Kesharaju, M., Nagarajah, R., Zhang, T., Crouch, I. (2014). Ultrasonic sensor based defect detection and characterisation of ceramics.

Originally published in Ultrasonics, 54(1), 312–317.
Available from: http://hdl.handle.net/1959.3/356775

Ultrasonic Sensor Based Defect Detection and Characterisation of Ceramics

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Abstract

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.

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

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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 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 multi-layer 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

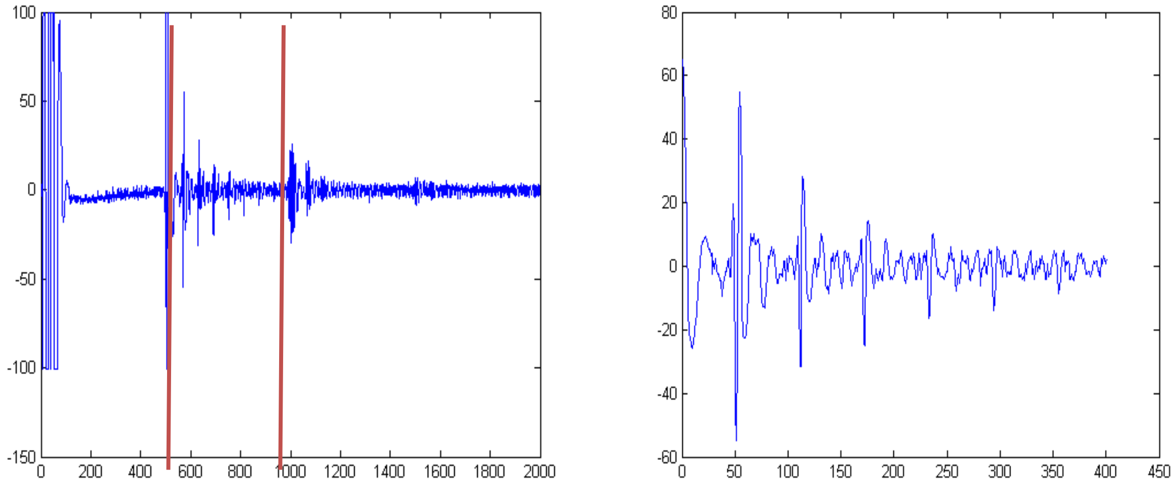
The silicon carbide samples used in the current study were supplied by Australian Defence Apparel (Melbourne, Australia). The percentage composition of SiC is 88%, as there is about 12% of residual silicone in these products. The pulse echo ultrasonic technique has been used to inspect three double-curved, ceramic tiles of 300mm in length and 7.5± 0.5mm in thickness. A contact transducer of 10 MHz frequency, 12.7mm 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.1.b .This is a type of dimension reduction that makes it feasible to classify each echo.



(a) (b)

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

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.

3. Signal Processing

Signals are a popular mean of representing information and signal processing has significance in many applications. In signal classification problem, pre-processing of raw signals is an initial phase and extracting informative features from the pre-processed signals became important basis to solve advance signal processing problems[15]. In this research, various ultrasonic signal features related to the time-domain and frequency domain, namely discrete wavelet transform (DWT) were investigated. Unlike previous work as described in the literature review, where only DWT coefficients were used as feature vectors; in this research wavelet coefficients and raw signal features were used as feature vectors.

3.1. Wavelet transform

Wavelet analysis of signals is increasingly becoming a popular tool in signal processing. Signal processing includes noise removal, compression, feature extraction and reconstruction[15]. In this work, a discrete wavelet transform with level 5 (L) decomposition is applied to the ultrasonic signal data base with 400 samples. The mother wavelet function used was 'Coiflet5' as the shape of the transient ultrasonic signal is similar to the shape of the wavelet function. Each signal is decomposed at 5 levels (L) to yield detail signals d_1 - d_5 and approximation signal a_5. The detail coefficients of d_1 belong to highest frequency component of the signal and d_2 coefficients are half the frequency component of d_1. In discrete terms, the 5 level decomposition of the signal S(t) can be written as

$$S(t)=a_5(t)+\sum_{n=1}^{5} dn(t) \qquad (1)$$

All the data collection was done by using a transducer with a central frequency (f_{cf}) of 10MHz. The time series A-scan signals were sampled at 100 MHz (f_q). The decomposition level (L) of the wavelet transform is determined by the sampling frequency (f_q) and frequency component to be identified in the signal, is expressed as [16]

