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Classification of pulsed eddy current GMR data on aircraft structures

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ABSTRACT

This paper presents a technique to automatically detect third-layer cracks at rivet sites in aircraft structures using the response signals collected by giant magneto-resistive (GMR) sensors. The inspection system uses pulsed waveform as the excitation source of a multi-line coil and captures the transient fields associated with the induced eddy currents via a GMR sensor, which was developed to detect cracking and corrosion in multi-layer aircraft structures. An automatic scan of the region around the rivet generates C-scan image data that can be processed to detect cracks under the rivet head. Using a 2-D image of each rivet head, feature extraction and classification schemes based on principal component analysis and the *k*-means algorithm have been successfully developed to detect cracks of varying size located in the third layers at a depth of up to 10 mm below the surface.
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1. Introduction

Eddy current testing methods have served as the primary nondestructive evaluation (NDE) technique for applications in the aviation industry [1]. However, the performance of traditional eddy current testing systems is limited by the depth of penetration of eddy currents into the sample due to the skin effect phenomenon. The detection and characterization of hidden cracks around fastener sites in multi-layered structures of aging aircraft is a major challenge in the aviation industry. For this reason, the development of reliable nondestructive inspection techniques to detect such cracks has remained an area of significant research focus. Research projects aimed at improving the conventional eddy current testing method have resulted in a variety of possibilities. Replacing the pick-up coil with magnetic sensors, developing a new design for the excitation coil, and using multiple frequency excitations have all been proposed as methods to increase the frequency bands of the excitation current [2–4] as well as received eddy current signal. The pulsed eddy current (PEC) testing technique is an emerging method in which a pulse or square waveform is used as the current source rather than the single sinusoidal excitation used in the traditional eddy current [5]. The PEC excitation technique comprises a broad spectrum of frequencies that offer advantages in the detection of surface and subsurface defects in multilayer structures [6].

The giant magneto-resistive (GMR) sensors are magnetic field sensors. Researchers are finding an increasing number of applications for GMR in eddy current NDE [7]. The main advantage of magnetic-field sensors is that they measure the magnetic flux density directly, while the traditional pick-up coils receive the rate of change of the induced magnetic field. Measuring the induced flux density directly allows the magnetic-field sensors to improve the low signal-to-noise ratio at low frequencies. A PEC–GMR inspection system was developed to solve the problem of detecting deep cracks at the sites of fasteners in multi-layer airframe geometry. A multi-line coil with symmetric structure was employed using pulse excitation and a GMR sensor positioned at the center of the coil geometry to measure the normal component of the magnetic field. The GMR sensor was used because of its ability to maintain high feasibility over a wide range of frequencies from DC to MHz [8]. The inspection data are transient signals collected at each sensor position via 2-D scan, which are then displayed as a C-scan image. Conventionally, the peak values and peak times are the common features used to represent 1-D pulse response signals, which can then be used to identify or classify the different response outputs relative to different crack states [9]. However, valid signal processing approaches for analysis of 2-D images of pulse response remains a challenge for signal processing algorithms in PEC applications. Principal component analysis (PCA) is a powerful statistical algorithm used to represent the input signals of the calculated principal components, which can be exploited as extracted features for human face identification, pattern recognition, data compression and image classification [10–13]. The authors in [14] applied the PCA approach to classify three categories of defects based on the 1-D signals tested by the PEC sensor system.

In this paper, we propose the application of principal component analysis to process 2-D images obtained using a

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PEC–GMR system. The C-scan image of different rivets is represented into PCs feature domain by reducing the dimensionality of the dataset. The useful classifier, *k*-means clustering, is applied to the data set in order to achieve a template for classification and detection of rivet features. The PCA-based *k*-means has enhanced the probability of detecting third-layer cracks around the rivet sites at a depth of 10 mm from the sample surface. The rest of the paper is organized as follows. Section 2 presents the PEC-GMR inspection system and data collection procedure. Section 3 discusses the feature extraction using PCA and *k*-means classification. Section 4 presents the experimental result and the classification performance of the system for the test rivets and Section 5 provides some concluding remarks.

2. PEC–GMR inspection system

The inspection system comprises a source coil and detection sensor. A planar copper sheet with symmetric multiple turns is applied as the source coil. The GMR sensor is placed at the center of the coil geometry, which enables the GMR sensor to measure only the normal component of the magnetic field, as shown in Fig. 1. When detecting rivet geometry, the normal component is only produced by the presence of rivet or the crack around rivet site or both, which forces the induced eddy current to bend direction. The symmetric property of the magnetic field is disturbed and the normal component of the induced flux density is yielded in response to the rivet or crack state. The 100 Hz square waveform is used as excitation current in order to detect cracks in deep layer structures.

