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ACOUSTIC EMISSIONS APPLICATIONS
ON THE NASA SPACE STATION

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ABSTRACT

Acoustic emission is being investigated as a way to continuously monitor the space station Freedom for damage caused by space debris impact and seal failure. Experiments run to date focused on detecting and locating simulated and real impacts and leakage. These were performed both in the laboratory on a section of material similar to a space station shell panel and also on the full-scale common module prototype at Boeing's Huntsville facility. A neural network approach supplemented standard acoustic emission detection and analysis techniques.

INTRODUCTION

The space station is an internally pressurized container carrying inside it everything necessary to support human life in space. Since the shell of the space station contains numerous penetrations it will always be susceptible to seal failure, and when in orbit it will also be exposed to impacts from meteoroids and debris. Although designed to minimize the effects of impacts, damage which breaches the shell threatens the lives of the astronauts. Even small penetrations may require an unacceptable amount of time and effort to locate if a manual scan is necessary. Monitoring under these conditions is best done with acoustic emission (AE), which can be configured as a continuous, remote, and operator-independent monitoring system capable of detecting and locating large and small damage sources.

From the point of view of AE monitoring requirements, the ideal container would permit detection of the weakest significant damage sources up to the maximum source-sensor distance, allow accurate and unambiguous location of all detected sources, and be wholly lacking in extraneous noise. The ideal monitoring instrument could detect all damage-related emissions, identify the type and extent of damage, find the location of the source, and pass this information along to an operator in a clear and unambiguous manner.

Fig. 1. Laboratory test specimen with test lines

PHYSICAL DESCRIPTION OF THE SPACE STATION SHELL

As configured in 1990, the space station was comprised of large modules connected by smaller modules referred to as resource nodes. Overlooking some detail, the modules may be described as three aluminum cylinders, each formed of four curved aluminum plates and connected end-to-end, with aluminum endcaps. At the junctions between these smaller cylinders is a double weld and a circumferential I-beam, while the longitudinal junctions are single welds. The plates themselves are about 3.8 x 3.9 meters, and about 3.2 millimeters thick between the support ribs. They were milled from 2.54-cm plate stock leaving a waffle-type pattern, then hammered over a last to attain the desired curvature with the ribs on the outside. Each section thickens slightly at the edge where the welds are formed. Our laboratory tests described below were performed on half of a plate cut down the longitudinal axis, illustrated in Fig. 1. Remaining work was done on the Common Module Prototype (CMP) at Marshall Space Center.

ACOUSTIC EMISSION INSTRUMENTATION AND CALIBRATION SOURCES

Instrumentation used to detect, analyze, record, and display AE data was a PNL-owned device built along the lines of prototype instruments developed for the U.S. Nuclear Regulatory Commission. Designated the System-88, this instrument was designed to provide four input channels of acoustic emission configurable as arrays of 1-4 sensors, along with eight parametric inputs. The device was modified for this program to provide eight channels of RMS acoustic emission in addition. After preliminary analysis, the machine stores the data, along with pertinent flags and tags, on high-density 16-track tape. The machine displays numerical data on the display screen, either acoustic emission event information or successive RMS values. Further analysis can be performed on a separate personal computer.

Calibration sources used in the laboratory were pencil lead breaks and a helium gas jet. For the former source, a small length of lead was broken while in contact with the specimen surface in order to produce a transient acoustic event. A continuous-type signal was produced by

forcing compressed helium through a small-diameter needle held at a constant distance normal to the specimen surface.

DETECTION AND LOCATION OF LEAKAGE

Laboratory Tests

Detection and location of leaks is a major thrust of the current effort. Using the shell section described above, simulated leaks were produced in the laboratory using pressurized air. A small hole was drilled in the plate, and the end of a larger-diameter hose epoxied to the side of the plate corresponding to the inside of the module. The end of the hose was positioned to cover the hole. Compressed air was then forced through the hole at one atmosphere, and the air flow rate and hole size recorded. An acoustic emission sensor was attached to the plate surface at various distances from the hole along a line parallel to the longitudinal axis of the plate, and RMS calculated from waveform samples.

