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# Nondestructive Evaluation and Self-Monitoring Materials

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# EXECUTIVE SUMMARY

Development of self-diagnostic materials in complex mechanical systems is a realistic goal which can be achieved by a systems approach to monitoring. A viable program to accomplish this result will require closely-linked activities in each of four categories:

1. Development of a database of machine diagnostics under normal operation by running a continuous monitoring program using state-of-the art materials sensors and data acquisition technology, guided by existing NDE experience on the system of interest. The HUMS (Health and Usage Monitoring System) helicopter diagnostic program may serve as a point of close interaction for such field research.
2. Research in systems analysis to improve predictive capabilities based on the data being established in 1). Results from this research will be used as feedback to improve the choice of sensors, sensor placing, and measurement timing in 1). A UAV system could prove to be a valuable test-bed for pushing the envelope of predictive capabilities.
3. Improved understanding and physical interpretation of the sensor signals in configurations relevant to those being used in 1) and 2). This understanding will be used to tailor the algorithms used in the analysis to the specific characteristics of the mechanical system.
4. Development of new sensing technologies which can be added to the system of monitors for improved functionality in continuing upgrades of the NDE system.

The categories are listed in order of priority. In particular, without activity in the first category, the benefits resulting from the activities in the remaining categories will serve long-term rather than more immediate needs.

# 1 INTRODUCTION

Quality management to provide improved maintenance of mechanical systems, such as aircraft, at decreased cost is an increasing requirement in both the military and civilian world. The issue is particularly pressing as the use-lifetime of complex military equipment is extended, sometimes well beyond the original equipment design lifetime. The pressure to extend the use of currently available systems is still further increased because unlike situations in prior generations of the military acquisition cycles, little or no new aircraft are being procured. Obsolescence is now being defined by the operational lifetime of the equipment in the field, as opposed to the interval defined by technology obsolescence and/or technology advances that dictated new acquisitions to procure improved military capabilities.

The traditional maintenance approach of overhaul or replacement at fixed time intervals is costly, because the time intervals must be set conservatively to insure safety. Furthermore, as equipment ages past its original design lifetime, inspections must be performed more frequently and thoroughly, increasing the cost still further. As one example, failures of the Navy's H-46 helicopter rotor head, which was operated in helicopters for over twice its original design lifetime, now necessitate one hour of inspection on such equipment for every hour of flight. This problem will only get more severe as the existing military fleet ages even further.

The perfect system would be one that announced its maintenance needs in a clear and timely fashion – in other words, the materials system would be “self-monitoring”. In concept, self-monitoring requires continuous (or frequent time interval) sampling of some physical signals from the system, coupled with a predictive understanding of how these signals relate to system health. This is easier said than done. However, as we will discuss in more detail below, this function can be accomplished using an iterative combination of physical understanding, experience in testing, and intelligently designed change-detection techniques.

This report is a response to a request from DARPA for a JASON study to evaluate existing and novel approaches to condition-based maintenance. Our guidance was to avoid the area of "smart materials", which is by itself an active area of research with which DARPA is quite familiar. In addition, the JASON study was narrowed to exclude the research area devoted to developing self-healing materials, i.e., materials that not only detect a change and produce a signal when the change occurs, but which also deform or reorganize structurally at either the macroscopic or microscopic level to counteract any harmful operational effects due to such changes. Instead, the JASON study focused primarily on methods through which condition-based maintenance could be facilitated, improved, and/or enhanced.



## 2 BACKGROUND

Even a superficial scan of the literature reveals that non-destructive evaluation (NDE) is a healthy, thriving field in many engineering departments of universities as well as in civilian and military establishments around the globe. For instance, there are extensive activities at Wright-Patterson Air Force Base (<http://www.ml.afrl.af.mil/divisions/mlm/mlp.html>), at Westinghouse Inc., and at a variety of other installations, with indices to NDE sites available in several locations. Any number of advanced technologies are being explored, and methods being developed span the gamut from time-resolved optical methods that are sensitive to local strains in materials to methods for encapsulating chemicals such that when a defect is formed, the chemical is released and a characteristic odor, which signals the presence of a defect in the part, is generated.

In contrast, NDE as practiced currently in the field in military situations is cumbersome, time-consuming, and costly. Operators scan areas as large as airplane fuselages by hand, painstakingly searching for a possible defect in a largely defect-free structure; furthermore, operators often cannot even see the display that records whether an anomaly is present or not during a segment of their search. In other cases, operators must attempt to squeeze complicated instrumentation into areas with limited physical access, areas that are around corners, etc. and still verify whether the part of concern is defective or not.

The problem, as defined to the JASON study members, involves not merely finding a crack or defect in a mechanical object (typically an aircraft wing, helicopter rotor head, etc.), but specifically finding a crack that will lead to imminent failure of the structure/component in question. Cracks below a certain size or shape abound in aging parts, but such cracks by themselves are not generally considered to be of major concern. In contrast, cracks that may lead to imminent failure demand prompt identification so that remediative action can be promptly taken. Improving diagnostic un-

derstanding to distinguish benign from dangerous cracks is an important component of developing a "self-monitoring" system. To complicate the situation further, such crack features are not particularly likely to be located at an easily observable surface location. Instead they may be below the surface of the part, or hidden in a joint or under a fastener. Additionally, the crack or defect could be in parts constructed of metals (ferrous or not) or of composite materials. Still another complication is that the shape of the parts/structures is typically complex (e.g. a helicopter rotor hub), although in some cases simpler large scale structures (airplane wings and fuselages) are also of concern. Throughput is therefore compromised in a trade-off with fleet readiness, training and operations constraints, and in most cases only limited suspect areas are inspected, and typically on a time-based schedule instead of on a condition-based schedule. In addition, detailed records of the historical state of an individual aircraft or component are typically not kept. Points of concern are noted and carried over, but otherwise each inspection is typically performed de novo.

Alternatives to traditional maintenance approaches are under development. As part of this study, we were briefed by the Navy on a developmental program in preventive maintenance, the HUMS (Health and Usage Monitoring System) program. In this program, the applicability of an integrated maintenance and monitoring system that was developed for commercial British rotorcraft is being tested on one Navy SH-60B helicopter. The components of the integrated system are illustrated in Figure 1. Optical trackers have been installed to allow a much easier alignment of the helicopter rotors. In addition, in situ monitors (primarily velocimeters and accelerometers) have been installed at key points on the helicopter frame, along with a data acquisition unit that continuously monitors their output during flight. This system has been in use for approximately three years, and 2100 flight hours, and has earned high praise from the pilots and system engineers involved in the program for its savings in maintenance effort and cost, and improvement in safety. Even with relatively simple, off-line data analysis and display capabilities, the continuous monitors have proven to be capable of providing key information for understanding flight anomalies. Personnel

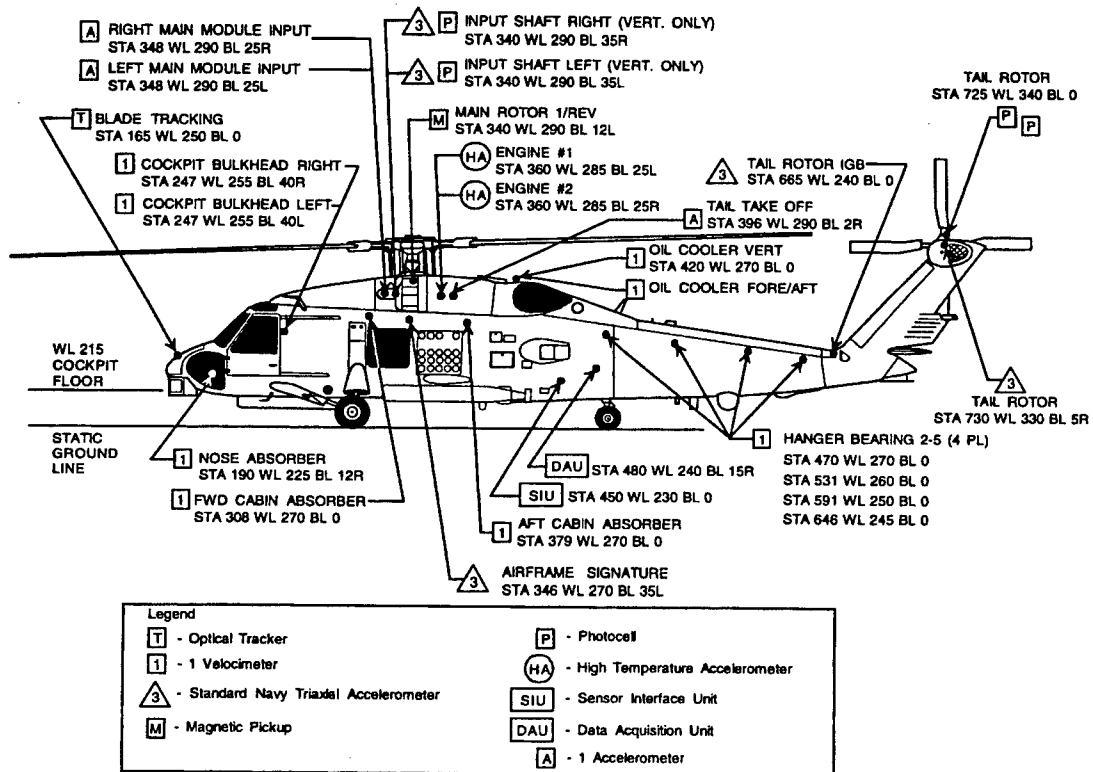


Figure 1: Distributed sensor suite used on the SH-B60 helicopter in the HUMS program.

involved in the program strongly urged that the system be broadly implemented in its present form, while further system improvements are being developed under the JAHUMS program.

