An Introduction to Structural Health Monitoring

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Abstract This introduction begins with a brief history of SHM technology development. Recent research has begun to recognise that a productive approach to the Structural Health Monitoring (SHM) problem is to regard it as one of statistical pattern recognition (SPR); a paradigm addressing the problem in such a way is described in detail herein as it forms the basis for the organisation of this book. In the process of providing the historical overview and summarising the SPR paradigm, the subsequent chapters in this book are cited in an effort to show how they fit into this overview of SHM. In the conclusions are stated a number of technical challenges that the authors believe must be addressed if SHM is to gain wider acceptance.

1 Introduction

The process of implementing a damage identification strategy for aerospace, civil and mechanical engineering infrastructure is referred to as *Structural Health Monitoring* (SHM). A wide variety of highly-effective local Non-Destructive Evaluation (NDE) tools are traditionally available for such monitoring. However, the majority of SHM research conducted over the last thirty years has attempted to identify damage in structures on a more global basis using permanently installed sensors. The past ten years has seen a rapid increase in the amount of research related to SHM as quantified by the significant escalation in papers published on this subject. The increased interest in SHM and its associated potential for significant life-safety and economic benefits has motivated the need for this book.

In the most general terms, damage is usually understood as changes introduced into a system that adversely affect its current or future performance. Implicit in this definition is the idea that damage is not meaningful

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without a comparison between two different states of the system, one of which is assumed to represent the initial, and often undamaged, state. This book is focused on the study of damage identification in structural and mechanical systems. Therefore, the definition of damage will be limited to changes to the material and/or geometric properties of these systems, including changes to the boundary conditions and system connectivity, which adversely affect the current or future performance of these systems.

In terms of length-scales, all damage begins at the material level. Although not necessarily universally accepted terminology, such damage is referred to as a defect or flaw and is present to some degree in all materials. Under appropriate loading scenarios the defects or flaws grow and coalesce at various rates to cause component, and then system-level, damage. The term damage does not necessarily imply total loss of system functionality, but rather that the system is no longer operating in its optimal manner. As the damage grows it will reach a point where it affects the system operation to a point that is no longer acceptable to the user. This point is referred to as failure. In terms of time-scales, damage can accumulate incrementally over long periods of time such as that associated with fatigue or corrosion damage evolution. On relatively shorter time-scales, damage can also result from scheduled discrete events such as aircraft landings and from unscheduled discrete events such as enemy fire on a military vehicle or natural hazards such as earthquakes.

The SHM process involves the observation of a structure or mechanical system over time using periodically-spaced measurements, the extraction of damage-sensitive features from these measurements, and the statistical analysis of these features to determine the current state of system health. For long-term SHM, the output of this process is periodically updated information regarding the ability of the structure to continue to perform its intended function in the light of the inevitable aging and damage accumulation resulting from the operational environments. Under an extreme event, such as an earthquake or unanticipated blast loading, SHM could be used for rapid condition screening. This screening is intended to provide, in near real-time, reliable information about system performance during such extreme events and the subsequent integrity of the system. A more detailed description of SHM can be found in Worden and Dulieu-Barton (2004).

Damage identification is carried out in conjunction with five closely related disciplines that include SHM, Condition Monitoring (CM, see Bently and Hatch (2003)), Non-Destructive Evaluation (NDE, see Shull (2002)), Statistical Process Control (SPC, See Montgomery (1997)) and Damage Prognosis (DP, see Farrar et al. (2001, 2003)). Typically, SHM is associated with on-line, global damage identification in structural systems such as aircraft and buildings. CM is analogous to SHM, but addresses damage identification in rotating and reciprocating machinery, such as used in manufacturing and power generation. NDE is usually carried out off-line in a local manner after the damage has been located, and requires access to the component or structure of interest. There are exceptions to this rule, as NDE is also used as a monitoring tool for *in situ* structures such as pressure vessels and rails. NDE is therefore primarily used for damage characterisation and as a severity check when there is *a priori* knowledge of the damage location. SPC is process-based rather than structure-based and uses a variety of sensors to monitor changes in a process, one cause of which can result from structural damage. Once damage has been detected, DP is used to predict the remaining useful life of a system.

