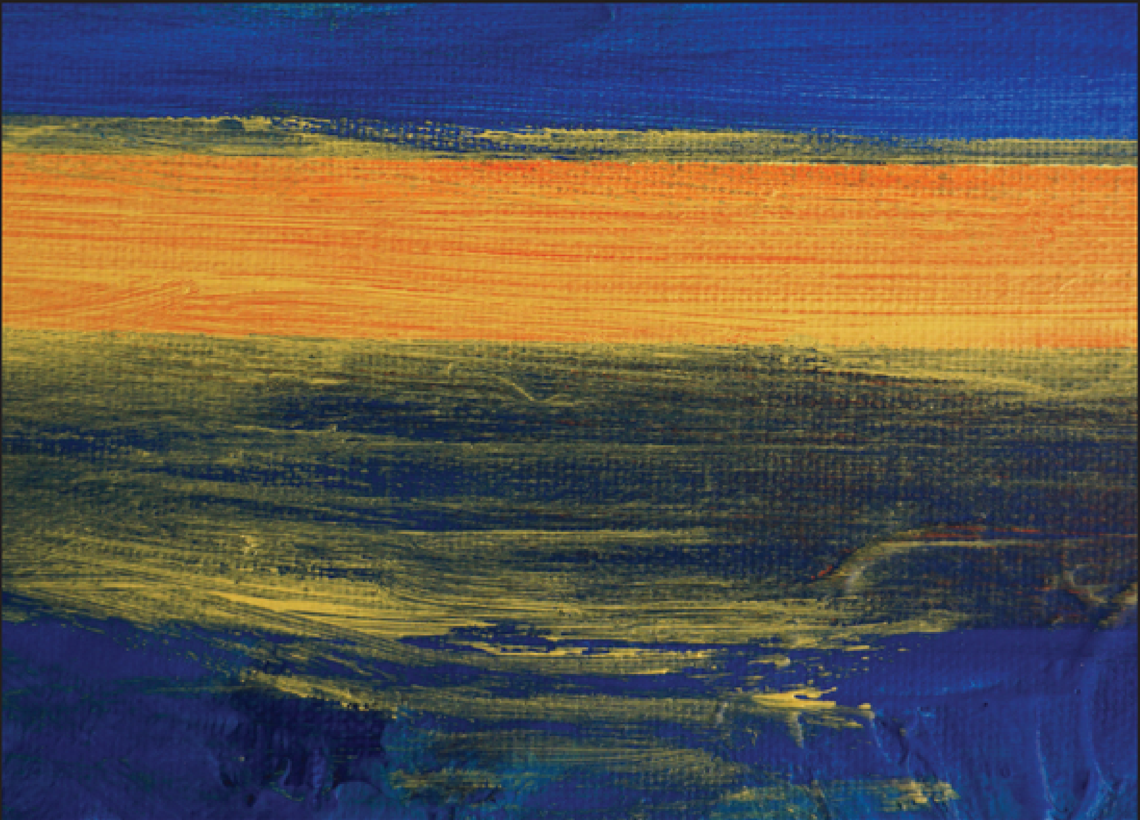

MODEL-BASED PROCESSING

AN APPLIED SUBSPACE IDENTIFICATION APPROACH

JAMES V. CANDY

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An Applied Subspace Identification Approach

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Jesus replied, "I am the way, the truth and the life. No one comes to the Father except through me." (John: 14:6)

Contents

Preface

This text encompasses the basic idea of the model-based approach to signal processing by incorporating the often overlooked, but necessary, requirement of obtaining a model initially in order to perform the processing in the first place. Here we are focused on presenting the development of models for the design of model-based signal processors (MBSP) using subspace identification techniques to achieve a model-based identification (MBID) as well as incorporating validation and statistical analysis methods to evaluate their overall performance [1]. It presents a different approach that incorporates the solution to the system identification problem as the integral part of the model-based signal processor (Kalman filter) that can be applied to a large number of applications, but with little success unless a reliable model is available or can be adapted to a changing environment [2]. Here, using subspace approaches, it is possible to identify the model very rapidly and incorporate it into a variety of processing problems such as state estimation, tracking, detection, classification, controls and communications to mention a few [3, 4]. Models for the processor evolve in a variety of ways, either from first principles accompanied by estimating its inherent uncertain parameters as in parametrically adaptive schemes [5] or by extracting constrained model sets employing direct optimization methodologies [6], or by simply fitting a black-box structure to noisy data [7, 8]. Once the model is extracted from controlled experimental data, or a vast amount of measured data, or even synthesized from a highly complex truth model, the long-term processor can be developed for direct application [1]. Since many real-world applications seek a real-time solution, we concentrate primarily on the development of fast, reliable identification methods that enable such an implementation [9–11]. Model extraction/development must be followed by validation and testing to ensure that the model reliably represents the underlying phenomenology – a bad model can only lead to failure!