$$fq/2^{(L+1)} \leq \ f_{cf} \leq \ fq/2^{L} \qquad (2)$$

Hence d_1, d_2 have frequency components of 25-50 MHz, 12.5-25 MHz respectively. The frequency of interest for this work, 10 MHz, lies in decomposition level d_3 as seen from the Fig.2 below. The choice of this level is made based on the reasoning that most of the signal energy is present in this frequency band whereas other levels will mainly consist of noise. All other frequencies are represented by very low amplitude in the wavelet transform domain and hence can be discarded without loss of information. Thus DWT also provides effective signal compression and data reduction[15].

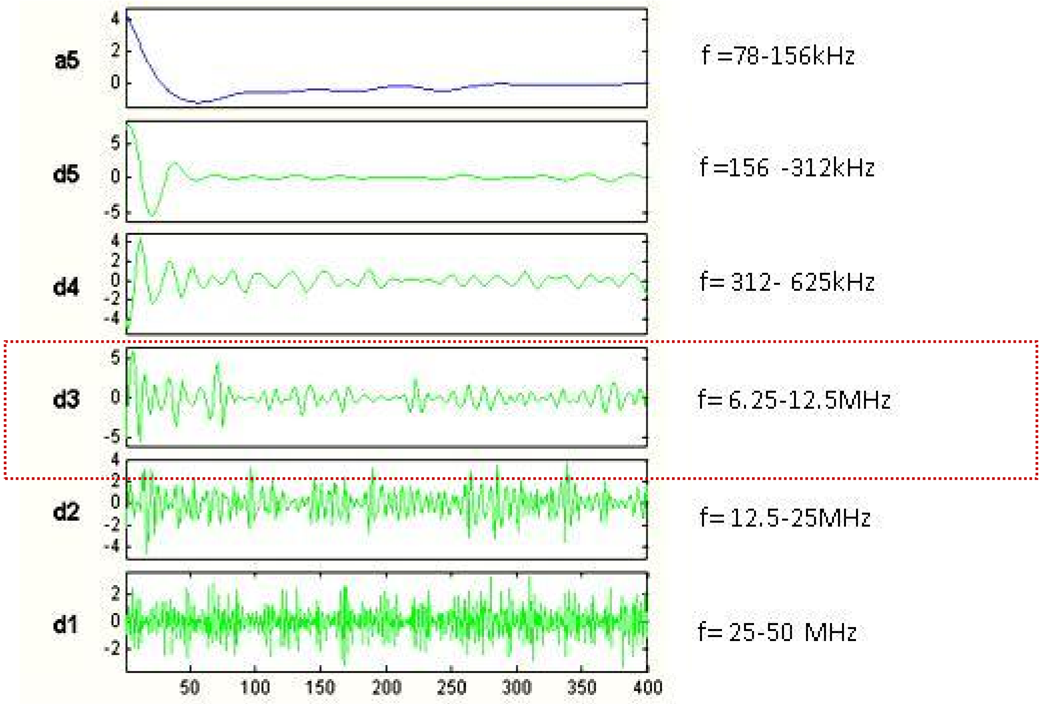


Fig.2. A-scan defect signal decomposition into details and approximate signals.

3.2. Feature extraction

In this research, eight (8) features were extracted from each signal representing three defect classes. The extracted features from the raw signals as well as from the detail coefficients (d_3) of level 3 (Fig.2) are listed below:

1. Front wall echo amplitude of the raw signal
2. First back-wall echo amplitude of the raw signal
3. Sum of energy samples of the raw signal
4. Skewness of the raw signal
5. Sum of energy samples of d_3 coefficients
6. Absolute Mean of d_3 coefficients
7. Kurtosis of the raw signal
8. Second back-wall echo amplitude of the raw signal

3.3. Data normalization

Data normalization is a common tool especially useful for modelling applications where the inputs are represented in widely different scales. Within the neural network, the same range of values for each input feature can be achieved through the normalization of the data. Data normalization can also speed up training time by starting the training process for each feature within the same scale. There are various types of data normalization techniques available. In the current research, min-max normalization is applied to the input feature dataset. When the normalization is applied, each feature lie within the new range of values but the principal distributions of the corresponding features within the new range of values will remain the same. This normalization has the advantage over other normalization techniques of exactly preserving all relationships in the data, and does not introduce any bias. It also allows more flexibility in designing the network and determining which features are more important[17].