1.1 Motivation for SHM Technology Development

Almost all private industries and government organisations want to detect damage in their products as well as in their manufacturing infrastructure at the earliest possible time. Such detection requires these industries to perform some form of SHM and is motivated by the potential life-safety and economic impact of this technology. As an example, the semiconductor manufacturing industry is adopting this technology to help minimise the need for redundant machinery necessary to prevent inadvertent downtime in their fabrication plants. Such downtime can cost these companies on the order of millions of dollars per hour. Aerospace companies in the US along with government agencies are investigating SHM technology for identification of damage to the space shuttle control surfaces hidden by heat shields. Clearly, such damage identification has significant life-safety implications. Also, there are currently no quantifiable methods to determine if buildings are safe for reoccupation after a significant earthquake. SHM may one day provide the technology to significantly reduce the uncertainty associated with such post-earthquake damage assessments. The prompt reoccupation of buildings, particularly those associated with manufacturing, can significantly mitigate economic losses associated with major seismic events. Finally, many portions of our technical infrastructure are approaching or exceeding their initial design life. As a result of economic issues, these civil, mechanical, and aerospace structures are being used in spite of aging and the associated damage accumulation. Therefore, the ability to monitor the health of these structures is becoming increasingly important.

Most current structural and mechanical system maintenance is done in a time-based mode. As an example missiles are retired after a set amount of captive-carry hours on the wing of an aircraft. SHM represents the group of technologies that will allow the current time-based maintenance philosophies to evolve into potentially more cost effective condition-based maintenance philosophies. The concept of condition-based maintenance is that a sensing system on the structure will monitor the system response and notify the operator that damage has been detected. Life-safety and economic benefits associated with such a philosophy will only be realised if the monitoring system provides sufficient warning such that corrective action can be taken before the damage evolves to a failure level. The trade-off associated with implementing such a philosophy is that it requires a more sophisticated monitoring hardware to be deployed on the system and it requires a sophisticated data analysis procedure that can be used to interrogate the measured data. It is also critical that any monitoring system installed should be at least as reliable as the structure or system of interest.

Finally, many companies that produce high-capital-expenditure products such as airframes, jet engines, and large construction equipment would like to move to a business model where they lease this equipment as opposed to selling it. With these models the company that manufactures the equipment would take on the responsibilities for it's maintenance. SHM has the potential to extend the intervals between scheduled maintenance and, hence, keep the equipment out in the field where it can continue to generate revenue for the owner. Also, the equipment owners would like to base their lease fees on the amount of system life used up during the lease time rather than on the current simple time-based lease fee arrangements. Such a business model will not be realised without the ability to monitor the damage initiation and evolution in the rental hardware.

1.2 Motivation for this Book

Directly reflecting the increased interest in this emerging technology, there have been several conference series initiated in the last fifteen years that focus directly on SHM; (the most recent examples in these series being[1,2,3,4].) Focussed meetings and conferences related to the condition mon-

[1] The 7^{th} International Workshop on Structural Health Monitoring, Palo Alto, CA, 2009.
[2] The 8^{th} International Conference on Damage Assessment of Structures, Beijing, China, 2009.
[3] 14^{th} International Symposium on Nondestructive Evaluation and Health Monitoring of Aging Infrastructure, San Diego, CA, 2009.
[4] The 4^{th} European Workshop on Structural Health Monitoring, Krakow, Poland, 2008

