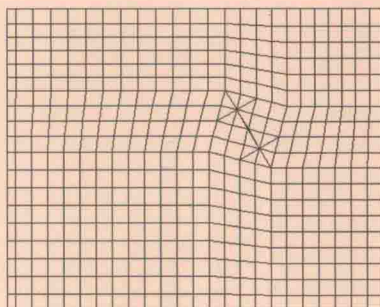
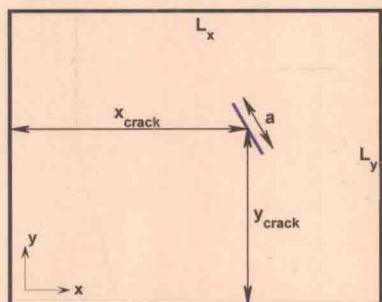
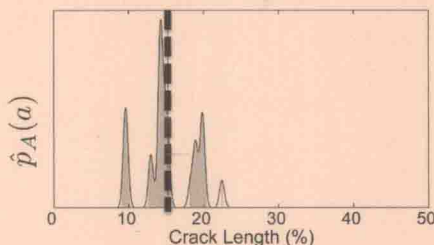


JONATHAN M. NICHOLS
KEVIN D. MURPHY



$$p_A(a) = \frac{p_H(\mathbf{y}|a)p_\pi(a)}{p_{\mathbf{Y}}(\mathbf{y})}$$



MODELING AND ESTIMATION OF STRUCTURAL DAMAGE

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Preface

This book is intended as a guide to solving the type of modeling and estimation problems associated with the physics of structural damage. These two topics (modeling and estimation) are intimately related, such that a discussion of one is at least partially incomplete without the other. The job of the model is to understand and predict behavior, in this case the observed behavior of a damaged structure. This model includes both deterministic (physics-driven) and stochastic components (e.g., measurement error). The parameters that describe the model, including damage, are typically unknown *a priori* and must be estimated from observed data. This book provides the readers with both the modeling tools needed to describe structural damage and the estimation tools needed to identify the damage parameters associated with those models.

More general discussions of both structural modeling and estimation theory can be found separately in other places. However, we have found that the modeling and estimation problems that arise in structural damage identification differ sufficiently from those found elsewhere to deserve separate treatment. We have also found that an integrated treatment of these topics is lacking in a single source. Therefore, it is the goal of this book to serve as that single source. That being said, much of the material presented generalizes to other types of modeling and estimation problems faced by researchers in structural dynamics. Readers interested in these more general problems will hopefully also find this a useful guide.

The material that follows was developed over a number of years and was influenced by the thinking of a number of talented individuals. Several of these individuals we feel deserve special mention for both their intellectual contributions and their friendship. First, we thank Dr. James D. Nichols (Jon's father), a Senior Scientist with the U.S. Geological Survey. His contributions to this work were both technical (see chapter on decision theory in particular) and philosophical. Over the past two decades, we have spent much time (over many beers) discussing efficient ways to conduct science. His strong advocacy for model-based, hypothesis-driven science can be seen in every chapter and, to a large extent, sets the tone for the entire book. Proponents of the "data-driven" world-view would be well served to have a pint or two discussing this topic with Jim.

We also thank PierGiovanni Marzocca of Clarkson University. Jon was fortunate enough to work with "Pier" during two summers at the U.S. Naval Research Laboratory (NRL). In addition to being a good collaborator, Pier was the driving force behind much of the Volterra series modeling which appears in several places in this book. Gustavo Rhode of Carnegie Mellon also deserves mention. Gustavo's attention to detail and technical brilliance in the theory of random processes taught us a great deal on how to think about, and write about, this

challenging subject. In the same subject area, Frank Bucholtz of NRL also deserves mention for his willingness to host “white board” discussions on probability and statistics. Frank has the rare ability to drill down into the details of a problem, no matter how seemingly trivial the topic might be, to the point where you either become an expert or leave his office convinced you understand nothing whatsoever.

