# Signal to Noise Studies on Thermographic Data with Fabricated Defects for Defense Structures

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## ABSTRACT

There is a growing international interest in thermal inspection systems for asset life assessment and management of defense platforms. The efficacy of flash thermography is generally enhanced by applying image processing algorithms to the observations of raw temperature. Improving the defect signal to noise ratio (SNR) is of primary interest to reduce false calls and allow for easier interpretation of a thermal inspection image. Several factors affecting defect SNR were studied such as data compression and reconstruction using principal component analysis and time window processing.

**Keywords:** thermal nondestructive evaluation, data processing, flash thermography, principal component thermography, defect signal to noise.
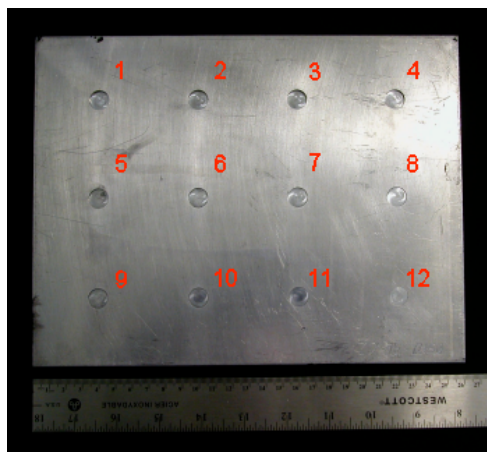
## 1. INTRODUCTION

Rapid, wide area, and noncontact inspections are beneficial to reduce maintenance costs and improve fleet readiness for both new and aging defense structural aircraft systems. Thermal nondestructive evaluation (NDE) has been shown to be useful for the noncontact detection of defects in composite, metallic, and hybrid composite/metallic structures. Large areas can be inspected rapidly with this technique because the measurement is based on the use of an infrared camera. Additionally, since digital inspection images are produced and stored, one can archive these images for future reference as part of a Structural Integrity Management philosophy.

As more thermography applications are transitioned from the laboratory into the field, software tools need to be developed to overcome the challenges associated with thermal NDE. Some of these challenges are the processing of large data sets, ease of use, and the optimal detection of subsurface defects to prevent false calls. The efficacy of flash thermography is generally enhanced by applying image processing algorithms to the observations of raw temperature. Improving the defect signal to noise ratio (SNR) is of primary interest to reduce false calls and allow for easier interpretation of a thermal inspection image. Several factors affecting defect SNR are studied such as data compression and reconstruction using principal component analysis (PCA) and time window processing.

Principal component thermography (PCT) is the application of PCA for the processing of thermal NDE data.[1] This algorithm is based on the decomposition of the thermal data into its empirical orthogonal functions and is therefore useful in determining a lower dimensional basis to represent a thermal data set. One major advantage of this processing technique is the defect contrast information from the entire data set is collapsed into a few images, and therefore the operator is not required to step through a set of many processed images to find the anomalies associated with defects. Another advantage of PCA is the use of fixed eigenvectors for repeated inspections of the same structure.[2] The fixed eigenvectors solution can be predetermined by using a model and/or experimental data. The model can used to account for varying degrees of simulated defects. Experimental data can be taken on a standard with a range of expected defects. This allows for a significant decrease in computation time since the eigenvector solution set is already pre-determined. Also by using the model, quantitative thermal inspections can be performed. Since thermal NDE signals are well behaved and slowly decaying response, the dominant variations of the data set is usually contained in the first few eigenvectors which makes this technique promising for data compression and noise removal after reconstruction. In this study, thermal data is obtained on samples with known defects. Obtaining optimal defect contrast using PCA is studied. In addition, a comparison is made using an experimentally determined fixed eigenvector solution. Lastly data reconstruction is performed using eigenvectors containing the defect contrast information.