itoring of rotating machinery are much older[5,6]. These conferences have shown that the topic of SHM is of interest to a wide range of industries and government agencies; They have also shown that many technical disciplines need to be integrated to properly address the SHM problem. In addition, the first refereed journal devoted specifically to SHM has recently been initiated[7], and others have followed. The proceedings of the specialised conferences as well as the extensive number of refereed journal articles devoted to various aspects of SHM show that significant knowledge and experience has been gained through the reported studies. Finally, the emergence of a number of specialised courses on SHM technologies and methodologies is further testimony to the interest expressed by industry. Despite the clear interest, there is a limited number of published textbooks and monographs on the subject of SHM (recent exceptions of note are Adams (2007); Giurgiutiu (2007); Staszewski et al. (2003)). A theme issue of the Transactions of the Royal Society of London was also devoted to the topic (Farrar and Worden (2007)), and makes a useful first port-of-call for an overview. Most notably, a comprehensive reference work has also recently appeared, Boller et al. (2009); although the focus of this work is not pedagogical. All of this means that it is timely to devote a new book in an effort to provide the engineering community with an up-to-date overview of SHM technology focussed on vibration-based methods and statistical pattern recognition - aspects of the subject which are arguably neglected in the coverage of SHM to date.

2 Brief Historical Overview

The current authors believe that damage identification - as determined by changes in the dynamic response of systems - has been practiced in a qualitative manner, using acoustic techniques (e.g tap tests on train wheels), since modern man has used tools. More recently, the development of quantifiable SHM approaches has been closely coupled with the evolution, miniaturisation and cost reductions of digital computing hardware. In conjunction with these developments SHM has received considerable attention in the technical literature and a brief summary of the developments in this technology over the last thirty years is presented below. Specific references are not cited; instead the reader is referred to a number of comprehensive sur-

[5]The 22^{nd} Conference on Condition Monitoring and Diagnostic Engineering Management - COMADEM, San Sebastian, Spain, 2009.

[6]The 63^{rd} Meeting of the Society for Machinery Failure and Prevention Technology, Dayton, OH, 2009.

[7]*Structural Health Monitoring, An International Journal*, Sage Publications, London.

veys (Doebling et al. (1996); Sohn et al. (2003); Randall (2004a,b), for more detailed summaries of this subject.

To date, the most successful applications of SHM technology have been for the monitoring of rotating machinery. The rotating machinery applications have taken an almost exclusively data-based (as opposed to model-based) approach to damage identification. The identification process is usually based on pattern recognition methods applied to displacement, velocity or acceleration time-histories (or spectra), generally measured at a single point on the housing or shafts of the machinery during normal operating conditions or start-up or shut-down transients. Often this pattern recognition is performed only in a qualitative manner based on a visual comparison of the spectra obtained from the system at different times; this is nonetheless pattern recognition. Databases have been developed that allow specific types of damage to be identified from particular features of the vibration signature. For rotating machinery systems the approximate damage location is generally known, making a single-channel fast-Fourier-transform (FFT) analyser sufficient for most periodic monitoring activities. Typical damage that can be identified includes loose or damaged bearings, misaligned shafts, and chipped gear teeth. Today, commercial software integrated with measurement hardware is marketed to help the user systematically apply this technology to the operating equipment.

The success of CM is due in part to:

1. Minimal operational and environmental variability associated with this type of monitoring,
2. Well-defined damage types that occur at known locations,
3. Large databases that include data from damaged systems,
4. Well-established correlation between damage and features extracted form the measured data, and
5. Clear and quantifiable economic benefits that this technology can provide.

These factors have allowed this application of SHM to make the transition from a research topic to industry practice several decades ago resulting in comprehensive condition management systems such as the U.S. Navy's Integrated Condition Assessment System. Condition monitoring is not discussed in any further detail here, the curious reader can find many interesting texts and reviews; a good recent review is by Randall (2004a,b).

During the 1970s and 1980s, global oil industry made considerable efforts to develop vibration-based damage identification methods for offshore platforms. This damage identification problem is fundamentally different from that of rotating machinery because the damage location is not known *a priori* and because the majority of the structure is not readily accessible for measurement. To circumvent these difficulties, a common methodology adopted by this industry was to simulate candidate damage scenarios with numerical models, examine the changes in resonance frequencies that were produced by these simulated changes, and correlate these changes with those measured on a platform. A number of very practical problems were encountered including measurement difficulties caused by platform machine noise, instrumentation difficulties in hostile environments, changing mass caused by marine growth and varying fluid storage levels, temporal variability of foundation conditions, and the inability of wave motion to excite higher vibration modes. These issues prevented adoptation of this technology, and efforts at further developing SHM technology for offshore platforms were largely abandoned in the early 1980s.

