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OBJECTIVE AUTOMATED CORROSION DETECTION USING ULTRASONIC LAMB WAVES

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ABSTRACT

This paper extends previous work developing an on-board corrosion monitoring system [1]. The system is being designed to detect early stage corrosion using a permanently installed ultrasonic sensor capable of generating Lamb waves and processing the data using a Synthetic Aperture Focusing Technique (SAFT).

The SAFT images contain noise and distortion. Systematic background artifacts, random noise (speckle) and distortions caused by the SAFT processing are the main sources of image degradation. This degradation reduces the accuracy of detecting emerging corrosion damage and can lead to false calls. Accounting for these sources of degradation is crucial for developing a reliable and robust automated corrosion detection system. Models for the three sources of image degradation are established prior to on-line processing. These models are adjusted locally to account for spatial variation of the degradation within image. A mathematical model reflected essence of the SAFT is used for identification of the SAFT point spread function (PSF). Statistical approach is applied on random background noise modeling using Weibull distribution. The statistical approach allows estimation of false alarm indication (PFI) and probability of detection (POD) of the detection process and flexibility in setting the automated detection levels in relationship to the PFI and POD to support an informed damage tolerance maintenance procedure.

KEYWORDS

Corrosion, Lamb waves, SAFT, deconvolution, point spread function, probability of detection.

INTRODUCTION

Corrosion in metallic aerospace structures can have a significant impact on the operational expense of maintaining vehicle airworthiness [2,3]. In order to control costs, operators prefer to perform corrosion repairs during scheduled downtimes and only if the extent of the corrosion requires intervention. Unfortunately, corrosion is often located in hidden areas that are prone to damage, and are difficult and time consuming to inspect. One approach to improving maintenance productivity is to develop inexpensive and robust tools for automated on-board corrosion monitoring.

Ultrasound is a widely used and powerful technique for nondestructive testing [4]. Furthermore, ultrasonic Lamb waves [6] in conjunction with Synthetic Aperture Focusing Techniques (SAFT) [7] have been investigated as promising approaches for inspecting plate-like structures such as the skin of an aircraft.

An automated on-board corrosion detection system based on ultrasonic Lamb wave inspection can be configured in a variety of way. Irrespective of whether on-board or ground based components providing the diagnosis of the fault condition, the intent of the system is to replace manual NDE inspections and to help operators to perform maintenance in a more cost effective manner. This is achieved if the aircraft suffers fewer unscheduled maintenance interruptions and/or reduced maintenance cost due to more effective and less time consuming inspections requirements.

All automated detection systems contain sources of error. Therefore it is crucial when implementing an automated corrosion detection system that the detection accuracy and reliability be known and accounted for. It common practice to define the quality of defect detection in term of Probability of Detection (POD) and Probability of False Indication (PFI) [9,10]. Knowledge of the POD and PFI provides a useful metric for quantifying and assessing the capabilities of the system. The POD gives the probability of detecting various defects (size, shape, orientation, etc.) under various inspection conditions. PFI gives the probability of false indications. The implemented detection system must be capable of detecting and quantifying the defect with a high level and known POD, as well as low PFI in order to achieve a robust diagnosis process that can serve within a damage tolerant design approach.

PROBABILITY OF DETECTION/PROBABILITY OF FALSE INDICATION

For damage tolerant applications, a quantitative evaluation of the capability of the defect detection system is needed. The need becomes essential for applications that are safety critical. Table 1 summarizes all possible situations that can occur in defect detection process. The result of the detection process can be true positive (defect is detected knowing defect is presented), false positive (defect is detected knowing defect is not presented), false negative (defect is not detected knowing defect is presented) and finally true negative (defect is not detected knowing defect is not presented).