## 2. SAMPLES STUDIED

Thermal NDE data was acquired on various samples with known defects. These samples were chosen to represent structural types commonly found on both new and existing defense aircraft. These samples were two aluminum plates, a composite panel, a composite honeycomb panel, and an aluminum plate with a composite repair patch. The first sample studied is an aluminium plate of 3.2 mm of thickness containing twelve 11.7 mm diameter circular material loss regions. The material loss percentage of each region varies from 82 to 2.5 % material loss and is presented in the table in Figure 1. The front side of the specimen was painted with black paint to increase the surface emissivity. A back surface photograph of this specimen is also shown in Figure 1. Shown in Figure 2 is an aluminum plate sample with rectangular material loss defects. The sample is a 17.4 x 20 cm aluminum plate of 3 mm of thickness containing 4 columns of 2.5 cm wide rectangular material loss regions. The defects are positioned into four columns with each defect in the same column having the same depth. The material loss percentages of the four columns are 85%, 66.7%, 35%, and 20%. The length of the rectangles varies from 10 mm to 1.5 mm. The specimen front side was painted with black paint to increase its surface emissivity. A photograph of the specimen is shown in Figure 2. The composite panel contained



| Defect number | % of material loss | Defect number | % of material loss |
|---|---|---|---|
| 1 | 82 | 7 | 25 |
| 2 | 70 | 8 | 20 |
| 3 | 60 | 9 | 15 |
| 4 | 50 | 10 | 10 |
| 5 | 45 | 11 | 5 |
| 6 | 30 | 12 | 2.5 |

Figure 1. Defect layout of aluminum plate with circular backside material loss defects.
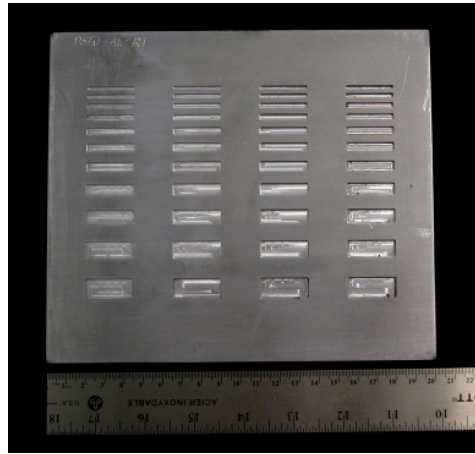
Figure 2.  Defect layout of aluminum plate with rectangular backside material loss defects.

manufactured delamination defects located at different depths.    The delaminations were created using a rectangular stamp to form an air gap.   The quasi-isotropic composite panel with a lay-up of [0/,45/,90/,-45/,0/,0,-45,90,45,0] is 30.5 x 30.5 centimeters in size.  The 10 ply panel is 0.20 cm thick.  The delamination defect areas are square with sizes of 14.5, 6.54, 3.6, and 1.6 square centimeters.  The inspection was performed on the reverse side of the sample and therefore the defects were buried at various depths of 50, 60, 70, 80 and 90 percent of the total thickness.  The sample configuration is shown in Figure 3.   Shown in Figure 4 is an aluminum plate containing a composite repair patch. The sample is 22.2 x 27.5 cm in size and is approximately 4 mm thick. The last sample studied is a composite honeycomb sandwich panel. The sandwich panel skins are 2 ply thick.  The sample has impact damage that is barely visible on surface.  The sample is 15.0 x 15.0 cm in size and is 26 mm thick. The specimen is shown in figure 5.
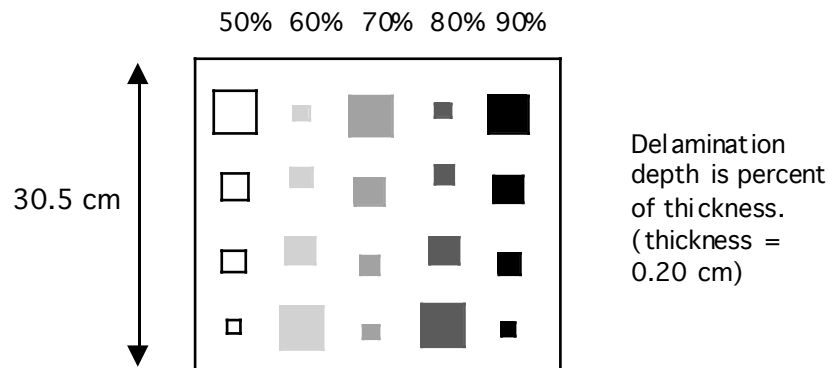