### 3 OVERARCHING STRATEGY FOR NDE

The overarching strategy that emerged from this background material is based on the knowledge that of the many cracks or corrosion points, those that will lead to imminent failure are rare events. Thus, in screening a component or structure, focusing on the location of the crack/defect may not be the optimum approach; instead, it may be more efficient to diagnose an anomaly in performance. One can then inspect the suspect structure more closely in order to diagnose the origin of the anomaly, and steps can then be taken to remediate the problem. Moreover, the more frequently one can inspect structures, the more likely one is to find cracks/defects before they have propagated to a critical size that will lead to imminent failure.

The primary basic recommendation of the JASON study is that a significant enhancement in the field-effectiveness of NDE can be achieved by taking advantage of modern advances in our ability to store large amounts of information and thereby compile and archive the historical record of many components and structures of concern. Integrating the inspection process with the database creation/compilation process not only would provide an extremely useful archive for performing correlative studies of part failure and performance, but also opens up new strategies for performing rapid, high-throughput inspections. Diagnosis of the condition of a structure would then be based on change detection, much like one's personal physician typically identifies the health of a patient by comparison with the results of baseline tests of that individual, in conjunction with normal variances in health indicators obtained from studies of the general population. This integration must occur from a systems perspective, and it is in this area where the participants of the JASON study perceive that DARPA could be most effective in facilitating advances to enable cost-effective, high-throughput, NDE.

Three broad categories of physical detection methods are amenable for use in such a change detection-based approach. These methods can be classified as:

- i. those that interrogate for the presence of anomalies on a point-by-point basis, and which might ultimately be incorporated in parallelized systems;
- ii. those that interrogate for anomalies using broad spatial search capabilities (and which may or may not geolocate the anomaly of concern);  
and
- iii. those which produce signals that are temporally (but perhaps not spatially) resolved.

Additionally, native materials used in aircraft/helicopter structures could be modified, in principle, for the purpose of facilitating the use of any of the above methods. Details of methods that fit into each of these categories are contained in the remainder of this report. These sections are not exhaustive in technical approaches, but instead attempt to focus on selected methods that seem to fit well into the structure outlined above.

Each of the techniques listed below is a candidate for providing useful information in a research program designed to an effective data-base self monitoring program. We do not envision that all of the techniques will need to be used. The research emphasis will include determining which subset of the techniques provides the most independent degrees of freedom in providing the information that is needed to develop a "self-monitoring" capability.

### **3.1 Point-by-point Screening**

Promising point-by-point NDE methods include ultrasound, microwave, and eddy current probes. All have well-demonstrated capabilities and well-developed instrumentation. However, all of these methods are local probes for the presence of some defect or flaw in a region of concern. They are thus inherently time-consuming to perform on large area structures. In addition, the present user interfaces are cumbersome and unoptimized.

It would be desirable to have all of these techniques parallelized into broad area search strategies. However, as these techniques are now implemented, a large amount of user judgment is involved in directing the scans and homing in and identifying areas of concern. Furthermore the complexities of the structures to be monitored also do not lend themselves to automated scanning in many cases. Thus considerable development effort would be required to parallelize microwave and ultrasound methods. As an example of such parallelization, we describe below a method of parallelizing optical inspection methods, which are often cited as being unwieldy, slow, and therefore unsuitable for use in the field. We then describe a method for registering monitoring techniques, which could be applied when automated or parallelized scanning is not possible. Finally, we note that point-by-point screening could be coupled with special materials coatings designed to provide a signal change when the underlying structure suffers defects such as corrosion or changes in strain.

### **3.1.1 Parallel optical scanning**

Optical detection of anomalies in large exposed surfaces, such as airplane wings, requires a system that combines good resolution with large area coverage. Assume that one is seeking to detect cracks with widths from 100 microns to a mm and lengths greater than a cm. Direct high resolution visual scans of the surface can provide such information, but for a typical CCD camera which has a few hundred pixels in each direction, this means that only approximately a square cm of surface can be scanned at a time. An alternative approach allows one to combine high resolution with large area detection by scanning a small laser spot over a large area.

The idea is to increase scanned area without sacrificing resolution, by confining the illumination to a region smaller than the resolution of the detector, and then looking at changes in the illumination as it is swept over a flaw. Consider a 30 cm by 30 cm area, covered with focused laser beams,

where the size of a red laser beam is approximately 300 microns, remaining constant over a distance of approximately 30 cm. As in laser light shows, a single laser can be converted into multiple beams with controlled positions.

Let the separation between spots be 1 cm. The resolution of a CCD camera allows the spots to be separated by about 10 pixels, so they can clearly be resolved easily. If an acousto-optic modulator with a 100 MHz center frequency is used to produce multiple beams, the 30 cm  $\times$  30 cm area can be covered with 900 spots, where each spot is separated by 1 cm in each direction. All 900 spots can be scanned during any 10 ms. Since the time/video frame is 30 ms, it would be desirable to acquire one array per video frame. Thus, the operational time/array would be 30 ms. Continuous lines 1 cm apart can be scanned in 1 second, and the entire 30 cm  $\times$  30 cm surface can be scanned in 30 seconds.

For a 100 mW total unsplit beam power, each spot will have 100 microwatts of power. If only 1 percent of that power gets to the CCD, the amount in each beam is still sufficient to activate a pixel. Once the 30 cm  $\times$  30 cm area is scanned, the area can be moved over and another 30 cm  $\times$  30 cm area can be scanned. A good separation between the laser and the scanned surface is about 10 meters, given that acousto-optic tuning angles are of the order of 30 mRad. It is desirable to view the scattered light with several cameras at various angles with respect to the direction of the central laser beam so that differences in scattering due to edges and rivets can be distinguished from differences due to cracks. This technique has the advantage that it does not depend on whether the surface is conducting, though very low reflectance surfaces may require more power than is estimated above.

### **3.1.2 Registration beacons: repeatable ultrasonic scanning and change detection**

Another significant improvement in operational NDE systems would involve registration of the probe from one scan region to the next. At present,



there is no digital record of the correlation between the measured signals obtained when ultrasound and/or eddy current detection is being performed. Position information is logged in manually when the operator observes something anomalous. Furthermore, when the operator removes the probe physically from the structure/part that is being inspected, there is no possibility to geolocate the position of the last data collected relative to the starting point of the new data stream. It is therefore now not possible to obtain a complete record of the state of a structure because the needed spatial information regarding the absolute location of any given data input stream is unavailable. In order to compare two maps from different inspection times, one must register the maps.

In this section we will discuss a method to register maps made at different times. The method involves the attachment of ultrasonic beacons at two or more fixed, repeatable locations. The scanning probe receives signals from the beacons, and the mapping system can then compute the instantaneous position of the probe with respect to the beacons by time delay. Figure 2 below shows two beacons are necessary to fix a location in two-dimensions (e.g., on the surface of an airframe). The beacons emit a series of ultrasonic

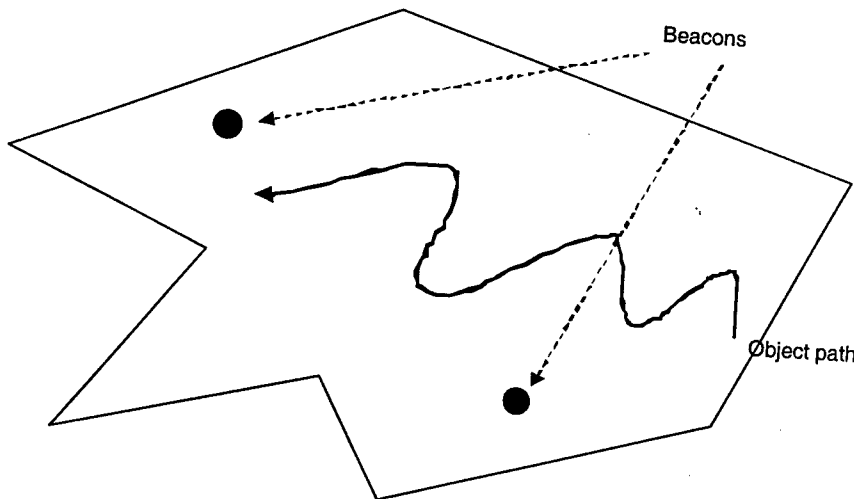


Figure 2: Registration beacons.

The beacons emit a series of ultrasonic pulses, crafted to afford sufficient time resolution  $Dt$ . Simple pulse waveforms can be used, or, if lower peak power is desired, pseudorandom spread spectrum signals can be used. In any case the resolution of registration will be about

$$\Delta d = c_s \Delta t,$$

where  $c_s$  is the speed of sound in the material of concern.

The beacon pulses may need to propagate a long distance so that one can map a large area in one pass, and therefore the pulses may attenuate severely. The path loss over path length  $x$  due to attenuation in the material is

$$\text{Path Loss} = -10 \log_{10} \exp \left( \frac{-2\pi x}{\lambda Q} \right) \quad (3-1)$$

$$= (5.5\text{dB}) \left( \frac{x}{1 \text{ m}} \right) \left( \frac{f}{1 \text{ MHz}} \right) \left( \frac{Q}{1000} \right)^{-1} \left( \frac{c_s}{5 \text{ km/s}} \right)^{-1}. \quad (3-2)$$

Path loss due to imperfect couplings at material interfaces, or into structural reverberation, is likely to be even more important in most structures. Pulse averaging (or synchronous demodulation) can make up for many dB of path loss.

