LA-UR- 09-04362

Approved for public release;
distribution is unlimited.

Title: Structural Health Monitoring for Ship Structures

Author(s): Charles Farrar, INST-OFF
Gyuhae Park, INST-OFF
Marian Angel, CCS-3
Matthew Bement, X-3
Liming Salvino, Naval Surface Warfare Center, Caderock

Intended for: 7th International Workshop on Structural Health Monitoring
Stanford University
Palo Alto, CA
September 9-11, 2009

Los Alamos
NATIONAL LABORATORY
EST. 1943

Cover page

09-04362

Title: *Structural Health Monitoring for Ship Structures*
Proceedings of the 7th International Workshop on Structural Health Monitoring 2009

Authors: Charles Farrar
Gyuhae Park
Marian Angel
Matthew Bement
Liming Salvino

(FIRST PAGE OF ARTICLE)

ABSTRACT

Currently the Office of Naval Research is supporting the development of structural health monitoring (SHM) technology for U.S. Navy ship structures. This application is particularly challenging because of the physical size of these structures, the widely varying and often extreme operational and environmental conditions associated with these ships' missions, lack of data from known damage conditions, limited sensing that was not designed specifically for SHM, and the management of the vast amounts of data that can be collected during a mission. This paper will first define a statistical pattern recognition paradigm for SHM by describing the four steps of 1.) Operational Evaluation, 2.) Data Acquisition, 3. Feature Extraction, and 4.) Statistical Classification of Features as they apply to ship structures. Note that inherent in the last three steps of this process are additional tasks of data cleansing, compression, normalization and fusion. The presentation will discuss ship structure SHM challenges in the context of applying various SHM approaches to sea trials data measured on an aluminum multi-hull high-speed ship, the *HSV-2 Swift*. To conclude, the paper will discuss several outstanding issues that need to be addressed before SHM can make the transition from a research topic to actual field applications on ship structures and suggest approaches for addressing these issues.

INTRODUCTION

The extensive literature on structural health monitoring (SHM) has documented the critical importance of detecting damage in structural systems at the earliest possible time. As a result the Office of Naval Research is now sponsoring applied research activities that are investigating the application of SHM to ship structures. This paper will summarize the challenges associated with this application. It is

Charles Farrar, Gyuhae Park, Marian Angel, Matthew Bement, Los Alamos National Laboratory, Los Alamos, New Mexico 87545, USA.
Liming Salvino, Structures and Composites, Code 65, Naval Surface Warfare Center, Carderock Div., 9500 Mac Arthur Blvd., West Bethesda, MD 20817, USA

emphasized that this paper focuses on SHM applied to ship structures as opposed mechanical systems onboard the ship. The reader is referred to the literature on the U.S. Navy's Integrated Condition Assessment System (ICAS) for a more detailed summary damage detection in ship mechanical systems [1].

One monitoring technique available for ship structures is vibration-based damage detection, which is based on the principal that damage in a structure, such as material yielding, a loosened connection or a crack, will alter the dynamic response of that structure. There has been much recent work in this area that is summarized in detailed reviews of vibration-based SHM [2,3]. Because of random and systematic variability in experimentally measured dynamic response data, statistical approaches are necessary to ensure that changes in a structure's measured dynamic response are a result of damage and not caused by operational and environmental variability. Although much of the vibration-based SHM literature focuses on deterministic methods for identifying damage from changes in dynamic system response, we will focus on approaches that follow a statistical pattern recognition paradigm for SHM [4]. This paradigm consists of the four steps of 1. Operational evaluation, 2. Data acquisition, 3. Feature extraction, and 4. Statistical classification of features. Each portion of the paradigm will now be discussed in the context of applying it to damage detection in ship structures.

THE STATISTICAL PATTERN RECOGNITION PARADIGM FOR SHM APPLIED TO SHIP STRUCTURES

The statistical pattern recognition paradigm for SHM will now be defined in more detail. Each subsection of this discussion attempts to highlight how the portions of this paradigm apply to SHM for ship structures in general and the HSV-2 *Swift* sea trials specifically (shown in Fig. 1). The HSV-2 *Swift* is a 98 meter wave-piercing catamaran that has been built to U.S. Navy specifications by Revolution Design in Tasmania, Australia. This high-speed vessel has gone through sea trials to establish safe operating limits based on performance measured obtained in calm water powering trails and rough water seakeeping and structures trials. During the sea trials strain gages and accelerometers were used to monitor the ship's structural response. Ship control functions and wind-wave environments were also monitored. Structural instrumentation included primary load strain ages, stress concentration strain gages, secondary load strain gages and strain ages used to monitor specific equipment locations such as the ramp and crane. A detailed summary of the instrumentation and testing protocol can be found in [5].