System identification [6] provides solutions to the problem of extracting a model from measured data sequences either time series, frequency data or simply an ordered set of indexed values. Models can be of many varieties ranging from simple polynomials to highly complex constructs evolving from nonlinear distributed systems. The extraction of a model from data is critical for a large number of applications evolving from the detection of submarines in a varying ocean, to tumor localization in breast tissue, to pinpointing the epicenter of a highly destructive earthquake, or to simply monitoring the condition of a motor as it drives a critical system component [1]. Each of these applications require an aspect of modeling and fundamental understanding (when possible) of the underlying phenomenology governing the process as well as the measurement instrumentation extracting the data along with the accompanying uncertainties. Some of these problems can be solved simply with a "black-box" representation that faithfully reproduces the data in some manner without the need to capture the underlying dynamics (e.g. common check book entries) or a "gray-box" model that has been extracted, but has parameters of great interest (e.g. unknown mass of a toxic material). However, when the true need exists to obtain an accurate representation of the underlying phenomenology like the structural dynamics of an aircraft wing or the untimely vibrations of a turbine in a nuclear power plant, then more sophisticated representations of the system and uncertainties are clearly required. In cases such as these, models that capture the dynamics must be developed and "fit" to the data in order to perform applications such as condition monitoring of the structure or failure detection/prediction of a rotating machine. Here models can evolve from lumped characterizations governed by sets of ordinary differential equations, linear or nonlinear, or distributed representations evolved from sets of partial differential equations. All of these representations have one thing in common, when the need to perform a critical task is at hand – they are represented by a mathematical model that captures their underlying phenomenology that must somehow be extracted from noisy measurements. This is the fundamental problem that we address in this text, but we must restrict our attention to a more manageable set of representations, since many monographs have addressed problem sets targeting specific applications [12, 13].

In fact, this concept of specialty solutions leads us to the generic state-space model of systems theory and controls. Here the basic idea is that all of the theoretical properties of a system are characterized by this fundamental set of models that enables the theory to be developed and then applied to any system that can be represented in the state-space. Many models naturally evolve in the state-space, since it is essentially the representation of a set of nth-order differential equations (ordinary or partial, linear or nonlinear, time (space) invariant or time (space) varying, scalar or multivariable) that are converted into a set of first-order equations, each of which is a state. For example, a simple mechanical system consisting of a single mass, spring, damper construct is characterized by a set of second-order, linear, time-invariant, differential equations that can simply be represented in state-space form by a set of two first-order equations, each one representing a state: one for displacement and one for velocity [12].

We employ the state-space representation throughout this text and provide sufficient background in Chapters 2 and 3.

System identification is broad in the sense that it does not limit the problem to various classes of models directly. For instance, for an unknown system, a model set is selected with some perception that it is capable of representing the underlying phenomenology adequately, then this set is identified directly from the data and validated for its accuracy. There is clearly a well-defined procedure that captures this approach to solve the identification problem [6–15]. In some cases, the class structure of the model may be known a priori, but the order or equivalently the number of independent equations to capture its evolution is not (e.g. number of oceanic modes). Here, techniques to perform order estimation precede the fitting of model parameters first, then are followed by the parameter estimation to extract the desired model [14]. In other cases, the order is known from prior information and parameter estimation follows directly (e.g. a designed mechanical structure). In any case, these constraints govern the approach to solving the identification problem and extracting the model for application. Many applications exist, where it is desired to monitor a process and track a variety of parameters as they evolve in time, (e.g. radiation detection), but in order to accomplish this on-line, the model-based processor must update the model parameters sequentially in order to accomplish its designated task. We develop these processors for both linear and nonlinear models in Chapters 4 and 5.