Beacon pulses will propagate through the structure as a mixture of compression, shear and surface waves, and since multipath propagation will take place in most structures, each pulse will have multiple arrivals at the probe. The simplest, and probably best, approach is to detect the first arrival of each pulse, and use that to establish the time delay. Different beacons avoid interfering with each other by broadcasting at different times, or with different spread spectrum codes.

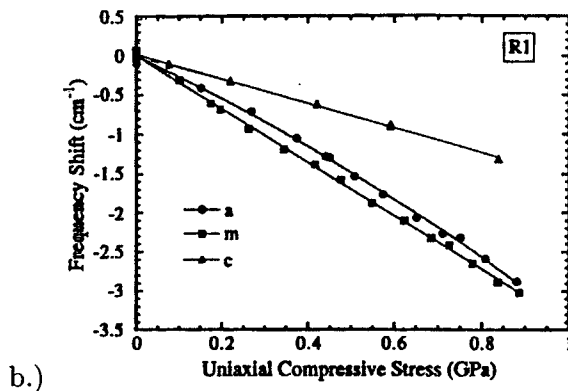
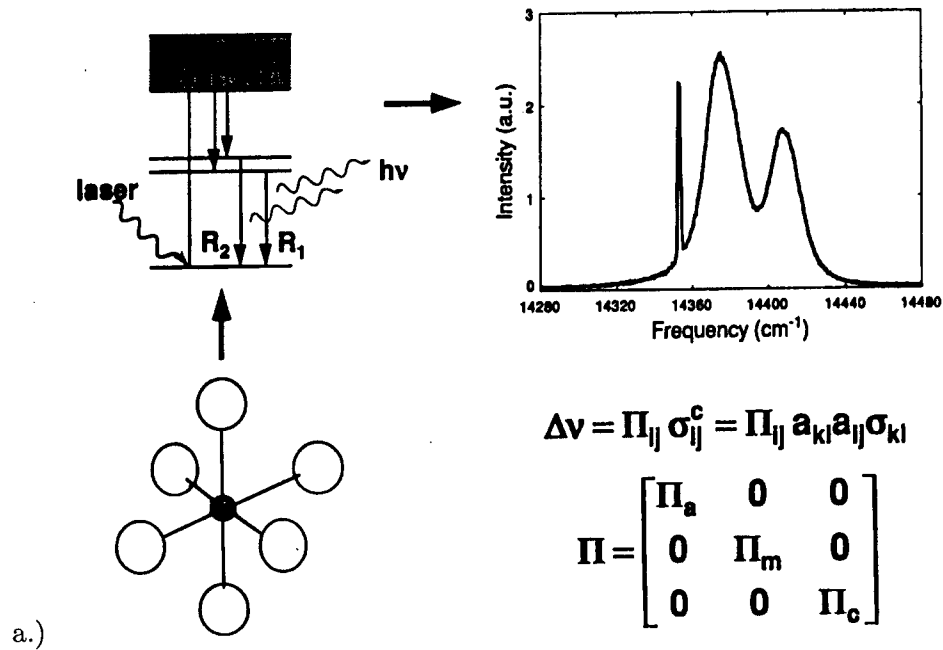
Path losses will generally be an increasing function of frequency  $f$ , and therefore it may be necessary to work at lower frequency than desirable for precision of location. Another promising option is to detect the arrival time of pulses to much better than one cycle by careful correlation in the receiver.

Again because the beacon signals propagate in a complex manner, absolute mapping in terms of physical distance is probably not achievable. However, relative mapping is all that is required for registration of two different maps. Differences in ambient temperature will change propagation times slightly and therefore slightly rescale the map registration. The temperature effect is unlikely to be large; if necessary, it can be calibrated out by measuring the time delays among the beacons themselves, and can also be corrected with a temperature measurement and with previous knowledge of the temperature coefficient of sound velocity in the dominant material (typically of relative order  $10^{-5}/C^{\circ}$ ).

Repeatability of the location of beacon attachment is clearly important, since it affects the entire map. Designing the attachment to be easily and reliably repeatable becomes highly dependent on the engineering details of the system considered. Reasonably good acoustic contact is necessary, but the quality of the contact need be neither perfect nor precisely repeatable.

### 3.1.3 Defect-sensitive coatings

The concept of coatings, such as "bruisable paints" and pH-sensing paints, which signal a point of damage or impending failure on a structure is an attractive possibility for "self-monitoring" behavior. In implementing such coatings, it is important to design the coating properties so that signal occurs reliably when dangerous conditions arise, but such that signals do not trigger unnecessary maintenance effort. An example of a successful coating sensor was provided by Prof. Clarke of UCSB, who uses the strain-sensitivity of Cr-doped aluminum oxide to monitor delamination of thermal barrier coatings on turbine engines. In this case, a shift in a spectral line has been quantitatively related to strain in the film, as illustrated in Figure 3. Delamination via spall can be detected and localized by scanning the excitation source beam over the sample of interest.



#### Piez spectroscopic Coefficients for R lines

	$\Pi_{11}$	$\Pi_{22}$	$\Pi_{33}$	$\Pi_{11} + \Pi_{22} + \Pi_{33}$
	(cm <sup>-1</sup> /GPa)			
R1	2.56 *	3.50	1.53	7.59
R2	2.65	2.80	2.16	7.61

\* Parabolic fitting  $\Lambda_{1111} = -0.8 \text{ cm}^2/\text{GPa}^2$

Figure 3: a.) Cr<sup>3+</sup>, an ubiquitous contaminant in Al<sub>2</sub>O<sub>3</sub>, has fluorescence lines which shift with applied strain. b.) Measurement of the frequency shift of the lines with uniaxial compressive stress along the three principle orthogonal directions of the oxide provides a calibration for stress sensing.

While this particular technique may be of limited usefulness in general aircraft maintenance, because it requires an epitaxial oxide, it illustrates the type of approach needed to make a useful coating monitor. Specifically, there is a signal (in this case a spectral shift) which can be quantitatively related to an impending failure mode.

## **3.2 Broad Area Search Methods**

Recognizing that NDE is a rather extensive field, it was not possible to evaluate the performance characteristics and limitations of all existing technologies that might be suitable for incorporation in a managed data-base NDE system. Instead, the JASON study participants compiled a listing of methods that seem promising for high throughput, broad area, search strategies for NDE. These methods are envisioned to be readily compatible with compiling a database that can serve as an analytical platform for monitoring the health state of a system, and also for establishing a historical record that will enable the use of change detection methods for specific structures of concern during any individual inspection. The methods that seem most promising from such a de novo consideration of the problem are:

- i) Radar
- ii) Optical Holography
- iii) Optical Speckle Interferometry
- iv) Multi-band Thermal Infrared.

### **3.2.1 Radar**

A linear crack in a piece of metal is in essence a slot antenna. As such, it should be detectable by looking for a resonance in frequency when

the illumination wavelength is comparable to the characteristic length of the crack feature. This might form the basis for a broad area screening method for detecting the appearance of cracks above a certain feature size in a large part, such as an airplane wing.

Consider the oversimplified view of such a part to be of length  $l$  and width  $w$ , with a crack of length  $d$ . A microwave/radar signal would be scanned in frequency across the part, and the return signal monitored for amplitude and phase. When the frequency is such that the illuminating wavelength,  $\lambda$ , is approximately equal to  $d$ , a resonance should be observed that can be detected through monitoring the amplitude of the return signal. In addition to a frequency sweep, use of two polarizations is desired, to account for the situation in which the critical crack feature is aligned along the polarization vector of the incoming illumination and therefore will not affect the signal under such conditions. This is not stressing and only adds a factor of 2 to the entire survey time, which can be relatively short.

The optimal use for such data would be in conjunction with a historical record of the parts of concern, so that characteristic patterns of change over certain frequency ranges could be identified relative both to the history of the individual part and to the generic identifiers of the mean properties of such parts as recorded in the database.

### 3.2.2 Optical holography

Optical methods seem to offer another opportunity for a high throughput NDE approach. Again change detection methods would be used, and an interferogram of the holographic image of a component or substructure would be compared to the historical record for that particular component and to the database for such components in general. Plastic flow is of course expected for materials during normal use, but cracks and other critically-sized defects might well lead to characteristic spatial aberrations that could

be identified by their spectral signatures in the interferograms taken over time of the component/substructure of concern.

### 3.2.3 Optical speckle holography/TV holography

A related method involves collection of the interferograms at a relatively high data rate when the component/subsystem is subjected to a stress. The principles of this method involve collection of reflected light and recording the interference pattern generated upon combination of the reflected light beam with its source beam (see Figure 4).

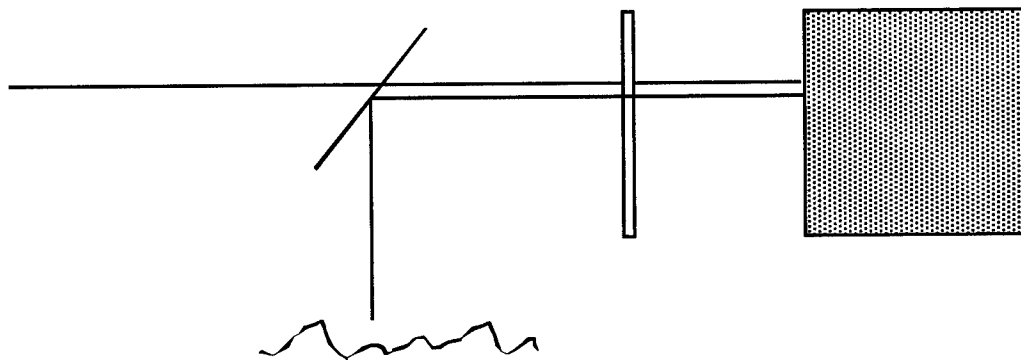


Figure 4: Optical speckle interferometry collect speckle interferograms at high data rates in response to stress, vibration, etc. to help resolve phase ambiguities.

