Suresh R. Devasahayam

Signals and Systems in Biomedical Engineering: Physiological Systems Modeling and Signal Processing

Third Edition

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Preface

In all Ages where Learning hath flourished, complaint hath been made of the Itch of Writing, and the Multitude of worthless Books, wherewith importunate Scribblers have pester'd the world; .... Therefore in Excuse of it, I plead that there are in [this book] some Considerations new and untouch'd by others...

– John Ray (1627–1705), Fellow of the Royal Society

Physiology is a set of processes by which homeostasis is maintained, and physiological measurement is a means of observing these processes. Formal tools for the study of processes and measured quantities are available in systems theory and signal processing. However, it is still uncommon for most students of human physiology to employ systems theory and signal processing in interpreting their experimental data. This book is an attempt to show that systems modeling can be used to develop simulations of physiological systems. Such simulations use formal relations (e.g., systems transfer functions) between the underlying processes and the observed measurements. The inverse of such relations suggests signal processing tools that can be applied to interpret experimental data. Signals and systems are naturally twinned and mutually complementary. Signal processing tools follow naturally from systems models of underlying processes, and the two can be used in several areas of science including human physiology.

An important purpose of systems modeling in physiology is to base the interpretation of experiments on a formal theoretical framework of the physiological behavior. A lot of experimental data collection may well be unnecessary if a good formal framework is available. To use a simple example, the recording of multi-lead ECG (electrocardiogram) is redundant in many ways. Quite simply, all the six frontal leads (L_I, L_{II}, L_{III}, aV_L, aV_R, aV_F) being algebraically related can be calculated *exactly* using only two channels of measurement and involve no assumption or approximation of any sort. This is a self-evident truth that is obvious to anyone who is familiar with the theory of the ECG. In the case of the coronal plane, the chest lead geometry is less well defined, and there is no voltage loop measurement as in the frontal plane; but still, two chest leads can be used to calculate the component of the cardiac vector in the coronal plane[1]; the approximation of the geometry in such a calculation is no worse than the approximation of the location of the physical electrodes for the chest/precordial leads in an individual, and will not lead to any confusion or error in diagnostic interpretation. Therefore, we don't need to have instruments that individually measure 12 leads (6 frontal plane leads and another 6 chest leads). The purpose of systems modeling is to determine such compact descriptions of underlying processes. To paraphrase an overused metaphor from Rutherford, "science isn't just stamp collecting."

Intuitive understanding of any process is important for experimenters. Such understanding will lead to easier interpretation of experimental data and better design of experiments. Engineering has always had a strong intuitive appeal to its practitioners – engineers are the most enthusiastic proponents of the idea of "thinking with your hands" and "the geometrization of mathematics." Complementarily, physiologists like to think in terms of analogy – models of respiration, gut motility, and cardiac pumping are used to teach these systems by appealing to intuition. Therefore, it is inevitable that physiologists borrow concepts from systems analysis used in electrical, mechanical, and chemical engineering. Bioengineering or biomedical engineering is where these physiologists and engineers meet.

Intuition developed in other areas can be brought to bear on the subject of physiology using simulations. The technology used in contemporary virtual reality systems allows us to see, hear, and feel the simulated environment. This is an opportunity to incorporate the mathematical description of systems physiology into simulated experiments. If the simulation "feels real," then the underlying mathematics and physics can be convincing. Simulations in physiology can be used to perform virtual experiments wherein one can use experimental conditions that are impossible in actual experiments due to ethical or practical considerations.

In philosophical arguments, the appeal to intuition is sometimes opposed to the appeal to logical reasoning. It is not in that sense that I argue for the use of intuition. I submit that if we can train our intuition to coincide with logical reasoning, then we can think quickly and effectively about the things at hand. The simulation of physiological models is an attempt to achieve this goal.