Table 1. Conditional probability in defect detection

		Defect	
		Present	Not present
Detection verdict	Positive	True positive (TP)	False positive (FP)
	Negative	False negative (FN)	True negative (TN)

Using this terminology the POD and PFI can be defined as

$$POD = \frac{TP}{TP + FN} = \frac{TP}{TOPC} \tag{1}$$

$$PFI = \frac{FP}{TN + FP} = \frac{FP}{TONC} \tag{2}$$

where *TOPC* is called Total Opportunities for Positive Calls and *TONC* Total Opportunities for Negative Calls.

Experimental determination of the POD/PFI can be an expensive and time consuming task requiring a suite of samples and extensive measurement trials. The detection system must be investigated for variety of defect types and sizes, for a range of considered materials, and for each assumed hardware configuration (e.g. different types of ultrasound probes). As a consequence some investigations have focused on modeling approaches to predict system POD values [e.g. 10]. Generally, the POD modeling is based on the assumption that the useful signal is corrupted by a noise possess. To separate the signal from the noise a threshold is introduced. If the signal exceeds the threshold value it is accepted as a useful signal, otherwise it is refused as noise. Since these are statistical processes and the probability of large noise amplitudes is not zero, there remains a certain probability of false alarms.

The relationship between a system POD and PFI is schematically depicted in Fig. 1. When a POD model has been developed and can be exercised, a number of additional payoffs arise:

- reduce time-cost constraints;
- improve validation and optimization of inspection procedures;
- improve component design and the definition of the life cycle;
- simulations can be developed, which can be used to train inspectors.

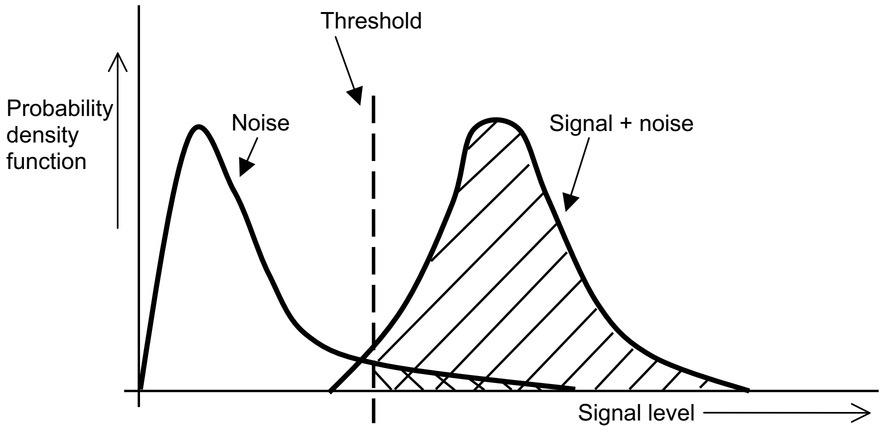

Fig. 1 Schematic representation of the POD model basis (double hatched area = PFI, double hatched area + hatched area = POD).

DEFECT DETECTION

The objectives of the present effort are to achieve automatic detection of emerging corrosion with low false call rates. Optimally, this should be expressed quantitatively in order to facilitate the use of a damage tolerant design philosophy. To accomplish this task it is necessary to understand and model noise and distortion within the ultrasound image generated by the SAFT algorithm. We have identified three types of noise in the processed images – systematic background noise, convolution distortion and random background noise. Fig. 2 shows simple block diagram of the defect detection process that accounts for each of these influences. Since the systematic background can be modeled using simple averaging from a set of baseline images, we will focus on the PSF and random background noise modeling.

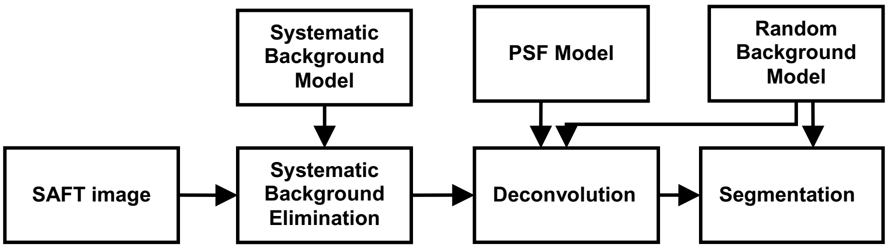

Fig. 2 Block diagram of the defect detection process.