Each spatial data point has, of course, a phase ambiguity of  $2\pi$ , which makes deconvolution of an arbitrary interferogram ambiguous. In practice, however, one uses knowledge of the initial shape of the part and acquires data at a modulation rate that is rapid compared to the deformation of the part due to the imposed stress. The time dependence of the images at any

location can then be used to resolve the phase ambiguity in most cases of interest.

The impulse could be either mechanical or thermal, for example, and the difference between the interferograms of the unstressed and stressed states would be recorded and also compared to those in the database. This might well reveal flaws and cracks that are difficult to observe in “static” images of the structure. A nice demonstration of the power of this technique is available on a web page of Optonor, Inc., ([www.optonor.no/index.html](http://www.optonor.no/index.html)) where vibrations of entire car doors have been recorded and displayed through use of the method. Cracks and flaws are readily identified through comparison of their holographic signatures under such stress to the holographic signatures of nondefective samples.

#### **3.2.4 Multi-band thermal infrared spectrometry**

Thermal infrared imaging clearly is another promising broad area search strategy for NDE. Classical broad-band thermal imaging is a well-established NDE method, which is useful in certain situations where the contrast between a defect/crack and other parts of a structure is large. However, in many regions, clutter is significant and the usefulness of thermal imaging is greatly reduced.

A method for removal of much of the clutter is to spectrally resolve the thermal images into several bands and to take advantage of the different thermal cooling/heating rates of crack/defect regions compared to other regions of the part of interest. This process has been exploited recently by a group at Livermore, led by Nancy del Grande, and seems quite promising. It also highly leverages DoD-supported work in thermal imaging systems, and progress in this area is of course directly transferable to improved NDE capabilities. We are not aware of the actual improvement in signal/clutter



that can be obtained on components of military interest, but believe that this method warrants serious consideration for such purposes.

### 3.3 Temporal Measurements

Data streams measured during a flight are potentially of the greatest value, because they provide a record of the true experience-base of the aircraft, and also provide a monitor of the aircraft under the conditions where it is most likely to fail. A large amount of in-flight data is already recorded in aircraft black-box recorders, but for the most part this data is not subjected to analysis. As will be discussed in Section 4, this data in itself is a valuable component of a database for condition monitoring and prediction. Since such data are already available, analysis of historical records from flight recorders should be part of the research program to develop an effective condition monitoring system.

The other obvious set of information to be monitored is the acoustical response of the system. The use of acoustic monitoring is a well-known and widely studied aspect of condition-based maintenance for machines both in industry and in the military. Such monitoring has provided valuable information in the HUMS system even with very limited analysis. As we will discuss below, changes in acoustic noise of a mechanical system under an external driver (which optimally would be the operation of the aircraft) should also occur due to the formation of defects such as cracks.

Other in-situ sensors for monitoring in-flight data will certainly include strain gauges, as illustrated for instance in Figure 1. We will not discuss this here, except to note that in recent realistic trials metal-foil strain gauges failed relatively early in the test, while optical-fiber strain gauges performed well throughout the test.[1]

Finally, we will discuss the potential of acoustic emission sensing as an in-situ sensor. This technique is highly attractive because the acoustic emission signal is directly related to crack formation. Serious technical difficulties that in the past have made acoustic emission problematic in a noisy environment seem to be yielding to advanced data acquisition and characterization techniques. Thus this technique certainly warrants continuing consideration as a component of a suite of sensors in a “self-monitoring” system.

### 3.3.1 Acoustic spectral resonance analysis for structural flaws

In this section, we wish merely to indicate the underlying physical mechanisms which may cause structural defects, such as cracks, to produce changes in the acoustic spectrum. A crack increases the mechanical compliance of an object, and decreases its vibrational eigenfrequencies, typically by an amount  $O(l/r)$ , where  $l$  is the crack length and  $r$  is a dimension of the part through which the crack extends. The amount of decrease depends on the mode and the crack location and orientation with some eigenmodes (those with stress nodes at the crack) unaffected and the frequencies of others reduced by a few times  $l/r$ . For example, in a short symmetric dumbbell with a transverse axially symmetric crack at the midpoint of its connecting bar which reduces the bar's effective radius from  $r$  to  $r - l$ , the frequency of the torsional mode is reduced by  $2(l/r)$ , while a crack on the outer surface of one of the dumbbell lobes has no effect at all to this order. A crack of depth  $l$  in a beam of radius  $r$  and length  $L$  reduces the eigenfrequencies of its low bending modes by  $O(l/L)$ .

If the eigenfrequencies of an intact part are known and the actual eigenfrequencies are measured, a discrepancy between them may indicate the existence of a crack. The sensitivity of this method is limited by the fact that mechanical contact between two parts will affect their eigenfrequencies. Contacts are not likely to be quantitatively reproducible, depending on such factors as the exact position in which rotating machinery stops and the

thickness of lubricating films and dirt and corrosion layers. Contacts are also dissipative, reducing the mechanical  $Q$  and making it difficult to measure small shifts in eigenfrequencies. Searching for shifts in eigenfrequencies due to structural defects therefore seems problematic.

However, narrow cracks also act as mechanical rectifiers; a crack supports a compressional load, but no tensional load, and supports a shear load only if there is sufficient compressional load. Figures 5 and 6 illustrate the relation between force and displacement at a crack, and show the time-dependence of the force across a crack subject to sinusoidal displacements. A crack therefore generates harmonics of an oscillating displacement field imposed on it. A simple calculation shows that only the even harmonics are produced, with amplitudes proportional to  $1/(n^2 - 1)$  where  $n = 2, 4, \dots$  is the harmonic order. Nonlinear interaction at the crack will further mix the harmonics, converting some of the even harmonic power to odd harmonics.

In practice, for very small amplitudes of excitation the crack may not function as an effective rectifier because the dirt, paint, corrosion products, etc., which may fill it have a mechanical stiffness which is small but which responds linearly to the excitation source function. Even an ideal clean crack will respond linearly at very small amplitudes because of the interatomic forces across it (which would produce cold welding if the surfaces were clean enough, healing the crack). Real cracks also have some finite (but small) opening width everywhere except at their tips, which sets a lower bound on the amplitude of oscillation required to show nonlinearity. All of these effects make it difficult to predict the details of measurable effects expected from a crack. However, it remains reasonable to expect cracks to contribute to the acoustic spectrum, and for the contribution to change as the crack propagates.

This general discussion shows how defect information may couple into the acoustic spectrum of a structure. Ideally, one would hope that changes in the acoustic spectrum due to defects could be detected during flight, where excitation of the acoustic spectrum would occur due to machine vibrations

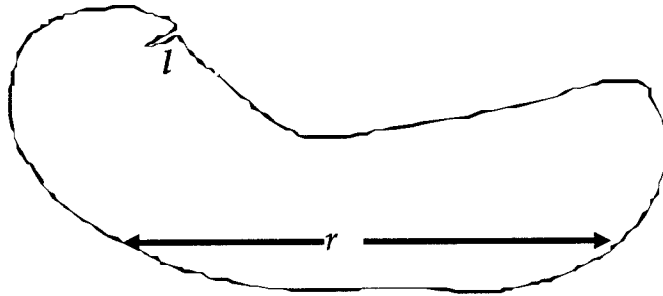


Figure 5: Cracked eigenfrequencies.

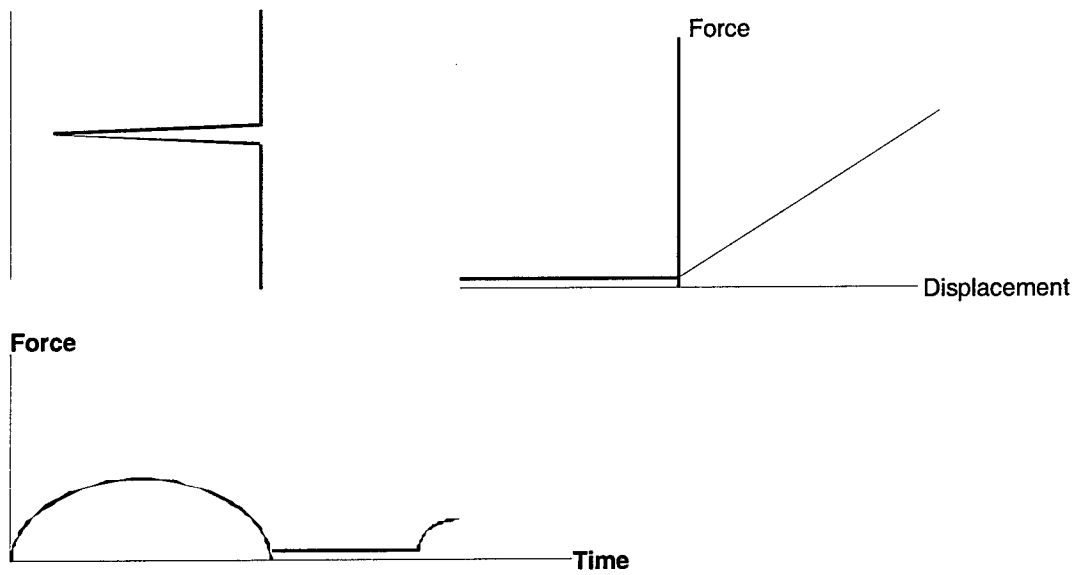


Figure 6: Cracks carry compressional loads, not tensional loads; i.e. are a nonlinear element.

and flight stress on the aircraft. Due to the complexity of the mechanical system, prediction of changes in the acoustic spectrum due to defects is not likely to be very accurate. A combination of focused experiments to determine whether measurable signals are detectable under conditions of interest, coupled with data-logging, should be included in a developmental research program to optimize the sensor system.