The first edition of this book used computer simulations to teach physiological systems modeling. Virtual experiments can quickly demonstrate the validity of mathematical models – simulation can impart experiential understanding and thereby convince the experimentalist that the mathematics effectively describes the biology. Physiological systems modeling helps both in gaining insight and in generating methods of analysis. Where the exercises in the first edition were graphical, the second edition encouraged the student to use animation and projections of 3D representations. In the 18 years since the first edition, the technology available to the student has considerably improved. Haptics and multimedia interfaces are readily

[1] $L_{III} = L_{II} - L_I$; $aVL = (L_I - L_{III})/k_o$; $aVR = -(L_I + L_{II})/k_o$; $aVF = (L_{II} + L_{III})/k_o$ $V_6 = (V_5 - V_1)/k_1$; $V_3 = (V_1 + V_5)/k_1$; $V_2 = (V_1 + V_3)/k_2$; $V_4 = (V_3 + V_5)/k_2$ See Chap. 6 for details.

available – and they can be profitably included in the simulation of physiological systems. Another improvement is that in this third edition, the simulations are more closely related to clinical examination and experimental physiology. Where the simulations in earlier editions used abstract tissue volumes and hypothetical excitable cells, the present simulations use stimulation of multiple nerves in the hand, electromyography with needle and surface electrodes, and so on, thereby using experimental arrangements that are more realistic to the physiologist.

Virtual reality-based simulations enhance communication between biologists and physical scientists. Realistic simulation can go a long way in making the mathematical models useful to the physiologist. If a model behaves realistically, then the model has effectively captured the essence of the underlying phenomena. Being able to see, hear, and touch the models can literally breathe life into the mathematics and physics of the models.

The book is in two parts. The first part comprising the first seven chapters presents the tools and techniques of systems analysis and signal processing. The second part comprising the remaining eight chapters presents specific physiological systems that are modeled. The first part may be initially skipped by those who are either disinterested in the mathematical detail or are already familiar with it. Every section in the chapters contains a summary box for those who would like to get an idea of the concepts without having to plough through the mathematical detail. The reader who wants a quick preview of the entire book can jump straight to the simulation programs (Extra Materials accompanying the book) and then go back to the text to read the mathematics and physiology behind the simulations. All the physiological simulations show some fairly realistic experimental or clinical situation, and the controls allow manipulation of the physiology as well as the measurement and analysis.

All the physiological models developed in the book have been implemented, and working versions of the models are available on the book's website. In this book, the mathematical analysis of the physiological systems leads to solutions in the form of working simulations. Most of the figures used in the text are generated by the simulations. The reader is strongly encouraged to try the physiological simulations which will run on almost any computer. All the physiological simulations in this book have been refined with constructive feedback from the physiologists, neurophysiologists, neurologists, and physiatrists at Christian Medical College, Vellore. Most of them have been demonstrated to larger audiences at conferences and workshops. Feedback from these colleagues have been invaluable in removing flaws and enhancing the simulations.

In the present edition, the simulations are implemented as Microsoft Windows executables as they are easy to interface with external hardware for haptics and multimedia. This is a departure from the previous edition where the simulations were all implemented in Java for cross-platform use. The Windows executables accompanying this edition have been tested to run under WINE and will therefore run in Linux and Mac – the graphical simulations run equally well (but the multimedia and haptics interfaces will need additional work to run under WINE).

The epigraph that opens this Preface served as a useful censor when writing the book. The epigraphs that open each chapter of the book are from scientists whose writing particularly illuminated the subject of the chapter; the interested student is sure to enjoy reading more of them.

Vellore, India Suresh R. Devasahayam

Acknowledgments

The three editions of this book span more than two decades of my teaching courses in biomedical signal processing and physiological systems modeling, first at the Indian Institute of Technology, Bombay (IIT Bombay), and then at the Christian Medical College, Vellore (CMC Vellore). In these two institutions, I have taught engineering and medical students at the undergraduate and postgraduate levels, often in mixed classes. The didactic methods, problems, and programming assignments have been tested by the students – I owe them a large debt of gratitude. Many colleagues have provided criticism and encouragement in specific areas of the text. Particular thanks are due to my colleagues at CMC Vellore, in the departments of physiology, neurophysiology, neurology, physical medicine and rehabilitation, and bioengineering, for using, criticizing, and disseminating the programs that accompany the book. They have liberally contributed to discussions, and I have made many close friends in the process.