OPERATIONAL EVALUATION APPLIED TO SHIP STRUCTURES

Operational evaluation attempts to answer four questions regarding the implementation of a damage identification capability: 1. What are the life-safety and/or economic justification 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.

For most large defense systems, the lifetime maintenance costs typically exceed the purchase price of those systems. Therefore, there is significant economic advantage to be gained by reducing these maintenance costs, which motivates the development of SHM systems for ship structures. Clearly, because people will be operating these ships in adverse environments, both man-made and natural, a robust SHM system can potentially prevent harm to the crew by alerting the operators to damage before it reaches a critical state. Therefore, there is also a life-safety motive for developing SHM systems for these ships.

For the HSV-2 *Swift* ship it is anticipated that three types of damage are of interest: 1. Yielding of structural elements, 2. Crack initiation and propagation (particularly at joints), and 3. Corrosion. However, there is no *a priori* knowledge of where this damage might occur and no definition of critical levels of damage that must be detected. Corrosion is not considered in any of the subsequent analyses of the sea trials primarily because it was felt that the instrumentation system used was not adequate to detect this type of damage and because the age of the ship and the short duration of the sea trials make corrosion an unlikely damage condition.

During the sea trials data were acquired in a variety of operational and environmental conditions including different ship speeds, different heading relative to the wave direction and different sea states [5]. Similar variations will be encountered when ships are deployed on their various missions. Other than variations in fuel loads, the mass of the ship does not appear to have changed in these sea trials and this variable has not been considered in the analyses of these sea trials data. However, careful consideration of variable mass loading will be necessary for an operational vessel carrying different military stores, and particularly if ice buildup is a possibility. Note that many of the ship's operational parameters (e.g. engine rpms, and ship speed) are currently monitored and can be recorded along with the primary SHM sensor readings. Such operational data will be key to the data normalizations process.

Because the current study did not design the data acquisition system, but rather is analyzing previously acquired data, answers to most of the Operational Evaluation questions regarding deployment of the data acquisition system were not addressed. For an aluminum structure limitations associated with data acquisition result from the physical size of the structure, wire maintenance, difficulties with wireless data transmission in metallic structures and issues such as insulation covering the structural elements. It is anticipated that a significant outcome of this study will be insight gained from analysis of these sea trials data that can be used to answer the Operational Evaluation questions when a system designed specifically for ship SHM is develop in the future.

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. This process will be application specific.

Figure 1. **All aluminum high-speed vessel HSV –2 *Swift***

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. Again, the data acquisition system for the HSV-2 *Swift* was previously defined, so this portion of the SHM process has not been specifically addressed in this study. Data utilized in this study represent dynamic ship structure response measurement including strain and acceleration intended to capture both local and global ship structure response. However, as previously mentioned, this sensing system was not designed with SHM in mind. There is a clear need for developing an optimal SHM sensing strategy based on the defined threshold levels of damage (identified during Operational Evaluation) and in consideration of a fixed sensing budget. However, currently a significant gap in SHM technology is the lack of any validated sensor network design procedure.

Because data can be measured under varying conditions, the ability to normalize the data becomes very important to the damage identification process. Figure 2 shows an example of two different strain measurements made while operating the ship at different speeds. A robust damage detection system will have to be able to normalize the data to account for such sources of variability. 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. 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 operational conditions, changes in the data reduction process, and unit-to-unit inconsistencies. For the HSV-2 *Swift* data such as ships speed, fuel levels and headings relative to the wave direction are measured and can be use to develop a data normalization scheme.