### 3.3.2 Acoustic emissions

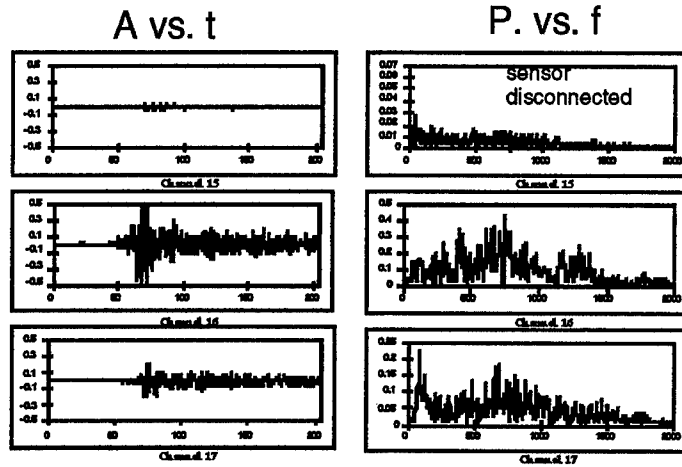
The nucleation and growth of fractures in brittle materials invariably releases mechanical energy in the form of acoustic emissions. Despite the name, acoustic emissions range from sub-sonic (seismic) to ultrasonic frequencies ( $\leq 10^1$  Hz to  $\geq 10^5$  Hz), and are therefore recorded with microphones (non-contact) or transducers (usually in direct contact with, or otherwise coupled to the sample) that are sensitive to the appropriate frequencies. Optical methods (e.g., vibrometry, displacement interferometry or velocimetry) can also be used, but have been more applicable to active-source ultrasonics than to the passive recording of acoustic emissions.

The traditional value of acoustic-emission measurements comes from the empirical observation that brittle materials typically exhibit a pattern of emissions prior to failure. Under deformation, the acoustic emissions begin as the elastic limit is exceeded, and their number per unit time increases as microfractures nucleate. This is followed by a relatively steady rate of emission over an extended time period, as fractures grow and begin to interact (cross and coalesce), finally leading to a burst of emissions as the material fails catastrophically. Thus, emission counts as a function of time have been the primary data obtained, without resolving location, energy release or other source parameters of the individual emission events (indeed, multiple fracture events are often temporally aliased and recorded as a single "emission").

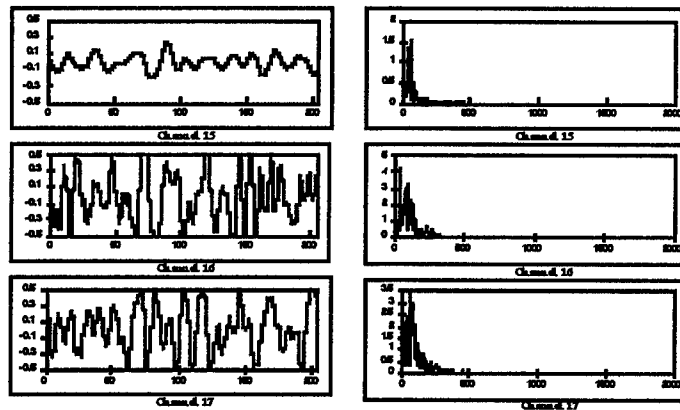
One of the problems with using acoustic emissions in monitoring equipment or complex materials is that there can be many other sources of noise that are recorded along with the emissions. Sliding or grinding between components, including completely benign motion of bolts or rivets, are typically recorded as emissions, for example. One way around this problem is to use independent sensors, such as strain gauges, to distinguish fracture-induced emissions from background noise (this has been successful in applications to structures, such as highway bridges, as well as for large equipment). Alternatively, improved data acquisition and analysis techniques make it possible to distinguish the signature of an acoustic emission event from system noise, as shown in Figure 7.

One of the most powerful methods of using acoustic emissions to monitor materials is through change detection. That is, emission rates are recorded throughout a conventional cycle of use of the material, and these are compared from one cycle to the next without trying to understand the underlying causes of the temporal pattern. One is looking for changes in the temporal pattern of acoustic emissions as the material ages over many (e.g., hundreds to thousands) of cycles, and extraneous noise due to benign motions is therefore not a concern. Small transducers can be located near highly stressed points within a structure or piece of equipment, and the resulting frequency-dependent amplitudes of acoustic emissions can be readily monitored using data loggers or minicomputers. That is, not just number counts (rates) but key measures of source characteristics, given by the amplitudes and frequency contents of the emissions, can be compared from cycle to cycle. A purely empirical approach, based on records obtained from components that have been aged to (and beyond) the point of failure, can then be used as a diagnostic for monitoring materials. Baseline records are derived from components aged either through multiple cycles in normal use, or under stress-, thermal- or other loads that accelerate the aging process.

More sophisticated means of data analysis, which can reveal information about stress distributions, are beginning to be used. For example, methods of seismological analysis can be applied to the output of transducer arrays



Acoustic Emission Signals



Structural Noise features

Figure 7: Data demonstrating the ability to distinguish background noise from acoustic emission events. These data were obtained in the Smart Metals program now underway at Wright Patterson AFB.

to obtain the average location and moment tensor (stress distribution within the source region) for individual bursts of emissions. Even at ultrasonic frequencies ( $\sim 10^5$ – $10^7$  Hz), the source information is averaged over spatial dimensions of tens to hundreds of  $\mu\text{m}$  and over multiple events. Nevertheless, average orientations of tension and compression directions can be determined in this manner, and these can be monitored as a function of time and of as a function of the locations of the emissions across the component being monitored. There is too little experience at this time to know how far such analyses can be taken, but it is worth noting that decades of experience with natural earthquakes have proven such methods to be very effective at geological scales.



## 4 MULTI-VARIATE ANALYSIS AND FAILURE PREDICATION

An enormous literature has been developed under the title of "health monitoring" in the context of nondestructive evaluation. Any monitoring program, at its outset, must collect relevant data from the system whose health is to be monitored and must also organize these data in a format where significant changes over time can be detected. The predominant focus of previous sections of the report have been devoted to sensors which can collect the desired data. This section is devoted to methods for organizing these data so that changes in the state of the monitored system can be detected. Strategies for reacting to detected changes are not discussed here—these clearly require some knowledge of the expected consequences of the change, and must be quite system specific.

Our framework supposes that the system of interest is dynamical and that its state can be determined by observations of time series of one or more variables. We may wish to keep the example of a helicopter gearbox in mind (and, indeed, we will use data from a monitored gearbox later in this section), and we assume we observe it in either a free running condition or undergoing a specified suite of inputs designed to examine its "health". The comparison to one's physician performing the proverbial tapping on the knee with a rubber hammer to determine the health of your reflexes and to establish your need for conditional maintenance is unavoidable.

Below we discuss the application of the standard approach to multivariate analysis to analysis of flight data. The results clearly indicate promise for this approach. Extensions of the approach being carried out by Triant Technology to deal with potential situations where some of the input measurements are faulty are also presented. We then proceed to describe a potentially more powerful and general analysis which is suitable for situations with non-linear couplings as well.

In the rather general presentations in the following two sections, the examples are based on a continuous stream of data as a function of time. We wish to emphasize that in fact the approaches can be used much more flexibly. Specifically, data obtained with different time intervals (e.g. a one point inspection which takes place between flights, and data monitored continuously during flight) can be incorporated into these data-handling schemes. Thus all three categories of input data discussed above can in principle be used within one well-designed analysis procedure.

We also wish to emphasize that the appropriate experimental design to obtain relevant data remains an important factor in multi-variate analysis. No amount of mathematical manipulation will serve to extract useful information if the input data do not cover all of the relevant degrees of freedom.

## 4.1 Linear Models and Fault Tolerance

Dr. Jack Mott from Triant Technologies, Inc. came to speak with the JASON study participants on 20 July 1998. His visit was prompted by our reading a paper written by Paul J. O'Sullivan of Triant Technologies [2]. This paper presents a rather clear formulation of the issues associated with the main problem at hand, and Dr. Mott presented an interesting example of the application of a standard multi-variate analysis applied to the standard information available from flight recorders.

In setting up a linear “exemplar-based” analysis, we ask the following question:

- once data has been collected from a device operating in a ‘healthy’ regime, what methods are useful for detecting change in the operating characteristics of that device?

The standard approach to this question is as follows:

In the first path  $N$  dynamical variables, such as the flight data listed in Table 1,  $x_1(t), x_2(t), \dots, x_N(t)$  are measured for times  $t = 1, 2, \dots, M$  in some sampling time units. The measurements are collected together in an  $N \times M$  matrix  $\mathbf{R}$ .

One then assumes that these  $N$  dynamical variables are **not independent**, but have a *linear* relationship among them. The relationship of the variable  $x_i(t)$  is expressed in terms of the matrix  $\mathbf{R}$ , the matrix with the row of measurements of  $x_i(t)$  removed, call it  $\mathbf{R}'$ , and the  $M - 1$  dimensional vector at any given time with the component  $x_i$  removed, call this  $\mathbf{x}'$ . In matrix notation, the relationship between the  $i^{\text{th}}$  measurement and the remaining measurements  $\mathbf{x}'$  will be

$$x_i = \mathbf{R}_i \cdot \mathbf{R}' \cdot [\mathbf{R}' \cdot \mathbf{R}'^T]^{-1} \cdot \mathbf{x}' \quad (4-1)$$

$T$  is transpose of a matrix.