The aerospace community began to study the use of vibration-based damage identification during the late 1970s and early 1980s in conjunction with the development of the space shuttle. This work has continued with current applications being investigated for the National Aeronautics and Space Administration's space station and future reusable launch vehicle designs. The Shuttle Modal Inspection System (SMIS) was developed to identify fatigue damage in components such as control surfaces, fuselage panels and lifting surfaces. These areas were covered with a thermal protection system making them inaccessible and, hence, impractical for conventional local non-destructive examination methods. The Shuttle Modal Inspection System has been successful in locating damaged components that are covered by the thermal protection system. All orbiter vehicles have been periodically subjected to SMIS testing since 1987. Space station applications have primarily driven the development of experimental/analytical methods aimed at identifying damage to truss elements caused by space debris impact. These approaches are based on correlating analytical models of the undamaged structure with measured modal properties from both the undamaged and damaged structure. Changes in stiffness indices as assessed from the two model updates are used to locate and quantify the damage. Since the mid-1990s, studies of damage identification for composite materials have been motivated by the development of a composite fuel tank for a reusable launch vehicle. The failure mechanisms, such as delamination caused by debris impacts, and corresponding material response for composite fuel tanks are significantly different than those associated with metallic structures. Also, the composite fuel tank problem presents challenges because the sensing systems must not provide a spark source. This challenge has lead to the development of SHM methodologies based on fibre-optic sensing systems. The overview Boller and Buderath (2007) provides a more detailed discussion of SHM applied to aerospace structures for the interested reader.

The civil engineering community has studied vibration-based damage assessment of bridge structures and buildings since the early 1980s. Modal properties and quantities derived from these properties such as modeshape curvature and dynamic flexibility matrix indices have been the primary features used to identify damage in bridge structures. Environmental and operating condition variability presents significant challenges in the bridge monitoring applications. The physical size of the structure also presents many practical challenges for vibration-based damage assessment. Regulatory requirements in Asian countries, which mandate that the companies that construct the bridges periodically certify their structural health, are driving current research and commercial development of bridge SHM systems. Good references on these specific issues are Brownjohn (2007); Lynch (2007) and a useful very recent collection of articles is by Karbhari and Ansari (2009). The International Society for Structural Health Monitoring of Intelligent Infrastructures (ISHMII) has emerged recently and has periodic conferences on SHM issues in civil engineering[8]. Some of the concerns with respect to civil infrastructure are highlighted in the chapter by Deraemaeker later in this volume.

In summary, the comprehensive reviews of the technical literature presented in Doebling et al. (1996); Sohn et al. (2003), show an increasing number of research studies related to damage identification. These studies identify many technical challenges to the adaptation of SHM that are common to all applications of this technology. These challenges include the development of methods to optimally define the number and location of the sensors, identification of the features sensitive to small damage levels, the ability to discriminate changes in these features caused by damage from those caused by changing environmental and/or test conditions, the development of statistical methods to discriminate features from undamaged and damaged structures, and performance of comparative studies of different damage identification methods applied to common data sets. These topics are currently the focus of various research efforts by many industries including defence, civil infrastructure, automotive, and semiconductor manufacturing where multi-disciplinary approaches are being used to advance the current capabilities of SHM and CM.

[8]SHMII - 4 Conference, ETH Zurich, Switzerland, 2009.

3 The Statistical Pattern Recognition Paradigm

There are many ways by which one can organise a discussion of SHM. The authors have chosen to follow the one described in the article Farrar et al. (2001), that defines the SHM process in terms of a four-step statistical pattern recognition paradigm. This process includes:

1. Operational evaluation,
2. Data acquisition, normalisation and cleansing,
3. Feature selection and information condensation, and,
4. Statistical model development for feature discrimination.

Almost all papers published in the fields of SHM and CM arguably address some parts of this paradigm, but the number of studies that address all portions of the paradigm is much more limited. An alternative approach to SHM which is often pursued is based on the solution of inverse problems using linear-algebraic methods; this is not discussed in any detail here, the reader can refer to Doebling et al. (1996); Sohn et al. (2003); Friswell (2007) for the background and further references.

