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NEURAL NETWORK PREDICTION OF FAILURE OF DAMAGED COMPOSITE PRESSURE VESSELS FROM STRAIN FIELD DATA ACQUIRED BY A COMPUTER VISION METHOD

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INTRODUCTION:

This effort used a new and novel method of acquiring strains called Sub-pixel Digital Video Image Correlation (SDVIC) on impact damaged Kevlar/epoxy filament wound pressure vessels during a proof test. To predict the burst pressure, the hoop strain field distribution around the impact location from three vessels was used to train a neural network. The network was then tested on additional pressure vessels. Several variations on the network were tried. The best results were obtained using a single hidden layer.

SDVIC is a fill-field non-contact computer vision technique which provides in-plane deformation and strain data over a load differential. This method was used to determine hoop and axial displacements, hoop and axial linear strains, the in-plane shear strains and rotations in the regions surrounding impact sites in filament wound pressure vessels (FWPV) during proof loading by internal pressurization. The relationship between these deformation measurement values and the remaining life of the pressure vessels, however, requires a complex theoretical model or numerical simulation. Both of these techniques are time consuming and complicated. Previous results using neural network methods had been successful in predicting the burst pressure for graphite/epoxy pressure vessels based upon acoustic emission (AE) measurements in similar tests (Walker, J. L., Hill, E. v. K., Workman, G. L., Russell, S. S., "A Neural Network/Acoustic Emission Analysis of Impact Damaged Graphite/Epoxy Pressure Vessels," *American Society for Nondestructive Testing, 1995 Spring National Conference, 20-24* March 1995). *The* neural network associates the character of the AE amplitude distribution, which depends upon the extent of impact damage, with the burst pressure. Similarly, higher amounts of impact damage are theorized to cause a higher amount of strain concentration in the damage effected zone at a given pressure and result in lower burst pressures. This relationship suggests that a neural network might be able to find an empirical relationship between the SDVIC strain field data and the burst pressure, analogous to the AE method, with greater speed and simplicity than theoretical or finite element modeling.

The process of testing SDVIC neural network analysis and some encouraging preliminary results are presented in this paper. Details are given concerning the processing of SDVIC output data such that it may be used as back propagation neural network (BPNN) input data. The software written to perform this processing and the BPNN algorithm are also discussed. It will be shown that, with limited training, test results indicate an average error in burst pressure prediction of approximately six percent,

SPECIMEN:

This study is part of a larger damage assessment program concerning impact damaged FWPV. The specimen utilized for this study conform to ASTM standard D2585-68 (1985), and represent sub-scale simulated solid rocket motor casings or fuel storage vessels with a 14.6 cm diameter. The bottles were formed by a series of helical and hoop plies, with the outermost being a hoop, as shown in Figure 1. At the NASA Marshall Space Flight Center's Productivity Enhancement Complex, DuPont Kevlar fibers were wet wound with Dow DPL862/W epoxy resin around an inner rubber bladder on a sand mandrel and then rotisserie cured to form each specimen. The undamaged burst pressure was approximately 20.7 MPa.

APPARATUS AND PROCEDURE:

An air driven water pump was used to internally pressurize each specimen as shown in Figure 2. This figure illustrates the SDVIC data acquisition hardware. Approximately 6.45 cm^2 around the impact zone on each impacted bottle, or at a random location on each un-impacted bottle, was viewed by a CCD camera with illumination by two 500 watt halogen quartz shop lamps. A random black and white speckle pattern was applied to the region of interest on each bottle by over-spray from ordinary flat or low gloss spray paint to assist in the image correlation process. A PC based image digitization board was used to acquire images during holds in the pressurization cycle. These images correspond to approximately 0,8,

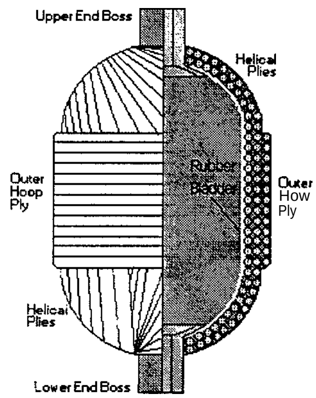

Figure 1. Specimen Geometry

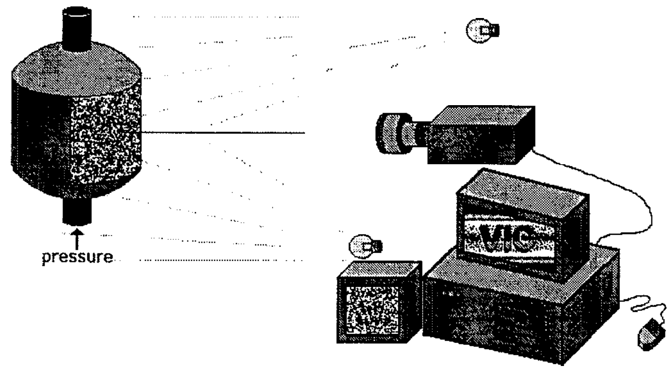

Figure 2. Data Acquisition Apparatus

17, 25, and 33 percent of the undamaged burst pressure for an un-impacted bottle. To minimize vibration effects, five frames were averaged for each image.

