnitude. A/D converters, quantization noise clipping, 706 crest factor, 640 dithering, 706-709 effective bits, 641 fixed-point binary word length, effects of, 634–642 oversampling, 704–706 reducing, 704-709 SNR (signal-to-noise ratio), 637–642, 711-714 triangular dither, 708 A/D converters, testing techniques A/D dynamic range, estimating, 714-715 histogram testing, 711 missing codes, detecting, 715-716 quantization noise, estimating with the FFT, 709–714 SFDR (spurious free dynamic range), 714-715 SINAD (signal-to-noise-and-distortion), 711–714 SNR (signal-to-noise ratio), 711–714 Adaptive filters, 184 Addition block diagram symbol, 10 complex numbers, 850 Additive white noise (AWN), 380

AGC (automatic gain control), 783–784 Aliasing definition, 36 frequency-domain ambiguity, 33-38 in IIR filters, 304–305 All-ones rectangular functions DFT for, 115-118 Dirichlet kernel, 115-118, 120 Allpass filters, definition, 893 AM demodulation filtering narrowband noise, 792–797 Hilbert transforms, 484-485 Amplitude definition, 8 loss. See Attenuation. Amplitude response, DFT complex input, 73 real cosine input, 83-84 Analog, definition, 2 Analog filters approximating, 302 vs. digital, 169 Analog signal processing, 2 Analog-to-digital (A/D) converters. See A/D converters. Analytic signals bandpass quadrature, 455 definition, 483 generation methods, comparing, 497 - 498half-band FIR filters, 497 time-domain, generating, 495-497

Anti-aliasing filters, 42, 555–558 Anti-imaging filters, 555–558 Arctangent approximation, 756-758 vector rotation. See Vector rotation with arctangents. Argand, Jean Robert, 848 Argand diagrams of complex numbers, 848 Argand plane, 440–441 Attenuation CIC filters, improving, 557–558 definition, 894 Automatic gain control (AGC), 783-784 Average, statistical measures of noise, 868-870 Average power in electrical circuits, calculating, 874-875 Averaging signals. See Signal averaging. AWN (additive white noise), 380

B

Band reject filters, 894 Band-limited signals, 38 Bandpass design, for FIR filters, 201–203 Bandpass filters comb filters, 400 definition, 895 from half-band FIR filters, 497 multisection complex FSFs, 398-403 Bandpass sampling 1st-order sampling, 46 definition, 43 optimum sampling frequency, 46 positioning sampled spectra, 48 real signals, 46 sampling translation, 44 SNR (signal-to-noise) ratio, 48-49 spectral inversion, 46-47 spectral replication, 44-45 Bandpass signals in the frequency-domain, 454-455 interpolating, 728-730 Bandwidth, definition, 895 Bartlett windows. See Triangular windows. Base 8 (octal) numbers, 624-625 Base 16 (hexadecimal) numbers, 625

Bell, Alexander Graham, 885 Bels, definition, 885 Bessel functions definition, 895 Bessel-derived filters, ripples, 901 Bessel's correction, 870-871 Bias DC, sources and removal, 761 in estimates, 870-871 fixed-point binary formats, 628 in signal variance, computing, 797–799 Bilateral Laplace transforms, 258 Bilinear transform method, designing IIR filters analytical methods, 302 definition, 257 example, 326–330 frequency warping, 319, 321-325, 328-330 mapping complex variables, 320-324 process description, 324-326 Bin centers, calculating absolute frequency, 139-140 Binary points, 629 Binary shift multiplication/division, polynomial evaluation, 773-774 Biquad filters, 299 Bit normalization, 653 Bit reversals avoiding, 158 fast Fourier transform input/output data index, 149-151 Bits, definition, 623 Blackman windows in FIR filter design, 195–201 spectral leakage reduction, 686 Blackman windows (exact), 686, 733 Blackman-Harris windows, 686, 733 Block averaging, SNR (signal-to-noise ratio), 770 Block convolution. See Fast convolution. Block diagrams filter structure, 172-174 quadrature sampling, 459-462 symbols, 10–11 uses for, 10 Block floating point, 656–657 Boxcar windows. See Rectangular windows.

Butterfly patterns in FFTs description, 145–149 optimized, 156 radix-2 structures, 151–154 single butterfly structures, 154–158 wingless, 156 Butterworth function definition, 895 derived filters, ripples, 901

С

Cardano, Girolamo, 439 Carrier frequency, 44 Cartesian form, quadrature signals, 442 Cascaded filters, 295-299, 895 Cascaded integrators, 563 Cascaded-comb subfilters, 412–413 Cascade/parallel filter combinations, 295-297 Cauer filters, 896 Causal systems, 258 Center frequency, definition, 895 Central Limit Theory, 723 Central-difference differentiators, 363–366 CFT (continuous Fourier transform), 59, 98-102 Chebyshev function, definition, 895 Chebyshev windows, 197-201, 927-930 Chebyshev-derived filters, ripples, 900 CIC (cascaded integrator-comb) filters cascaded integrators, 563 comb section, 553 compensation FIR filters, 563–566 definition, 895 implementation issues, 558-563 nonrecursive, 765-768 recursive running sum filters, 551–552 structures, 553-557 substructure sharing, 765–770 transposed structures, 765-770 two's complement overflow, 559-563 Circular buffers, IFIR filters, 388–389 Clipping A/D converter quantization noise, 706 Coefficients. See Filter coefficients. Coherent sampling, 711 Coherent signal averaging. See Signal averaging, coherent.

Comb filters. See also Differentiators. alternate FSF structures, 416-418 bandpass FIR filtering, 400 cascaded-comb subfilters, 412–413 with complex resonators, 392–398 frequency response, 903-904 second-order comb filters, 412–413 Comb section. CIC filters, 553 Commutative property, LTI, 18–19 Commutator model, polyphase filters, 524 Compensation FIR filters, CIC filters, 563-566 Complex conjugate, DFT symmetry, 73 Complex down-conversion decimation, in frequency translation, 782 quadrature signals, 455, 456-462 Complex exponentials, quadrature signals, 447 Complex frequency, Laplace variable, 258 Complex frequency response, filters, 277 Complex mixing, quadrature signals, 455 Complex multipliers, down-converting quadrature signals, 458 Complex number notation, quadrature signals, 440-446 Complex numbers. See also Quadrature signals. Argand diagrams, 848 arithmetic of, 848-858 definition, 439 as a function of time, 446–450 graphical representation of, 847-848 rectangular form, definition, 848-850 rectangular form, vs. polar, 856–857 roots of, 853-854 trigonometric form, 848-850 Complex phasors, quadrature signals, 446 - 450Complex plane, quadrature signals, 440-441, 446 Complex resonators with comb filters, 392–398 FSF (frequency sampling filters), 394-398 Complex signals. See Quadrature signals. Conditional stability, Laplace transform, 268Conjugation, complex numbers, 851–852