A second series of tests used various hole sizes and a sensor positioned a constant distance from the source. The size of the initial hole was reduced by filling it with epoxy and inserting a wire, which was removed before the epoxy completely set up. After each set of measurements, the hole was drilled to a slightly larger size. Air pressure was maintained at 1 atm. for each hole size, and the flow rate recorded.

Leak-signal RMS amplitudes tended to be greater near the source, although the response varied considerably. A low loss rate at relatively large source/sensor distances combined with a signal level that remained significantly above the background noise indicated that even small leaks may be detectable over large distances. Location dependence of the RMS voltage level was again observed as illustrated in Fig. 2. The RMS voltage plotted against leak rate was linear, but with some deviation evident at the lowest leak rates.

CMP Tests

Calibration measurements were made using an air jet in a manner similar to the helium jet used in the laboratory tests. These tests

Fig. 2. Average RMS voltage vs. source-sensor distance for a simulated leak

Fig. 3. CMP test layout. The section of the endcap between 90 and 180 degrees is adjacent to the shell section on the right. Source locations are marked by "+".

were performed to examine the response of the CMP to continuous-type acoustic emissions and to examine a normalization technique for RMS signals. The RMS levels of air jet signals originating at 5 cm from each sensor along a line directed toward the center of the array were used for normalization. In all cases, values used were the averaged results of five successive measurements.

Leak testing of the CMP provided some interesting logistics problems due to safety issues and the desire to maintain the integrity of the module. In the end, two small holes, producing leak rates of 28.5 and 4.2 lbs/day at 14.7 psi, were drilled through the shell wall a few centimeters apart at the position shown in Fig. 3. These holes could be closed remotely and independently by a solenoid valve developed and installed by Boeing personnel. This made it possible to measure two different leak rates at operating pressure. The module was pressurized, and RMS voltage measured and recorded from each sensor and for each hole. Comparison measurements were also obtained during de-pressurization. Along with RMS measurements, waveform samples were obtained using pairs of sensors and the Nicolet oscilloscope.

Normalized RMS signal level plotted against source-sensor distance is illustrated in Fig. 4. Geometric effects preclude reliable in-situ sensor response normalization, but on the whole, normalization did tend to improve the behavior of the data. It may be possible to identify the leak source location within the area of a sensor array using amplitude comparison. A second source location approach for continuous-type signals, based on a cross-correlation technique developed by Grabec [1], Akizuki et al. [2], and Kupperman [3] did not produce promising results. The approach is worth further investigation however, since due to time and funding limitations our work was of necessity somewhat rudimentary.

NEURAL NETWORK APPROACH TO LEAK LOCATION

The importance of leak source location led two of the authors to examine a neural network approach [4], utilizing data obtained in the laboratory from a ribbed aluminum plate. A two-sensor array was used to record air jet acoustic emissions on a plate section previously used

Fig. 4. Normalized RMS voltage vs. source-sensor distance for CMP leakage.

elsewhere for impact tests. Forty source locations were examined, covering an area of about 51 x 61 centimeters. The source locations were arranged in a rectangular matrix with a nearest-neighbor distance of about 10 centimeters, and surface-mounted sensors at the lower left and upper right corner positions. Four signal records were obtained from each source location. Signals from both sensors were digitized at 2 MHz, recorded on tape, and transferred to a mainframe for further analysis.

Description of the Neural Network

The neural network chosen for this study was a non-linear, multi-layered perceptron trained using back-propagation learning. A schematic diagram of the network is shown in Fig. 5. Two input layers are composed of 512 elements each, while the output layer is composed of 40 elements. For this application, successive elements of the input layer are assigned successive data points of the AE signals, while each element of the output layer corresponds to one of the source locations on the test plate.