The SDVIC image processing software was used to correlate each non-zero image with the image acquired at O pressure. This software utilizes a pattern recognition algorithm to determine with sub-pixel resolution the relative position, and thus deformation, of small image subsets between two images. An automated routine repeats this process for a grid of subsets covering the entire region of interest, resulting in tabulated and false color plotted full-field displacement and strain data. Figure 3 and 4 are a false color plot of the hoop strains and a photograph of an impact damaged graphite/epoxy pressure vessel respectively. The underlying hoop plies had ripped vertically as a result of the impact an a previous low level pressurization. The SDVIC software package is available from NASA COSMIC.

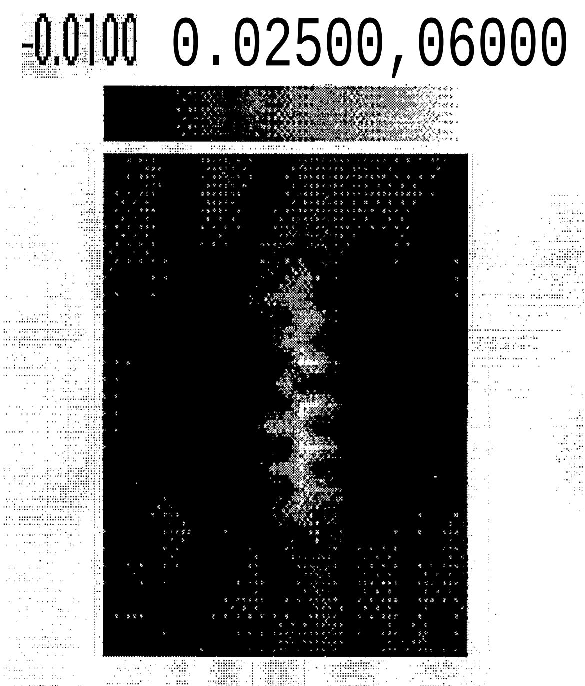

Figure 3. Hoop Strain in Gr-Ep Vessel.

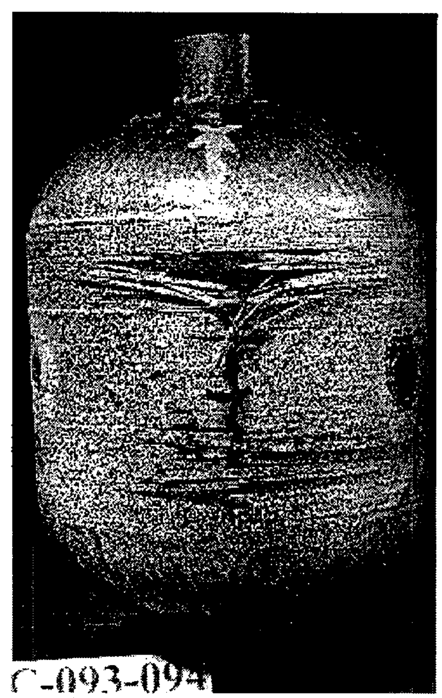

Figure 4. Failed Gr-Ep Vessel.

DATA REDUCTION:

In the case of AE neural network analysis, the amplitude distribution is divided into a series of discrete categories, with the population of each supplied as the input to the corresponding input layer neuron. The six deformation fields (in-plane displacement and the inplane strains and rotations) generated by SDVIC processing are each composed from a grid of 134 x 134 measurements, for a total of 17,956 data points. It is not practical to attempt processing with this many input neurons. Therefor, the tabulated SDVIC deformation field data is summarized by a group of distributions analogous to the AE amplitude distribution, With some qualitative foresight as to the failure characteristics of these specimens, the hoop strain was chosen as the single parameter which most strongly represents the damage, and is the only input to the neural net.

It is theorized that an increase in impact damage severity, corresponding to a decrease in burst pressure, will cause more of the strain field to contain higher strain values due to the strain concentrating effect of that damage. That is, at a given internal pressure an un-impacted bottle maybe expected to have a narrow distribution of hoop strain values about some average. An impacted bottle with the pressure, field of view, and all image correlation parameters repeated should have a lower and wider distribution due to a shift toward higher strain values. Figure 5. illustrates that a bottle with a burst pressure of 17.9 MPa has a taller, narrower distribution than one with a burst pressure of only 11.7 MPa. From another point of view, the area under this curve represents a strain x area product, which resembles a strain energy.