Constant-coefficient transversal FIR filters, 184 Continuous Fourier transform (CFT), 59, 98 - 102Continuous lowpass filters, 41 Continuous signal processing definition, 2 frequency in, 5-6 Continuous signals, definition, 2 Continuous systems, time representation, 5 Continuous time-domain, Laplace transform, 258-259 Converting analog to digital. See A/D converters. Convolution. See also FIR (finite impulse response) filters, convolution. fast, 716–722 LTI, 19 overlap-and-add, 720–722 overlap-and-save, 718-720 Cooley, J., 135 CORDIC (COordinate Rotation DIgital Computer), 756–758 Coupled quadrature oscillator, 787 Coupled-form IIR filter, 834-836 Crest factor, 640 Critical Nyquist, 37 Cutoff frequencies definition, 896 designing FIR filters, 186

D

Data formats base systems, 624 definition, 623 place value system, 624 Data formats, binary numbers. *See also* Fixed-point binary formats; Floating-point binary formats. 1.15 fixed-point, 630–632 block floating point, 656–657 converting to hexadecimal, 625 converting to octal, 624–625 definition, 623 dynamic range, 632–634

precision, 632-634 representing negative values, 625-626 Data overflow. See Overflow. dB (decibels), definition, 886, 896 dBm (decibels), definition, 892 DC bias, sources of, 761 block-data DC removal, 762 defined, 62 from a time-domain signal, 812-815 DC removal, real-time using filters, 761–763 noise shaping property, 765 with quantization, 763-765 Deadband effects, 293 DEC (Digital Equipment Corp.), floatingpoint binary formats, 654-655 Decibels bels, definition, 885 common constants, 889-891 dB, definition, 886, 896 dBm, definition, 892 Decimation. See also Interpolation. combining with interpolation, 521-522 definition, 508 to implement down-conversion, 676-679 multirate filters, 521-522 sample rate converters, 521–522 drawing downsampled spectra, 515-516 frequency properties, 514–515 magnitude loss in the frequencydomain, 515 overview, 508-510 time invariance, 514 time properties, 514-515 example, 512–513 overview, 510-511 polyphase decomposition, 514 Decimation filters choosing, 510 definition, 896 Decimation-in-frequency algorithms, FFTs radix-2 butterfly structures, 151-154, 734-735 Decimation-in-time algorithms, FFTs index bit reversal, 149-151 radix-2 butterfly structures, 151-154

single butterfly structures, 154–158, 735-737 Demodulation AM, 484-485 FM, 486 quadrature signals, 453-455, 456-462 Descartes, René, 439 Detection envelope, 784–786 peak threshold, with matched filters, 377, 379–380 quadrature signals, 453-454 signal transition, 820-821 single tone. See Single tone detection. DFT (discrete Fourier transform). See also DTFT (discrete-time Fourier transform); SDFT (sliding DFT). analyzing FIR filters, 228-230 computing large DFTs from small FFTs, 826-829 definition, 60 examples, 63–73, 78–80 versus FFT, 136-137 frequency axis, 77 frequency granularity, improving. See Zero padding. frequency spacing, 77 frequency-domain sampling, 98–102 inverse, 80-81 linearity, 75 magnitudes, 75–76 picket fence effect, 97 rectangular functions, 105–112 resolution, 77, 98-102 scalloping loss, 96–97 shifting theorem, 77-78 spectral estimation, improving. See Zero padding. time reversal, 863-865 zero padding, 97-102 DFT leakage. See also Spectral leakage, FFTs. cause, 82-84 definition, 81 description, 81–82 predicting, 82-84 sinc functions, 83, 89 wraparound, 86-88

DFT leakage, minimizing Chebyshev windows, 96 Hamming windows, 89–93 Hanning windows, 89-97 Kaiser windows, 96 rectangular windows, 89–97 triangular windows, 89-93 windowing, 89–97 DFT processing gain average output noise-power level, 103 - 104inherent gain, 102–105 integration gain, 105 multiple DFTs, 105 output signal-power level, 103-104 single DFT, 102–105 SNR (signal-to-noise ratio), 103–104 DIF (decimation-in-frequency), 734–735 Difference equations example, 5 IIR filters, 255–256 Differentiators central-difference, 363-366 differentiating filters, 364 first-difference, 363-366 narrowband, 366-367 optimized wideband, 369-370 overview, 361-363 performance improvement, 810–812 wideband, 367-369 Digital differencer. See Differentiators. Digital Equipment Corp. (DEC), floatingpoint binary formats, 654–655 Digital filters. See also specific filters. vs. analog, 169 definition, 896 Digital signal processing, 2 Direct Form I filters, 275–278, 289 Direct Form II filters, 289-292 Direct Form implementations, IIR filters, 292-293 Dirichlet, Peter, 108 Dirichlet kernel all-ones rectangular functions, 115-118, 120general rectangular functions, 108–112 symmetrical rectangular functions, 113-114

Discrete convolution in FIR filters. See also FIR (finite impulse response) filters, convolution. description, 214-215 in the time domain, 215-219 Discrete Fourier transform (DFT). See DFT (discrete Fourier transform). Discrete Hilbert transforms. See Hilbert transforms. Discrete linear systems, 12–16 Discrete systems definition, 4 example, 4–5 time representation, 5 Discrete-time expression, 4 Discrete-time Fourier transform (DTFT), 101, 120-123 Discrete-time signals example of, 2 frequency in, 5–6 sampling, frequency-domain ambiguity, 33-38 use of term, 2 Discrete-time waveforms, describing, 8 Dispersion, statistical measures of noise, 869 DIT (decimation-in-time), 735–737 Dithering A/D converter quantization noise, 706-709 with filters, 294 triangular, 708 Dolph-Chebyshev windows in FIR filter design, 197 Down-conversion Delay/Hilbert transform filter, 817-818, 819-820 filtering and decimation, 676–679 folded FIR filters, 818 frequency translation, without multiplication, 676-679 half-band filters, 817-818 single-decimation technique, 819-820 Down-conversion, quadrature signals complex, 455, 456-462 complex multipliers, 458 sampling with digital mixing, 462 - 464

Downsampling, decimation drawing downsampled spectra, 515-516 frequency properties, 514–515 magnitude loss in the frequencydomain, 515 overview, 508-510 time invariance, 514 time properties, 514-515 DTFT (discrete-time Fourier transform), 101, 120–123. See also DFT (discrete Fourier transform). Dynamic range binary numbers, 632–634 floating-point binary formats, 656-658 SFDR (spurious free dynamic range), 714-715

E

Elliptic functions, definition, 896 Elliptic-derived filters, ripples, 900 Envelope delay. See Group delay. Envelope detection approximate, 784-786 Hilbert transforms, 483–495 Equiripple filters, 418, 901 Estrin's Method, polynomial evaluation, 774-775 Euler, Leonhard, 442, 444 Euler's equation bilinear transform design of IIR filters, 322 DFT equations, 60, 108 impulse invariance design of IIR filters, 315 quadrature signals, 442–443, 449, 453 Exact Blackman windows, 686 Exact interpolation, 778-781 Exponent, floating-point binary format, 652 Exponential averagers, 608-612 Exponential moving averages, 801–802 Exponential signal averaging. See Signal averaging, exponential. Exponential variance computation, 801-802