We also owe a large debt of gratitude to Ned Moore (Kevin’s former Ph.D. student), now of Central Connecticut State University. Ned was tasked with the practical implementation of many of the system identification techniques described in this book. Chapter 9 would certainly not have existed without his help. In addition, we thank Chris Earls of Cornell University, and his students Chris Stull and Heather Reed, who were behind the bulk of the work on identifying dents in plate structures.

Finally, we would be remiss in not acknowledging Dr. Paul Hess of the Office of Naval Research. For many years now, Paul has been a strong proponent of the model-based view of damage identification. Certainly, without his support a great deal of the material in this book would never have been developed.

On a more personal note, the second author thanks the first author, Jon. It was Jon who opened the door to this modeling and estimation world for me; I’m richer for it. In the process, Jon also introduced me to my wife. So I’m doubly in his debt. And on that note, I also thank my wife Françoise for her unbounded supply of patience and support.

Jon would like to thank his wife Susan and two children, Kirstin and Cassidy, for their patience with this project. Jon would also like to thank his parents, Lois and Jim, for their continued support and advice; this book is dedicated to them.

Jonathan M. Nichols
Crofton, MD, October 2015

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1

Introduction

1.1 Users' Guide

Anyone who has done a fair bit of technical writing will likely agree that the best way to truly understand a topic is to try and clearly explain that topic to others. There is no better way to expose one's own technical deficiencies than to sit down and try and describe a subject in writing. This is certainly true of the material presented in this book. In fact, our original intent was not to write a book but rather document what we had learned about modeling and estimation so as to improve our own understanding and to keep from having to "relearn" the material over time.

In particular, we wanted to focus on some of the details of modeling and estimation that are frequently overlooked or implicitly assumed without explanation. Understanding the origins of these assumptions has helped us tremendously in our own research and we hope the book provides a similarly useful reference for others. One of our chief aims is therefore to clearly explain the roots of modeling and estimation for structural response data, tracing the mathematical reasoning back to the originators. So much of what we do in engineering sciences builds on the brilliance of A. Kolmogorov (probability), G. D. Birkhoff (signal processing), N. Wiener (spectral analysis), and J.-L. Lagrange (mechanics), to name a few. Time and time again we have seen that those who are making the most meaningful contributions in their respective fields of study are those who return to these foundations before moving forward.

That being said, there are different ways one can use this book. For example, one could choose to learn the details of probability theory in Chapter 2 or simply proceed to the later, more applied chapters and simply reference back to the mathematics when needed. The same is true for much of Chapter 3. The material of Chapter 6 explains the origins of estimation theory; however, one could move straight to Chapters 7–10 where that material is applied to problems in damage detection and identification. In short, the detail is provided, but it may not be necessary for much of what the reader is trying to accomplish. The idea was to at least give the reader the option of exploring modeling and estimation to whatever depths he or she deems appropriate.

From a structural modeling point of view, the book is well-suited to those who have taken basic undergraduate courses in mechanics of solids and dynamics. In terms of mathematics, the book presumes familiarity with basic calculus operations, series expansions

(e.g., Taylor series), as well as differential equations. Familiarity with probability theory and spectral analysis is also a plus, although we have taken great pains to explain these topics carefully and clearly for the interested reader. This likely places the useful starting range of the book somewhere in the later undergraduate years. This is consistent with courses currently being taught in the structural health monitoring (SHM) field at various universities. Our brief survey of such courses places the majority in the junior or senior years, continuing on as part of a graduate program.

1.2 Modeling and Estimation Overview

Most of us who entered into science and engineering disciplines did so because at some level we were fundamentally interested in questions about how things work. Whether the curiosity relates to atmospheric events, cell biology, or (more to the point of this book) why bridges don't fall down, the common link is a desire to understand the world around us. As we have all learned by now, this understanding is achieved through modeling and prediction. We construct models of the phenomenon of interest and predict outcomes. Models that predict well are retained; those that do not are discarded.

The main goal of science is, in fact, to produce useful models of reality so that we may reliably predict outcomes. There is a tremendous power in prediction. It allows us to generalize what we have observed to things that we have not yet observed. Thus, every time we build a bridge with a different design from a previous one, we don't have to worry about whether or not it will collapse. We can sufficiently model this new design and confidently predict its integrity over the intended lifetime. The model further allows us to try a number of different designs and predict their efficacy without having to build and test each architecture.