In 2018, CMC Vellore celebrates its hundredth year of medical education. It is unique in India in providing a hospitable environment for such a book. In no other institution in India is it possible, as yet, for medical students and engineering students to learn and work together at all levels. Lectures on signal processing and physiological system were attended enthusiastically in the departments of physiology, neurological sciences, and physical medicine. These lectures gave me invaluable insight into the different ways that engineers and physiologists look at the same thing. They also challenged me to come up with ways of describing physiological processes that were intuitively appealing and mathematically concise.

Much thanks to my family. More than half the writers quoted in the chapter epigraphs are from books we've shared at home; thanks to Isobel and our children for many an enjoyable conversation around these books – this has surely colored my writing.

While many people have contributed in several different ways to this book, all responsibility for errors is mine alone. I apologize for errors that have escaped all my attempts to filter them out.

Vellore, India — Suresh R. Devasahayam
2018

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About the Author

Suresh Devasahayam has taught students of science, technology, engineering, and medicine for more than 25 years, first at the Indian Institute of Technology, Bombay, for about 12 years and then at the Christian Medical College, Vellore.

In teaching such a variety of students, it has been important to span a wide range of *language* skills – from formal mathematical language for students of the physical sciences to natural language for students of the biological sciences. These two extremes of communication in science also represent the difference between theoretical argument from first principles and empirical knowledge; therefore, his research and teaching has included both theoretical analysis and physiological experiments. He has greatly enjoyed the extension of language by the use of dynamic graphs and animations through computer simulations.

His formal training includes a Baccalaureate in Electronics and Communications Engineering from the College of Engineering, Guindy, followed by Master's and Doctoral degrees in Bioengineering from the University of Illinois at Chicago. His research is in the areas of physiological measurement, medical instrumentation, signal processing, systems modeling, and neurorehabilitation.

Part I
Signal Processing for Physiology

Chapter 1
Introduction to Measurement and Analysis in Physiology

> *There is* one *thing of which one can say neither that it is one metre long, nor that it is not one metre long, and that is the standard metre in Paris. But this is, of course, not to ascribe any extraordinary property to it, but only to mark its peculiar role in the language-game of measuring with a metre-rule.*
>
> – Ludwig Wittgenstein

Signal measurement is based on a preliminary model of the system under observation. That is to say, if you want to measure something, you have an idea of how that quantity changes with time, how large it is, how it is different from other things nearby, and so on. The notion of interference or noise depends on such a model of the system. For example, when recording speech in a room, outside traffic sounds are considered noise and must be removed. On the other hand, a study of traffic involving the recording of traffic and engine sounds will consider the traffic sounds as signal and any speech of passersby as noise. In both cases the observer needs to have a clear idea of what constitutes the desired signal and what is the undesired noise. As far as possible, noise should be avoided during the acquisition of the signal – in the above illustration, by using directional microphones, for example. If the pickup of noise is unavoidable, then post-acquisition noise reduction techniques can be used. The quality of signal measurement has a profound impact on subsequent interpretation. A basic application of signal analysis is to use a measurement model to remove unwanted portions or "noise" from the measured signal. Before any noise reduction is performed, a conceptual model of the signal necessarily exists in the mind of the observer. The observer has an idea of how the signal is different from noise. It is this model that determines how effectively the "true" signal will be elucidated from the noisy recording. Another example from auditory signals is that, during a music concert, conversation among the audience is noise and the music is the desired signal. The selection of noise reduction techniques will depend on this conceptual model of signal that distinguishes it from noise.

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1.1 Measurement and Analysis

The purpose of measuring physiological signals is to obtain insight into the system which produces the signal. The measured quantity uses the local space and time as the frame of reference. Consider the following cases: (i) the recording of the electrocardiogram (ECG) contains information about the underlying electrical activity of the heart, (ii) the measurement of the aortic pressure contains information about the fluid dynamics of the cardiovascular system, (iii) a photograph describes the light -reflecting properties of the objects in a scene, and (iv) a radiograph describes the density of an object which results in attenuation of X-rays going through it. In each of these cases, a specific physical quantity is measured by the measuring system, and we also notice that the physical quantity varies with time (in the first two cases) or spatial position (in the last two cases). Therefore, time or spatial position is the independent variable for the quantity being measured in these examples.

