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An introduction to structural health monitoring

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The process of implementing a damage identification strategy for aerospace, civil and mechanical engineering infrastructure is referred to as structural health monitoring (SHM). Here, damage is defined as changes to the material and/or geometric properties of these systems, including changes to the boundary conditions and system connectivity, which adversely affect the system's performance. A wide variety of highly effective local non-destructive evaluation tools are available for such monitoring. However, the majority of SHM research conducted over the last 30 years has attempted to identify damage in structures on a more global basis. The past 10 years have 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 theme issue.

This introduction begins with a brief history of SHM technology development. Recent research has begun to recognize that the SHM problem is fundamentally one of the statistical pattern recognition (SPR) and a paradigm to address such a problem is described in detail herein as it forms the basis for organization of this theme issue. In the process of providing the historical overview and summarizing the SPR paradigm, the subsequent articles in this theme issue are cited in an effort to show how they fit into this overview of SHM. In conclusion, technical challenges that must be addressed if SHM is to gain wider application are discussed in a general manner.

Keywords: structural health monitoring; condition monitoring; non-destructive testing/evalution

1. Introduction

In the most general terms, *damage* can be defined as changes introduced into a system that adversely affect its current or future performance. Implicit in this definition is the concept that damage is not meaningful without a comparison between two different states of the system, one of which is assumed to represent the initial, and often undamaged, state. This theme issue is focused on the study

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One contribution of 15 to a Theme Issue 'Structural health monitoring'.

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 a 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 a 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 accumulation. 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 phenomena hazards such as earthquakes.

The process of implementing a damage identification strategy for aerospace, civil and mechanical engineering infrastructure is referred to as *structural health monitoring* (SHM). This 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 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 is 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 & Dulieu-Barton (2004).

Damage identification is carried out in conjunction with five closely related disciplines that include SHM, condition monitoring (CM; Bentley & Hatch 2003), non-destructive evaluation (NDE; Shull 2002), statistical process control (SPC; Montgomery 1997) and damage prognosis (DP; which is summarized within this theme issue in Farrar & Lieven (2007); see also Farrar *et al.* (2003)). Typically, SHM is associated with online–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 those used in manufacturing and power generation. NDE is usually carried out off-line in a local manner after the damage has been located. 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 characterization 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. This theme issue will primarily address SHM and CM, and will conclude with an article that introduces the damage prognosis problem.

(a) *Motivation for SHM technology development*

Almost all private and government industries 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 minimize 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 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 that can be used to significantly minimize 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 is the technology 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 realized 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.

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 maintenance of that equipment. SHM has the potential to extend the maintenance cycles and, hence, keep the equipment out in the field where it can continue to generate revenues 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 realized without the ability to monitor the damage initiation and evolution in the rental hardware.

(*b*) *Motivation for this theme issue*

Directly reflecting the increased interest in this emerging technology, there have been several new conferences developed in the last 8 years that focus directly on SHM.[1–4] Conferences related to the condition monitoring 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. These conferences have also shown that many technical disciplines must be integrated to properly address the SHM problem. In addition, the first refereed journal devoted specifically to SHM has recently been initiated.[7] The proceedings of these conferences as well as the extensive number of refereed journal articles devoted to various aspects of SHM show that significant knowledge and experiences have been gained through the reported studies. Therefore, this *Phil. Trans. R. Soc. A* issue is devoted to this topic in an effort to provide the engineering community with an up to date overview of SHM technology.

2. Brief historical overview

It is the authors' speculation 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, miniaturization 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 30 years is presented below. Specific references are not cited, instead the reader is referred to Doebling *et al.* (1996), Sohn *et al.* (2003) and Randall (2004*a*,*b*) for more detailed summaries of this subject.

To date, the most successful application of SHM technology has been for CM of rotating machinery. The rotating machinery application has taken an almost exclusive non-model based approach to damage identification. The identification process is based on pattern recognition applied to displacement, velocity or acceleration time histories (or spectra) generally measured at a single point on the

[1] The Fourth International Structural Health Monitoring Workshop, Palo Alto, CA, 2003.

[2] The Sixth International Symposium on Nondestructive Evaluation of Aging Infrastructure, San Diego, CA, 2003.

[3] The Fifth International Conference on Damage Assessment of Structures, Southampton, UK, 2003.

[4] The Second European SHM Workshop, Munich, Germany, 2004.

[5] Condition Monitoring And Diagnostic Engineering Management, COMADEM, Cambridge, UK, 2004.

[6] The 58th Meeting of the Society for Machinery Failure and Prevention Technology, Virginia, Beach, VA, 2004.

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

housing or shafts of the machinery during normal operating conditions and start up or shutdown 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. 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 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 (i) minimal operational and environmental variability associated with this type of monitoring, (ii) well-defined damage types that occur at known locations, (iii) large databases that include data from damaged systems, (iv) well-established correlation between damage and features extracted from the measured data, and (v) clear and quantifiable economic benefits that this technology can provide. These factors have allowed this application of SHM to have made the transition from a research topic to industry practice several decades ago resulting in comprehensive condition management systems such as the US Navy's Integrated Condition Assessment System.

During the 1970s and 1980s, the 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 unknown 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 resonant 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, varying fluid storage levels, temporal variability of foundation conditions and the inability of wave motion to excite higher vibration modes. These issues prevented adaptation of this technology and efforts at further developing this 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 SMIS 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 structures. 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 to those associated with metallic structures. Moreover, the composite fuel tank problem presents challenges because the sensing systems must not provide a spark source. This challenge has led to the development of SHM based on fibre optic sensing systems. Boller & Buderath (2007) provide a more detailed discussion of SHM applied to aerospace structures in a subsequent article contained in this theme issue.