Although this proposed text is designed primarily as a graduate text, it will prove useful to practicing signal processing professionals and scientists, since a wide variety of case studies are included to demonstrate the applicability of the model-based subspace identification approach to real-world problems. The prerequisite for such a text is a melding of undergraduate work in linear algebra (especially matrix decomposition methods), random processes, linear systems, and some basic digital signal processing. It is somewhat unique in the sense that many texts cover some of its topics in piecemeal fashion. The underlying model-based approach of this text is the thread that is embedded throughout in the algorithms, examples, applications, and case studies. It is the model-based theme, together with the developed hierarchy of physics-based models, that contributes to its uniqueness coupled with the new robust, subspace model identification methods that even enable potential real-time methods to become a reality. This text has evolved from four previous texts, [1, 5] and has been broadened by a wealth of practical applications to real-world, model-based problems. The introduction of robust subspace methods for model-building that have been available in the literature for quite a while, but require more of a systems theoretical background to comprehend. We introduce this approach to identification by first developing model-based processors that are the prime users of models evolving to the parametrically adaptive processors that jointly estimate the signals along with the embedded model parameters [1, 5]. Next, we introduce the underlying theory evolving from systems theoretic realizations of state-space models along with unique representations (canonical forms) for multivariable structures [16, 17]. Subspace identification is introduced for these deterministic systems. With the theory and algorithms for these systems in hand, the algorithms are extended to the stochastic case, culminating with a combined solution for both model sets, that is, deterministic and stochastic.

In terms of the system identification area, this text provides the link between model development and practical applications in model-based signal processing filling this critical gap, since many identification texts dive into the details of the algorithms without completing the final signal processing application. Many use the model results to construct model-based control systems, but do not focus on the processing aspects. Again the gap is filled in the signal processing community, by essentially introducing the notions and practicalities of subspace identification techniques applied to a variety of basic signal processing applications. For example, spectral estimation, communications, and primarily physics-based problems, which this text will demonstrate in the final chapters. It is especially applicable for signal processors because they are currently faced with multichannel applications, which the state-space formulations in this text handle quite easily, thereby opening the door for novel processing approaches. The current texts are excellent, but highly theoretical, attempting to provide signal processors with the underlying theory for the subspace approach [9–12]. Unfortunately, the authors are not able to achieve this, in my opinion, because the learning curve is too steep and more suitable for control system specialists with a strong systems theoretical background. It is difficult for signal processors to easily comprehend, but by incorporating the model-based signal processing approach, which is becoming more and more known and utilized by the signal processing community as the connection will enable the readers to gently "bridge the gap" from statistical signal processing to subspace identification for subsequent processing especially in multichannel applications. This is especially true with readers familiar with our previous texts in model-based processing [1, 6]. It will also have an impact in the structural dynamics area due to our case studies and applications introducing structural/test engineers to the model-based identifiers/processors [16]. They already apply many of these identification techniques to their problem sets.

The approach we take is to introduce the concept of subspace identification by first discussing the ideas of signal estimation, identification to model-based signal processing (MBSP) leading to the concept of model-based identification (MBID) [1, 5]. Here the model set is defined, and a variety of techniques ranging from the black-box approach to well-defined structural models employing parameter estimation techniques are developed. After introducing these concepts in the first chapter, random signals and systems are briefly discussed leading to the concept of spectral estimation, which provides an underlying cornerstone of the original identification problem.

Next, state-space models are introduced in detail evolving from continuous-time, sampled-data to discrete-time systems leading to the stochastic innovations model linking the classical Wiener filter to the well-known Kalman filter [2]. With this in hand, multivariable (multiple-input/multiple-output) systems are developed simply as time series, to sophisticated canonical forms, leading to the matrix fraction transfer function descriptions. Chapter 3 is concluded with approximate nonlinear Gauss–Markov representations in state-space form.

Model-based processors are highlighted in the next two chapters 4 and 5 ranging from developments of the linear representations leading to the optimal Kalman filter [2]. Next the suite of nonlinear processors is developed initiated by the linearized processor leading to the special cases of the extended and unscented Kalman filters and culminating with the novel particle filter evolving from the Bayesian approach [5]. These techniques are extended to the joint signal/parameter estimation problem to create the parametric adaptive processors. Throughout these chapters, examples and case studies are introduced to solidify these fundamental ideas.