Mott determines this form of the relationship by minimizing the distance between an expected  $x_i$  taken linear in  $\mathbf{x}'$  and the  $i^{\text{th}}$  component of the observation. With this linear relationship established for each component  $x_i$  of the observations  $\mathbf{x}$ , he then has a connection among his observations. If the data collected are sufficient, this then will characterize the 'healthy' state of a system.

Mott gave us examples of this process using analysis of data measured from the standard information available from the flight recorder of an F-18 fighter (See Table 1). He showed a quite impressive ability to determine one of the measured variables, in his case indicated air speed, in terms of the other dynamical variables of the system, as shown in Figure 8. His linear relationship constituted his model of the system in the sense that if  $K$  of the dynamical variables were independent and  $N - K$  determined by the other  $K$ , then by knowing  $K$  measurements—which ones were independent was not known nor does it matter—the other  $N - K$  can be determined if the system is in the same state of health as when the measurements were made.

Table 1. F/A-18 Monitored Variables.

VARIABLE	DESCRIPTION
#1	IND AIR SPD
#2	HUD AOA
#3	LONG STK POS
#4	TEF POS LEFT
#5	TEF POS RIGHT
#6	LEF POS OUT LEFT
#7	LEF POS OUT RIGHT
#8	PITCH RATE
#9	PITCH
#10	NORMAL ACCEL
#11	STAB POS LEFT
#12	STAB POS RIGHT
#13	LAT STK POS
#14	ROLL RATE
#15	ROLL
#16	RUD POS LEFT
#17	RUD POS RIGHT
#18	YAW RATE
#19	LAT ACC
#20	PLA LEFT
#21	PLA RIGHT
#22	EGT LEFT
#23	EGT RIGHT
#24	LP SPEED LEFT
#25	LP SPEED RIGHT
#26	HP SPEED LEFT
#27	HP SPEED RIGHTTT
#28	AIL POS LEFT
#29	AIL POS RIGHT
#30	FUEL FLOW LEFT
#31	FUEL FLOW RIGHT
#32	LEF POS IN LEFT
#33	LEF POS IN RIGHT

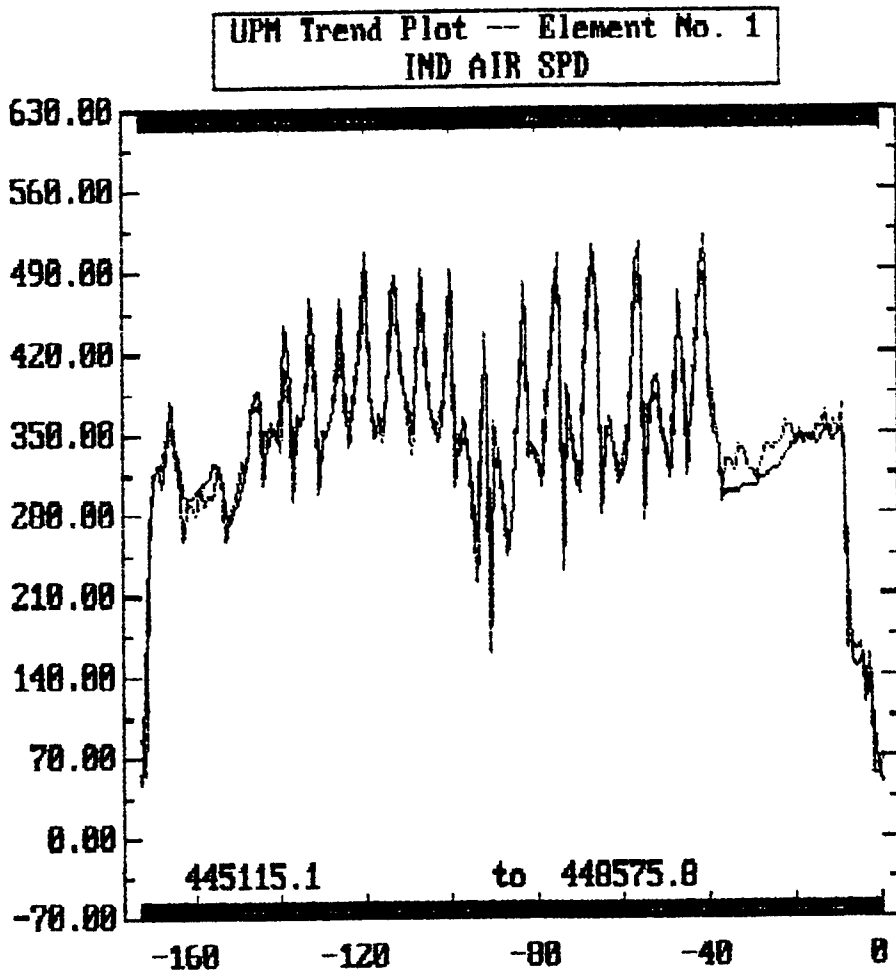


Figure 8: Mott's data vs. prediction.

Deviations from the determined relationships among the variables—knowing  $N - K$  when  $K$  are measured—constituted the signs of bad performance.

The issue of determining what amount of deviation from the determined linear connection among the variables constitutes bad health of the system is an area which will clearly need additional research. Mott showed clearly that observable deviations will appear under faulty flight conditions — the specific example was operating the aircraft with improper values of the leading-edge flap positions, as shown in Figure 9.

Mott's methods will probably benefit from a variety of methods recently introduced in nonlinear modeling, but which are applicable to linear modeling as a special case, and which have been discussed to date in the chemical engineering community [3]. Further development of such approaches should be included in the research program on analysis methods.

The second topic Mott discussed dealt with a situation where some of the sensors are faulty or non-functional altogether. To deal with this situation of a reduced valid data space, consider making  $N$  measurements again and selecting  $K$  of the observed dynamical variables into a vector  $\mathbf{c}$ . Then assume a **linear** relationship between the vector  $\mathbf{c}$ , the appropriate pieces of the observation matrix  $\mathbf{R}$ , and the observations  $\mathbf{x}$

$$\mathbf{x}_T = \mathbf{R} \cdot \mathbf{c}. \quad (4-2)$$

The vector  $\mathbf{c}$  is then determined by asking that this relationship be satisfied in a least squares sense, namely that,

$$(\mathbf{x} - \mathbf{R} \cdot \mathbf{c})^2 \quad (4-3)$$

be minimum as a function of the components of  $\mathbf{c}$ . This gives

$$\mathbf{c} = [\mathbf{R}^T \cdot \mathbf{R}]^{-1} \cdot \mathbf{R} \cdot \mathbf{x}. \quad (4-4)$$

If we have a new set of measurements  $\mathbf{x}_{\text{new}}$ , then on the basis of this selected relationship between  $\mathbf{x}$  and the independent dynamical variables  $\mathbf{c}$

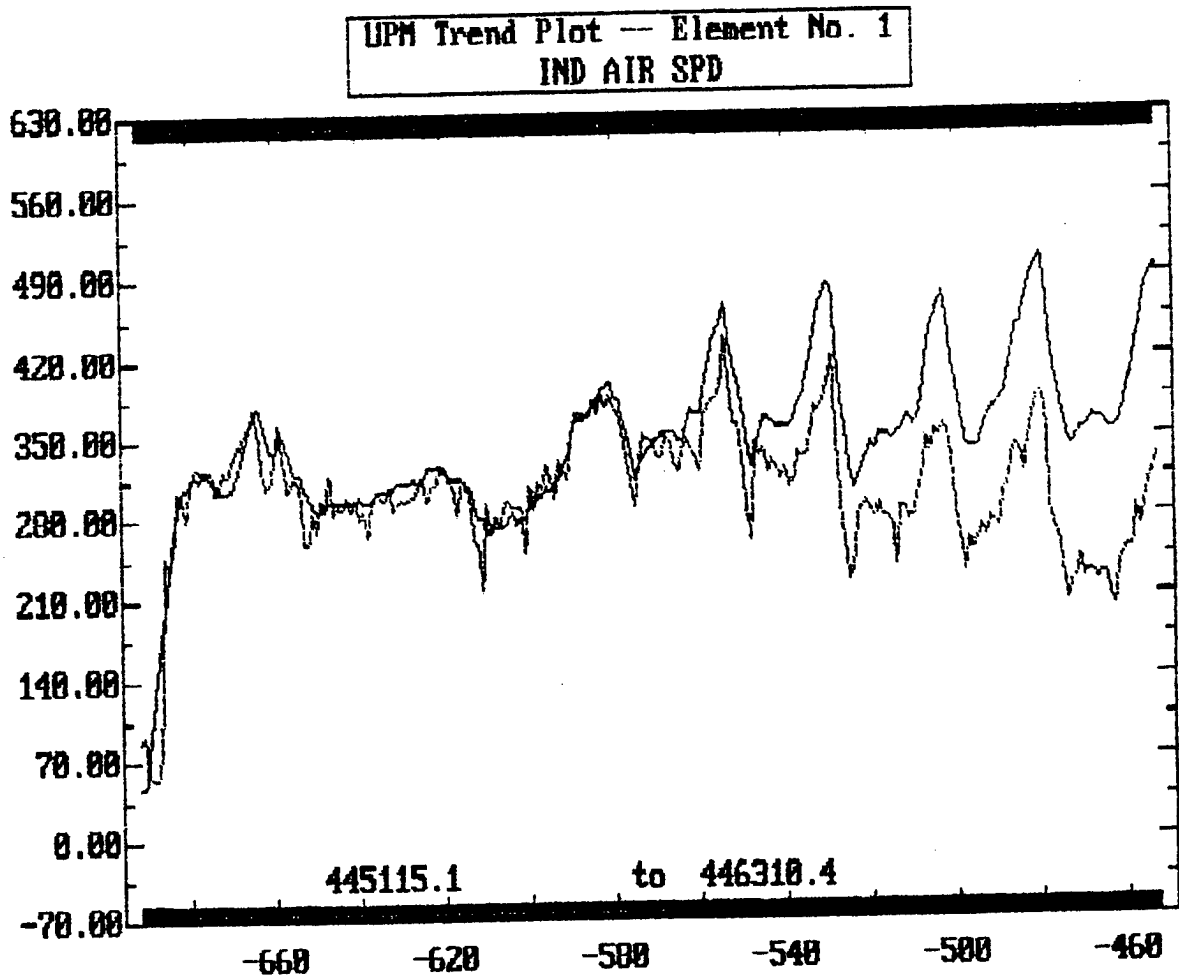


Figure 9: Mott's data vs. prediction for faulted system.