All measurements are predicated on a model of the system producing the quantity being measured. For example, when we measure blood pressure, we have an idea of the heart as an oscillating pump which results in cyclical variation of pressure in the cardiovascular system. In contrast, when we measure water pressure in a water supply pipe, if we were to see a time-varying pressure, it would indicate that something is wrong. So the same kind of measurement involves different interpretations in different systems.

The measurement process for clinical diagnosis, for example, is generally conducted within the constraints of a physiological model. Basic research into human physiology involves the use of measurement to revise or modify the model. Figure 1.1 shows the scheme of model-based measurement as an iterative process. Formulating a model from the experimental data is an important part of the process. One can start by seeing a pattern in the observed process and then describing the pattern in some mathematically compact form as far as possible.

In clinical practice physiological measurement can be used for classification of pathology using the system parameters determined from the measurement. In such a case, determining the system parameters is a method of reducing the quantity of data. Classification can be more easily done on system parameters than on raw data. The model development and validation shown in Fig. 1.1 is the domain of research scientists, while the analysis of specific data for the purpose of classification and diagnosis as shown in Fig. 1.2 is the domain of application scientists and physicians.

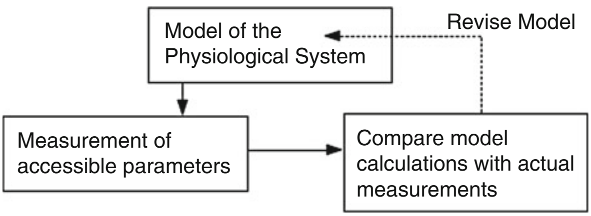

Fig. 1.1 Model-based measurement is an iterative process

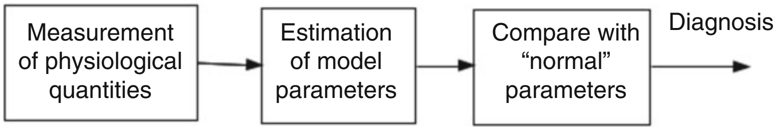

Fig. 1.2 Using physiological models for diagnosis of pathology

In these block schematic diagrams, organs and processes are shown as boxes – they will usually be referred to as "systems." Arrows that point into a box are called inputs to the system. Arrows that point out of a system are called outputs from the system.

System Model

A physiological system model is a formal relationship between inputs and output of the system. A formal relationship means:

- If the system parameters are known and the inputs are known, then the output can be calculated
- If the output is known and the system parameters are known, then the inputs can be calculated
- If the output and inputs are known (measured), then the system parameters can be calculated

In general, two different types of models can be constructed: (i) black box models that use mathematical relationships between the input and output that have no correspondence to any real entities within the system and (ii) biophysical models that contain subsystems corresponding to chemical, electrical, and structural entities within the system. These are schematically shown in Fig. 1.3.

An example of a black box model would be a single equation that can be used to describe the membrane potential during a nerve action potential, using the propagation velocity as a parameter and time as the independent variable. An equation of the form $e(v,t) = vt(2 - vt)^{-vt}$ can be used to describe an action potential. $e(t)$ is the membrane potential, v is the propagation velocity, and t is the time. In contrast, a biophysical model of the action potential was developed by Hodgkin-Huxley taking into account the chemical ionic transports across the membrane. While the black box model allows us to quickly calculate the way an action potential will change in nerves with different conduction velocities, it does not attempt to relate such changes to changes in electrical and molecular phenomena.