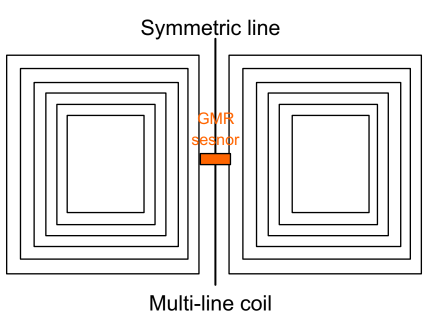

Fig. 1. The schematic geometry of coil and GMR sensor.

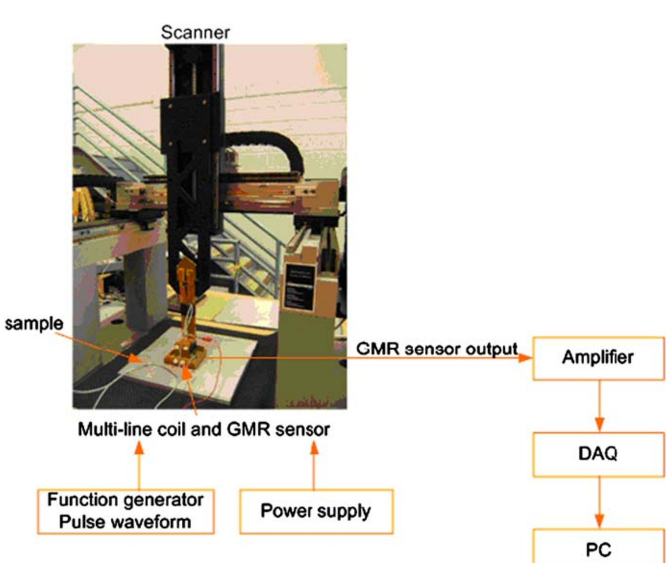

Fig. 2. The overall block diagram with a scanning system.

As shown in Fig. 2, an automatic high-resolution scanning system is used to generate the 2-D scan around each rivet region. A magnet is used to supply the bias field for the GMR sensor working in the linear region. The two-stage amplifier is designed to amplify the output signal of the GMR sensor. The normal component of the transient magnetic field measured by the GMR sensor at each scan position is sampled, digitized and then stored on a PC. An aluminum sample with three layers of thicknesses (6, 4 and 4 mm) and four rivets is used to simulate the multi-layer structure of an aircraft. The rivet head is of 6 mm diameter at the top and 3 mm diameter at the bottom and extends through the three layers. In the third layer, cracks of radial length 1, 3 and 5 mm are machined into the three rivet sites. The first rivet is crack free. The specimen geometry is shown in Fig. 3.

For each rivet, the 1-D transient signals detected by the GMR sensor are collected for analysis. The transient output at each position around the rivet site is measured by the GMR sensor with a 2-D scan at a 50 KHz sampling frequency. At each scanning position, the signal collected by the GMR sensor is averaged over 256 cycles of transient output for duration of 2.56 s, reducing the noise effect. The typical 1-D transient output of one scanning point is shown in Fig. 4(a). It should be observed that the transient output at each scanning position presents a different magnitude of information. Therefore, in this paper, the peak value of each transient output was obtained to generate the C-scan image for each rivet. The C-scan images based on the peak value information for the three-layer aluminum sample are shown in Fig. 4(b). The 2-D image in the first column shows the rivet free of cracks. The remaining images present the rivets that have had cracks machined into the third layer around rivet site.

3. Feature extraction and classifier

PCA processing of signals is an optimal transformation method for dimensionality reduction and data compression that computes the covariance and keeps the subspace with larger variance. In this section, our effort was focused on the reduction of the input dimensionality of the feature vector. In PCA processing, the diagonalization of the covariance matrix is sometimes called the Karhunen–Loéve transform (KLT) [11,12]. The projection of data onto the eigenvector yields the principal components of the data. The covariance matrix of the data set can be expressed as

$$C_x = E\left\{(x-\mu_x)(x-\mu_x)^T\right\} \tag{1}$$

where the elements of C_x, denoted byc_{ij}, represent the covariance between the random variable components x_i andx_j. Since the covariance matrix is always real, symmetric, and positive definite, we can find an orthogonal matrix of eigenvectors of C_x that diagonalizes the covariance matrix. The eigenvalues are derived by finding the solutions to the characteristic equation

$$|C_x - \lambda I| = 0 \tag{2}$$

where I is the identity matrix having the same order as C_x and $|\bullet|$ denotes the determinant of the matrix. The corresponding eigenvalues λ_i are derived from the solutions to the equation

$$C_x \mathbf{e}_i = \lambda_i \mathbf{e}_i, \quad i = 1, 2, \ldots, n \tag{3}$$

If the data vector has n components, the characteristic equation is of order n. Solving for eigenvalues and corresponding eigenvectors in general is a non-trivial task. Several numerical methods have been developed to solve this problem including the more recent neural solution [14]. Arranging the eigenvectors in the order of descending eigenvalues (largest first), one can create

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