F

Fast convolution, 716–722 FFT (fast Fourier transform) averaging multiple, 139 constant-geometry algorithms, 158 convolution. See Fast convolution. decimation-in-frequency algorithms, 151 - 154decimation-in-time algorithms, 149–158 versus DFT, 136–137 exact interpolation, 778–781 fast FIR filtering, 716–722 hints for using, 137–141 history of, 135 interpolated analytic signals, computing, 781 interpolated real signals, interpolating, 779-780 interpreting results, 139–141 inverse, computing, 699-702, 831-833 in place algorithm, 157 radix-2 algorithm, 141–149 radix-2 butterfly structures, 151-158 signal averaging, 600-603 single tone detection, 737-738, 740-741 vs. single tone detection, 740–741 software programs, 141 time-domain interpolation, 778–781 Zoom FFT, 749-753 FFT (fast Fourier transform), real sequences a 2N-point real FFT, 695–699 two N-point real FFTs, 687–694 FFT (fast Fourier transform), twiddle factors derivation of the radix-2 FFT algorithm, 143 - 149DIF (decimation-in-frequency), 734–735 DIT (decimation-in-time), 735–737 Fibonacci, 450-451 Filter coefficients definition, 897 for FIRs. See Impulse response. flipping, 493-494 for FSF (frequency sampling filters), 913-926 quantization, 293-295

Filter order, 897 Filter taps, estimating, 234–235, 386–387 Filters. See also FIR (finite impulse response) filters; IIR (infinite impulse response) filters; Matched filters; specific filters. adaptive filters, 184 allpass, 893 analog vs. digital, 169 band reject, 894 bandpass, 895 cascaded, 895 Cauer, 896 CIC, 895 DC-removal, 762-763 decimation, 896 differentiating, 364. See also Differentiators. digital, 896 down-conversion, 676–679 equiripple, 418 highpass, 898 linear phase, 899 lowpass, 899 narrowband noise, 792-797 nonrecursive, 226-230, 290-291, 899 optimal FIR, 418 overview, 169-170 parallel, 295–297 passband, 900 process description, 169-170 prototype, 303 quadrature, 900 real-time DC removal, 762-763 recursive, 290-291, 900 recursive running sum, 551–552 Remez Exchange, 418 sharpening, 726–728 structure, diagramming, 172-174 time-domain slope detection, 820-821 transposed structure, 291–292 transversal, 173–174. See also FIR (finite impulse response) filters. zero-phase, 725, 902 Filters, analytic signals half-band FIR filters, 497 I-channel filters, 496 in-phase filters, 496

Filters, analytic signals (con't) Q-channel filters, 496 quadrature phase filters, 496 time-domain FIR filter implementation, 489 - 494Finite-word-length errors, 293–295 FIR (finite impulse response) filters. See also FSF (frequency sampling filters); IFIR (interpolated FIR) filters; IIR (infinite impulse response) filters. coefficients. See Impulse response. constant coefficients, 184 definition, 897 fast FIR filtering using the FFT, 716-722 folded structure. See Folded FIR filters. frequency magnitude response, determining, 179 frequency-domain response, determining, 179 group delay, 211-212 half-band. See Half-band FIR filters. vs. IIR filters, 332–333 impulse response, 177-179 narrowband lowpass. See IFIR (interpolated FIR) filters. nonrecursive, analyzing, 226-230 phase response in, 209-214 phase unwrapping, 210 phase wrapping, 209, 900 polyphase filters, 522-527 sharpening, 726–728 signal averaging. See Signal averaging, with FIR filters. signal averaging with, 178, 180–184 stopband attenuation, improving, 726-728 tapped delay, 181-182 transient response, 181–182 z-transform of, 288-289 FIR (finite impulse response) filters, analyzing with DFTs, 228-230 estimating number of, 234-235 fractional delay, 233 group delay, 230–233 passband gain, 233–234 stopband attenuation, 234–235 symmetrical-coefficient FIR filters, 232-233

FIR (finite impulse response) filters, convolution description, 175-186 discrete, description, 214-215 discrete, in the time domain, 215-219 fast convolution, 716-722 impulse response, 177–178 inputs, time order reversal, 176 signal averaging, 175–176 theorem, applying, 222–226 theorem, description, 219-222 time-domain aliasing, avoiding, 718-722 time-domain convolution vs. frequency-domain multiplication, 191-194 FIR (finite impulse response) filters, designing bandpass method, 201–203 cutoff frequencies, 186 with forward FFT software routines, 189 Fourier series design method. See Window design method, FIR filters. Gibbs's phenomenon, 193 highpass method, 203-204 low-pass design, 186–201 magnitude fluctuations, 190–194 Optimal design method, 204–207 Parks-McClellan Exchange method, 204-207 passband ripples, minimizing, 190–194, 204-207. See also Windows. Remez method, 204–207 stopband ripples, minimizing, 204–207 time-domain coefficients, determining, 186 - 194time-domain convolution vs. frequency-domain multiplication, 191-194 very high performance filters, 775-778 window design method, 186-194 windows used in, 194-201 1st-order IIR filters, signal averaging, 612-614 1st-order sampling, 46 First-difference differentiators, 363–366 Fixed-point binary formats. See also Floating-point binary formats.

1.15 format, 630-632 bias, 628 binary points, 629 decimal numbers, converting to 1.5 binary, 632 fractional binary numbers, 629-632 hexadecimal (base 16) numbers, 625 integer plus fraction, 629 lsb (least significant bit), 624 msb (most significant bit), 624 octal (base 8) numbers, 624–625 offset, 627-628 overflow, 629 Q30 format, 629 radix points, 629 representing negative values, 625-626 sign extend operations, 627 sign-magnitude, 625-626 two's complement, 626-627, 629 Fixed-point binary formats, finite word lengths A/D converter best estimate values, 635 A/D converter quantization noise, 634-642 A/D converter vs. SNR, 640–642 convergent rounding, 651 crest factor, 640 data overflow, 642-646 data rounding, 649–652 effective bits, 641 round off noise, 636-637 round to even method, 651 round-to-nearest method, 650-651 truncation, 646-649 Floating-point binary formats. See also Fixed-point binary formats. bit normalization, 653 common formats, 654-655 DEC (Digital Equipment Corp.), 654-655 description, 652 dynamic range, 656–658 evaluating, 652 exponent, 652 fractions, 653 gradual underflow, 656 hidden bits, 653 IBM, 654–655 IEEE Standard P754, 654-655 mantissa, 652

MIL-STD 1750A, 654-655 min/max values, determining, 656-657 unnormalized fractions, 656 word lengths, 655 FM demodulation algorithms for, 758-761 filtering narrowband noise, 792-797 Hilbert transforms, 486 Folded FIR filters designing Hilbert transforms, 493 down-conversion, 818 frequency translation, without multiplication, 678 half-band filters, sample rate conversion, 548 Hilbert transforms, designing, 493 multipliers, reducing, 702-704 nonrecursive, 419-420 tapped-delay line, 389 Folding frequencies, 40 Forward FFT computing, 831-833 software routines for designing FIR filters, 189 Fourier series design FIR filters. See Window design method, FIR filters. Fourier transform pairs, FIR filters, 178 - 179Fractional binary numbers, 629–632 Fractional delay, FIR filters, 233 Frequency continuous vs. discrete systems, 5 of discrete signals, determining. See DFT (discrete Fourier transform). discrete-time signals, 5–6 properties, interpolation, 519 resolution, improving with FIR filters, 228-230 units of measure, 2-3 Frequency attenuation, FIR filters, 182 Frequency axis definition, 77 DFT, 77 in Hz, 118 normalized angle variable, 118 in radians/seconds, 118–119 rectangular functions, 118–120 with zero padding, 100