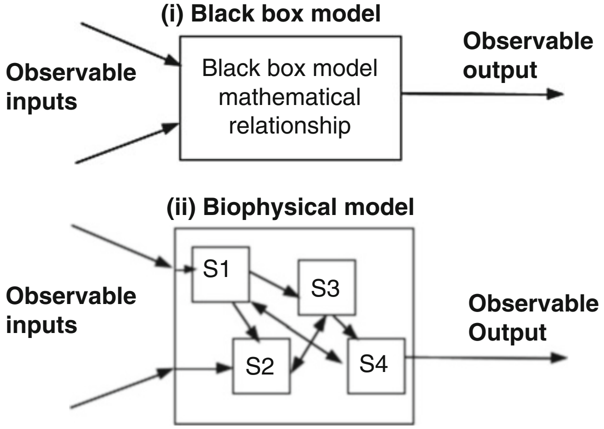

Fig. 1.3 Black box and biophysical models

Input and Output Signals

The above discussion has repeatedly used the terms *signal*, *input* (or *input signal*), and *output* (or *output signal*). The notion of a signal is central to most physiological measurement. A signal is any physical quantity that varies as a function of one or more independent variables. If there is one independent variable, the signal is said to be a one-dimensional (1-D) signal, if it varies with two independent variables, it is a two-dimensional (2-D) signal, and so on, for multidimensional signals. Many principles of measurement and analysis are common to all signals with the dimension of the signal affecting the complexity of measurement and analysis but not the basic principles involved.

- One-dimensional signals have a single independent variable, usually time. The amplitude of the signal varies with time, i.e., the amplitude is a function of time. Examples of 1-D signals are (a) variation of aortic pressure and (b) variation of muscle force. The signal is usually represented as $p(t)$, where t is the independent variable (usually time) and p is the dependent variable (the amplitude or strength of the signal).
- Two-dimensional signals have two independent variables. In the case of a picture, the two variables are along the length (x) and breadth (y) of the image. The light intensity, or color, varies with the position on the image; color is a function of the x and y variables. Examples of 2-D signals are (a) light intensity reflected from a black and white photograph and (b) the elevation of terrain above sea level. The signal is usually represented as $p(x, y)$, where x and y are the independent variables (along the length and breadth in the case of flat pictures) and p is the dependent variable (the amplitude or strength of the signal).

- Three-dimensional signals have three independent variables. In the case of a solid object, the three variables are along the length (x), breadth (y), and height (z) of the object. The density of the material varies with the position within the object – the mass density is a function of x, y, and z variables. A motion picture is also an example of a 3-D signal. The three independent variables are the screen length (x), breadth (y), and time (t).

Input signals are given to the system under study so that the internal states of the system are modified by the given input. Input signals are often, but not always, controlled by the observer. Output signals are quantities that are measured by the observer. In the process of observing the system, the observer ought not to alter the state or behavior of the system. However, the very process of measuring quantities (observing output) requires the transfer of some energy to the measuring instrument. If the transferred energy is significant, then the observation will alter the system under study and thereby distort the measurement.

Summary of Sect. 1.1

Physiological signal measurement provides insight into the underlying physiological process.
The measured signal is likely to be contaminated by unwanted interference which we term "noise." Removal of the noise is based on prior knowledge that defines how to distinguish signal from noise. A system or process takes input signals and produces signals of its own called output signals.
Signals are functions of independent variables. For example, the ECG is a time-varying voltage – time is the independent variable and voltage the dependent variable.

1.2 Physiological Measurement

The schematic block diagram of physiological measurement in Fig. 1.4 shows signal pickup followed by analogue processing and output. The signal is generated by the physiological process and is usually some physical quantity that varies in time (time signals) or space (images). The transducer converts this physical quantity into electrical signals amenable to subsequent processing by instruments. The analogue processing comprises amplifiers to magnify the desired signal, filters to reduce unwanted "noise," etc. In older instruments the output device is a display or paper chart recorder that is used to present the information to the user. Modern instruments convert the analogue signal into digital form suitable for computer analysis. The