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. Signal

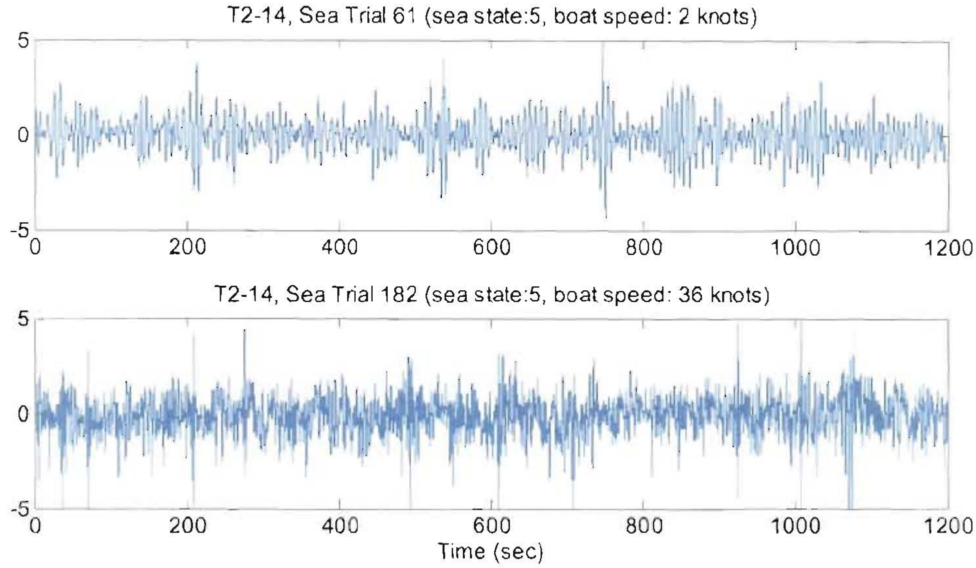

Figure 2. **Variability in dynamics response resulting when measurements were made with the ships operating at different speeds.**

processing techniques such as filtering and re-sampling can also be thought of as data cleansing procedures. In this study we have relied upon one of the co-author's familiarity with these sea trials to select specific data sets for subsequent analyses. It was assumed that all the sensors are functioning properly for these data sets.

FEATURE EXTRACTION AND INFORMATION CONDENSATION

A damage-sensitive *feature* is some quantity extracted from the measured system dynamic response data that is used to indicate the presence of damage in a structure. Identifying features that can accurately distinguish a damaged structure from an undamaged one is the focus of most SHM technical literature. Fundamentally, the feature extraction process is based on fitting some model, either physics-based or data-based, to the measured system response data. The parameters of these models or the predictive errors associated with these models then become the damage-sensitive features. As an example, Figure 3 shows the prediction of order 15 autoregressive time series model to the measured strain gage from the HSV-2 *Swift*. As can be seen in this figure, the time series model accurately models the response data and subsequent changes in this modeling capability can be used as an indicator of damage. An alternate approach is to identify features that directly compare the data waveforms or spectra of these waveforms.

Ideally one should select a feature that is sensitive to the presence of damage in the structure and insensitive to all forms of operational and environmental variability. However, in most real-world applications, features that are sensitive to damage are also sensitive changes in the dynamic system response not related to damage [6]. If multiple types of damage are possible, as is the case with HSV-2 *Swift*, it may require different features to be extracted from the data in an effort to identify these different types of damage.

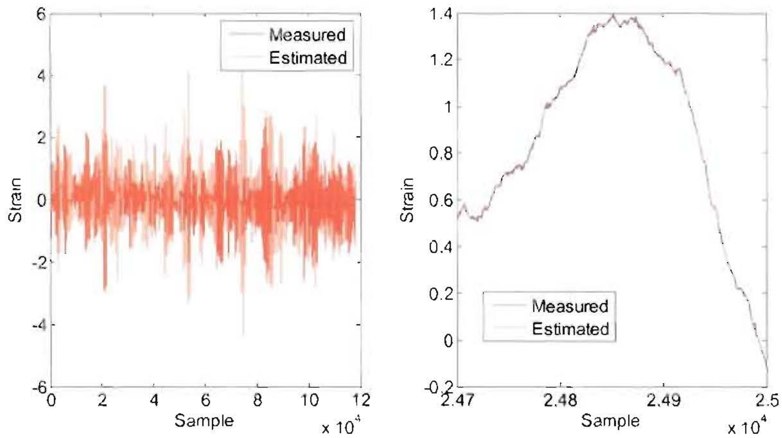

Figure 3: Comparison of the measured and estimated time histories using the AR(15) model fit to Run 61 from strain gage T2-14.

One of the most common methods of feature extraction is based on correlating observations of measured system response quantities with the first-hand observations of the degrading system made by the system operators or maintenance personnel. Another method of developing features for damage detection 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 subjected to a realistic degradation, 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. Note that any such destructive testing approaches to feature identification can be costly and are typically prohibitively expensive for large capital expenditure systems such as ship structures. Insight into the appropriate features can be gained from several sources and is usually the result of information from some combination of these sources.