presumed to underly the observations, we would “expect” measurements

$$\mathbf{x}_e = \mathbf{R} \cdot [\mathbf{R}^T \cdot \mathbf{R}]^{-1} \cdot \mathbf{R} \cdot \mathbf{x}_{\text{new}}. \quad (4-5)$$

Deviations from this expectation are considered indications of the loss of health of the system being monitored.

Mott points out that the “dot products” used in the determination of  $\mathbf{c}$  or  $\mathbf{x}_e$  (e.g. determination of linear relationships among the observed variables and between the observed variables and the dynamically independent variables) are not robust against ‘outliers’ associated with noisy measurements (e.g. He replaced the inner products with a company-proprietary ‘metric’—we do not know it is a metric in the mathematical sense, but it might be—which is more tolerant of noise or loss of a sensor. This method has primarily been developed using an *ad hoc* approach. The derivation of his ‘fault tolerant’ results from first principles should be worth doing, and such further investigation would be a useful component of the research program on analysis methods.

## 4.2 Non-Linear Systems

In contrast to the method used above, modeling the dynamics of a linear or nonlinear system does not require observation of all state variables of a system [4]. Knowledge of a single observed dynamical variable,  $s(t)$ , along with its time delays, has long been known to allow construction of a proxy state space characterized by  $d$ -dimensional vectors

$$\mathbf{y}(t) = [s(t), s(t + T\tau_s), s(t + 2T\tau_s), \dots, s(t + T\tau_s(d - 1))], \quad (4-6)$$

with  $T$  an integer selected so  $s(t + T\tau_s)$  and  $s(t + (T + 1)\tau_s)$  are dynamically independent views of the system of interest. The components of  $\mathbf{y}$  stand in for the unmeasured state variables, and they provide a state space which has essentially all of the properties of the unobserved actual state of the system.



In  $\mathbf{y}$ -space there are a variety of methods for establishing global or local evolution models of the form

$$\mathbf{y}(t + 1) = \mathbf{G}(\mathbf{y}(t)), \quad (4-7)$$

or

$$\frac{d\mathbf{y}(t)}{dt} = \mathbf{F}(\mathbf{y}(t)). \quad (4-8)$$

These models, namely the  $d$ -dimensional functions  $\mathbf{F}(\mathbf{y})$  and  $\mathbf{G}(\mathbf{y})$  are the embodiment of the observed data from the healthy system. If the system changes, then comparing the model with the changed system output will provide a basis for detecting those changes. We will not discuss the various ways for finding the ‘vector fields’  $\mathbf{F}$  and  $\mathbf{G}$  [4, 5], but here we concentrate on their use in “health monitoring”.

#### 4.2.1 Nonlinear system health monitoring

We begin with a model of the healthy nonlinear system. In general, such nonlinear systems are unstable everywhere on their system orbits, so the point of view expressed by “the basic idea is to compare the output of the model to the measurements of the process” [6] will not succeed if one attempts to compare directly the state of the model  $\mathbf{y}(t)$  with the state of the monitored system  $\mathbf{x}(t)$ . These two state vectors, if they are ever similar, will diverge exponentially rapidly in time because of the intrinsic instabilities of the nonlinear system.

To accomplish anything, we require other ways to compare the model output  $\mathbf{y}(t)$  with the measured observations  $\mathbf{x}(t)$ . We describe below three ways that should facilitate such a comparison, and which should therefore be explored:

- **III Monitor Indicators of Instability.** Changes in the healthy system of small consequence are of little importance, and detecting and acting

on them increases the false alarm rate. If we are concerned with significant or catastrophic changes in the originally healthy system, then it may make sense to monitor the dynamical characteristics which represents the instabilities in the nonlinear system. These are the Lyapunov exponents—the positive ones anyway—and we will discuss a method for tracking the largest Lyapunov exponent which, when tested on Navy supplied Helicopter gearbox data, indicated changes in system health quite clearly.

- Synchronize the observations with the model. If the system changes because of ‘bad health’, then in this scenario, if the model is constructed from data on the healthy system, the synchronization will break down, and one can detect that.
- Statistical tests asking if the observations  $\mathbf{x}(t)$  and the model output  $\mathbf{y}(t)$  come from the same source. Since the outputs of the system and the model are complex, one cannot hope to directly compare the time series value. Thus what is needed is a statistical test asking if the outputs come from the same source or, more technically, if the orbits defined by the model output and the observations lie on the same attractor. When the tests show that the sources are different, the healthy system has changed.

#### 4.2.2 MII

Catastrophic failure is an expression of the substantial departure of the system from the healthy state that it began in. Even in the healthy state, if we have two nearby observations  $\mathbf{x}(t)$  and  $\mathbf{x}'(t)$ , they will move away from each other exponentially rapidly

$$|\mathbf{x}(t) - \mathbf{x}'(t)| \approx e^{\lambda_1 t} |\mathbf{x}(0) - \mathbf{x}'(0)|. \quad (4-9)$$

The quantitative measure of this instability is the largest Lyapunov exponent  $\lambda_1$ . If  $\lambda_1$  changes, it represents alterations in the instability structure of the

system, and this suggests that monitoring this indicator of instability would be an excellent statistic for announcing changes in the healthy system. In particular, if  $\lambda_1$  increases in time, that would suggest that small perturbations to the formerly healthy system could lead to rapid disruptions in system development [9].

To implement this MII monitoring of  $\lambda_1$  we break the observations up into windows of length  $\theta$  in time. This time should be long compared to both the sampling time  $\tau_s$  and compared to  $1/\lambda_1$ , yet short compared to the time scale on which changes in the healthy system occur. Using data over an interval of length  $\theta$ , we evaluate  $\lambda_1(\theta, L)$   $L\tau_s$  steps in time along the segment of trajectory of length  $\theta$ . The evaluation of  $\lambda_1$  from time series is rather standard [4].

One can continuously monitor  $\lambda_1(\theta, L)$  by starting with the beginning of the time series, say at  $t_0$ . The first segment of data on which to evaluate  $\lambda_1(\theta, L)$  runs from  $s(t_0)$  to  $s(t_0 + \theta)$ ; call this value  $\lambda_\theta(t_0)$ . The next segment runs from  $s(t_0 + \tau_s)$  to  $s(t_0 + \theta + \tau_s)$ . Call this  $\lambda_\theta(t_0 + 1)$ . Continuing in this fashion we build up a series of Lyapunov exponents evaluated over a window  $\theta$ .

Frison has determined time series of  $\lambda_\theta(t)$  for data from a CH46 helicopter gearbox. These data were collected both in the healthy state and in various states of intentional damage to the gears. In Figure 10 we show the largest Lyapunov exponent  $\lambda(\theta, t)$  for the healthy gearbox in black and the same statistic for three states of damaged gearbox in red, green and blue. It is clear that damage has raised the value of  $\lambda_\theta(t)$  and that it distinctly separated the healthy variation from the variation in the damaged state. The same separation of largest Lyapunov exponents was seen for other data on another helicopter gearbox. This time the gearbox was not damaged, but was monitored in this fashion after it had been running for ten hours following calibration and then monitored again 190 hours later.