Frequency domain definition, 6 Hamming windows, 683-686 Hanning windows, 683–686 listing sequences, 7 performance. IIR filters, 282-289 quadrature signals, 451-454 spectral leak reduction, 683-686 windowing in, 683-686 windows, 683-686 Frequency magnitude response definition, 897 determining with FIR filters, 179 Frequency response LTI, determining, 19 for Mth-order IIR filter, 275-276 Frequency response, FIR filters determining, 179–186 factors affecting, 174 modifying, 184–186 Frequency sampling design method vs. FSF, 393-394 Frequency sampling filters. See FSF (frequency sampling filters). Frequency translation, bandpass sampling, 44 Frequency translation, with decimation complex down-conversion, 782 complex signals, 781–783 real signals, 781 Frequency translation, without multiplication by 1/2 the sampling rate, 671–673 by 1/4 the sampling rate, 674–676 down-conversion, 676-679 inverting the output spectrum, 678-679 Frequency translation to baseband, quadrature signals, 455 Frequency warping, 319, 321–325, 328–330 FSF (frequency sampling filters). See also FIR (finite impulse response) filters. complex resonators, 394-398 designing, 423-426 frequency response, single complex FSF, 904-905 history of, 392-394 linear-phase multisection real-valued, 409 - 410

modeling, 413–414 multisection complex, 398–403 multisection real-valued, 406–409 vs. Parks-McClellan filters, 392 real FSF transfer function, 908–909 stability, 403–406 stopband attenuation, increasing, 414–416 stopband sidelobe level suppression, 416 transition band coefficients, 414–416 Type IV example, 419–420, 423–426

G

Gain. See also DFT processing gain. AGC (automatic gain control), 783-784 IIR filters, scaling, 300–302 integration, signal averaging, 600-603 passband, 233–234 windows, 92 Gauss, Karl, 439, 444 Gaussian PDFs, 882-883 General numbers, 446. See also Complex numbers. Geometric series, closed form, 107, 859-861 Gibbs's phenomenon, 193 Goertzel algorithm, single tone detection advantages of, 739 description, 738-740 example, 740 vs. the FFT, 740–741 stability, 838-840 Gold-Rader filter, 834-836 Gradual underflow, floating-point binary formats, 656 Gregory, James, 23 Group delay definition, 897-898 differentiators, 365 filters, computing, 830–831 FIR filters, 211-212, 230-233

H

Half Nyquist, 37 Half-band FIR filters analytic signals, 497

Index

as complex bandpass filters, 497 definition, 898 description, 207-209 down-conversion, 817-818 frequency translation, 802-804 Half-band FIR filters, sample rate conversion fundamentals, 544-546 implementation, 546-548 overview, 543 Hamming, Richard, 366 Hamming windows in the frequency domain, 683–686 spectral peak location, 733 Hann windows. See Hanning windows. Hanning windows description, 89–97 DFT leakage, minimizing, 89–97 in the frequency domain, 683-686 spectral peak location, 733 Harmonic sampling. See Bandpass sampling. Harmonics of discrete signals, determining. See DFT (discrete Fourier transform). Harris, Fred, 791 Heaviside, Oliver, 257 Hertz, 3 Hertz, Heinrich, 3 Hexadecimal (base 16) numbers, 625 Hidden bits, floating-point binary formats, 653 Highpass filters, definition, 898 Highpass method, designing FIR filters, 203-204 Hilbert, David, 479 Hilbert transformers, designing common mistake, 493–494 even-tap transformers, 493 frequency-domain transformers, 494-495 half-band filter coefficient modification, 804-805 half-band filter frequency translation, 802-804 odd-tap transformers, 493 time-domain FIR filter implementation, 489 - 494time-domain transformers, 489–494

Hilbert transforms AM demodulation, 484-485 definition, 480 envelope detection, 483–495 example, 481-482 FM demodulation, 486 impulse response, 487–489 one-sided spectrum, 483 signal envelope, 483-495 Hilbert transforms, analytic signals definition, 483 generation methods, comparing, 497-498 half-band FIR filters, 497 time-domain, generating, 495–497 Histogram testing, A/D converter techniques, 711 Homogeneity property, 12 Horner, William, 773 Horner's Rule, 772–774 Human ear, sensitivity to decibels, 886

I

IBM, floating-point binary formats, 654-655 I-channel filters, analytic signals, 496 IDFT (inverse discrete Fourier transform), 80 - 81IEEE Standard P754, floating-point binary formats, 654-655 IF sampling. *See* Bandpass sampling. IFIR (interpolated FIR) filters. See also FIR (finite impulse response) filters. computational advantage, 384-385, 391 definition, 381 expansion factor M, 381, 385–386 filter taps, estimating, 386-387 image-reject subfilter, 382–384, 390 implementation issues, 388-389 interpolated, definition, 384 interpolators. See Image-reject subfilter. lowpass design example, 389-391 optimum expansion factor, 386 performance modeling, 387-388 prototype filters, 382 shaping subfilters, 382, 385

IIR (infinite impulse response) filters. See also FIR (finite impulse response) filters; FSF (frequency sampling filters). allpass, 893 analytical design methods, 302 coupled-form, 834-836 definition, 899 design techniques, 257. See also specific techniques. difference equations, 255–256 vs. FIR filters, 253, 332–333 frequency domain performance, 282-289 infinite impulse response, definition, 280 interpolated, example, 837-838 phase equalizers. See Allpass filters. poles, 284-289 recursive filters, 290-291 scaling the gain, 300–302 SNR (signal-to-noise ratio), 302 stability, 263–270 z-domain transfer function, 282-289 zeros, 284-289 z-plane pole / zero properties, 288–289 z-transform, 270-282 IIR (infinite impulse response) filters, pitfalls in building coefficient quantization, 293–295 deadband effects, 293 Direct Form implementations, 292–293 dither sequences, 294 finite word length errors, 293–295 limit cycles, 293 limited-precision coefficients, 293 overflow, 293-295 overflow oscillations, 293 overview, 292-293 rounding off, 293 IIR (infinite impulse response) filters, structures biquad filters, 299 cascade filter properties, 295-297 cascaded, 295-299 cascade/parallel combinations, 295–297 changing, 291-292 Direct Form 1, 275–278, 289 Direct Form II, 289-292 optimizing partitioning, 297-299

