Ultrasonics 54 (2014) 312–317

Contents lists available at ScienceDirect

Ultrasonics

journal homepage: www.elsevier.com/locate/ultras

Ultrasonic sensor based defect detection and characterisation of ceramics

Manasa Kesharaju [a,b,*], Romesh Nagarajah [a], Tonzhua Zhang [a], Ian Crouch [c]

[a] Swinburne University of Technology, Faculty of Engineering & Industrial Sciences, Melbourne, Victoria, Australia-3122
[b] Defence Materials Technology Centre (DMTC LTD), Melbourne, Victoria, Australia-3122
[c] Australian Defence Apparel, Gaffney St, Coburg, Melbourne, Victoria, Australia-3058

A R T I C L E I N F O

Article history:
Received 7 January 2013
Accepted 31 July 2013
Available online 8 August 2013

Keywords:
Ultrasonic testing
Defect classification
Neural networks
Wavelet transform
Linear discriminant analysis

A B S T R A C T

Ceramic tiles, used in body armour systems, are currently inspected visually offline using an X-ray technique that is both time consuming and very expensive. The aim of this research is to develop a methodology to detect, locate and classify various manufacturing defects in Reaction Sintered Silicon Carbide (RSSC) ceramic tiles, using an ultrasonic sensing technique. Defects such as free silicon, un-sintered silicon carbide material and conventional porosity are often difficult to detect using conventional X-radiography. An alternative inspection system was developed to detect defects in ceramic components using an Artificial Neural Network (ANN) based signal processing technique. The inspection methodology proposed focuses on pre-processing of signals, de-noising, wavelet decomposition, feature extraction and post-processing of the signals for classification purposes. This research contributes to developing an on-line inspection system that would be far more cost effective than present methods and, moreover, assist manufacturers in checking the location of high density areas, defects and enable real time quality control, including the implementation of accept/reject criteria.

1. Introduction

The quality and integrity of engineering ceramics, especially those used in high-performance body armour systems, is of paramount importance because a number of material characteristics affect the service life of the finished product. Some of these aspects include microstructure, mechanical properties, physical properties and elemental distribution [1]. The Reaction Sintered Silicon Carbide (RSSC) ceramic tile used in this research has been manufactured by a reaction bonding process which involves the infusion of liquid silicon into a porous ceramic preform. Net shape components, with complex shapes, can be fabricated by this reaction forming technique [2]. This can lead to a number of characteristic defects such as islands of free silicon metal, closed areas of un-sintered material, as well as conventional porosity. Most of these casting-like defects occur during the high temperature process as the liquid silicon infiltrates the green compact. At the current time, the ceramic tiles are inspected offline. This involves considerable time and expensive equipment. Identification of defect types depends exclusively on the experience and knowledge of the operator. Along with this, X-radiography is not able to distinguish microstructural differences in areas of similar bulk density. Therefore, industry would benefit from a new on-line system, possibly based on an ultrasonic approach, that would be far more discerning and more cost effective with a built-in set of accept/reject criteria.

An ultrasonic inspection method has been developed that provides useful information about the integrity/possible defects in ceramic tiles. The ultrasonic wave, generated by a transducer propagates through the material and is reflected by defects and the back surface of the sample. The signals reflected by defects possess information about defect size, location and orientation. Automated signal classification is becoming increasingly important in many applications, including armour ceramics. The main aim for the use of such systems is the need for accurate interpretation of large volumes of inspection data with minimum errors thus increasing the confidence in testing and safety of armour ceramics in future applications [3–7]. This research proposes an automated ultrasonic sensor based technique that processes the signals acquired from ceramic tiles and locates and classifies any defects present.

Machine learning systems perform two main functions, feature extraction and classification. Over the last decade, extensive research has taken place on the development of efficient and reliable methods for the selection of features in the design of machine learning systems, where features constitute inputs to a classifier. The significant issue in classification is the choice of an appropriate classifier. Some classical classifiers are Fisher's linear discriminant and K-Nearest Neighbours [8]. Recently, classifiers such as neural networks (NN), neuro-fuzzy classifiers, tree classifiers and support

* Corresponding author at: Swinburne University of Technology, Faculty of Engineering & Industrial Sciences, Melbourne, Australia. Tel.: +61 3 92144343.
E-mail address: mkesharaju@swin.edu.au (M. Kesharaju).

0041-624X/$ - see front matter © 2013 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.ultras.2013.07.018