Next, we introduce the foundations for the heart of the text – subspace identification first constrained to deterministic systems. Here we develop the fundamental realization problem that provides the basis of subspace identification using Hankel matrices. Many of the underlying systems theoretical results introduced by Kalman [18] in the 1960s are captured by properties of the Hankel matrix. The problem is extended to the deterministic identification problem by incorporating input/output sequences [15]. Perhaps one of the most important contributions to realization theory is the concept of a balanced realization enabling the evolution of robust algorithms. All of these concepts are carefully developed in this chapter. Canonical realizations, that is, the identification of models in unique canonical forms is an important concept in identification [16–18]. Here, much of this effort has been ignored over the years primarily because the concept of a unique representation can lead to large errors when identifying the model. However, it is possible to show that they can also be considered a viable approach, since they transform the Hankel array to the so-called structural matrix enabling both the order and parameters to be identified simultaneously, leading to an invariant system description [17, 19]. Finally, we introduce the ideas of projection theory showing how orthogonal/oblique projections lead to popular deterministic identification techniques [9–11]. Chapter 6 is concluded with a detailed case study on the identification application for a mechanical/structural system.

Chapter 7 is the extension of the deterministic identification problem to the stochastic case. Here, in the realization context, covariance matrices replace impulse response matrices, while deterministic input/output sequences are replaced with noisy multichannel sequences – the real-world problem.

As in Chapter 6, we develop stochastic realization theory starting with the "indirect" realization approach [4] based on covariance matrices for infinite and finite sequences to develop the basis of stochastic realization theory. The main ideas evolve from the work of Akaike [20, 21] and the development of predictor spaces leading to the fundamental results from the systems theoretic viewpoint. The optimal solution to this problem proceeds from classical spectral factorization techniques leading to the steady-state Kalman filter and the fundamental innovations model that is an integral part of subspace realizations [1, 20–29]. Next, subspace methods are reintroduced for random vector spaces and provided as solutions to the stochastic realization problem followed by the so-called combined subspace technique extracting both deterministic and stochastic models simultaneously [9–13]. This chapter concludes with a case study discussing the design of a processor to detect modal anomalies in an unknown cylindrical structure.

The text concludes with a chapter describing sets of real-world applications of these techniques. The applications range from failure detection, to the threat detection of fission sources, to the identification of chirp signals for radar/sonar application, to the parametrically adaptive processor design for localization and tracking in the ocean environment, and to the design of an MBP chirp-based signals as well as a critical radiation system – the scintillator.

Appendices are included for critical review as well as problem sets and notes for the MATLAB software used in the signal processing/controls/identification areas at the end of each chapter.

References

1 Candy, J. (2006). *Model-Based Signal Processing*. Hoboken, NJ: Wiley/IEEE Press.
2 Kalman, R. (1960). A new approach to linear filtering and prediction problems. *Trans. ASME J. Basic Eng.* 82: 34–45.
3 Van Der Veen, A., Deprettere, E., and Swindlehurst, A. (1993). Subspace-based methods for the identification of linear time-invariant systems. *Proc. IEEE* 81 (9): 1277–1308.
4 Viberg, M. (1995). Subspace based signal analysis using singular value decomposition. *Automatica* 31 (12): 1835–1851.
5 Candy, J. (2016). *Bayesian Signal Processing: Classical, Modern and Particle Filtering Methods*, 2e. Hoboken, NJ: Wiley/IEEE Press.
6 Ljung, L. (1999). *System Identification: Theory for the User*, 2e. Englewood Cliffs, NJ: Prentice-Hall.
7 Ljung, L. and Soderstrom, T. (1983). *Theory and Practice of Recursive Identification*. Cambridge: MIT Press.