parallel filter properties, 295-297 transposed, 291-292 transposed Direct Form II, 289-290 transposition theorem, 291-292 Imaginary numbers, 439, 446 Imaginary part, quadrature signals, 440, 454-455 Impulse invariance method, designing IIR filters aliasing, 304-305 analytical methods, 302 definition, 257 Method 1, description, 305–307 Method 1, example, 310–313 Method 2, description, 307–310 Method 2, example, 313–319 preferred method, 317 process description, 303-310 prototype filters, 303 Impulse response convolution in FIR filters, 177-178 definition, 898–899 FIR filters, 177–179 Hilbert transforms, 487–489 Incoherent signal averaging. See Signal averaging, incoherent. Infinite impulse response (IIR) filters. See IIR (infinite impulse response) filters. Integer plus fraction fixed-point binary formats, 629 Integration gain, signal averaging, 600-603 Integrators CIC filters, 553 overview, 370 performance comparison, 373–376 rectangular rule, 371-372 Simpson's rule, 372, 373–376 Tick's rule, 373-376 trapezoidal rule, 372 Intermodulation distortion, 16 Interpolated analytic signals, computing, 781 Interpolated FIR (IFIR) filters. See IFIR (interpolated FIR) filters. Interpolated real signals, interpolating, 779 - 780Interpolation. See also Decimation. accuracy, 519

bandpass signals, 728–730 combining with decimation, 521-522 definition, 384, 508 drawing upsampled spectra, 520–521 exact, 778-781 frequency properties, 519 history of, 519 linear, 815-816 multirate filters, 521–522 overview, 516-518 sample rate converters, 521–522 time properties, 519 time-domain, 778-781 unwanted spectral images, 519 upsampling, 517–518, 520–521 zero stuffing, 518 Interpolation filters, 518 Inverse DFT, 80-81 Inverse discrete Fourier transform (IDFT), 80 - 81Inverse FFT, 699-702, 831-833 Inverse of complex numbers, 853 Inverse sinc filters, 563–566 I/Q demodulation, quadrature signals, 459 - 462

J

Jacobsen, Eric, 775 *j*-operator, quadrature signals, 439, 444–450

K

Kaiser, James, 270 Kaiser windows, in FIR filter design, 197–201 Kaiser-Bessel windows, in FIR filter design, 197 Kelvin, Lord, 60 Kootsookos, Peter, 603, 724 Kotelnikov, V., 42

L

Lanczos differentiators, 366–367 Laplace transfer function conditional stability, 268 description, 262–263

determining system stability, 263-264, 268 impulse invariance design, Method 1, 305-307, 310-313 impulse invariance design, Method 2, 307-310, 313-319 in parallel filters, 295–297 second order, 265-268 Laplace transform. See also Z-transform. bilateral transform, 258 causal systems, 258 conditional stability, 268 for continuous time-domain, 258-259 description, 257–263 development of, 257 one-sided transform, 258 one-sided/causal, 258 poles on the s-plane, 263-270 stability, 263-270 two-sided transform, 258 zeros on the s-plane, 263-270 Laplace variable, complex frequency, 258 Leakage. See DFT leakage. Leaky integrator, 614 Least significant bit (lsb), 624 l'Hopital's Rule, 110 Limit cycles, 293 Linear, definition, 12 Linear differential equations, solving. See Laplace transform. Linear interpolation, 815–816 Linear phase filters, 899 Linear systems, example, 13–14 Linear time-invariant (LTI) systems. See LTI (linear time-invariant) systems. Linearity, DFT, 75 Linear-phase filters DC removal, 812-815 definition, 899 Logarithms and complex numbers, 854-856 measuring signal power, 191 Lowpass design designing FIR filters, 186-201 IFIR filters, example, 389–391 Lowpass filters, definition, 899 Lowpass signals definition, 38 sampling, 38-42

lsb (least significant bit), 624 LTI (linear time-invariant) systems analyzing, 19-21 commutative property, 18-19 convolution, 19 DFT (discrete Fourier transform), 19 discrete linear systems, 12-16 frequency response, determining, 19 homogeneity property, 12 intermodulation distortion, 16 internally generated sinusoids, 16 linear, definition, 12 linear system, example, 13–14 nonlinear system, example, 14-16 output sequence, determining, 19 overview, 12 proportionality characteristic, 12 rearranging sequential order, 18-19 time-invariant systems, 17-18 unit impulse response, 19-20

Μ

MAC (multiply and accumulate) architecture polynomial evaluation, 773 programmable DSP chips, 333 Magnitude approximation (vector), 679-683 of complex numbers, 848 definition, 8-9 DFT, 75-76 Magnitude and angle form of complex numbers, 848-850 Magnitude response of DFTs aliased sinc function, 108 all-ones rectangular functions, 115-118 fluctuations. See Scalloping. general rectangular functions, 106–112 overview, 105-106 sidelobe magnitudes, 110-111 symmetrical rectangular functions, 112-115 Magnitude response of DFTs, Dirichlet kernel all-ones rectangular functions, 115-118, 120 general rectangular functions, 108–112 symmetrical rectangular functions, 113-114

Magnitude-angle form, quadrature signals, 442 Mantissa, floating-point binary formats, 652 Matched filters definition, 376 example, 378-380 implementation considerations, 380 peak detection threshold, 377, 379-380 properties, 376-378 purpose, 376 SNR (signal-power-to-noise-power ratio), maximizing, 376 McClellan, James, 206. See also Parks-McClellan algorithm. Mean (statistical measure of noise) definition, 868-869 PDF (probability density function), 879-882 of random functions, 879-882 Mean (statistical average), of random functions, 879-882 Mehrnia, A., 386 MIL-STD 1750A, floating-point binary formats, 654-655 Missing A/D conversion codes, checking, 715-716 sample data, recovering, 823-826. See also Interpolation. Mixing. See Frequency translation. Modeling FSF (frequency sampling filters), 413–414 Modulation, quadrature signals, 453–454 Modulus of complex numbers, 848 Most significant bit (msb), 624 Moving averages CIC filters, 551–552 as digital lowpass filters, 20-21, 173, 231 sample rate conversion, CIC filters, 551-552 Moving averages, coherent signal averaging exponential moving averages, computing, 801-802 exponential signal averaging, 801-802 moving averages, computing, 799-801 nonrecursive moving averagers, 606-608

recursive moving averagers, 606-608 time-domain averaging, 604-608 msb (most significant bit), 624 Multiplication block diagram symbol, 10 CIC filters, simplified, 765–770 complex numbers, 850-851 Multirate filters decimation, 521-522 interpolation, 521–522 Multirate systems, sample rate conversion filter mathematical notation, 534-535 signal mathematical notation, 533-534 z-transform analysis, 533–535 Multirate systems, two-stage decimation, 511

Ν

Narrowband differentiators, 366-367 Narrowband noise filters, 792–797 Natural logarithms of complex numbers, 854 Negative frequency, quadrature signals, 450 - 451Negative values in binary numbers, 625-626 Newton, Isaac, 773 Newton's method, 372 Noble identities, polyphase filters, 536 Noise definition, 589 measuring. See Statistical measures of noise. random, 868 Noise shaping property, 765 Nonlinear systems, example, 14–16 Nonrecursive CIC filters description, 765-768 prime-factor-R technique, 768–770 Nonrecursive filters. See FIR filters Nonrecursive moving averagers, 606–608 Normal distribution of random data, generating, 722-724 Normal PDFs, 882-883 Normalized angle variable, 118–119 Notch filters. See Band reject filters. Nyquist, H., 42 Nyquist criterion, sampling lowpass signals, 40