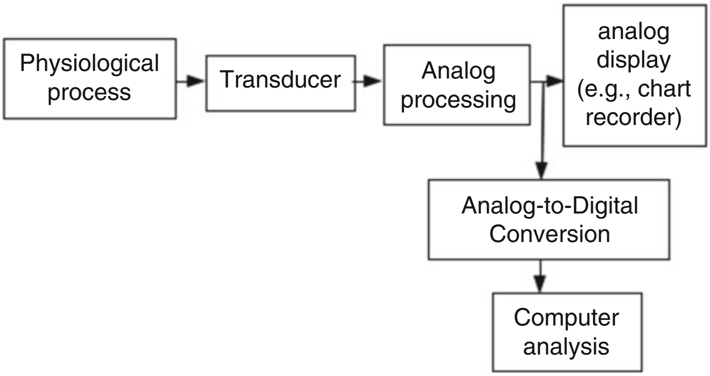

Fig. 1.4 General schematic of a measurement system

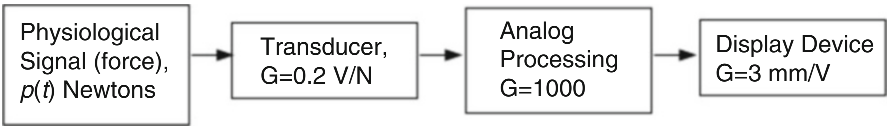

Fig. 1.5 A measurement system

digitized signal can be analyzed on a computer either immediately as the signal comes in (online processing) or stored in the computer for later more complex analysis (offline processing).

Cascading Systems

The block diagram in Fig. 1.5 gives an example of a physiological signal being measured and analyzed. It is a pictorial representation of the measured signal being passed through several sub-blocks in the system before final presentation to the user. Each of the blocks in the system modifies the signal in a manner characteristic of the block. The blocks must be chosen/designed such that the desired signal is obtained as clearly as possible while minimizing the effect of the unwanted noise. A simple block will not change the shape of the signal but might change its amplitude – either magnification or diminution. The scaling performed by each block (gain, G) is written inside. The final output is the cumulative amplification of all the blocks. For example, if the physiological signal is muscle force $p(t)$ newtons, the transducer produces 0.2 volts/newton, the analogue processor is a simple amplifier with amplification of 1000, and the display device produces a deflection of 3 mm/volt, then the final output is $600p(t)$ mm/newton, as shown in Fig. 1.5.

Thus cascading systems (or subsystems) produce a cumulative effect on the input signal. The situation is somewhat more complex when the blocks do not produce simple scaling of the input but affect the shape of the signal as well. To understand such complex systems which are commonly encountered in real life, we shall later look at ways of dealing with them.

A system with several subsystems will have an overall behavior that is the cumulative effect of the subsystems. The set of subsystems include everything from the transducer to the final output device. Some subsystems are expressly introduced to alter the measurement in specific ways, e.g., frequency filtering, noise reduction circuits, etc. Other subsystems like the transducer and output device are intended to transfer the signal without any change – as far as possible. However, in practice, these subsystems have imperfect characteristics and introduce undesirable changes in the signal. This degradation is different from the addition of "noise" or "interference" signals. The degradation is due to the inability of the subsystem to transfer the information perfectly. Knowledge of the characteristics of these subsystems will enable us to compensate for such deficiencies. In this chapter we'll look at some methods of characterizing subsystems like transducers used to pick up physiological signals. An important concept in such characterization is the ability to determine or predict the change effected in any signal by the characterized subsystem. With this knowledge we can work backwards to estimate the original signal.

Transduction of Physiological Signals

Transduction is the conversion of one form of energy into another, or the conversion of one physical quantity to another. A simple example is a mercury thermometer which converts temperature into displacement of the mercury level. Transduction can involve several stages; for example, a load cell-based force transducer comprises (i) conversion of force to displacement and (ii) conversion of the displacement to resistance change. Usually, the final output is an electrical quantity so that electronic circuits can be used for further processing. In the present example of the load cell-based force transducer, the resistance change is converted in a bridge circuit to a voltage change which can be amplified and filtered by electronic circuits. All real transducers are imperfect and can introduce noise, distortion, and time-dependent degradation. We have already mentioned the idea of noise in measurement. Distortion is the result of the transduction being different at different magnitudes of the signal. An example of time-dependent degradation of the signal is due to "sluggishness" of the transducer which is unable to respond quickly enough to the signal. This is different from long-term variation in the behavior of the transducer due to aging of the device – this is usually not a concern in modern devices.