All models are, by definition, wrong, of course. They are simply abstractions of reality that we find useful for their ability to make predictions. One cannot hope to model *exactly* the observed data, nor would we want to. Increasing model complexity without significantly improving prediction is essentially pointless. As Einstein put it, "It can scarcely be denied that the supreme goal of all theory is to make the irreducible basic elements as simple and as few as possible without having to surrender the adequate representation of a single datum of experience" [1]. This guiding principle of modeling is sometimes referred to as the principle of parsimony and plays a prominent role throughout this book.

In engineering we are taught to derive *deterministic models* by applying some basic physical principles, for example, $F = ma$, and invoking some simplifying assumptions (parsimony!) about our operating regime to yield a set of governing equations. For example, to predict the vibrational response of a cantilevered beam to an initial tip displacement, we could start with Newton's laws, make some simplifying assumptions about the homogeneity of the material comprising the beam, amplitude of the resulting vibrations, and so on, and develop a solution. This solution is expected to be a good predictor of our observed response in the regime defined by our assumptions. There is no need for us to solve the full (nonlinear) governing equations.

However, even with the most sophisticated of models there will always be some remaining error in our predictions. We acknowledge that we cannot describe the exact behavior and instead describe "expected" or "typical" behavior using *probabilistic models*. Sensor noise is often the primary culprit in this type of error. For example, we might attach a resistive strain gage to our cantilevered beam and record the response. We can describe most of what we observe using our aforementioned deterministic model, however we can't predict the exact

voltage that will be read because of both residual model error and sensor noise. There are a number of different “noise” mechanisms, however at this stage, it will suffice to say that noise gives rise to observations that we cannot explain with a deterministic model.¹ Instead, we describe the *probability distribution* of the response, that is, predict the values we are likely to observe. It may at first seem quite unsatisfying to have to resort to a (partially) probabilistic description of our data, however probabilistic models are quite powerful and are every bit as useful as deterministic models in describing the world around us. We will demonstrate that so long as we can describe our uncertainty, we can minimize its influence on our ability to predict.

Thus, our observations are to be characterized by both deterministic and probabilistic components. In fact, the key ingredients to any structural estimation problem are (i) a probabilistic model describing the uncertainty in the observed data and (ii) a deterministic structural model (or models) governed by a set of model parameters. Given these two ingredients, we can begin to discuss the subject of estimation. This subject can be loosely defined as the process of extracting our deterministic and probabilistic model parameters given the data we have observed. The subject of estimation is absolutely essential to damage identification as it is through estimation that we connect our model to reality. At the end of the day, we will declare “good” estimates to be the ones that are highly probable. As we will see, there are two fundamentally different viewpoints on how to arrive at “most probable.” Once we have our model parameters, our data model is completely specified and we can turn to the task of making predictions and, ultimately, decisions regarding the maintenance of a particular structure.

As implied by the title, our focus is on the modeling and estimation of structural damage. This particular problem poses some unique challenges in both arenas. With regard to the former, the structural damage will alter the model of the pristine structure, often in a nontrivial way. Moreover, the damage model should reduce to the undamaged model in the limiting case that some damage-related parameter goes to zero, that is, the model should predict both healthy and damaged response data. In terms of damage parameter estimation, the problem is similarly challenging. Typically, one would like to identify damage before it becomes large and influences structural performance. However, the smaller the damage the less influence it will have on the observed data, making it more difficult to estimate the associated damage parameters. Special attention is therefore paid to both the estimates *and* the uncertainty in the estimates which, for small damage, can be large. Quantifying this uncertainty is essential to making decisions regarding how the structure is maintained. This relationship is made explicit in the final chapter of the book.