The goal of the network training procedure is to build internal representations of the inputs which contain sufficient information to identify the source location. The system shown in Fig. 5 thus contains two subnetworks: one to extract features for AE signal compression, and the second to perform pattern recognition for leak location. In the training stage, an autoassociation is first performed in the feature extraction network to compress the data into the 85-component feature vector. The compressed data is then used to train the leak location subnetwork. In the present case, to achieve optimal performance it was necessary to fine-tune the autoassociative network with feedback from the leak location network. An important point is that compression or other changes in representation can preserve, but may obscure, essential signal characteristics which then cannot be efficiently accessed by subsequent stages.

Fig. 5. Neural network configuration

Training the Neural Network

The goal of training a neural network is to find values of some set of internal variables which permit correct classification of the data. Ideally, the values found are sufficiently general that no subsequent training is necessary.

The training set of 20 AE signal records was divided into a sixteen-record "subtraining" set and a four-record cross-validation set. The back-propagation learning algorithm was then run repeatedly while training on the subtraining set and validating on the cross-validation set. The object was to find values of the initial parameters; e.g., learning rate, momentum coefficient, initial connection weights, etc., which produced peak performance with the cross-validation set. These parameters were then used to train the network using the complete AE training sets. In this particular case, the following parameters produced good performance: a learning rate of 0.15, a momentum coefficient of 0.65, a range of initial connection weight values of $[-0.2, 0.2]$, and target output element activation levels of 0.2 and 0.8. The low learning rate arises because of the necessity of very small learning steps. The output activation levels just mean that the output element corresponding to the correct location must have a value at or exceeding 0.8 while all other values are at or below 0.2. During examination of the test set, location was assigned to the element with the largest output.

A set of learning trials was also performed to optimize the network size. During these trials, the number of processing elements in the hidden layers was systematically varied and performance compared among the various configurations.

Experiments

Two sets of experiments were performed, the first containing signals representative of all locations in both the training and test sets, and the second where signals from eight locations were withheld from the training sets, but were included in the test sets.

For the first set of experiments, seven disjoint test sets of 24 signals were selected from the 160 recorded waveforms. This allowed seven tests to be performed, with each record at some point belonging to a training set and a test set. For the second set of experiments, 24-sample training sets were built from waveforms randomly selected from 32 of the 40 source locations. The test sets included signals from the remaining eight source locations as well as other locations, testing the ability of the network to locate signals with characteristics not specifically trained for.

Results of the experiments are shown in Table 1. Classification performance when the network was trained using signals from all locations was significantly more accurate than when trained using random locations and unfamiliar test signals. Although not indicated in the table, over 85% of the waveforms left out of the training sets were located within 20 centimeters (two positions) of the true source location for both experiments.

Table 1. Neural Network Test Results

Leak Location Dependent Series				Leak Location Independent Series			
Test No.	Within 5 cm	Within 10 cm	Mean Error (cm)	Test No.	Within 5 cm	Within 10 cm	Mean Error (cm)
1	50%	75%	10	1	0%	71%	12
2	49%	71%	10	2	9%	72%	12
3	50%	79%	9	3	4%	79%	12
4	63%	91%	7	4	0%	79%	13
5	42%	79%	9	5	0%	63%	12
6	42%	79%	9	6	4%	59%	14
7	49%	79%	9	7	13%	67%	12

DISCUSSION

The above tests and experiments indicate that the detection and location of impacts will not be a problem, and that detection of even very small leaks resulting from impact will be detectable dependent on ambient noise. With regard to leakage the issues are: a) the minimum leak rates that must be detected, b) the minimum rate which can be detected by a reasonable array configuration in situ, c) whether it is sufficient to use an "impact followed by leakage" tactic to locate leak signals, and d) the characteristics of ambient background noise. The use of signal level to aid in source location and provide source-strength estimates is impeded by the position dependence of signal

amplitudes, while the cross-correlation technique does not appear to be effective. The neural network approach offers a possible solution to the problem, if an effective training set for leakage can be obtained. Obtaining training data from a gas jet is fairly simple, but the weights and other parameters must then be transferrable to leak data. An alternative is to train with real leak data, but of course acquiring such data would be difficult and expensive.

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