Summary of Sect. 1.2

Physiological measurement is the conversion of the quantity of interest into another physical quantity suitable for further analysis. In most contemporary systems where electronic devices are used for analysis, the converted signal is an electrical quantity, usually voltage or current.
The transducer forms the first subsystem in the measurement on the physiological system under observation.
Characterizing the cascade of subsystems that comprise the measurement system allows us to understand and compensate for degradation of the signal in the measurement process.

1.3 Interference and Noise

During the recording of any signal, invariably some undesirable signals loosely termed *noise* are also picked up. This noise may inhere in the measuring apparatus, or it may be generated by other systems in the vicinity of the recording. In physiological measurement it is very common to find that other physiological signals provide undesirable noise to the measurement. The quality of measurement will have a significant effect on its analysis and interpretation. Measurement is often degraded by interfering signals that are unavoidably included in the measurement. For example, (a) while recording the ECG using chest leads, EMG from the intercostal muscles may be picked up, and (b) while recording the EMG from the muscles in the back, the ECG may be picked up. In the first case the ECG is the desired signal and the EMG is the undesired signal, which we call noise. In the second case the EMG is the desired signal and the ECG is the undesired "noise" signal. The undesired noise signals are unavoidable in both these cases because they are all electrical events taking place in the body. The mixture of signal and noise may be expressed as: Measured signal = Desired signal + Undesired Interference.

This is shown schematically in Fig. 1.6. A lot of signal processing is concerned with the removal of noise from signals being measured.

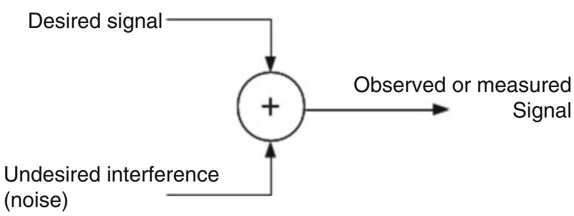

Fig. 1.6 Noise added to desired signal

Noise removal is very application specific, and as the simple example of the ECG and EMG suggests, a clear understanding of the physiology is required for selection of noise removal techniques. A more mundane example of situation-specific distinction of noise from signal is the case of a driver for whom traffic noise may contain useful information and telephonic speech may constitute interference for the purpose of driving; but in an office, traffic noise would be unwelcome interference and telephone conversation is useful to office work.

Noise and signal are usually well mixed, and separating them is not easy. Transformation of the measured signal to another domain or space may give better separation of the signal and noise. The more separate or distinct they are, the easier it is to remove the noise, as otherwise, some signal may also be discarded along with the noise. This concept of transforming signals to another domain is very useful, and it is similar to changing one's perspective or point of view when observing something – say, a close finish of a race between runners.

Removal of noise often requires a compromise between the amount of noise to be removed and the amount of signal to be preserved. A good understanding of this compromise is essential for effective noise reduction. The importance of this compromise cannot be overstated and will be repeated often in emphasis of its importance. Tremendous advances in the algorithms and techniques for noise reduction have been made in the last few decades. Improvements in electronics, new algorithms, and advances in computational power and speed have all contributed to great ease in achieving substantial reduction of noise. However, one should not be blasé about noise contamination with the idea that it can always be removed, as the removal will almost always be imperfect – it's better to have avoided noise during recording.

It is important to identify the source of noise, as several alternative methods of noise reduction may then present themselves. For example, rearrangement of the recording arrangement can reduce noise pickup from electromagnetic sources. Avoiding noise contamination by good recording technique is preferable by far to later removing noise from contaminated signals.