We also cover cases where the goal is to detect the damage presence, not necessarily identify the complete damage state (magnitude, location, orientation, etc.). The approach we will take is still based on the physics of damage, however in this case the problem will be viewed as one of model selection. Specifically, we will consider cases where damage results in a non-linearity in a structure that is otherwise (when healthy) best described by a linear model. Our job will be to assess the likelihood that our observed data were produced by one of those two models (linear vs. nonlinear). While not as powerful as approaches that identify specific damage-related parameters, model selection can be used successfully in situations where there is a large amount of uncertainty in the detailed physics of the damage. Moreover, we will show that even this simple assumption about the physics of damage divorces the practitioner from

¹ The mathematical history of “noise” is actually a fascinating subject summarized nicely in a review article by Cohen [2].

having to rely on basic “change detection” in a structure’s response as a damage detection strategy.

1.3 Motivation

So why should we focus on the modeling of structural damage in the first place? After all, the material in this book can be applied toward many other problems in structural dynamics (in fact, the original intent of this work was to provide a general reference in structural system identification). In looking back at our own research and that of many of our colleagues, problems involving “structural damage” were a recurring theme. The motivations for this research are varied and typically include a statement suggesting that an understanding of damage physics is necessary for development of some future “automated” system for monitoring the condition of a structure and making decisions about how to best maintain it (best typically implied to mean, “least costly”). Indeed, there is an increasing recognition in both military and commercial communities that an understanding of damage physics is of paramount importance. Consider, for a moment, three situations where one may want to understand and predict the condition of a structure:

1. Improve safety
2. Reduce maintenance costs
3. Increase operational envelope.

Each of these items is a strong motivating factor for understanding damage physics with large financial and performance incentives.

In the Department of Defense, there are financial pressures to reduce maintenance costs while at the same time increasing the operational envelope of a given asset (e.g., increasing ship speed while reducing the number of repairs). For example, certain classes of ships have experienced wide-spread cracking of deck plates, requiring millions of dollars annually to repair. Figure 1.1 shows two sample cracks, one taken from a top-side view, the other from



(a)



(b)

Figure 1.1 (a) Top-side view of a recently repaired deck plate crack and (b) view of the crack from inside the ship. This crack would normally be hidden beneath several inches of insulation

beneath the deck plate showing a crack that is normally hidden beneath the insulation. The cause of this cracking has been investigated and is now understood to be due to stress corrosion caused by sensitization of the aluminum alloy used in construction (5456 material). However, in order for this type of cracking to initiate and persist, the material must be sustaining large stresses. It is the origin of these stresses that is still largely unknown (at least at the time of this writing).

In a partial response to this question, one of the deck plates of the affected ship was instrumented with a fiber-optic strain sensing system (see Figure 1.2). The ship then underwent a series of high speed turns during transit, the goal being to test the strain response at the edge of the operational envelope. The strain time-history in Figure 1.2 shows only a minor signal resulting from these maneuvers, measuring $<15 \mu\epsilon$ (micro-strain) in amplitude. This translated to a stress amplitude of <1 ksi, far below the yield stress for this material (≈ 33 ksi). This is certainly useful information, however it does not offer much in the way of predictive power. All we can say with any certainty is that these particular maneuvers are unlikely to be the source of the cracking.

Clearly, a predictive model that could accurately forecast high stress conditions, crack lengths and locations, and/or plate stiffness would be of much greater value. Ship operators need to understand when a crack has evolved to the point where it is compromising the safety of the crew or of the ship. Should the ship's captain turn around or complete the mission? In the absence of a model, this information is simply not available. In Chapter 10 we address this particular problem in its entirety and show how a model-based approach can be used to make decisions regarding how best to use a maritime asset in transit.

US Army ground vehicles have also been the subject of damage identification efforts. A number of these vehicles were experiencing cracking in the wheel spindle (part of the wheel hub assembly); cracks greater than 0.2 in. meant that the part required replacement [4]. The