4. Artificial Neural Network

Neural networks are nonlinear mapping processes that allow training and adaptability for signal classification applications. The learning process enables neural networks to recognize the target patterns without mathematical models of the target signals[13]. Back propagation networks are multi-layer networks with the hidden layers of sigmoid transfer function and a linear output layer. The transfer function in the hidden layer should be differentiable and thus, either log-sigmoid or tan-sigmoid functions are typically used[17]. In this research, the tan-sigmoid, 'tansig' and 'purelin' are used for hidden layers and the output layer. They calculate the layer's output from its net input. Each hidden layer and output layer is made of artificial neurons, which are connected through adaptive weights. The training function selected for the network is 'trainlm' (Levenberg-Marquardt).

4.1. Proposed NN structure

In this research, various combinations of layers and neurons were investigated (20, 18, 17, 15, 10, and 8). Finally, a feed-forward neural network was selected with 8 input nodes, 14 hidden nodes and an output layer with 1 node for classifying 3 classes of signals. The block diagram of the supervised network architecture is shown in Fig.3. The developed NN was trained for a number of epochs until the error goal of e^{-8} was reached [18]. At this stage the training was stopped and the network was ready for testing. The error goal of e^{-8} was set to improve the network training performance.

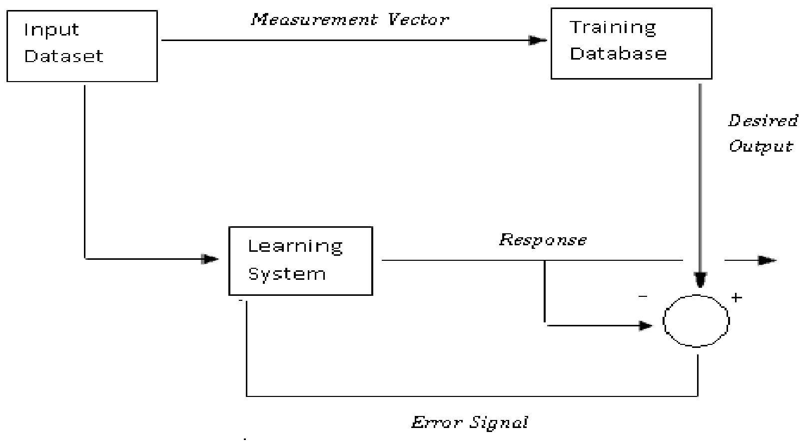


Fig.3. Block diagram of supervised network architecture

4.2. Training and Testing

The features extracted (shown in section 3.2) from each ultrasonic signal were used as input to the neural network by means of a MATLAB software program. For a neural network to reliably classify defects, the training database must contain sufficient data to represent each type of defect for the training operation to be effective. Therefore, a database was created containing a total of 204 sets. From these 30, 34, 40 data sets were randomly chosen for each class of defect to create a separate test set consisting of 102 signals that have been used for testing the trained network.

Before training the network, the input data was normalized suitably using min-max normalization. The training data was fed into the network and after several iterations; the network delivered required result as shown in Fig.4. Once the network training completed the test data was fed into the network. Test data did not contain any data used for training the network.