0

Octal (base 8) numbers, 624–625 Offset fixed-point binary formats, 627–628 1.15 fixed-point binary format, 630-632 Optimal design method, designing FIR filters, 204-207 Optimal FIR filters, 418 Optimization method, designing IIR filters definition, 257 description, 302 iterative optimization, 330 process description, 330–332 Optimized butterflies, 156 Optimized wideband differentiators, 369-370 Optimum sampling frequency, 46 Order of filters, 897 polyphase filters, swapping, 536–537 Orthogonality, quadrature signals, 448 Oscillation, quadrature signals, 459–462 Oscillator, quadrature coupled, 787 overview, 786-789 Taylor series approximation, 788 Overflow computing the magnitude of complex numbers, 815 fixed-point binary formats, 629, 642-646 two's complement, 559-563 Overflow errors, 293–295 Overflow oscillations, 293 Oversampling A/D converter quantization noise, 704-706

Ρ

Parallel filters, Laplace transfer function, 295–297
Parks-McClellan algorithm designing FIR filters, 204–207 vs. FSF (frequency sampling filters), 392 optimized wideband differentiators, 369–370
Parzen windows. See Triangular windows.
Passband, definition, 900

Passband filters, definition, 900 Passband gain, FIR filters, 233–234 Passband ripples cascaded filters, estimating, 296–297 definition, 296, 900 IFIR filters, 390 minimizing, 190-194, 204-207 PDF (probability density function) Gaussian, 882-883 mean, calculating, 879-882 mean and variance of random functions, 879-882 normal, 882-883 variance, calculating, 879-882 Peak correlation, matched filters, 379 Peak detection threshold, matched filters, 377, 379-380 Periodic sampling aliasing, 33-38 frequency-domain ambiguity, 33-38 Periodic sampling 1st-order sampling, 46 anti-aliasing filters, 42 bandpass, 43-49 coherent sampling, 711 definition, 43 folding frequencies, 40 Nyquist criterion, 40 optimum sampling frequency, 46 real signals, 46 sampling translation, 44 SNR (signal-to-noise) ratio, 48–49 spectral inversion, 46-47 undersampling, 40 Phase angles, signal averaging, 603–604 Phase delay. See Phase response. Phase response definition, 900 in FIR filters, 209-214 Phase unwrapping, FIR filters, 210 Phase wrapping, FIR filters, 209, 900 Pi, calculating, 23 Picket fence effect, 97 Pisa, Leonardo da, 450-451 Polar form complex numbers, vs. rectangular, 856-857 quadrature signals, 442, 443–444

Poles IIR filters, 284–289 on the s-plane, Laplace transform, 263 - 270Polynomial curve fitting, 372 Polynomial evaluation binary shift multiplication/division, 773-774 Estrin's Method, 774–775 Horner's Rule, 772–774 MAC (multiply and accumulate) architecture, 773 Polynomial factoring, CIC filters, 765–770 Polynomials, finding the roots of, 372 Polyphase decomposition CIC filters, 765–770 definition, 526 diagrams, 538–539 two-stage decimation, 514 Polyphase filters benefits of, 539 commutator model, 524 implementing, 535-540 issues with, 526 noble identities, 536 order, swapping, 536-537 overview, 522-528 polyphase decomposition, 526, 538-539 prototype FIR filters, 522 uses for, 522 Power, signal. See also Decibels. absolute, 891–892 definition, 9 relative, 885-889 Power spectrum, 63, 140–141 Preconditioning FIR filters, 563–566 Prewarp, 329 Prime decomposition, CIC filters, 768-770 Prime factorization, CIC filters, 768–770 Probability density function (PDF). See PDF (probability density function). Processing gain or loss. See DFT processing gain; Gain; Loss. Prototype filters analog, 303 FIR polyphase filters, 522 IFIR filters, 382
Q

Q30 fixed-point binary formats, 629 Q-channel filters, analytic signals, 496 Quadratic factorization formula, 266, 282 Quadrature component, 454–455 Quadrature demodulation, 455, 456–462 Quadrature filters, definition, 900 Quadrature mixing, 455 Quadrature oscillation, 459–462 Quadrature oscillator coupled, 787 overview, 786-789 Taylor series approximation, 788 Quadrature phase, 440 Quadrature processing, 440 Quadrature sampling block diagram, 459 - 462Quadrature signals. See also Complex numbers. analytic, 455 Argand plane, 440–441 bandpass signals in the frequencydomain, 454-455 Cartesian form, 442 complex exponentials, 447 complex mixing, 455 complex number notation, 440-446 complex phasors, 446–450 complex plane, 440-441, 446 decimation, in frequency translation, 781-783 definition, 439 demodulation, 453-454 detection, 453-454 down-conversion. See Downconversion, quadrature signals. Euler's identity, 442-443, 449, 453 exponential form, 442 in the frequency domain, 451–454 generating from real signals. See Hilbert transforms. generation, 453-454 imaginary part, 440, 454–455 in-phase component, 440, 454-455 I/Q demodulation, 459–462 *j*-operator, 439, 444–450 magnitude-angle form, 442

mixing to baseband, 455 modulation, 453-454 negative frequency, 450–451 orthogonality, 448 polar form, 442, 443-444 positive frequency, 451 real axis, 440 real part, 440, 454-455 rectangular form, 442 representing real signals, 446–450 sampling scheme, advantages of, 459 - 462simplifying mathematical analysis, 443-444 three-dimensional frequency-domain representation, 451-454 trigonometric form, 442, 444 uses for, 439-440 Ouantization coefficient/errors, 293-295 noise. See A/D converters, quantization noise. real-time DC removal, 763-765

R

Radix points, fixed-point binary formats, 629 Radix-2 algorithm, FFT butterfly structures, 151–154 computing large DFTs, 826-829 decimation-in-frequency algorithms, 151 - 154decimation-in-time algorithms, 151-154 derivation of, 141-149 FFT (fast Fourier transform), 151–158 twiddle factors, 143–149 Raised cosine windows. See Hanning windows. Random data Central Limit Theory, 723 generating a normal distribution of, 722 - 724Random functions, mean and variance, 879-882 Random noise, 868. See also SNR (signal-to-noise ratio).

Real numbers definition, 440 graphical representation of, 847-848 Real sampling, 46 Real signals bandpass sampling, 46 decimation, in frequency translation, 781 generating complex signals from. See Hilbert transforms. representing with quadrature signals, 446 - 450Rectangular form of complex numbers definition, 848-850 vs. polar form, 856-857 Rectangular form of quadrature signals, 442 Rectangular functions all ones, 115-118 DFT, 105–112 frequency axis, 118–120 general, 106-112 overview, 105–106 symmetrical, 112–115 time axis, 118-120 Rectangular windows, 89–97, 686 Recursive filters. See IIR filters Recursive moving averagers, 606–608 Recursive running sum filters, 551–552 Remez Exchange, 204–207, 418 Replications, spectral. See Spectral replications. Resolution, DFT, 77, 98-102 Ripples in Bessel-derived filters, 901 in Butterworth-derived filters, 901 in Chebyshev-derived filters, 900 definition, 900-901 designing FIR filters, 190–194 in Elliptic-derived filters, 900 equiripple, 418, 901 out-of-band, 901 in the passband, 900 in the stopband, 901 rms value of continuous sinewaves, 874-875 Roll-off, definition, 901 Roots of complex numbers, 853-854 polynomials, 372