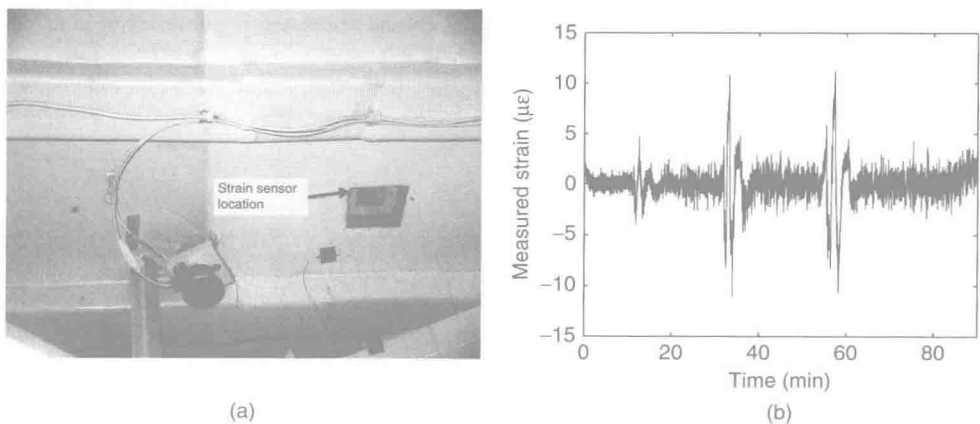


Figure 1.2 (a) Fiber-optic strain sensors are affixed to the underside of an aluminum deck plate, located behind the insulation and (b) detrended strain time-history showing the influence of high speed maneuvers (turns) on the measured response of the deck at a particular location. The magnitude of the signal ($<15 \mu\epsilon$) suggests stresses far below the yield stress of the plate. *Source:* Adapted from [3], Figure 9, reproduced with permission of the Society of Naval Architects and Marine Engineers

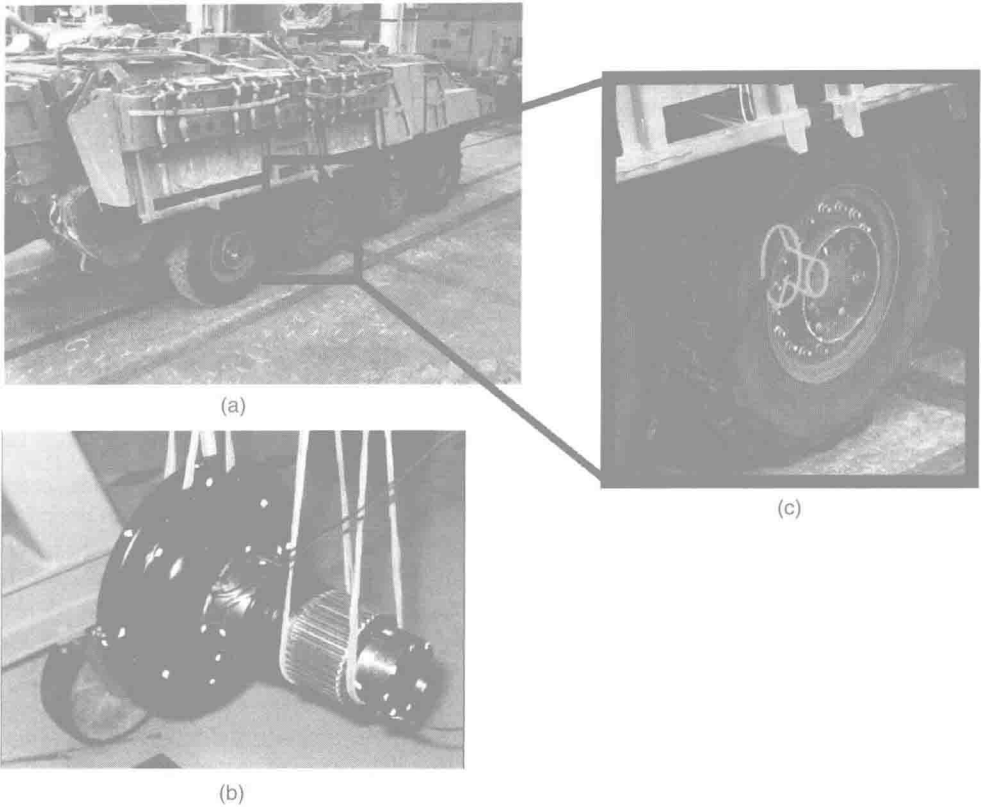


Figure 1.3 Wheel spindle crack on US Army ground vehicles (a) proved a challenging problem in damage detection. The spindle (b) is hidden behind the wheel and wheel assembly (c), making it difficult to identify the damage presence without removing the vehicle from service, removing the assembly, and visually inspecting the part. Automated methods for detecting damage in these types of situations have the potential to eliminate costly repairs and downtime. *Source:* Adapted from [5], Figure 1.5, reproduced with permission of John Wiley & Sons