PSF MODELING

Ultrasound images are distorted by several phenomena in the signal transmission channel. The distortion can be modeled using convolution model

$$y(n) = x(n) \otimes h(n) \tag{3}$$

where *y(n)* is distorted signal, *x(n)* is original ultrasound signal and *h(n)* represents distortion point spread function (PSF). Deconvolution methods try to reduce the effect of the PSF on the measured signal. Accurate knowledge of the PSF is important for satisfactory restoration of the original signal. The determination of the PSF is the most challenging stage of the deconvolution process. In ultrasound imaging, the PSF generally varies with position in the image.

Several approaches to the PSF determination can be found in literature. A rough PSF estimate can be obtained by measuring signal reflected from a line target oriented perpendicularly to the scanning plane [11]. An alternative approach is modeling the PSF mathematically, using either a space-invariant model [12] or a more complex model, which accounts for the spatial variance of the PSF [12]. Yet another alternative is to estimate the PSF directly from the image using homomorphic filtration [13]. For our purpose we will assume that the PSF is primarily influenced by the process of image formation and we will use a model of the SAFT focal point as a function of image position described by Thomson in [14].

Using Thomson's model the position variable PSF of the SAFT can be defined as

$$I(r, r_0) = \int_{-\frac{A}{2}}^{\frac{A}{2}} \frac{f(u) e^{i2\pi fu}}{|r_s - r_0|^2} dr_s \tag{4}$$

$$u = \frac{2}{c}\left(|r_s - r| - |r_s - r_0|\right) \tag{5}$$

where *f(u)* is ultrasound pulse waveform, *A* is transducer aperture, *f* ultrasound pulse frequency, *c* ultrasound velocity for investigated material, *r* is position variable for the PSF evaluation, r_0 is position vector of the center of the position variable PSF and r_s represents position vector of single transducer elements.

An evaluation of the PSF in transducer natural focus and spatial distribution of the PSF size at full width half maximum (FWHM) is shown in Fig. 3. Once the estimated PSF was established we used it for image deblurring using either a Lucy-Richardson [15] or Wiener [16] deconvolution algorithm. A random background noise model (described below) was used to control the deconvolution process.