Rosetta Stone, 450 Rounding fixed-point binary numbers convergent rounding, 651 data rounding, 649–652 effective bits, 641 round off noise, 636–637 round to even method, 651 round-to-nearest method, 650–651 Roundoff errors, 293

S

Sample rate conversion. See also Polyphase filters. decreasing. See Decimation. definition, 507 with IFIR filters, 548-550 increasing. See Interpolation. missing data, recovering, 823–826. See also Interpolation. by rational factors, 540-543 Sample rate conversion, multirate systems filter mathematical notation, 534–535 signal mathematical notation, 533-534 z-transform analysis, 533-535 Sample rate conversion, with half-band filters folded FIR filters, 548 fundamentals, 544-546 implementation, 546-548 overview, 543 Sample rate converters, 521–522 Sampling, periodic. See Periodic sampling. Sampling translation, 44 Sampling with digital mixing, 462–464 Scaling IIR filter gain, 300–302 Scalloping loss, 96–97 SDFT (sliding DFT) algorithm, 742-746 overview, 741 stability, 746-747 SFDR (spurious free dynamic range), 714-715 Shannon, Claude, 42 Shape factor, 901 Sharpened FIR filters, 726–728 Shifting theorem, DFT, 77–78

Index

Shift-invariant systems. See Timeinvariant systems. Sidelobe magnitudes, 110–111 Sidelobes Blackman window and, 194–197 DFT leakage, 83, 89 FIR (finite impulse response) filters, 184 ripples, in low-pass FIR filters, 193–194 Sign extend operations, 627 Signal averaging. See also SNR (signalto-noise ratio). equation, 589 frequency-domain. See Signal averaging, incoherent. integration gain, 600–603 mathematics, 592-594, 599 multiple FFTs, 600-603 phase angles, 603-604 postdetection. See Signal averaging, incoherent. quantifying noise reduction, 594–597 rms. See Signal averaging, incoherent. scalar. See Signal averaging, incoherent. standard deviation, 590 time-domain. See Signal averaging, coherent. time-synchronous. See Signal averaging, coherent. variance, 589-590 video. See Signal averaging, incoherent. Signal averaging, coherent exponential averagers, 608-612 exponential moving averages, computing, 801-802 exponential smoothing, 608 filtering aspects, 604–608 moving averagers, 604-608 moving averages, computing, 799–801 nonrecursive moving averagers, 606-608 overview, 590-597 recursive moving averagers, 606-608 reducing measurement uncertainty, 593, 604-608 time-domain filters, 609-612 true signal level, 604–608 weighting factors, 608, 789 Signal averaging, exponential 1st-order IIR filters, 612-614

dual-mode technique, 791 example, 614 exponential smoothing, 608 frequency-domain filters, 612-614 moving average, computing, 801–802 multiplier-free technique, 790-791 overview, 608 single-multiply technique, 789–790 Signal averaging, incoherent 1st-order IIR filters, 612–614 example, 614 frequency-domain filters, 612-614 overview, 597-599 Signal averaging, with FIR filters convolution, 175-176 example, 170-174, 183-184 as a lowpass filter, 180–182 performance improvement, 178 Signal envelope, Hilbert transforms, 483 - 495Signal power. See also Decibels. absolute, 891-892 relative, 885-889 Signal processing analog, 2. See also Continuous signals. definition, 2 digital, 2 operational symbols, 10–11 Signal transition detection, 820–821 Signal variance biased and unbiased, computing, 797-799, 799-801 definition, 868-870 exponential, computing, 801–802 PDF (probability density function), 879-882 of random functions, 879-882 signal averaging, 589–590 Signal-power-to-noise-power ratio (SNR), maximizing, 376 Signal-to-noise ratio (SNR). See SNR (signal-to-noise ratio). Sign-magnitude, fixed-point binary formats, 625-626 Simpson, Thomas, 372 SINAD (signal-to-noise-and-distortion), 711-714 Sinc filters. See CIC (cascaded integrator-comb) filters.

Sinc functions, 83, 89, 116 Single tone detection, FFT method drawbacks, 737-738 vs. Goertzel algorithm, 740-741 Single tone detection, Goertzel algorithm advantages of, 739 description, 738–740 example, 740 *vs.* the FFT, 740–741 stability, 838-840 Single tone detection, spectrum analysis, 737-741 Single-decimation down-conversion, 819-820 Single-multiply technique, exponential signal averaging, 789–790 Single-stage decimation, vs. two-stage, 514 Single-stage interpolation, vs. two-stage, 532 Sliding DFT (SDFT). See SDFT (sliding DFT). Slope detection, 820-821 Smoothing impulsive noise, 770–772 SNDR. See SINAD (signal-to-noise-anddistortion). SNR (signal-to-noise ratio) vs. A/D converter, fixed-point binary finite word lengths, 640–642 A/D converters, 711-714 bandpass sampling, 48-49 block averaging, 770 corrected mean, 771 DFT processing gain, 103–104 IIR filters, 302 measuring. See Statistical measures of noise. reducing. See Signal averaging. smoothing impulsive noise, 770-772 SNR (signal-power-to-noise-power ratio), maximizing, 376 Software programs, fast Fourier transform, 141 Someya, I., 42 Spectral inversion around signal center frequency, 821-823 bandpass sampling, 46-47 Spectral leakage, FFTs, 138–139, 683–686. See also DFT leakage.

Spectral leakage reduction A/D converter testing techniques, 710-711 Blackman windows, 686 frequency domain, 683-686 Spectral peak location estimating, algorithm for, 730-734 Hamming windows, 733 Hanning windows, 733 Spectral replications bandpass sampling, 44–45 sampling lowpass signals, 39-40 Spectral vernier. See Zoom FFT. Spectrum analysis. See also SDFT (sliding DFT); Zoom FFT. center frequencies, expanding, 748–749 with SDFT (sliding DFT), 748-749 single tone detection, 737-741 weighted overlap-add, 755 windowed-presum FFT, 755 Zoom FFT, 749–753 Spectrum analyzer, 753–756 Spurious free dynamic range (SFDR), 714-715 Stability comb filters, 403-404 conditional, 268 FSF (frequency sampling filters), 403 - 406IIR filters, 263–270 Laplace transfer function, 263–264, 268 Laplace transform, 263–270 SDFT (sliding DFT), 746-747 single tone detection, 838-840 z-transform and, 272–274, 277 Stair-step effect, A/D converter quantization noise, 637 Standard deviation of continuous sinewaves, 874-875 definition, 870 signal averaging, 590 Statistical measures of noise average, 868-870 average power in electrical circuits, 874-875 Bessel's correction, 870-871 biased estimates, 870-871 dispersion, 869 fluctuations around the average, 869