The minimum and maximum strain varies from specimen to specimen, and the neural network approach requires the same number of inputs for each specimen. Thus, each individual strain field was converted to a strain distribution with the same number of categories, but not necessarily the same category ranges. For example, if there are 20 strain categories and input neurons, then the first input neuron always receives the number of data points which fall in the lowest twentieth (or five percent) of the strain distribution.

The hoop strain distributions used in this test are shown in Figure 6. in order of increasing burst pressure from front to back. This set of nine specimen represent a range of impact damage levels from none to that which reduced the actual burst pressure by approximately one quarter of the undamaged value. Seventeen strain categories and input neurons were used. The data used here was obtained during a 6.89 MPa hold in the proof cycle, or at approximately one third of the undamaged burst pressure. This level of pressurization should cause no damage to an un-impacted specimen.

NEURAL NETWORK PROCESSING:

A software program called VICNet was written to convert the tabulated SDVIC strain field data into strain distribution tables for the entire population of specimens at once. The program then input the strain distributions and actual burst pressures for three of the nine bottles, which had been designated as the training data set. The VICNet back propagation neural network (BPNN) routine analyzed the training set to adjust internal weights and biases such that the neural network output was within an average of 5% deviation from each actual burst pressure. In addition to the seventeen input neurons and single output neuron, a hidden layer of 3 intermediate neurons were used. The results of this training, which required only 85 iterations and less than 10 seconds, are shown in Table 1.

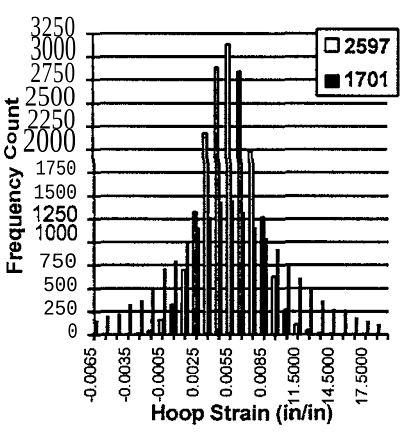

Figure 5. Comparison of Strain Distributions for Different Burst Pressures

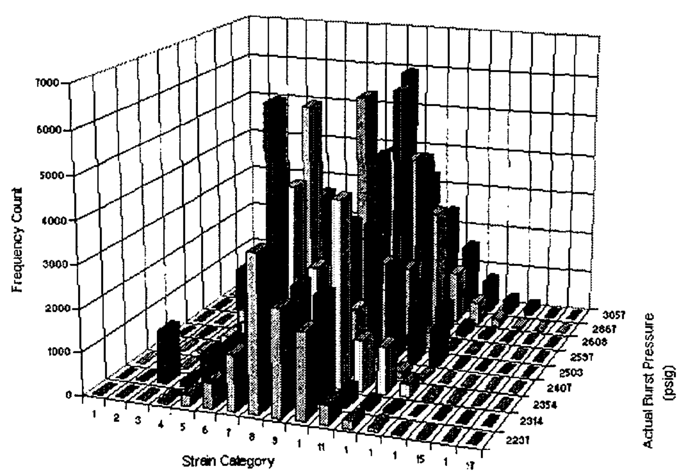

Figure 6. VICNet Hoop Strain Distributions for BPNN Input

Table 1. Training Results

Actual Burst Pressure (MPa)	VICNet-BPNN output	% Error
15.4	15.9	3.4
18.0	18.7	4.3
21.1	19.5	-7.3
Average Magnitude Difference		5.0

Table 2. Test Results

Actual Burst Pressure (MPa)	VICNet-BPNN output	% Error
15.9	15.1	-5.2
16.2	16.5	2.0
17.2	18.0	4.5
17.9	19.2	7.2
19.7	18.2	-8.0
16.5	15.2	-8.2
Average Magnitude Error		5.9

The VICNet BPNN routine then input the strain distributions for the remaining specimens which were designated as the test data set. These distributions were processed by the neural network in a single pass using the internal weights and biases determined from training, The actual burst pressures were in no way accessible to the software algorithm. The test results are shown in Table 2. Multiple independent repetitions of this training and testing have yielded similar average uncertainties.

CONCLUSIONS:

It has been shown that a back propagation neural network routine can, with some degree of accuracy, be trained to predict the burst pressure of impact damaged structures based upon SDVIC strain field data collected from other similar structures. In the case of the filament wound pressure vessels studied here, an average testing error of about six percent has been demonstrated. To be completely thorough, future testing will be conducted in which this method is used to predict the burst pressure of the specimen prior to actual burst testing. It will also be determined whether similar analysis at lower proof loads will provide similar levels of uncertainty. Further research will also be conducted to determine the extent to which a neural network which has been trained on SDVIC data from one size of specimen may be used to predict failure of another size of similar specimen. If this is successful, then a network which has been trained on an appropriate set of smaller, less expensive specimen may be used to predict the failure of a larger, more expensive service article which may have sustained some form of damage.