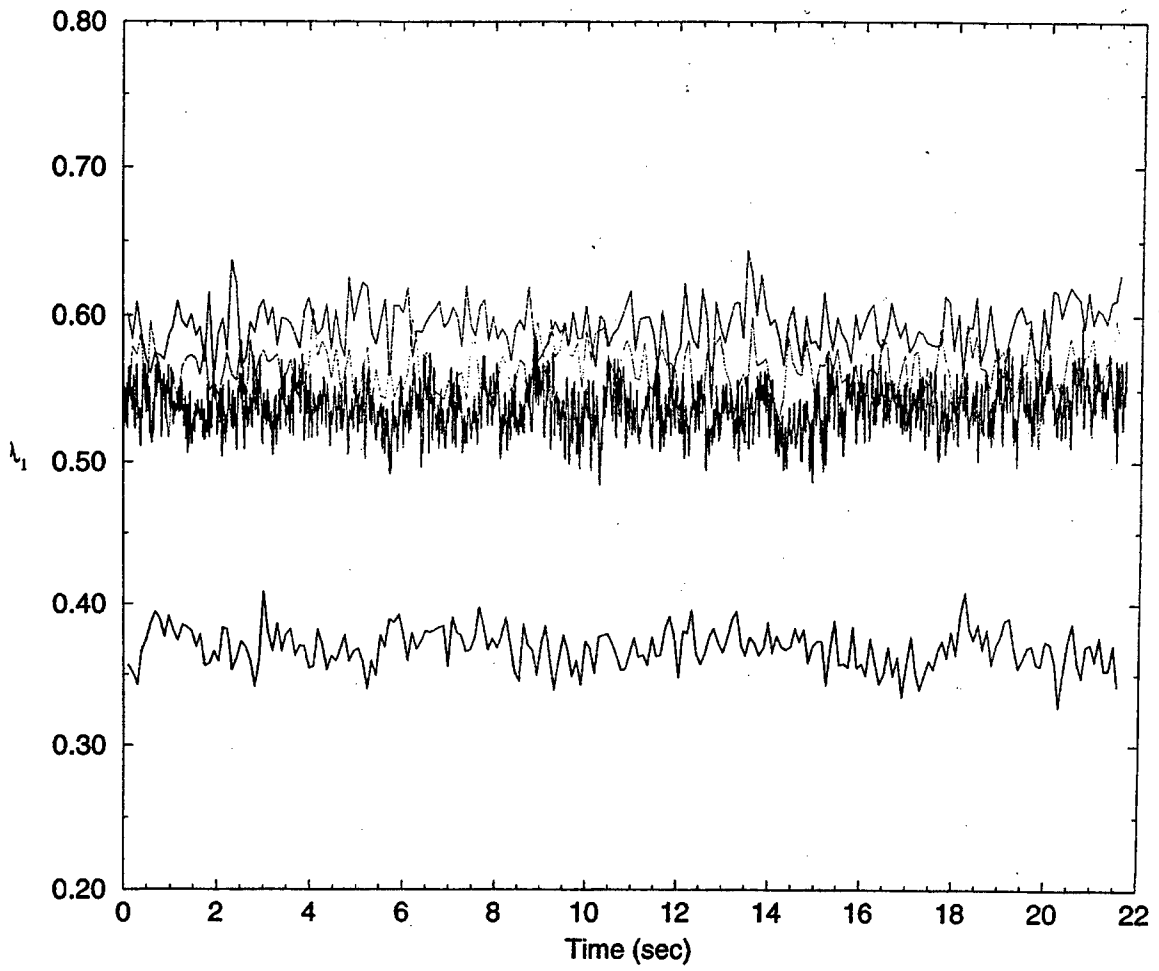


Figure 10: Largest Lyapunov exponent.

This MII method has the advantage over the previous techniques that it does not require a model to be made of the healthy state of the system. It instead compares in a direct fashion the evaluation of a statistic associated with the instability of the nonlinear system, first as evaluated in the healthy state and then as evaluated in an altered state.

### 4.2.3 Synchronization of system and model

If one couples two identical nonlinear systems with state vectors  $\mathbf{x}(t)$  and  $\mathbf{y}(t)$  each satisfying

$$\frac{d\mathbf{x}(t) \text{ or } \mathbf{y}(t)}{dt} = \mathbf{F}(\mathbf{x}(t) \text{ or } \mathbf{y}(t)), \quad (4-10)$$

in a unidirectional fashion:

$$\frac{d\mathbf{x}(t)}{dt} = \mathbf{F}(\mathbf{x}(t)), \quad (4-11)$$

$$\frac{d\mathbf{y}(t)}{dt} = \mathbf{F}(\mathbf{y}(t)) + \mathbf{g}(\mathbf{x}(t) - \mathbf{y}(t)), \quad (4-12)$$

then for a wide range of values for the coupling matrix  $\mathbf{g}$ , a solution of these equations with  $\mathbf{y}(t) = \mathbf{x}(t)$  is possible and stable. When this synchronized solution is stable, it provides a way to monitor the output of the system as its health changes. Changes in the system of interest manifest themselves in the drift of the system dynamics from the model constructed on the basis of healthy system dynamics. As the system drifts so its dynamics becomes

$$\frac{d\mathbf{x}(t)}{dt} = \mathbf{H}(\mathbf{x}(t)), \quad (4-13)$$

where  $\mathbf{F}(\mathbf{x}) \neq \mathbf{H}(\mathbf{x})$ , then the orbits  $\mathbf{y}(t) = \mathbf{x}(t)$  no longer represent a solution to the coupled system/model, and we have detected change.

In the case we noted, where only one state variable,  $s(t)$ , of the system is observed, then the model built on  $s(t)$  and its time delays can only reproduce behavior of  $s(t)$ . So the setup for the synchronization monitoring would be that the system runs freely, changing, if that is what happens:

$$\frac{d\mathbf{x}(t)}{dt} = \mathbf{F}(\mathbf{x}(t)), \quad (4-14)$$

and the dynamical variable  $s(t)$  among all the  $\mathbf{x}$ 's is coupled into the model

$$\frac{d\mathbf{y}(t)}{dt} = \mathbf{F}(\mathbf{y}(t)) + g_{11}(s(t) - y_1(t)). \quad (4-15)$$

If  $g_{11}$  is large enough, the model output  $y_1(t)$  should equal the system observations  $s(t)$ . As the system drifts into other performance, perhaps unhealthy, this equality fails to be satisfied.

This method avoids the trap of asking that model output, uncoupled to the system behavior, produce orbits  $\mathbf{y}(t)$  to be compared to the system output, which as noted above, is fruitless in nonlinear systems. By driving the model to the synchronization condition  $y_1(t) = s(t)$ , we test the health of the system by asking if the model for it still holds. As the system alters, this equality will fail.

The papers on the subject available to us [5] stop at this interesting junction and have not applied this idea to a complex system of real interest. The method is "tested" on simulations and a laboratory nonlinear circuit, and issues associated with its robustness in the presence of noise in the coupling mechanism have been looked at. At present there seems to be no formulation of a good statistic for the deviation  $y_1(t) - s(t)$ . It has a certain, as it happens small, value or variation in time in the healthy state, and no quantitative measure of change has been formulated in the papers. This method seems promising and we encourage testing it out on some systems of real interest and working out a good statistic for determining what  $y_1(t) \neq s(t)$  means dynamically.

#### 4.2.4 A statistic for drift of the system from the model

If we have observations of the system of interest in the healthy state, call them  $s_h(t)$ , and we return to the system at a later time and measure these variables again, a set of observations  $s(t)$  is collected. We wish to know whether the two sets of observations came from the same source—i.e.

whether the source of the  $s(t)$  is the same as the source of the observations  $s_h(t)$ . The method of Kennel and Mees [7] first builds a predictive model for the healthy sequence of observations using a method called “Context” developed by J. Rissanen [8] and then evaluates a kind of chi-squared statistic comparing the new observations  $s(t)$  with the predicted output of the model  $s_h(t)$ . The comparison is not made measurement by measurement—that is, the orbits are not compared directly—but a statistical attribute of the new measurements is compared with a similar statistical attribute of the healthy system observations  $s_h(t)$ . The measurements are first transformed into a data stream with redundancy into data streams whose redundancy is removed as much as possible. This is similar to the process used in standard data compression. The resulting data stream from  $s_h(t)$  and that from  $s(t)$  are tested by asking if these redundancy-free representations could have come from the same probability distribution of symbols in the data stream. This leads to a kind of least squares test of equality of probability distributions, and the properties of this statistic are well characterized as a chi-squared distribution with known degrees of freedom. If the  $\chi^2$  value coming from the comparison of the data streams  $s_h(t)$  and  $s(t)$  is larger than some value, this translates into a known probability they came from different underlying probability distributions. The point of removing redundancy is to assure ourselves that we are comparing independent pieces of information about each observation of the system.

## 5 CONCLUSIONS

We consider it both feasible and desirable to develop an integrated maintenance system for aircraft, and for other mechanical systems of DoD importance. Even in the simplest stages of development, as demonstrated by the HUMS program, such a system can have substantive positive impact on cost and safety. There is still substantial need for improvement in such systems, especially in the choice and implementation of sensor suites, necessitating continuing effort, as in the JAHUMS and the Smart Metallic Structures programs.

We also consider it worth serious research effort to investigate the implementation of advanced analytical procedures to augment human evaluation of the sensor suite input. The large volume of data that will be available from integrated sensor systems will contain cross-correlations not readily interpretable from simple inspection (witness the neglect of the huge volumes of data already available in black-box flight recorders). High-risk research in the area of predictive analysis may well have substantive future pay-off in the design of systems in which not only maintenance needs, but also real-time flight adaptations, can be extrapolated from the sensor system information. Testing of such cutting edge applications could be well implemented as part of a UAV development program.

Predictive maintenance of complex mechanical systems requires intelligent design of a broad base of sensors which can cover the system's degrees of freedom. The implementation of such a system is feasible given modern data acquisition, storage and analysis capabilities. The most effective sensor suite to be used will be strongly dependent on the real system of interest. Research to develop the best sensor suite will be greatly facilitated by 1) close interaction with personnel experienced in operation and maintenance of the system and 2) development of a large data base on sensor responses



under a variety of conditions. Development and evaluation of algorithms to detect change, and ultimately to distinguish harmless from dangerous change, will be an iterative process that must be closely coupled to the choice of the sensor suite.

After the preparation of a draft of this report an article appeared in *Physics Today* [10] reporting experimental confirmation of the prediction of Section 3.3.1 that damaged (cracked) materials produce harmonics and other nonlinear combinations of frequencies at which they are acoustically excited. This supports our suggestion that this method may be useful in finding cracks, and it should be tested in geometries and materials of practical interest.

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