Figure 3.  Defect layout configuration for composite panel with delamination defects.
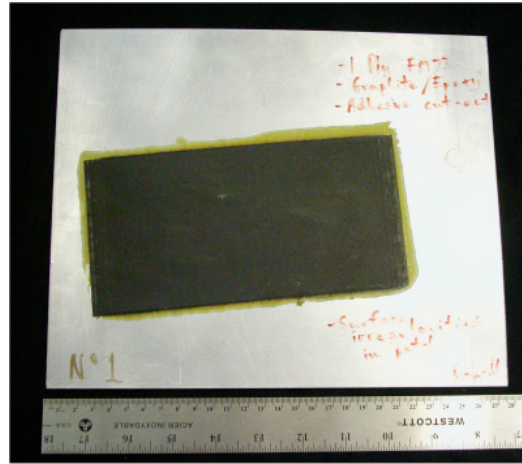
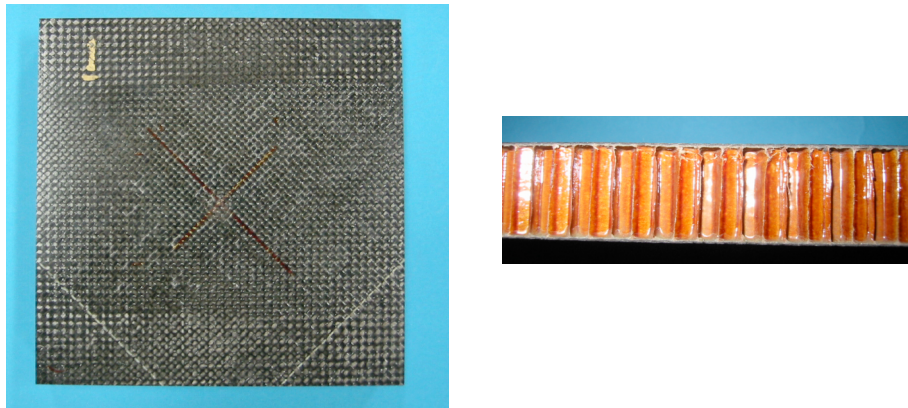Figure 4. Aluminum plate sample with composite repair patch.



Figure 5.  Top and side view of composite honeycomb core panel with impact damage.

## 3.  DATA ANALYSIS AND RESULTS

Thermographic flash inspection data was acquired using an EchoTherm[TM] commercially available inspection system. The EchoTherm[TM] uses two power flash lamps. The power flashes provide a global energy of 4.8 kJ.  Depending on system used, either a FLIR SC 3000 or a FLIR Phoenix infrared camera were used to record the specimen surface radiation.   The SC 3000 operates in the long wavelength infrared band with a pixel resolution of 240x320.  The Phoenix infrared camera operates in the mid wavelength IR band with a pixel resolution of 256x320.  Both cameras have sensitivities of less than 25 mK.

### 3.1 Principal Component Thermography (PCT)
PCT is a relatively new processing technique for analysis of thermal data using PCA.  This analysis technique takes advantage of the slowly decaying temperature response after flash heating and is based on the decomposition of the

thermal data into its principal components or eigenvectors.[1]   The largest eigenvector associated with the largest eigenvalue primarily represents the dominant decaying temporal feature of the thermal data.  Any variance from this dominant feature will be accounted for in the subsequent eigenvectors and is used to obtain defect contrast information. A major advantage of this processing technique is its capacity to reduce the dimensionality of the data, and therefore the processed data set is reduced to a few images containing the defect contrast.  The PCA is computed by defining a data matrix A, where the number of columns is equivalent to the number of sampled images and the number of image pixel points is equivalent to the number of rows. The matrix A is adjusted by subtracting the mean along the time dimension. The matrix A can then be decomposed as:

$$A^{\mathrm{T}}A \;=\; \mathrm{U} * \Gamma^{2} * \mathrm{U}^{\mathrm{T}} \tag{1}$$

where $\Gamma$ is a diagonal matrix containing the singular values and U is an orthogonal matrix which contains the eigenvectors describing the time variations. The eigenvectors of the covariance matrix $A^{T}A$ can then be calculated to obtain the columns of U.  The matrix E can be defined as the subset of the columns of U wherein typically the first n columns or eigenvectors of U completely describe the data temporal variance and eigenvectors greater than n accounts for the noise in the data and have eigenvalues corresponding to relatively very small values (close to zero).  Typically, n equal to three or four completely describes the total data variance without regard to noise.