Unwanted signals, interference, and disturbances are collectively termed noise. Usually noise is something that is added to the desired signal. Other ways of signal degradation are distortion and nonlinearity – while distortion and nonlinearity may appear like noise, they are quite different and are due to defects in the transduction and recording system rather than contamination by an interfering signal. Noise can be from a well-defined source with well-defined characteristics, or it can be from a mixture of sources and causes that change over time. Noise signals can have a pattern and even rhythm, or they can vary unpredictably and be "random."

Figure 1.7 shows an example of a randomly varying noise signal that is added to the desired signal (ECG in this case). In the resulting signal the features of the ECG are difficult to discern. Such random noise commonly arises from thermal effects in electronic devices.

Figure 1.8 shows an example of a rhythmically varying noise signal, a sinusoidally varying noise being added to the desired signal (ECG). Here too, the features of the ECG are difficult to discern. The source of sinusoidal noise in this

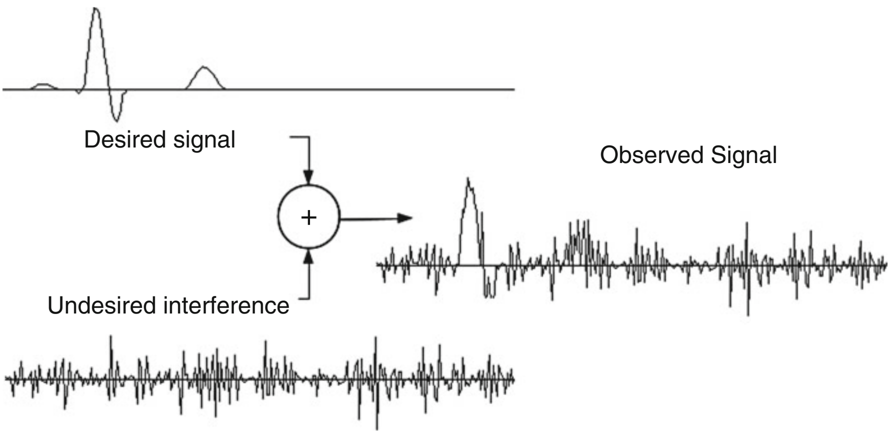

Fig. 1.7 Additive noise: random noise added to ECG

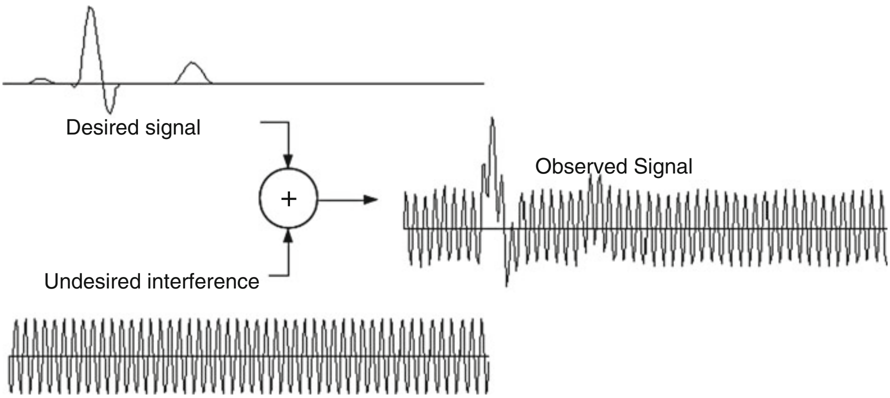

Fig. 1.8 Additive noise: 50 Hz powerline noise added to ECG

case is the electromagnetic interference from the electrical powerline in the building. In all cases of signal contamination by noise, first and foremost attempts should be made to reduce the noise pickup by improving the measurement setup. In the case of noise from extraneous electromagnetic sources, substantial noise reduction can be achieved by using a conductive shield around the signal lines. Physical methods of noise reduction are often addressed by empirical rules since detailed analysis of the noise sources is complex and difficult, as well as unnecessary if an empirical solution works.

Only if physical methods of noise reduction fail should we resort to post-acquisition noise removal. Once the noisy signal is acquired, the signal and noise are mixed, and signal processing methods of noise removal will involve a compromise of the amount of noise removed versus the amount of signal retained.