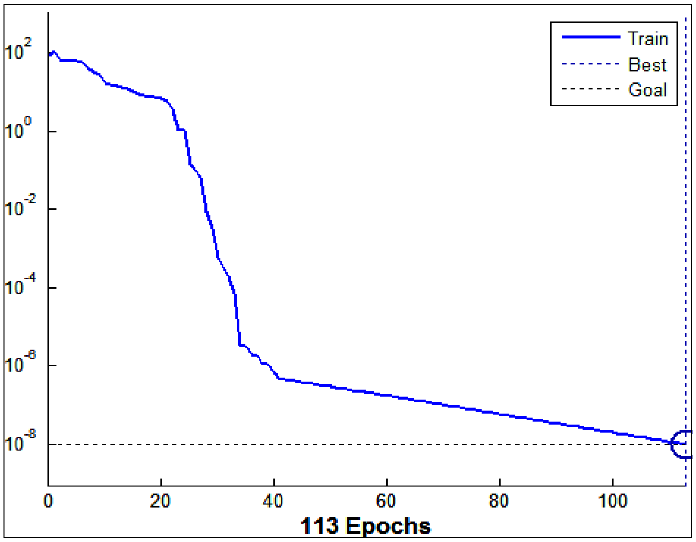
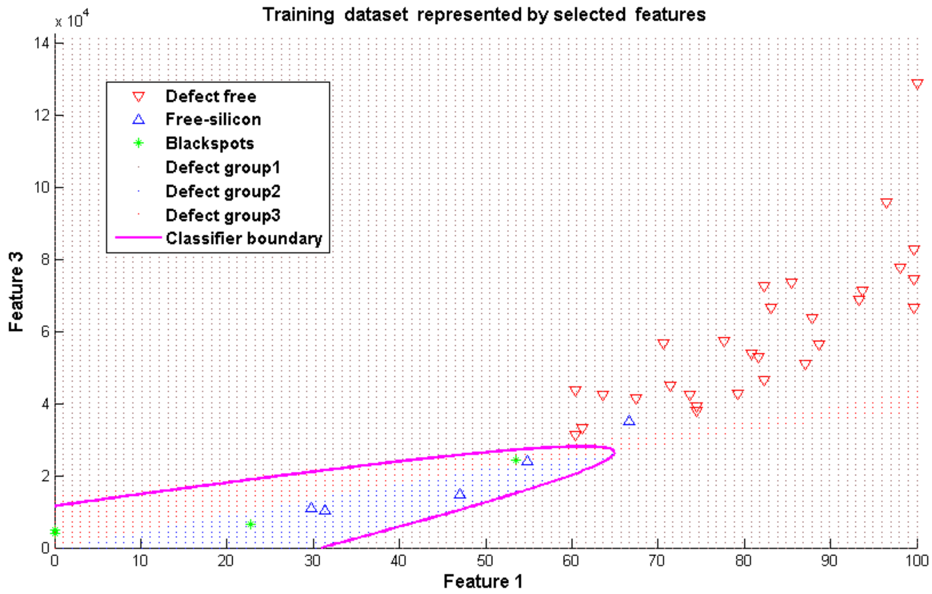


Fig.4. The relationship between error value and number of epochs

5. Linear Discriminant Analysis

There are many possible techniques for classification of data and Linear Discriminant Analysis (LDA) is very commonly used technique for data classification. This method maximizes the ratio of between class variance to the within-class variance in any specific data set thus ensuring maximal separability[19]. Generally, LDA is applied to the data classification problem in speech recognition. This method provides more class separability and draws a decision region between the given classes. This method also helps to better understand the distribution of the feature data. Fig.5 shows the scatter plot of the training dataset by top two features selected.



(a).

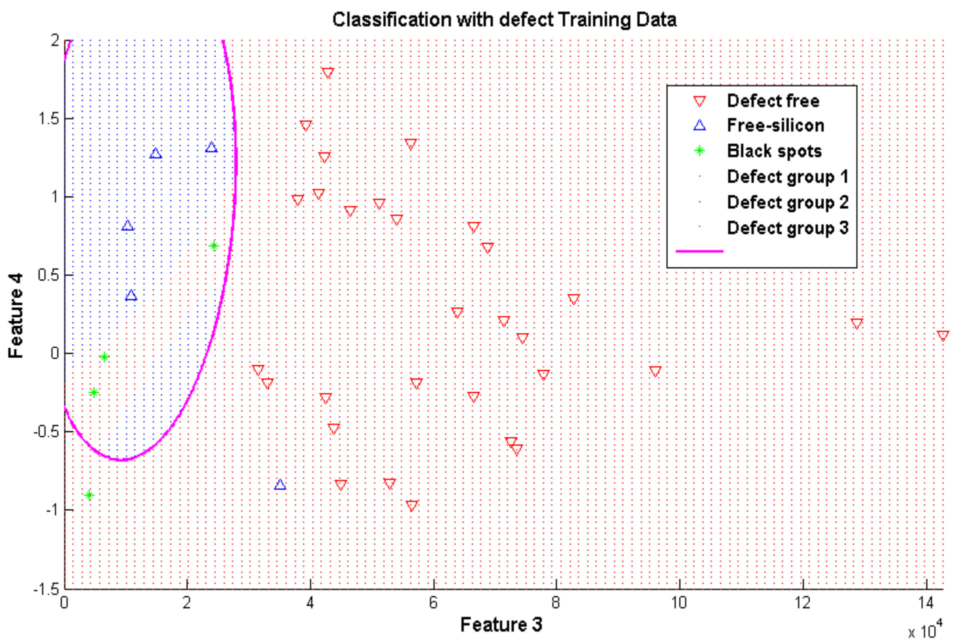


Fig.5. (a) and (b) LDA based classifier decision boundaries for three-class problem