$$E \;=\; [\; u_{1},\, u_{2},\, .. \; u_{n} \;] \tag{2}$$

The PCA matrix image set F is defined as:

$$F \;=\; E\, \mathrm{A}^{\mathrm{T}} \tag{3}$$

and is calculated by the dot product of the time variations, E, by the transpose of the measured temperature response (matrix A), pixel by pixel.   The columns of F can be partitioned into the respective eigenvector images.  The second or third eigenvector PCA image provides good contrast for defect detection.

Shown in Figure 6 is the PCA image of the aluminum sample with circular material loss defects.  All material loss defects down to 2.5% were detected (dark areas).  The PCA image was calculated from the second eigenvector. The thermal data was taken using the SC3000 IR camera at a frame rate of 20 Hz and the first 60 frames were analyzed.  A horizontal line plot was generated over the deepest defects (around image line 172).   The line plot represents the average of 5 horizontal lines and this is shown in Figure 6.  From the line plot, an average SNR value for each defect was calculated.  Each SNR value was calculated by taking the absolute value difference of the averaged pixels over the defect (11 pixels) minus the average of the background pixels (16 pixels) and dividing by the standard deviation of the background pixels. The background value was subtracted from the defect value before dividing by the background standard deviation to obtain the defect SNR.   The averaged defect SNR value was calculated for the four deepest defects and is also plotted in Figure 6 as a function of delay from flash.  The peak SNR value is obtained by starting the processing on the second image (delay of 0.1 seconds) after the flash.  The lower SNR obtained before 0.1 seconds is due to the residual interaction of the flash heat source and the background not coming to equilibrium.  The lower SNR after 0.1 seconds is due to loss of information attributed to removing too many images.  By window processing the data, the peak SNR can be obtained for the deepest defects.

Shown in Figure 7 is the PCA image of the composite sample with delamination defects.  All delamination defects were detected (dark areas) except the 1.6x1.6 cm delamination buried at 90% of the thickness.   The PCA image was calculated from the third eigenvector. The thermal data was taken using the Phoenix IR camera at a frame rate of 60 Hz and the first 600 frames were analyzed.  A horizontal line plot was generated over the deepest defects (around image line 110).  The line plots represents the average of 5 horizontal lines and this is shown in Figure 7.  From the averaged line plot, an average SNR value for the deepest defects were calculated by taking the absolute value difference of the averaged pixels over the defect (11 pixels) minus the average of the background pixels (16 pixels) and dividing by the standard deviation of the background pixels. The background value was subtracted from the defect value before dividing by the background standard deviation to obtain the defect SNR.  The averaged SNR value calculated for the four deepest defects is also plotted in Figure 7 as a function of delay from flash.  The peak SNR value is obtained by

starting the processing on the 110th image (delay of 1.63 seconds) after the flash. The lower SNR obtained before 1.63 seconds is due primarily to the background not coming to equilibrium. The lower SNR after 1.6 seconds is again due to loss of information attributed to removing too many images. By window processing the data, the peak SNR can be obtained for the deepest defects.
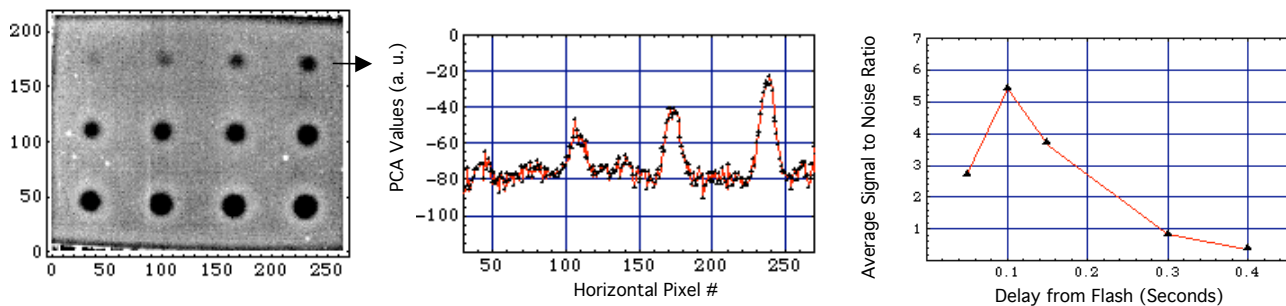