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 mode shape 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 to the bridge monitoring application. 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. In this theme issue, articles by Brownjohn (2007) and Lynch (2007) discuss further the applications of SHM to civil engineering infrastructure.

In summary, the review of the technical literature presented by Doebling *et al.* (1996) and Sohn *et al.* (2003) shows 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 datasets. 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.

3. The statistical pattern recognition paradigm

There are many ways by which one can organize a discussion of SHM. The authors have chosen to follow the one described in a previous *Phil. Trans. R. Soc. A* article (Farrar *et al.* 2001) that defines the SHM process in terms of a four-step statistical pattern recognition paradigm. This following four-step process includes:

(i) operational evaluation,
(ii) data acquisition, normalization and cleansing,
(iii) feature selection and information condensation, and
(iv) statistical model development for feature discrimination.

All papers published in the fields of SHM and CM address some parts of this paradigm, but the number of studies that address all portions of the paradigm is much more limited.

(*a*) *Operational evaluation*

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

(i) What are the life-safety and/or economic justification for performing SHM?
(ii) How is damage defined for the system being investigated and, for multiple damage possibilities, which cases are of the most concern?
(iii) What are the conditions, both operational and environmental, under which the system to be monitored functions?
(iv) 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.

(*b*) *Data acquisition, normalization 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 interval at which the data should be collected is another consideration that must be addressed.

As data can be measured under varying conditions, the ability to normalize the data becomes very important to the damage identification process. As it applies to SHM, data normalization is the process of separating changes in sensor reading caused by damage from those caused by varying operational and environmental conditions. One of the most common procedures is to normalize the measured responses by the measured inputs. When environmental or operational variability is an issue, the need can arise to normalize 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 minimized 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.

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 the knowledge gained by individuals directly involved with the data acquisition. As an example, an inspection of the test set-up 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 resampling can also be thought of as data cleansing procedures.

Finally, it should be noted that the data acquisition, normalization and cleansing portion of the SHM process should not be static. Insight gained from the feature selection process and the statistical model development process will provide information regarding changes that can improve the data acquisition process. A number of articles contained in this theme issue specifically address various aspects of the data acquisition and data normalization issues as they apply to SHM (Lynch 2007; Sohn 2007; Park & Inman 2007; Todd *et al.* 2007).

(*c*) *Feature extraction and information condensation*

The area of the SHM 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, numerous articles in this theme issue are devoted to the feature extraction portion of SHM (Fassois & Sakellariou 2007; Friswell 2007; Mal *et al.* 2007; Staszewski & Robertson 2007). Inherent in this feature selection process is the condensation of the data. The best features for damage identification are, again, application specific.

One of the most common feature extraction methods is based on correlating measured system response quantities, such as vibration amplitude or frequency, with the first-hand observations of the degrading system. Another method of developing features for damage identification is to apply engineered flaws, similar to ones expected in actual operating conditions, to systems and develop an initial understanding of the parameters that are sensitive to the expected damage. The flawed system can also be used to validate that the diagnostic measurements are sensitive enough to distinguish between features identified from the undamaged and damaged system. 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 flaws are 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.

The operational implementation and diagnostic measurement technologies needed to perform SHM produce more data than traditional uses of structural dynamics information. A condensation of the data is advantageous and necessary 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 an operational environment, 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. To further aid in the extraction and recording of quality data needed to perform SHM, the statistical significance of the features should be characterized and used in the condensation process.

(*d*) *Statistical model development*

The portion of the SHM process that has received the 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 the 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 general classification referred to as *supervised learning*. *Group classification* and *regression analysis* are categories of the supervised learning algorithms. *Unsupervised learning* refers to algorithms that are applied to data not containing examples from the damaged structure. *Outlier* or *novelty detection* is the primary class of algorithms applied in unsupervised learning applications. All of the algorithms analyse statistical distributions of the measured or derived features to enhance the damage identification process.

The damage state of a system can be described as a five-step process along the lines of the process discussed in Rytter (1993) to answer the following questions.

(i) *Existence*. Is there damage in the system?
(ii) *Location*. Where is the damage in the system?
(iii) *Type*. What kind of damage is present?
(iv) *Extent*. How severe is the damage?
(v) *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 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, the extent of damage and remaining useful life of the structure. The statistical models are also used to minimize false indications of damage. False indications of damage fall into two categories: (i) *false-positive* damage indication (indication of damage when none is present) and (ii) *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. Articles appearing within this theme issue that focus on the statistical modelling portion of the SHM process include Hayton *et al.* (2007), Sohn (2007) and Worden & Manson (2007).

4. Challenges for SHM

The basic premise of 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. 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 non-technical 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.

5. Theme issue organization

This theme issue has organized the articles in the context of statistical pattern recognition paradigm. It is the authors' opinion that all studies that have been published in this field address one or more parts of this paradigm. Articles have been solicited that specifically address parts 2–4 of the paradigm. In addition, a group of three articles have been included that summarize current applications of this technology to machinery monitoring, aerospace structures and civil infrastructure. This theme issue concludes with an article on damage prognosis, which is the prediction of a system's remaining life given the current assessment of structural health and some estimate of future loading environments. Damage prognosis has just recently emerged as a topic of large-scale, multi-disciplinary research efforts.

The articles contained herein attempt to strike a balance between providing an overview of the subject matter (including issues, challenges, current limitations and successes associated with the respective technology) while showing some specific applications and results. Throughout the issue, emphasis will be placed on the need to take an integrated approach to the development of SHM solutions by coupling the measurement hardware portions of the problem directly with the data interrogation algorithms.

6. Concluding comments

The development of robust SHM technology 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 not evolve in a manner that is not necessarily optimal for solving the SHM problem. Finally, the problem of global SHM is 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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