question, of course, is how does one know when the crack has reached the critical length? An inefficient strategy would periodically pull a vehicle out of service, remove the entire wheel assembly, and check for the appearance of a crack. However, removal of an asset from service while in-theater is a costly action to take (in terms of dollars and downtime). The particular vehicle in question is shown in Figure 1.3 along with a depiction of the spindle location behind the wheel (indicated by the black arrow) and a closeup of the spindle itself. In response to this problem, researchers at Purdue University, led by Dr Douglas Adams, developed a simple test for spindle cracks that could be performed *in situ*. On the basis of a finite element model of the component, it was determined that a crack would alter the frequency response of the assembly in a specific manner. The test therefore uses estimates of the frequency response (a subject we discuss at length in Sections 3.3 and 6.4) to detect the crack presence without removing the entire assembly [4].

In civil and commercial domains, similar safety and financial pressures have yielded additional research toward the development of various “monitoring” technologies. Bridges and other components of the civil infrastructure are now being monitored at various sites around the globe for the express purpose of assessing structural integrity. The goal of these installations is typically to monitor peak loads or displacements to confirm they are within normal operating ranges. As an example, consider the strain monitoring system depicted in Figure 1.4 and installed on the I-10 bridge in New Mexico. Performed in 1997, the goal of this installation was to demonstrate the feasibility of such a system for the monitoring of civil structures. In this case, a fiber-optic strain monitoring system developed at the Naval Research Laboratory was used to monitor the strain response of the bridge at various points. Among other things, the system was used to study the peak strains observed as a function of the type of traffic traversing the bridge. Figure 1.5 shows a histogram of strain response data obtained over many days of operation. The histogram clearly shows two distinct peaks, associated with vehicles of different sizes. Car traffic produces smaller strain signals ($\sim 30 \mu\epsilon$), while trucks yield larger strains as expected ($\sim 50 \mu\epsilon$).

Each of these case studies is an example of what is commonly referred to as “SHM.” The next section discusses this field in more detail, describing the basic approaches and philosophies used in tackling this challenging problem. While this book is not meant to be a “SHM” book, it certainly provides tools that are likely to be useful to those in the field. In what follows we therefore attempt to place our work in the context of this more general area of study.

1.4 Structural Health Monitoring

The field of SHM comprises a body of work aimed at the identification of damage for the reasons discussed in the previous section. We should state upfront that the material presented here is not at all meant to be a comprehensive look at the SHM field as it is understood by most practitioners. A good overview of the SHM field, including numerous approaches to damage detection and identification, is given by Farrar and Worden [6] and also Adams [5]. Perhaps the most glaring omission in this book is a discussion of the types of sensors used to acquire structural response data. Data acquisition is certainly an integral part of any SHM system and has been given extensive treatment in numerous references (see, e.g., [7] or Chapter 4 and Appendix B of [5]). While our experimental examples make use of such systems, a detailed discussion of their construction and operation is not provided.

In addition, one can loosely group SHM techniques into “local” versus “global” methods. The former, as one might guess, uses data acquired from localized areas of a structure where damage is presumed to exist. The latter, global approach, is the focus of most of the examples in this work and presumes that the entire structure is being interrogated (e.g., is undergoing vibration) and that we are measuring this response at one or more locations. This represents a more challenging problem as identification requires locating the damage from these observations. However the global approach has the obvious advantage that *a priori* damage location information is not required.

Nonetheless, many of these “local” approaches to the damage identification problem have achieved solid results in a variety of contexts and therefore deserve mention (see, e.g., [8] for an overview). Thermography [9], eddy-current techniques [10], and ultrasound [11] (to name a few) have all been used to identify localized structural damage; none of these are given in-depth treatment in this book. However, this is not to say that the methods developed in