3.1 Operational Evaluation

Operational evaluation attempts to answer four questions regarding the implementation of a damage identification capability:

1. What are the life-safety and/or economic justifications for performing the SHM?
2. How is damage defined for the system being investigated and, for multiple damage possibilities, which cases are of the most concern?
3. What are the conditions, both operational and environmental, under which the system to be monitored functions?
4. What are the limitations on acquiring data in the operational environment?

Operational evaluation begins to set the limitations on what will be monitored and how the monitoring will be accomplished. This evaluation starts to tailor the damage identification process to features that are unique to the system being monitored and tries to take advantage of unique features of the damage that is to be detected.

3.2 Data Acquisition, Normalisation and Cleansing

The data acquisition portion of the SHM process involves selecting the excitation methods, the sensor types, number and locations, and the data acquisition/storage/transmittal hardware. Again, this process will be application-specific. Economic considerations will play a major role in making these decisions. The intervals at which data should be collected is another consideration that must be addressed.

Because data can be measured under varying conditions, the ability to normalise the data becomes very important to the damage identification process. As it applies to SHM, data normalisation is the process of separating changes in sensor readings caused by damage from those caused by varying operational and environmental conditions. One of the most common procedures is to normalise the measured responses by the measured inputs. When environmental or operational variability is an issue, the need can arise to normalise the data in some temporal fashion to facilitate the comparison of data measured at similar times of an environmental or operational cycle. Sources of variability in the data acquisition process and with the system being monitored need to be identified and minimised to the extent possible. In general, not all sources of variability can be eliminated. Therefore, it is necessary to make the appropriate measurements such that these sources can be statistically quantified. Variability can arise from changing environmental and test conditions, changes in the data reduction process, and unit-to-unit inconsistencies. These issues are discussed in some detail in the chapter by Kullaa later in this volume; a recent survey on environmental variations in SHM which is of value is given in Sohn (2007).

Data cleansing is the process of selectively choosing data to pass on to or reject from the feature selection process. The data cleansing process is usually based on knowledge gained by individuals directly involved with the data acquisition. As an example, an inspection of the test setup may reveal that a sensor was loosely mounted and, hence, based on the judgment of the individuals performing the measurement, this set of data or the data from that particular sensor may be selectively deleted from the feature selection process. Signal processing techniques such as filtering and re-sampling can also be thought of as data cleansing procedures.

Finally, it should be noted that the data acquisition, normalisation, and cleansing portion of the structural health-monitoring process should not be static. Insight gained from the feature selection and statistical model development processes will invariably provide information regarding changes that can improve the data acquisition process. Issues relating to data acquisition and processing will be discussed in all of the later chapters in this book.

3.3 Feature Extraction and Information Condensation

The area of the structural health-monitoring process that receives the most attention in the technical literature is the identification of data features that allows one to distinguish between the undamaged and damaged structure. As such, the chapters in this book will devote considerable space to the feature extraction portion of SHM; in particular, the pattern recognition context of feature selection is the major focus of sections in the chapters by Kullaa and Worden. Inherent in the feature selection process is the condensation of the data. The best features for damage identification are, again, application-specific. In the context of vibration-based SHM, the features are usually those measurements associated with structural dynamic (or *modal*) testing. The extraction of dynamic parameters: frequencies, dampings, modeshapes etc., is an art in itself; the chapter by Reynders and De Roeck in this volume discusses an algorithm for this purpose which is state-of-the-art.

One of the most common feature extraction methods is based on correlating measured system response quantities, such as vibration amplitude or frequency, with first-hand observations of the degrading system. Another method of developing features for damage identification is to apply engineered damage, similar to that expected in actual operating conditions, to systems and develop an initial understanding of the parameters that are sensitive to the expected damage. The damaged system can also be used to establish that the diagnostic measurements are sensitive enough to distinguish between features identified from the undamaged and damaged systems. The use of analytical tools such as experimentally-validated finite element models can be a great asset in this process. In many cases the analytical tools are used to perform numerical experiments where the damage is introduced through computer simulation. Damage accumulation testing, during which significant structural components of the system under study are degraded by subjecting them to realistic loading conditions, can also be used to identify appropriate features. This process may involve induced-damage testing, fatigue testing, corrosion growth, or temperature cycling to accumulate certain types of damage in an accelerated fashion. Insight into the appropriate features can be gained from several types of analytical and experimental studies as described above and is usually the result of information obtained from some combination of these studies.