8 Soderstrom, T. and Stoica, P. (1989). *System Identification*. New York: Academic Press.
9 van Overschee, P. and De Moor, B. (1996). *Subspace Identification for Linear Systems: Theory, Implementation, Applications*. Boston, MA: Kluwer Academic Publishers.
10 Katayama, T. (2005). *Subspace Methods for System Identification*. London: Springer.
11 Verhaegen, M. and Verdult, V. (2007). *Filtering and System Identification: A Least-Squares Approach*. Cambridge: Cambridge University Press.
12 Juang, J. (1994). *Applied System Identification*. Upper Saddle River, NJ: Prentice-Hall PTR.
13 Aoki, M. (1990). *State Space Modeling of Time Series*, 2e. London: Springer.
14 Norton, J. (1986). *An Introduction to Identification*. New York: Academic Press.
15 Ho, B. and Kalman, R. (1966). Effective reconstruction of linear state variable models from input/output data. *Regelungstechnik* 14: 545–548.
16 Luenberger, D. (1967). Canonical forms for linear multivariable systems. *IEEE Trans. Autom. Control* AC-12: 290–293.
17 Candy, J., Warren, M., and Bullock, T. (1977). Realization of an invariant system description from Markov sequences. *IEEE Trans. Autom. Control* AC-23 (12): 93–96.
18 Chen, C. (1984). *Linear System Theory and Design*. New York: Holt, Rinehart & Winston.
19 Guidorzi, R. (1975). Canonical structures in the identification of multivariable systems. *Automatica* 11: 361–374.
20 Akaike, H. (1974). Stochastic theory of minimal realization. *IEEE Trans. Autom. Control* 19: 667–674.
21 Akaike, H. (1975). Markovian representation of stochastic processes by canonical variables. *SIAM J. Control* 13 (1): 162–173.
22 Faurre, P. (1976). Stochastic realization algorithms. In: *System Identification: Advances and Case Studies* (ed. R. Mehra and D. Lainiotis), 1–23. New York: Academic Press.
23 Larimore, W. (1990). Canonical variate analysis in identification, filtering and adaptive control. In: *Proceedings of the 29th Conference on Decision and Control*, Hawaii, USA, 596–604.
24 Tse, E. and Wiennert, H. (1975). Structure determination and parameter identification for Multivariable stochastic linear systems. *IEEE Trans. Autom. Control* 20: 603–613.
25 Glover, K. and Willems, J. (1974). Parameterizations of linear dynamical systems: canonical forms and identifiability. *IEEE Trans. Autom. Control* 19: 640–646.
26 Denham, M. (1974). Canonical forms for identification of multivariable linear systems. *IEEE Trans. Autom. Control* 19: 646–656.

27 Candy, J., Bullock, T., and Warren, M. (1979). Invariant system description of the stochastic realization. *Automatica* 15: 493–495.
28 Candy, J., Warren, M., and Bullock, T. (1978). Partial realization of invariant system descriptions. *Int. J. Control* 28 (1): 113–127.
29 Sullivan, E. (2015). *Model-Based Processing for Underwater Acoustic Arrays.* New York: Springer.

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Glossary

ADC	analog-to-digital conversion
AIC	Akaike information criterion
AR	autoregressive (model)
ARMA	autoregressive moving average (model)
ARMAX	autoregressive moving average exogenous input (model)
ARX	autoregressive exogenous input (model)
AUC	area-under-curve (ROC curve)
BSP	Bayesian signal processing
BW	bandwidth
CD	central difference
CDF	cumulative distribution
CM	conditional mean
CRLB	Cramer–Rao lower bound
C-Sq	Chi-squared (distribution or test)
CT	continuous-time
CTD	concentration–temperature–density (measurement)
CVA	canonical variate analysis
EKF	extended Kalman filter
EM	expectation–maximization
FPE	final prediction error
GLRT	generalized likelihood ratio test
G-M	Gaussian mixture
GM	Gauss–Markov
G-S	Gaussian sum
HD	Hellinger distance
HPR	high probability region
IEKF	iterated–extended Kalman filter
i.i.d.	independent-identically distributed (samples)
KD	Kullback divergence
KL	Kullback–Leibler
KLD	Kullback–Leibler divergence

KSP	Kalman–Szego–Popov (equations)
LD	lower diagonal (matrix) decomposition
LE	Lyapunov equation
LKF	linear Kalman filter
LMS	least mean square
LS	least-squares
LTI	linear, time-invariant (system)
LZKF	linearized Kalman filter
MA	moving average (model)
MAICE	minimum Akaike information criterion
MAP	maximum a posteriori
MATLAB®	mathematical software package
MBID	model-based identification
MBP	model-based processor
MBSP	model-based signal processing
MC	Monte Carlo
MDL	minimum description length
MIMO	multiple-input/multiple-output (system)
MinE	minimum probability of error
ML	maximum likelihood
MOESP	multivariable output error state-space algorithm
MMSE	minimum mean-squared error
MSE	mean-squared error
MV	minimum variance
N4SID	numerical algorithm for subspace state-space system identification
NMSE	normalized mean-squared error
N-P	Neyman–Pearson (detector)
ODP	optimal decision (threshold) point
PDF	probability density function (continuous)
P-E	probability-of-error (detector)
PEM	prediction error method
PF	particle filter
PI-MOESP	past-input multivariable output error state-space algorithm
PMF	probability mass function (discrete)
PO-MOESP	past-output multivariable output error state-space algorithm
PSD	power spectral density
RC	resistor capacitor (circuit)
REBEL	recursive Bayesian estimation library
RLC	resistor–inductor–capacitor (circuit)
RLS	recursive least-squares
RMS	root mean-squared
RMSE	root minimum mean-squared error

