Rotating Current Excitation with TMR sensor for Inspection of Magnetized Steel Fasteners

Zhiyi Su¹, Daniel Piero¹, Anders Rosell¹,², Lalita Udpa¹, Satish Udpa¹

¹Department of Electrical and Computer Engineering, Michigan State University, East Lansing, MI 48824 USA
²GKN Aerospace Engine Systems, Trollhättan, Sweden

Abstract

Detection of fatigue cracks under fasteners poses one of the major challenges in the non-destructive evaluation (NDE) of aging aircraft fleet. The major challenges in defect detection is due to the fact that most cracks originate close to the rivet sites in arbitrary orientation. In the case of steel fasteners the defect indications are masked by the dominant signal from steel fasteners. Further, the steel fasteners can be randomly magnetized which distorts the field measurements due to strong remanence fields and permeability variations. In this paper we present a novel sensor utilizing rotating current excitation rent (EC) together with giant magnetoresistive (GMR) sensors. The rotating excitation current ensures sensitivity to defects of arbitrary orientations. The distortions due to variable magnetization levels of different steel rivets in the multilayer component are addressed by signal processing using an invariance transformation procedure that renders the signal insensitive to variability in relative permeability of rivet material. This paper will present results of simulating the rotating current probe design along with experimental validation. The invariance transformation formulation will be presented along with implementation results on simulated and experimental data.

1. Introduction

Eddy current (EC) coil using magnetoresistance (MR) sensors has recently emerged as a viable modality for rapid inspection of multilayered components with rivets. Ultra-low frequency excitation along with MR sensors have been developed to increase penetration depth, and also good signal to noise ratio (SNR) to ensure that we can obtain high sensitivity to deeply embedded defects. A major challenge for EC-MR inspection is that most cracks originate at fastener sites at different radial directions. Secondly, in the case of steel fasteners the defect indications are masked by the dominant signal from steels fasteners [1, 2]. Further, the steel fasteners can be randomly magnetized which further distorts the field measurements due to strong remanence fields and variability in permeability. This paper presents an invariance transformation algorithm that renders the signal insensitive to changes in permeability while maintaining sensitivity to defects.
2. Invariance Transformation

Mandayam [3] developed a novel invariant pattern recognition technique based on approximation theory for permeability invariance transformation of magnetic flux leakage signals. This paper implements an algorithm for permeability of MR signals as described next.

The basic idea in this paper is that given two signals $X_A$ and $X_B$, characterizing the same phenomenon, two distinct initial features, $x_A(d, \mu_r)$ and $x_B(d, \mu_r)$, are chosen, where $\mu_r$ represents relative permeability of the fastener and $d$ represents a defect related parameter, the transformation method estimates a feature $h$, which is a function of $x_A$ and $x_B$ and invariant to $\mu_r$. In other words, we need to find a function, $f$, such that

$$f(x_A(d, \mu_r), x_B(d, \mu_r)) = h(d)$$

(1)

Given two functions $g_1(x_A)$ and $g_2(x_B)$, a sufficient condition to obtain a signal invariant to $\mu_r$ can be derived as

$$h(d) \circ g_1(x_A) = g_2(x_B)$$

(2)

where $\circ$ refers to a homomorphic operator. Then the desired $\mu_r$-invariant response is given by:

$$f(x_A, x_B) = g_2(x_B) \circ g_1^{-1}(x_A) = h(d)$$

(3)

To implement this approach, the functions $h$, $g_1$ and $g_2$ have to be specified. Here, $h$ can be a linear function of $d$ and $g_2$ where $g_2$ is the identity function $g_2(x_B) = x_B$. Having chosen $h$ and $g_2$ a suitable functional form is assumed for $g_1$, whose coefficients are determined. In this work we choose the two signals $X_A$ and $X_B$ as the real ($B_r$) and imaginary ($B_i$) components of the magnetic flux density along the z direction ($B_z = B_r + jB_i$) with features Pr and Pi derived from peak values of the real and imaginary components respectively. Figure 1 shows Pr and Pi as functions of relative permeability for three different defect profiles. Pr and Pi characterize the same defect signal, but have different variations with respect to $\mu_r$. 
In this study, $g_1$ is approximated using radial basis function networks, i.e.,

$$ g_1 = \sum_{j=1}^{N} w_j \phi\left( \|x - c_j\| \right) $$

where $N$ is the number of cluster centers, $c_j$ is the $j$-th cluster center and it has the same dimension as $x_A$, i.e. $c_j = [c_{j1}, c_{j2}]^T$, $w_j$ is the $j$-th weight coefficient. Also, $\phi$ is a Gaussian function defined as $\phi(\|x - c\|) = \exp\left( -\frac{\|x - c\|^2}{2\lambda^2} \right)$ and $\lambda$ is the radius of the Gaussian kernel. Equation (4) is solved at known discrete data points $(d_i, \mu_{rk})$ and is guaranteed a $\mu_r$-invariant signal at these points.

### 3. Results

A numerical model was built with COMSOL®. For simplicity, the primary field is produced by an infinite current sheet carrying a uniform surface current density. Ten different values of relative permeability are assumed for the fastener and notch defects of three different lengths are considered. Simulated signals corresponding to $\mu_r=1, 3, 5, 7, 9$ are used to train the RBF network according to equation (4) and signals related to $\mu_r=2, 4, 6, 8, 10$ are used as a test data set. Figure 2 show real, imaginary and magnitudes of the magnetic field signal for training data sets. Raw data are shown in blue solid lines where overall signal strength increases with $\mu_r$. Processed data are shown in red dashed lines and they collapse all close to the signal corresponding to $\mu_r=1$, which is used as the target signal during training.
<table>
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<th>Defect length</th>
<th>Real component</th>
<th>Imaginary component</th>
<th>amplitude</th>
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**Figure 2.** Training data set and output signals. Blue solid lines: raw data. Red dashed lines: output invariant signal.

### 4. Conclusions and future work

This paper presents a procedure for permeability invariance transformation that is feasible for removing sensitivity of EC signals to material permeability changes. Results obtained from numerical simulations and experiments will be presented at the conference. The invariance transformed signals can be used in further processing and evaluation for defect classification and quantification.

### References