Figure 6. Second PCA image of aluminum plate with line plot over first row of material loss defects.
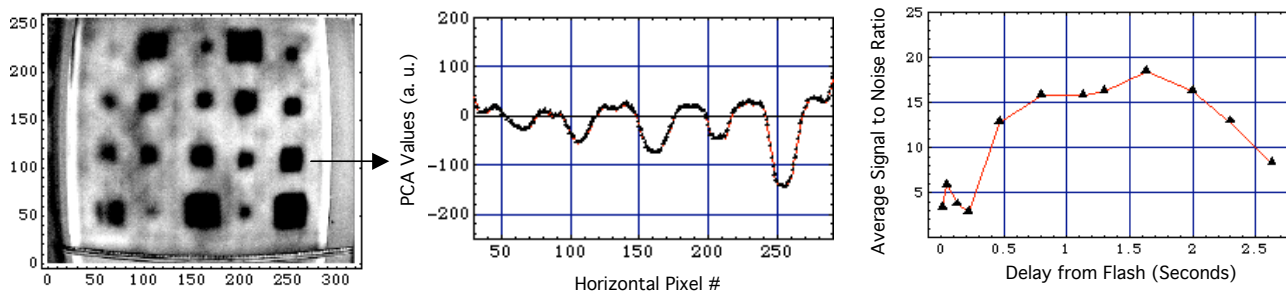


Figure 7. Third PCA image of composite panel with line plot over delamination defects.

### 3.2 Fixed Eigenvector PCA

Another advantage of PCA is the use of fixed eigenvectors for repeated inspections of the same structure. The fixed eigenvectors can be predetermined by using a model that accounts for varying degrees of simulated defects and/or data taken on a standard with a range of expected defects.[2] This allows for significant decreases in computation time since the E matrix is already pre-determined. The PCA matrix image set can then be calculated as:

$$F = E_{Fixed} \, \mathrm{A}^{\mathrm{T}} \tag{4}$$

where $E_{Fixed}$ is the predetermined eigenvector solution set. The fixed eigenvector set previously calculated from the aluminum plate with circular material loss defects is used on the aluminum sample with rectangular defects. A comparison of the PCA images, shown in Figure 8, is made between using the fixed and the calculated eigenvector set. The same material thickness, measurement parameters, and defect type allows for the use of the fixed eigenvector solution. The SNR ratio for both images was calculated for the 4 widest defects at 20% material loss. The averaged SNR ratio percent difference was less than 0.03% indicating excellent agreement. The computation time improvement can be significant and is dependent on the covariance matrix size. For this example the computation time was reduced by approximately 10 seconds for a covariance matrix size of 47x47. For covariance matrix sizes of 200x200 and