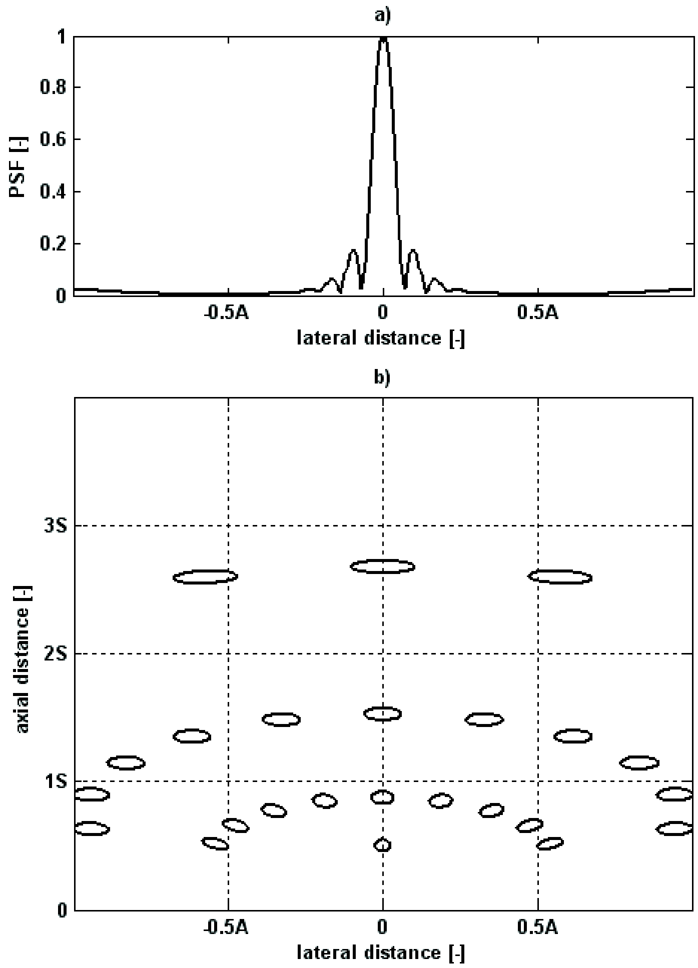

Fig. 3 Mathematical model of the SAFT PSF (A … transducer aperture, S … near-field length) – number of transducer elements = 24, element diameter = 1.2mm, pulse frequency = 0.9MHz, ultrasound velocity = 5200m/s
a) lateral cross-section of the PSF in transducer natural focus;
b) spatial distribution of the PSF size at FWHM.

RANDOM BACKGROUND NOISE MODELING AND THRESHOLDING

Random background noise in ultrasound signal arises from random distribution of grain boundaries in metal, small material irregularities and inhomogeneities. Although these are rarely considered flaws their random distribution leads to a speckle structure in the resulting reconstructed SAFT image. The Weibull distribution function has been shown to provide the best approximation of the random background noise generated in SAFT images [1][17]. The distribution is described by following probability density function (PDF)

$$p(x) = \frac{b}{\lambda}\left(\frac{x}{\lambda}\right)^{b-1} e^{-\left(\frac{x}{\lambda}\right)^{b}}, \quad x \geq 0, b > 0, \lambda > 0 \tag{6}$$

where λ is Weibull scale parameter and *b* is Weibull shape parameter. Since the statistical properties of the random background in the image are position dependent, the estimation of the Weibull parameters is made locally. The same set of baseline images as is used for systematic background modeling may be used for modeling of random background noise.

Knowledge of the random background noise can be used advantageously in the image segmentation and defect detection processing. We use a algorithm that adapts the threshold value according to the image position to ensure a certain fault call rate is maintained. Using Weibull distribution (Eq. (6)), we can derive for the threshold value

$$V_T = \lambda(-\ln PFI)^{\frac{1}{b}} \tag{7}$$

where *PFI* is required probability of false indication. This approach allows us to take control of quality of defect detection process and ensures constant probability of false indication through the image.

EXPERIMENT

We tested our algorithm using artificial data. The data included simulated SAFT processed ultrasound images and collected data. First, a set of 16 defect-free images was used for determination of the systematic background and random background noise models. Next, an image with simulated defects was generated. The test image contained five holes at particular locations were generated assuming ideal point reflectors.

To examine the analysis process we compared two cases. In the first case, deconvolution was not used and the in second case, deconvolution was applied to achieve distortion removal. Results of the processing are shown in Fig. 4. The thresholded images was further processed to reduce speckle noise, also known as salt and pepper noise, by means of simple morphological operators and the final borders were detected using common edge detection operator e.g. Canny operator.

Fig. 5 shows impact of the deconvolution on the PDF of the random background noise and the useful signal. It can be seen that the gravity mass of the noise PDF is shifted to small signal values while the gravity mass of the useful signal is moved towards high signal levels. Thus lower PFI and higher POD were achieved.