vector machines (SVM) have found wide applications [8]. Limited work has been done in classifying defects in ceramic components especially in armour ceramics [9]. Sambath [10] in his research presented a signal processing technique based on a wavelet transform, which enhanced the sensibility of flaw detection to characterize defects. An artificial neural network (ANN) combined with discrete wavelet transform (DWT) coefficients as input to NN, have been applied to interpret ultrasonic signals during weld bead inspection. Martin [11] had developed an artificial neural network model for the ultrasonic pulse echo technique to classify resistance spot welds into four classes. He used a back propagation multilayer feed forward ANN training algorithm for the classification of spot welds. Feature inputs to the ANN consisted of ten component vectors that contained information on relative heights of the echoes and the distance between consecutive echoes. A success rate of 100% was achieved. Obaidat [12] in his research developed a methodology to detect defects using ultrasonic-based NDT using multilayer perceptron's. The author found that results obtained by using the discrete wavelet transform and neural networks were superior to those obtained using neural networks on their own. Sungjoon [13] in ultrasonic testing of materials reported that the grain scattering echoes are randomly distributed across the entire frequency band of the measured signal, while the flaw signal is more visible in lower frequency bands. The author presented a study comparing neural network flaw detection techniques with conventional post-processing methods using split spectrum processing (SSP) that showed superior results for neural networks. Lee [14] has addressed important issues in signal feature extraction approaches and provided an overview on superiority of the discrete wavelet transform (DWT) to Fast Fourier Transform (FFT) as a feature extraction method. In the current research, a signal processing technique based on min-max normalization and discrete wavelet transform (DWT) along with feature extraction technique has been used to classify various defects (un-sintered silicon, black spots, porosity).Neural network is compared to Linear Discriminant Analysis (LDA) method in providing classification accuracy results.

2. Experimental procedures

2.1. Ceramic materials

The silicon carbide samples used in the current study were supplied by Australian Defence Apparel (Melbourne, Australia). The percentage composition of SiC is 88%, as there is about 12% of residual silicone in these products. The pulse echo ultrasonic technique has been used to inspect three double-curved, ceramic tiles of 300 mm in length and 7.5 ± 0.5 mm in thickness. A contact transducer of 10 MHz frequency, 12.7 mm element diameter has been chosen for scanning the defective ceramic tiles .The air gap between the specimen and probe was eliminated by applying thick lubricant on the surface of the specimen. Different defects such as porosity, free silicon and un-sintered material were generated in the ceramic tiles during and after the manufacturing process. The location of these defects was recorded using the X-ray technique.

The experimental procedure followed is listed below:

- Collecting and acquiring the ultrasonic A-scan signals from different types of defects.
- Extracting features by using signal pre-processing techniques (de-noise, data compression and wavelet transform).
- Training the neural network to classify defects.
- Testing the trained network.

2.2. Acquisition and gating of signals

The acquired analogue signals produced while scanning the tiles were converted to digital signals by using an A/D converter and stored on a computer system. Ultrasonic signals were acquired at sampling frequency of 100 MHz and each of the A-scan signals consists of 2000 data points. As existing practice in the industry involves classifying each captured A-scan ultrasonic signal, gating is necessary for reducing the size of the data. Hence, a gating technique has been applied to each of the signals, that checks and positions the time-gating on digitally captured A-scan image as shown in Fig. 1.a. A signal segment of interest that contains 400 data points is then singled out as shown in Fig. 1b . This is a type of dimension reduction that makes it feasible to classify each echo.

Three ceramic tiles containing various defects were scanned to create a data base of 204 ultrasonic A-scans. 102 signals were used for training the network and the remaining 102 signals used for testing the neural network after the network had been trained. The training dataset of 102 signals consisted of 30 (defect free), 42 (free silicon) and 30 (un-sintered material). The desired outputs dataset (targets) has been created to assist in training the network by showing the network what the desired response to a given stimulus should be.

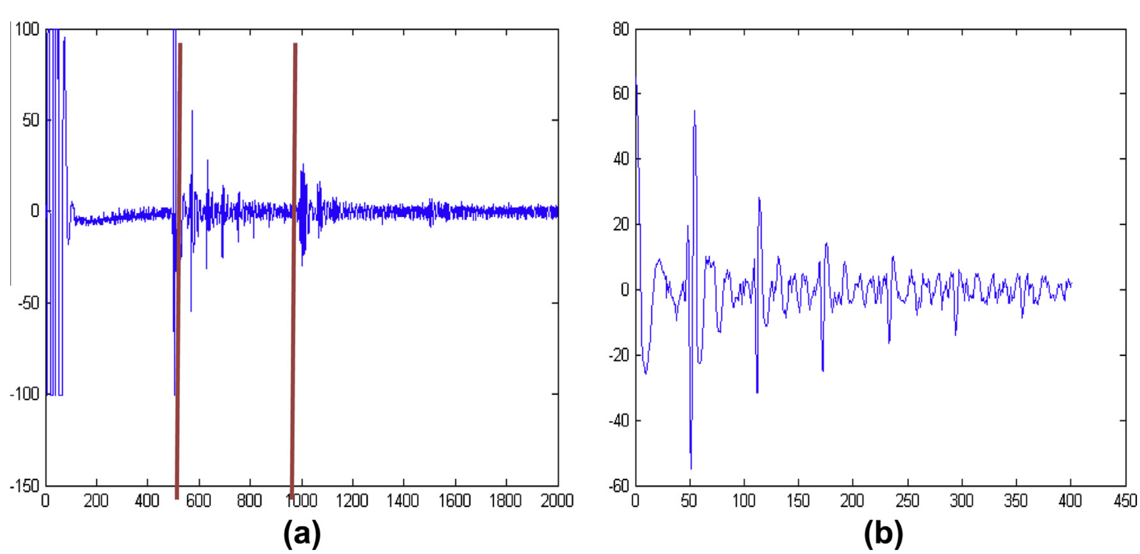

Fig. 1. (a) An example of a ultrasonic signal gated on the captured A-scan signal and (b) a signal singled out.