300x300 the computation time is reduced by53 and 98 seconds respectively. This computation time is greatly decreased with larger covariance matrix dimensions.
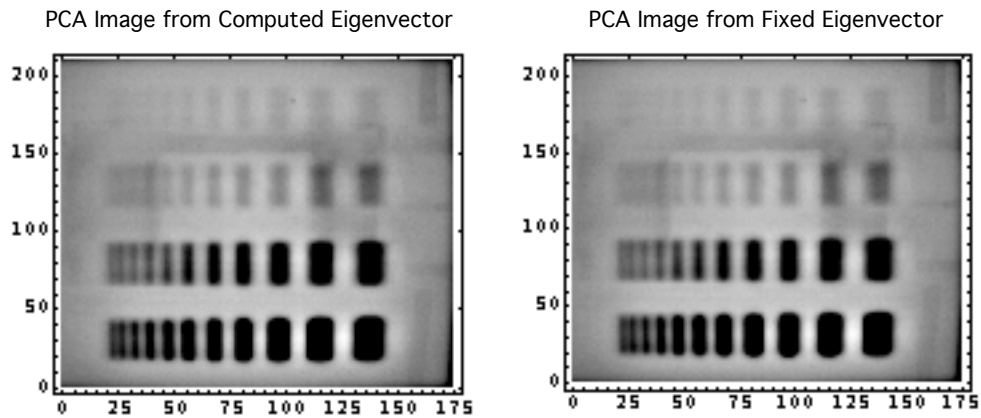
PCA Image from Computed Eigenvector            PCA Image from Fixed Eigenvector



Figure 8. Comparison of PCA image computed from a previously calculated or fixed eigenvector.

### 3.3 Data Reconstruction Using PCA

Since the defect contrast information from the data set is collapsed into a few images, relative depth information is lost. Relative defect depth information is important to determine failure modes. For example, with composite impact damage, there can be fiber/matrix cracking on the surface followed by underlying delamination damage. Sometimes the delamination damage may mask the near surface cracking. Relying on defect contrast may not be a good indicator of defect depth since depth of damage and extent of damage may be different. For instance, a delamination buried near the surface with a small air gap may give a similar signal to noise value, than a delamination buried deeper with a larger air gap. The size of defect can also affect SNR. By reconstructing the data using only the eigenvectors of interest (only those with variations due to the defects), relative defect depths may be approximated qualitatively. The reconstruction can be calculated as follows:

$$A^T_{reconstruct} \; = \; E^T F \qquad\qquad (5)$$

where $E^T$ and F are calculated using the eigenvectors of interest and $A^T_{reconstruct}$ is the reconstructed data set. An example of this reconstruction and its excellent noise reduction qualities is shown in Figure 9 where eigenvectors 1-3 are used. Shown in Figure 10 are the reconstructed images using eigenvectors 2–4. If eigenvectors 1-4 were used then the reconstructed data set would be very close to the original data set with most of the temporal noise removed.
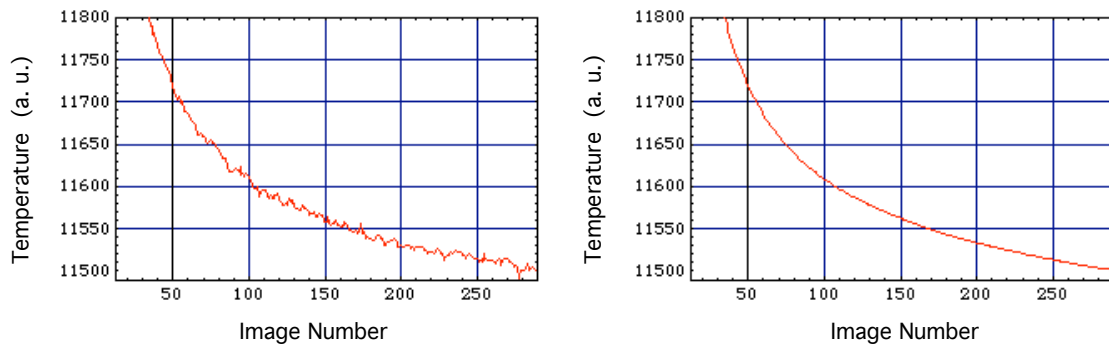


Figure 9. Comparison of reconstructed thermal responses from the composite repair sample.