SUMMARY

We proposed a reliable corrosion detection algorithm in support of SAFT ultrasound image processing for corrosion defect detection. This new algorithm configuration is motivated by the need for an on-board corrosion monitoring system.

a)

b)

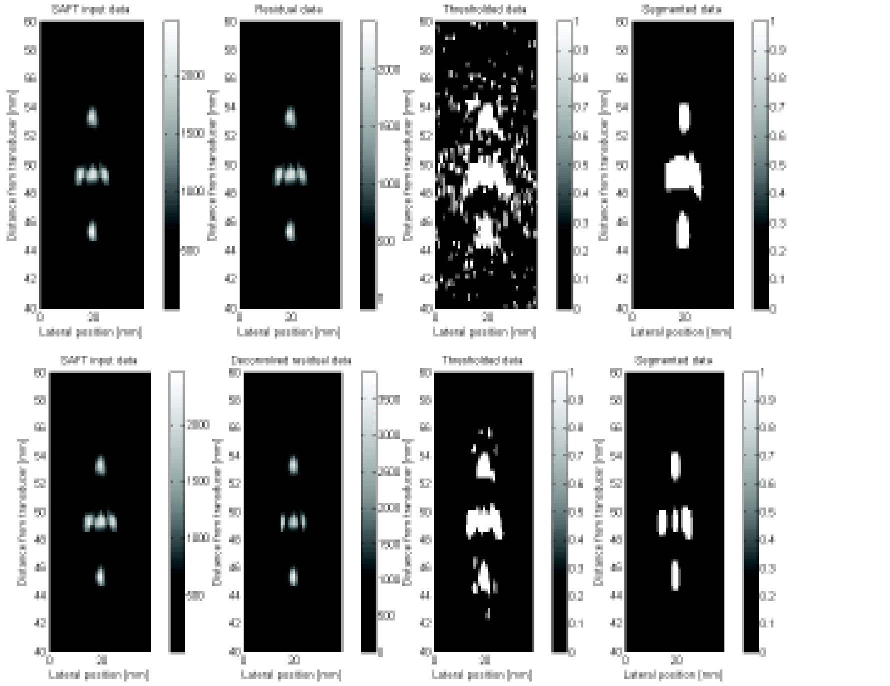

Fig. 4 Results of detection algorithm a) without removal of the convolution distortion, b) using deconvolution.

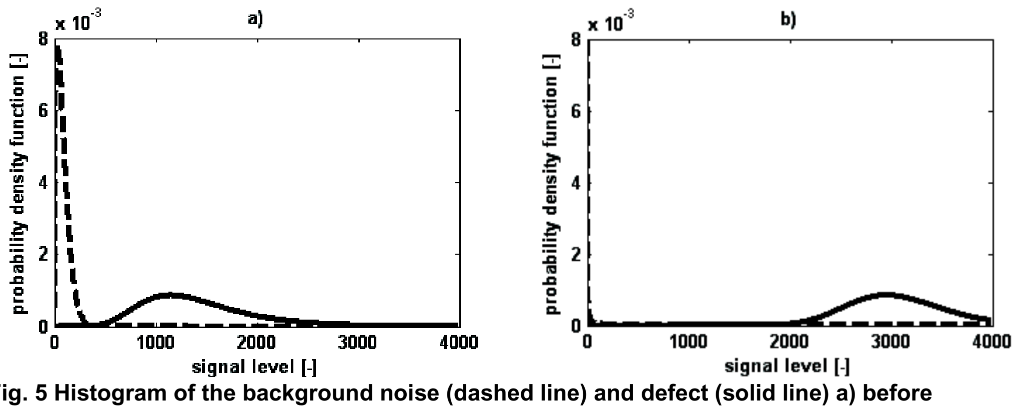

Fig. 5 Histogram of the background noise (dashed line) and defect (solid line) a) before deconvolution, b) after deconvolution.

The algorithm is based on models for the noise and distortion processes that degradation the SAFT processed ultrasound images. The processing comprises image deconvolution and image segmentation. The PSF for the deconvolution algorithm is determined locally to account for its variation with image position. The image segmentation processing is used to determine significantly corrosion affected regions within the image. For that purpose, we have adopted adaptive thresholding algorithm that allows local adjusting of the threshold with regard to the random background noise. A major contribution of our proposed approach is capability of control of the detection process quality, which can be expressed in terms of the PFI and the POD.

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