overview, 867-870. See also SNR (signal-to-noise ratio). of real-valued sequences, 874 rms value of continuous sinewaves, 874-875 of short sequences, 870-871 standard deviation, definition, 870 standard deviation, of continuous sinewaves, 874-875 summed sequences, 872-874 unbiased estimates, 871 Statistical measures of noise, estimating SNR for common devices, 876 controlling SNR test signals, 879 in the frequency domain, 877-879 overview, 875-876 in the time domain, 876–877 Statistical measures of noise, mean definition, 868-869 PDF (probability density function), 879-882 of random functions, 879-882 Statistical measures of noise, variance. See also Signal variance. definition, 868-870 PDF (probability density function), 879-882 of random functions, 879-882 Steinmetz, Charles P., 446 Stockham, Thomas, 716 Stopband, definition, 901 Stopband ripples definition, 901 minimizing, 204–207 Stopband sidelobe level suppression, 416 Structure, definition, 901 Structures, IIR filters biquad filters, 299 cascade filter properties, 295-297 cascaded, 295-299 cascade/parallel combinations, 295–297 changing, 291-292 Direct Form 1, 275-278, 289 Direct Form II, 289-292 optimizing partitioning, 297-299 parallel filter properties, 295-297 transposed, 291–292

transposed Direct Form II, 289-290 transposition theorem, 291–292 Sub-Nyquist sampling. See Bandpass sampling. Substructure sharing, 765–770 Subtraction block diagram symbol, 10 complex numbers, 850 Summation block diagram symbol, 10 description, 11 equation, 10 notation, 11 Symbols block diagram, 10–11 signal processing, 10–11 Symmetrical rectangular functions, 112 - 115Symmetrical-coefficient FIR filters, 232 - 233Symmetry, DFT, 73–75

T

Tacoma Narrows Bridge collapse, 263 Tap, definition, 901 Tap weights. See Filter coefficients. Tapped delay, FIR filters, 174, 181-182 Taylor series approximation, 788 Tchebyschev function, definition, 902 Tchebyschev windows, in FIR filter design, 197 Time data, manipulating in FFTs, 138-139 Time invariance, decimation, 514 Time properties decimation, 514-515 interpolation, 519 Time representation, continuous vs. discrete systems, 5 Time reversal, 863-865 Time sequences, notation syntax, 7 Time-domain aliasing, avoiding, 718–722 analytic signals, generating, 495-497 coefficients, determining, 186-194 convolution, matched filters, 380 convolution vs. frequency-domain multiplication, 191-194 equations, example, 7

Time-domain (cont.) FIR filter implementation, 489-494 Hilbert transforms, designing, 489–494 interpolation, 778-781 slope filters, 820-821 Time-domain data, converting from frequency-domain data. See IDFT (inverse discrete Fourier transform). to frequency-domain data. See DFT (discrete Fourier transform). Time-domain filters coherent signal averaging, 609-612 exponential signal averaging, 609-612 Time-domain signals amplitude, determining, 140 continuous, Laplace transform for, 258 DC removal, 812-815 definition, 4 vs. frequency-domain, 120-123 Time-invariant systems. See also LTI (linear time-invariant) systems. analyzing, 19–21 commutative property, 18-19 definition, 17-18 example of, 17-18 Tone detection. See Single tone detection. Transfer functions. See also Laplace transfer function. definition, 902 real FSF, 908-909 z-domain, 282–289 Transient response, FIR filters, 181–182 Transition region, definition, 902 Translation, sampling, 44 Transposed Direct Form II filters, 289-290 Transposed Direct Form II structure, 289 - 290Transposed filters, 291–292 Transposed structures, 765–770 Transposition theorem, 291–292 Transversal filters, 173–174. See also FIR (finite impulse response) filters. Triangular dither, 708 Triangular windows, 89-93 Trigonometric form, quadrature signals, 442,444 Trigonometric form of complex numbers, 848-850

Truncation, fixed-point binary numbers, 646–649 Tukey, J., 135 Two's complement fixed-point binary formats, 626–627, 629 overflow, 559–563 Two-sided Laplace transform, 258 Type-IV FSF examples, 419–420, 423–426 frequency response, 910–912 optimum transition coefficients, 913–926

U

Unbiased estimates, 871 Unbiased signal variance, computing, 797-799, 799-801 Undersampling lowpass signals, 40. See also Bandpass sampling. Uniform windows. See Rectangular windows. Unit circles definition, 271 z-transform, 271 Unit circles, FSF forcing poles and zeros inside, 405 pole / zero cancellation, 395–398 Unit delay block diagram symbol, 10 description, 11 Unit impulse response, LTI, 19–20 Unnormalized fractions, floating-point binary formats, 656 Unwrapping, phase, 210 Upsampling, interpolation, 517–518, 520-521

V

Variance. *See* Signal variance. Vector, definition, 848 Vector rotation with arctangents to the 1st octant, 805–808 division by zero, avoiding, 808 jump address index bits, 807 overview, 805 by $\pm \pi/8$, 809–810 rotational symmetries, 807 Vector-magnitude approximation, 679–683 von Hann windows. *See* Hanning windows.

W

Warping, frequency, 319, 321-325, 328-330 Weighted overlap-add spectrum analysis, 755 Weighting factors, coherent signal averaging, 608, 789 Wideband compensation, 564 Wideband differentiators, 367-370 Willson, A., 386 Window design method, FIR filters, 186-194 Windowed-presum FFT spectrum analysis, 755 Windows Blackman, 195–201, 686, 733 Blackman-Harris, 686, 733 exact Blackman, 686 FFTs, 139 in the frequency domain, 683–686 magnitude response, 92-93 mathematical expressions of, 91 minimizing DFT leakage, 89-97 processing gain or loss, 92 purpose of, 96 rectangular, 89-97, 686 selecting, 96 triangular, 89-93 Windows, Hamming description, 89-93 DFT leakage reduction, 89–93 in the frequency domain, 683-686 spectral peak location, 733 Windows, Hanning description, 89-97 DFT leakage, minimizing, 89–97 in the frequency domain, 683-686 spectral peak location, 733 Windows used in FIR filter design Bessel functions, 198-199 Blackman, 195–201

Chebyshev, 197–201, 927–930 choosing, 199–201 Dolph-Chebyshev, 197 Kaiser, 197–201 Kaiser-Bessel, 197 Tchebyschev, 197 Wingless butterflies, 156 Wraparound leakage, 86–88 Wrapping, phase, 209, 900

Z

z-domain expression for Mth-order IIR filter, 275–276 z-domain transfer function, IIR filters, 282 - 289Zero padding alleviating scalloping loss, 97-102 FFTs, 138-139 FIR filters, 228–230 improving DFT frequency granularity, 97 - 102spectral peak location, 731 Zero stuffing interpolation, 518 narrowband lowpass filters, 834-836 Zero-overhead looping DSP chips, 333 FSF (frequency sampling filters), 422-423 IFIR filters, 389 Zero-phase filters definition, 902 techniques, 725 Zeros IIR filters, 284–289 on the s-plane, Laplace transform, 263 - 270Zoom FFT, 749–753 z-plane, 270-273 z-plane pole / zero properties, IIR filters, 288-289 z-transform. See also Laplace transform. definition, 270 description of, 270-272 FIR filters, 288-289 IIR filters, 270-282 infinite impulse response, definition, 280 z-transform (*cont.*) polar form, 271 poles, 272–274 unit circles, 271 zeros, 272–274 z-transform, analyzing IIR filters digital filter stability, 272–274, 277 Direct Form 1 structure, 275–278 example, 278–282 frequency response, 277–278 overview, 274–275 time delay, 274–278 z-domain transfer function, 275–278, 279–280