One of the main issues faced in using statistical classifiers in a SHM context is that the amount of *training data* - the *a priori* data needed in order to establish the diagnostic - grows explosively with the dimension of the feature vector. Because data sets acquired by engineering experimentation are typically small, it becomes crucial to reduce the dimension of feature vectors without compromising their information content. Many statistical (and other) methods are available for these purposes, including principal component analysis and factor analysis, techniques which are discussed in some detail in the later chapters by Kullaa and Worden.

The operational implementations of the diagnostic measurement technologies needed to perform SHM invariably produce more data than is traditional in the use of structural dynamics information. A condensation of the data is usually advantageous and can be essential when comparisons of many feature sets obtained over the lifetime of the structure are envisioned. Also, because data will be acquired from a structure over an extended period of time and in potentially many operational environments, robust data reduction techniques must be developed to retain feature sensitivity to the structural changes of interest in the presence of environmental and operational variability (again, the reader can consult Sohn (2007) for a survey). To further aid in the extraction and recording of the high-quality data needed to perform SHM, the statistical significance of the features should be characterised and used in the condensation process. The discipline of *data-mining* has emerged recently as a means of bringing together methods for the extraction of information from large data sets; however, although there are projects successfully applying data-mining in a SHM context Liang and Austin (2004), they are rather rare.

3.4 Statistical Model Development

The portion of the SHM process that has arguably received least attention in the technical literature is the development of statistical models for discrimination between features from the undamaged and damaged structures. Statistical model development is concerned with the implementation of algorithms that operate on the extracted features to quantify the damage state of the structure. The algorithms used in statistical model development usually fall into three categories. When data are available from both the undamaged and damaged structure, the statistical pattern recognition algorithms fall into the group concerned with *supervised learning*; Group classification and regression analysis are examples of learning algorithms which fall into this category. The term *unsupervised learning* refers to those algorithms that are applied to data *not* containing examples from the damaged structure. As engineering structures are typically produced at very high cost; unsupervised learning is often the only course of action as it is not economically viable to damage structures in order to produce data for supervised learning. The group of algorithms based around the idea of *outlier* or *novelty* detection is the primary one applied in the unsupervised learning context. All of the algorithms analyse statistical distributions of the measured or derived features to enhance the damage identification process.

The damage identification process for a system or structure can be summarised in terms of a hierarchical structure along the lines discussed in Rytter (1993); where the objective is to answer the following questions:

Existence: Is there damage in the system?;
Location: Where is the damage in the system?;
Type: What kind of damage is present?;
Extent: How severe is the damage?; and
Prognosis: How much useful life remains?

Answers to these questions in the order presented, represent increasing knowledge of the damage state. When applied in an unsupervised learning mode, statistical models are typically used to answer questions regarding the existence (and sometimes the location) of damage. When applied in a supervised learning mode and coupled with analytical models, the statistical procedures can be used to better determine the type of damage and the extent of damage. Prognosis of remaining useful life is more difficult and will usually require detailed physical models of the damage processes of interest and good predictions of the future loading regime of the structure of interest.

The statistical models are also required to minimise false indications of damage. False indications of damage fall into two categories: (1) False-positive damage indication (indication of damage when none is present), and (2) False-negative damage indication (no indication of damage when damage is present). Errors of the first type are undesirable as they will cause unnecessary downtime and consequent loss of revenue as well as loss of confidence in the monitoring system. More importantly, there are clear safety issues if misclassifications of the second type occur. Many pattern recognition algorithms allow one to weigh one type of error above the other, this weighting may be one of the factors decided at the operational evaluation stage.