Figure 10 shows the separation of the evolution of the defects as a function of image number where image number 12 shows the early time, image number 30 shows some disbond areas on the left (dark areas) and finally image number 100 reveals the deeper disbond defects on the right. Shown in figure 11 are the reconstruction results on the composite honeycomb sample. The near surface impact damage is shown in the reconstructed image number 7 and overall damage is shown in image number 25. By reconstructing the data using only the eigenvectors with defect contrast information, it is possible to determine qualitatively the defect depth in a relative fashion.
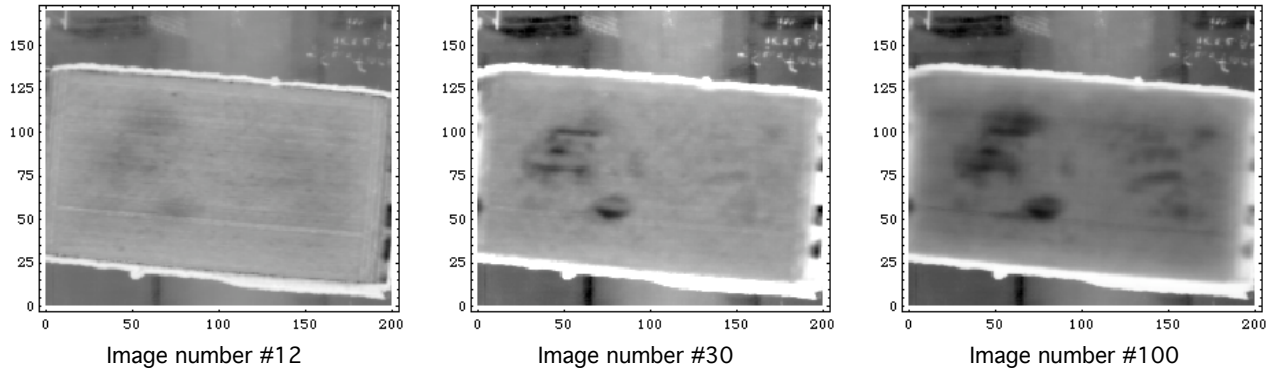


| Image number #12 | Image number #30 | Image number #100 |

Figure 10. Comparison of reconstructed inspection images for composite repair sample.
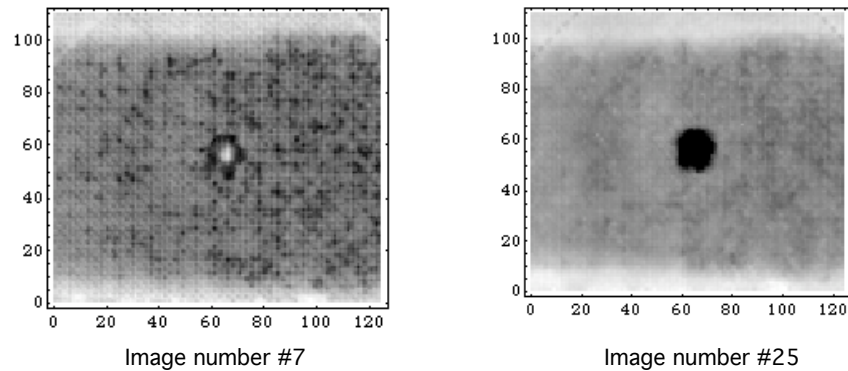


| Image number #7 | Image number #25 |

Figure 11. Comparison of reconstructed images for the honeycomb sandwich panel.

## 4. CONCLUSIONS

It has been demonstrated that improved defect SNR is obtained by window processing the data using an optimal starting time while using PCA. The optimal SNR is obtained when the background reaches equilibrium. By window processing the data, the peak SNR can be obtained for the deepest defects. In addition, insignificant loss in SNR was demonstrated in Figure 8 when using the fixed eigenvector solution. The averaged SNR ratio percent difference for the four deepest defects was less than 0.03% indicating an excellent agreement between the computed and fixed eigenvector set images. The computation time is significantly improved allowing for fast processing of large amounts of data sets. PCA can be used to reconstruct a set of images which can separate near surface defects from far surface defects. By reconstructing the data using only the eigenvectors with defect contrast information, it is possible to qualitatively determine the defect depth in a relative fashion. A more thorough future study of the time variation matrix

may reveal a means to quantitatively determine defect depth. In addition, because of the excellent noise rejection quality of PCA, quantitative defect depth measurement can be determined by using a separation time method which compares the reconstructed thermal response to a thermal model.

## REFERENCES

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