With the HSV-2 *Swift* in mind, crack formation will be accompanied by local strain relief that manifests itself as a DC offset in the local strain gage readings. However, based on St. Venant's Principle, this strain relief will not be observed at any significant distance from the crack location. Yielding is also associated with DC offsets in local strain readings resulting from the permanent deformation that characterizes this phenomena. Yielding is particularly difficult to detect in metallic structures based on dynamic response measurements because once the load that produced yielding has been removed, the structure typically exhibits similar stiffness properties as it did prior to yielding. If crack opens and closes under subsequent loading then there will be specific features such a harmonic generation that are indicative of this process. Also, crack initiation and growth is usually accompanied by the propagation of an elastic wave and the transient response associated with such an event can be detected with a strain gage, acoustic emissions sensor or accelerometer given appropriate location of these sensors, appropriate sensitivity of the sensors and appropriate sampling parameters.

STATISTICAL MODEL DEVELOPMENT

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 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 analyze 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 four-step process to answers the following questions: 1. **Existence**: Is there damage in the system?; 2. **Location**: Where is the damage in the system?; 3. **Type**: What kind of damage is present?; 4. **Extent**: How severe is the damage? Answers to these questions in the order presented represent increasing knowledge of the damage state.

In this study we are primarily concerned with identifying the *Existence* of damage in an unsupervised learning mode. The use of unsupervised approached is motivated by our lack of knowledge regarding the damage condition corresponding to any of the data sets made available for this study and by the fact that a SHM system deployed on a ship will most likely have to function in an unsupervised learning mode. Because three of the damage types identified as concerns for aluminum ship structures (corrosion, cracking and yielding) have distinct characteristics, we believe it is possible to address the *Type* of damage question as well. Because the ship is sparsely instrumented relative to its size, it is not clear if the *Location* question can be adequately addressed if damage has the potential to occur at random locations over wide areas of the ship's structure. Most structural systems have areas that are more susceptible to damage than other, and ideally instrumentation is concentrated in these areas. In the case of the HSV-2 *Swift*, we assume that the local T2 strain gages has been placed with this consideration in mind, but it is not clear if there are additional locations of concern without local strain measurements.

SUMMARY

The U.S. Navy has a tradition of proactive damage detection capability development for ship machinery. More recently, in the interest of reducing lifecycle costs and increasing combat asset readiness, the Office of Naval Research has begun to develop a comparable capability for damage detection in ship structures. This paper has presented a four-step statistical pattern recognition paradigm that the authors believe must be used to guide the development of SHM for ship structures. There are many technical challenges associated with this SHM application. These challenges include (but certainly are not limited to) the ability to define the damage to be detected in a quantifiable manner *a priori*, the ship's physical size, designing the SHM data acquisition system, the widely varying operational and environmental conditions, and the management of the large data volumes that will be obtained with an SHM system (not discussed herein because of length restrictions). However, the authors believe that following this paradigm through a sustained SHM system development and validation process can lead to a robust deployed SHM system that will yield a positive rate of return on investment for the U.S. Navy.

ACKNOWLEDGEMENT

This work was funded by the Office of Naval Research Structural Reliability Program under the direction Dr. Paul Hess.

REFERENCES

1 DiUlio, M., C. Savage, C., B. Finley, B. and E. Schneider, (2003) "Taking the Integrated Condition Assessment System to the Year 2010," *13th Int. Ship Control Systems Symposium*, Orlando, Fl.

2 Doebling, S., Farrar, C., Prime, M., Shevitz, D. (1998) "A Review of Damage Identification Methods that Examine Changes in Dynamic Properties," *Shock and Vibration Digest*. 30:91-105.

3 Sohn, H., Farrar, C.R., Hemez, F.M., Shunk, D.S., Stinemates, D.W., Nadler, B.R., and Czarnecki, J.J. (2004). *"A Review of Structural Health Monitoring Literature from 1996-2001."* Los Alamos Nat. Lab report LA-13976-MS.

4 Farrar, C.R. and Worden, K. (2007). "An Introduction to Structural Health Monitoring." *Philosophical Transactions of the Royal Society A*. 365:303-315.

5 Brady, T. F., R. J. Bachman, M. J. Donnelly and D. B. Griggs (2004) " HSV-2 *Swift* Instrumentation and Technical Trials Plan," Technical report, Naval Surface Warfare Center. Carderock report NSWCCD-65-TR-2004/18.

6 Worden, K., Farrar, C. R., Manson, G. and Park, G. (2007) "The Fundamental Axioms of Structural Health Monitoring," *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences* Issue **463** (2082).