From the scatter plots in Fig.5.a and b, it can be observed that the defect classes were defined properly but there are cases where an overlap between defect classes was observed. Hence obtaining a decision region in original space will be very difficult in those cases. Further, to classify three types of defect classes the testing data was fed into the LDA classifier and the classification results were shown in Fig.6 for 102 testing signals. It is seen from Fig.6 that, using LDA classifier the testing data was not classified well and there is a misclassification of defect signals. Also based on the desired outputs dataset, the overall accuracy of classification was calculated as 82%.

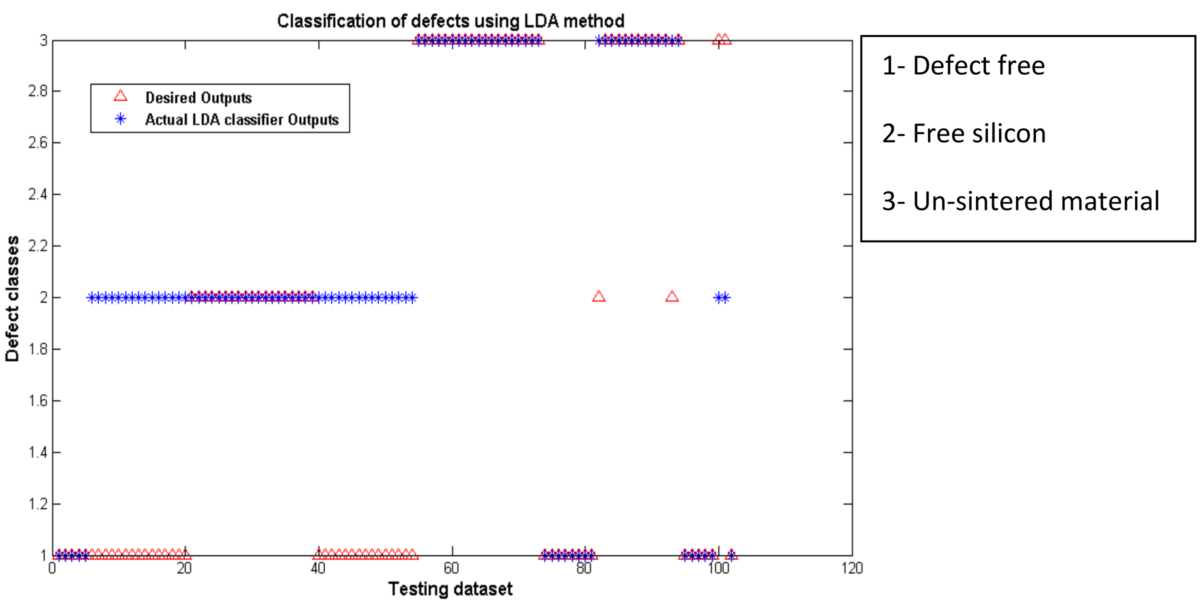


Fig.6. Target values and Linear discriminant analysis output values for 102 testing signals

6. Results and discussion

The aim of this research was to obtain a well-trained neural network capable of performing the expert operator's function of inspecting ceramic tiles and classifying various defects from the ultrasonic signals generated. For that reason, the neural network must have an appropriate ability to generalize. The test set consisting of 102 sets was used for assessing the ability of neural network to generalize. A post-possessing technique has been used to convert actual outputs from the output layer back into the same units that were used for the desired outputs (original targets). The network output and the corresponding targets were passed through post regression analysis. It returned three parameters, which correspond to the slope and the *y*-intercept of the best linear regression relating targets to network outputs. If there were a perfect fit, i.e. outputs exactly equal to targets, the slope would be 1, and the *y*-intercept would be 0. A linear regression plot in Fig.7 shows a measure of how well the variation in the actual output is represented by the desired outputs (targets). The R-value 0.98 between the outputs and targets represents the correlation coefficient.