ROC	receiver operating characteristic (curve)
RPE	recursive prediction error
RPEM	recursive prediction error method
SID	subspace identification
SIR	sequential importance sampling-resampling
SIS	sequential importance sampling
SMC	sequential Markov chain
SNR	signal-to-noise ratio
SPRT	sequential probability ratio test
SPT	sigma-point transformation
SSIS	sequential sampling importance sampling
SSP	state-space processor
SSQE	sum-squared error
SVD	singular-value (matrix) decomposition
UD	upper diagonal matrix decomposition
UKF	unscented Kalman filter
UT	unscented transform
WSSR	weighted sum-squared residual statistical test
W-test	whiteness test
Z	Z-transform
Z-M	zero-mean statistical test

1

Introduction

In this chapter, we introduce the idea of model-based identification, starting with the basic notions of signal processing and estimation. Once defined, we introduce the concepts of model-based signal processing, that lead to the development and application of subspace identification. Next, we show that the essential ingredient of the model-based processor is the "model" that must be available either through the underlying science (first principles) or through the core of this text – model-based identification.

1.1 Background

The development of processors capable of extracting information from noisy sensor measurement data is essential in a wide variety of applications, whether it be locating a hostile target using radar or sonar systems or locating a tumor in breast tissue or even locating a seismic source in the case of an earthquake. The nondestructive evaluation (NDE) of a wing or hull of a ship provides a challenging medium even in the simplest of arrangements requiring sophisticated processing especially if the medium is heterogeneous. Designing a controller for a smart car or a drone or for that matter a delicate robotic surgical instrument also depends on providing enhanced signals for feedback and error corrections. Robots replacing humans in assembly lines or providing assistance in mundane tasks must sense their surroundings to function in a such a noisy environment. Most "hi-tech" applications require the incorporation of "smart" processors capable of sensing their operational environment, enhancing noisy measurements and extracting critical information in order to perform a preassigned task such as detecting a hostile target and launching a weapon or detecting a tumor and extracting it. In order to design a processor with the required capability, it is necessary to utilize as much available a priori information as possible. The design may incorporate a variety of disciplines to achieve the desired results. For instance, the processor must be able to sense the operational environment, whether it be highly cluttered electromagnetic propagation

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at an airport or a noisy ocean acoustic environment in a busy harbor. Array radiation measurements in the case of an active radar system targeting signals of great interest can detect incoming threats, while passive listening provided by an acoustic array aids in the detection of submarines or similarly tumors in the human body for ultrasonics as well. The ability of the processor to operate effectively in such harsh environments requires more and more sophistication, rather than just simple filtering techniques. It is here that we address not only the need, but also the a priori requirements for a design. For instance, the detection and localization of a quiet diesel submarine cannot be achieved without some representation of the noisy, varying ocean incorporated in the processing scheme. How does such information get embedded? This is the question for not only the signal processor, but also the ocean acoustician and sensor designer to ponder. The solution boils down to the melding of this information enabling the development of a processor capable of performing well. So we see that except in an exceptional case, the knowledge of the underlying phenomenology that governs just how a signal propagates in an uncertain medium or environment coupled with that of how a sensor can make a reasonable measurement to provide the desired information and a processor capable of extracting that information defines a "team" consisting of a phenomenologist, sensor designer and signal processor that can enable a solution to the problem at hand. In this text, we discuss such an approach that incorporates all of these capabilities. We start with the basic processor and then progress to a scheme capable of incorporating the underlying phenomenology, measurement systems, and uncertainties into the processor. In order to do so, we start with defining signal processing and signal estimation, followed by the fundamental model-based signal processor and then approaches to obtain the required model from experimental as well as application data sets.

1.2 Signal Estimation

Signal processing is based on one fundamental concept – extracting critical information from uncertain measurement data [1, 2]. Processing problems can lead to some complex and intricate paradigms to perform this extraction especially from noisy, sometimes inadequate measurements. Whether the data are created using a seismic geophone sensor from a monitoring network or an array of hydrophone transducers located on the hull of an ocean-going vessel, the basic processing problem remains the same – extract the useful information. Techniques in signal processing (e.g. filtering, Fourier transforms, time–frequency and wavelet transforms) are effective; however, as the underlying process generating the measurements becomes more complex, the resulting processor may require more and more information about the process phenomenology to extract the desired information. The challenge is