The chapter by Worden later in this volume discusses pattern recognition approaches to SHM in detail and the chapter by Kullaa discusses some powerful statistical algorithms in detail.

4 Challenges for SHM

The basic premise of vibration-based SHM feature selection is that damage will significantly alter the stiffness, mass or energy dissipation properties of a system, which, in turn, alter the measured dynamic response of that system.

Although the basis for feature selection appears intuitive, its actual application poses many significant technical challenges. The most fundamental challenge is the fact that damage is typically a local phenomenon and may not significantly influence the lower-frequency global response of structures that is normally measured during system operation. (As an adjunct or alternative to vibration-based approaches to SHM, a number of strategies based on the use of high-frequency waves have developed as a means of detecting small damage; the last chapter of this book by Kudela and Ostachowicz, is concerned with one such approach.) Stated another way, this fundamental challenge is similar to that in many engineering fields where the ability to capture the system response on widely varying length and time scales, as is needed to model turbulence or to develop phenomenological models of energy dissipation, has proven difficult.

Another fundamental challenge is that in many situations feature selection and damage identification must be performed in an unsupervised learning mode; that is, data from damaged systems are not available. Damage can accumulate over widely varying time scales, which poses significant challenges for the SHM sensing system. This challenge is supplemented by many practical issues associated with making accurate and repeatable measurements over long periods of time at a limited number of locations on complex structures often operating in adverse environments.

Finally, a significant challenge for SHM is to develop the capability to define the required sensing system properties before field deployment and, if possible, to demonstrate that the sensor system itself will not be damaged when deployed in the field. If the possibility of sensor damage exists, it will be necessary to monitor the sensors themselves. This monitoring can be accomplished either by developing appropriate self-validating sensors or by using the sensors to report on each other's condition. Sensor networks should also be 'fail-safe'. If a sensor fails, the damage identification algorithms must be able to adapt to the new network. This adaptive capability implies that a certain amount of redundancy must be built into the sensor network.

In addition to the challenges described above, there are other nontechnical issues that must be addressed before SHM technology can make the transition from a research topic to actual practice. These issues include convincing structural system owners that the SHM technology provides an economic benefit over their current maintenance approaches and convincing regulatory agencies that this technology provides a significant life-safety benefit. All these challenges lead to the current state of SHM technology, where outside of condition monitoring for rotating machinery applications, SHM remains a research topic that is still making the transition to field demonstrations and subsequent field deployment. There are lots of ongoing and new structural monitoring activities, but these systems have been put in place without a pre-defined damage to be detected and without the corresponding data interrogation procedure. As such, these monitoring activities do not represent a fully integrated hardware/software SHM system with pre-defined damage identification goals. A final non-technical challenge is concerned with providing the educational materials and opportunities for engineers to learn the (rapidly-developing) state-of-the-art in SHM technologies and analysis.

5 Concluding Remarks

The development of robust SHM technologies has many elements that make it a potential "Grand Challenge" for the engineering community. First, almost every industry wants to detect damage in its structural and mechanical infrastructure at the earliest possible time. Industries' desire to perform such monitoring is based on the tremendous economic and life-safety benefits that this technology has the potential to offer. However, as previously mentioned with the exception of rotating machinery condition monitoring, there are few examples of where this technology has made the transition from research to practice.

Significant future developments of this technology will, in all likelihood, come by way of multi-disciplinary research efforts encompassing fields such as structural dynamics, signal processing, motion and environmental sensing hardware, computational hardware, data telemetry, smart materials, and statistical pattern recognition, as well as other fields yet to be defined. These topics are the focus of significant discipline-specific research efforts, and it is the authors' speculation that to date not all technologies from these fields that are relevant to the SHM problem have been explored by the SHM research community. Furthermore, there are few efforts that try to advance and integrate these technologies with the specific focus of developing SHM solutions. Without such a focus in mind, these technologies may well evolve in manner that is not optimal for solving the SHM problem. Finally, the problem of global SHM is so significantly complex and diverse that it will not be solved in the immediate future. Like so many other technology fields, advancements in SHM will most likely come in small increments requiring diligent, focused and coordinated research efforts over long periods of time.

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