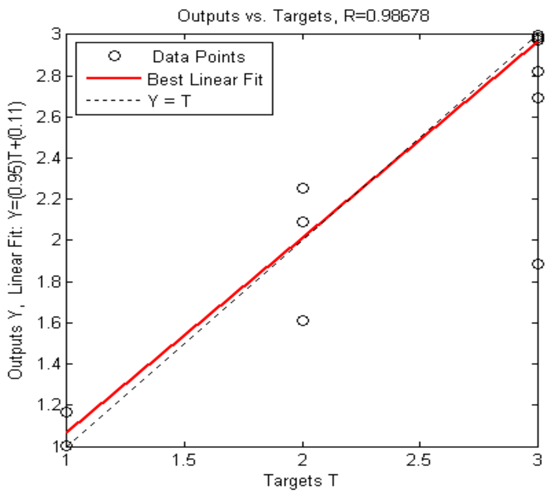


Fig.7. A linear regression plot

The back propagation neural network architecture has been selected based on the performance. Best result and corresponding parameter values are shown after several trials with various combinations of parameters like number of hidden layer neurons, input features, activation function and training algorithm. The input feature vectors were presented to the neural network that compared each experimental output vector with its respective desired outputs (target). Target values and neural network values for 102 testing vectors are represented in a graphical form shown in Fig.8. The results show that the neural network combined with discrete wavelet transform (DWT) has produced a classification accuracy of 98%. DWT not only provides excellent feature extraction, but also provides significant data reduction and filters the noise from the signals thereby reducing the computational burden considerably. The results indicate that feature selection for input to neural network is very important for good performance.

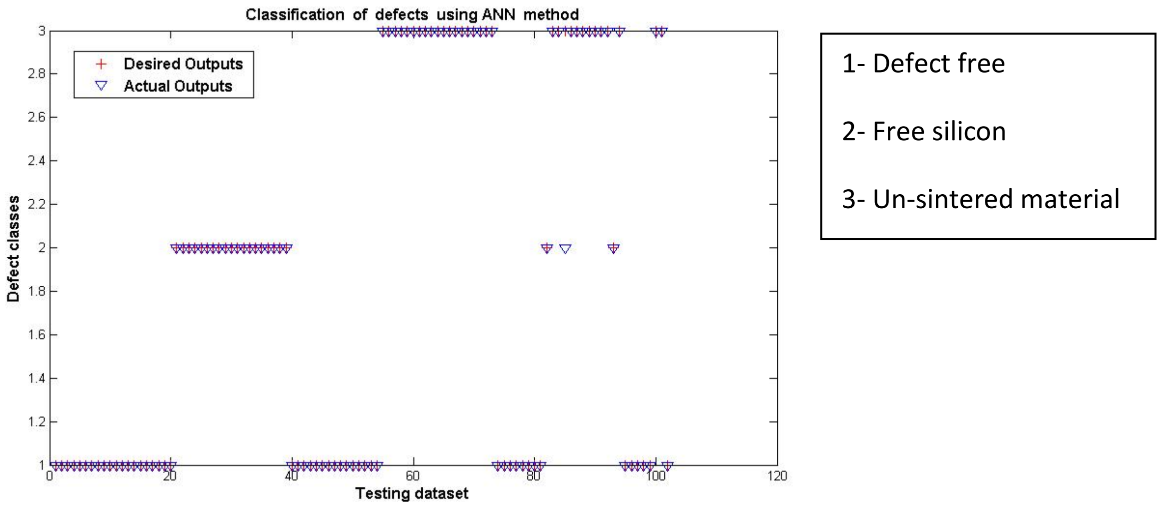


Fig.8. Target values and neural network output values for 102 testing signals

6. Conclusions

In this paper, a new method for identifying defects in ceramic components using ultrasonic sensing, neural networks (NN) and discrete wavelet transforms (DWT) is proposed. It has to be emphasized that the success rate of this method is higher compared to other methods reported in the literature. From the classification results generated by LDA and neural networks , it can be concluded that the neural networks approach to defect classification is very effective. It is a suitable approach for developing an online quality control system for non-destructive evaluation of ceramic tiles. Finally, the artificial neural network (ANN) has been chosen over other classifiers as it contributes to a fast and user friendly system, which assists industrial operators and technicians by reducing their effort and time spent in classifying the defect signals obtained through ultrasonic testing.

Acknowledgements

The authors wish to express their gratitude to Defence Materials Technology Centre (DMTC) for their financial support.

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