World Academy of Science, Engineering and Technology
International Journal of Electrical and Computer Engineering
Vol:1, No:9, 2007

Classification of Defects by the SVM Method and the Principal Component Analysis (PCA)

M. Khelil, M. Boudraa, A. Kechida, and R. Drai

***Abstract*—**Analyses carried out on examples of detected defects echoes showed clearly that one can describe these detected forms according to a whole of characteristic parameters in order to be able to make discrimination between a planar defect and a volumic defect. This work answers to a problem of ultrasonics NDT like Identification of the defects. The problems as well as the objective of this realized work, are divided in three parts: Extractions of the parameters of wavelets from the ultrasonic echo of the detected defect - the second part is devoted to principal components analysis (PCA) for optimization of the attributes vector. And finally to establish the algorithm of classification (SVM, Support Vector Machine) which allows discrimination between a plane defect and a volumic defect.

We have completed this work by a conclusion where we draw up a summary of the completed works, as well as the robustness of the various algorithms proposed in this study.

***Keywords*—**NDT, PCA, SVM, ultrasonics, wavelet.

I. INTRODUCTION

THE Non Destructive Testing (NDT) has to allow obtaining the highest possible detection probability, the most exact size and the exact orientation of dangerous defects that the specimen to test can contain.

The identification or the knowledge of detected defects nature is very difficult in Ultrasonic technique. This stage of the inspection is based on the experience of the expert controller. This one proceeds by changing the angle of ultrasonic beam and a lot of other tricks in order to find out a diagnosis on the defect nature: planar or volumic. This verdict is very important since norms and standard accept some volumic defects but refuse others planar defects. Therefore the acceptance or the refusal of defect could stop the functioning of an industrial installation.

Analyses carried out on examples of detected defects echoes showed clearly that one can describe these detected forms according to a whole of characteristic parameters in order to be able to make discrimination between a planar defect and a volumic defect.

This work answers to a problem of ultrasonics NDT like Identification of the defects. In reference [1], we applied artificial neurons networks (ANN) as a classification method.

Manuscript received October 15, 2005. This work was supported by the Centre de recherche Scientifique et Technique en Soudage et Contrôle (CSC), Route de Dely Ibrahim BP 64, Cheraga, Algiers, Algeria.

M. Khelil is with CSC, (phone & fax : 213 21 36 18 50; e-mail: mohkhelil@yahoo.com).

M. Boudraa is with USTHB University, Electronique institute Bab Ezzouar, Algiers, Algeria (e-mail: mboudraa@usthb.dz).

A. Kechida and R. Drai are with CSC, (phone & fax : 213 21 36 18 50).

In this study, we use Support Vector Machine (SVM). This paper will be divided into three parts:

In the first part, we describe the extraction from the detected defect signal, the wavelet parameters by the Discrete Wavelet Transform (DWT).

With these parameters, we build an attribute vector and then, we optimize this one by Principal Components Analysis (P.C.A) method, this stage will be seen in second part. In the third part, we carry out defects classification by SVM method into: planar or volumic defects. Results of this paper will be compared to those obtained in [1].

II. WAVELET TRANSFORM

The wavelets are a very particular elementary functions ($\psi_{a,b}$), these are the shortest vibrations and most elementary that one can consider. There are several families of wavelets which correspond to different compositions, but the structure of their calculation remains however the same. These wavelets have different properties and they thus allow to perform different types of analysis. They are generated from a function $\psi(t)$ named mother wavelet by dilation and translation. This function is selected so that these translations and these dilations make it possible to obtain a complete representation in frequency and to split any function without information loss. From this single function, let build a family of functions which are basic wavelets:

$$\psi_{a,b}(t) = |a|^{-1/2}\,\psi\left(\frac{t-b}{a}\right) \quad a>0 \ \text{ and } \quad a \in R \ , \ b \in R \tag{1}$$

For signal analysis applications, we choose to restrict dilation-translation values (a,b) to a discrete subset. In practice, we use discrete wavelet transform (DWT) and we take generally

$$\psi_{j,k}(t) = 2^{j/2}\psi(2^j t - k) \quad j,k \in Z \tag{2}$$

The purpose of S.MALLAT algorithm is to extract characteristics from a signal on various scales achieving by successive high pass and low pass filtering. The wavelet coefficients are the successive continuation of the approximation and details coefficients calculated by S.MALLAT decomposition algorithm on different levels using DAUBECHIES window.

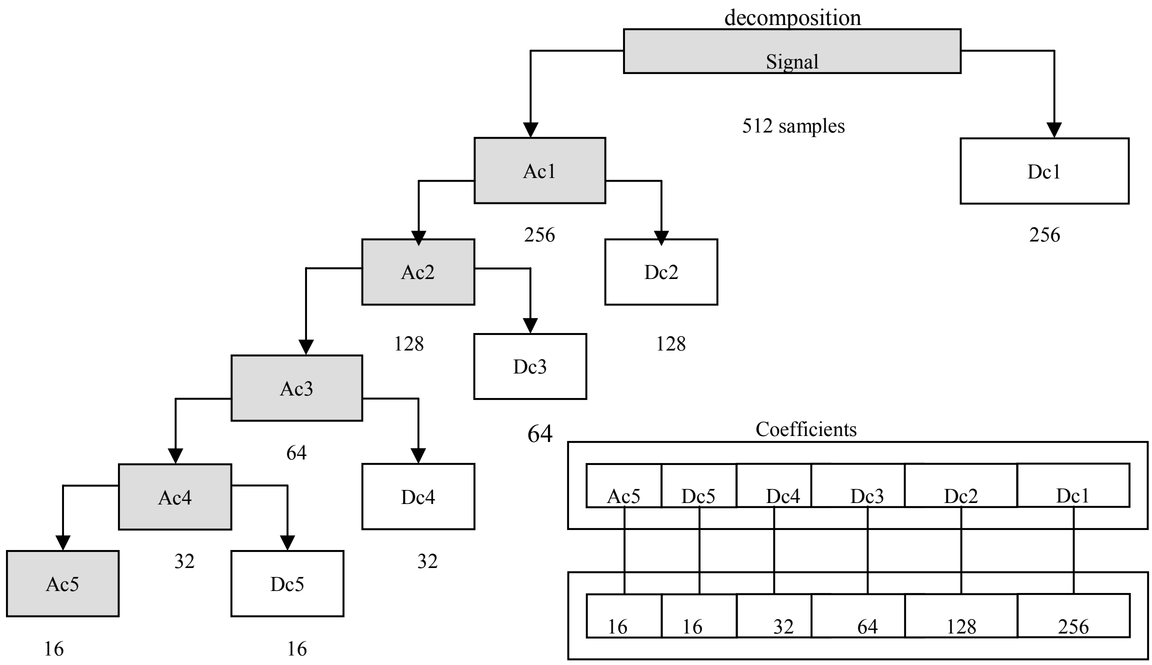


Fig. 1 Example of Wavelets coefficients calculation

III. PRINCIPAL COMPONENTS ANALYSIS (PCA)

The principal components analysis (ACP) is a mathematical technique allowing to reduce a complex system of correlations in a smaller number of dimensions [2].

X being a table of P numeric variables (in columns) describing N individuals (in lines), we propose to seek a representation of N individuals (signal) *e1*, *e2*. . . , e*n* in a subspace of initial space. In other words, we have to define K new variables, combination of P of initial space, which would make lose less possible information. These K variables will be called principal component and the axes which they determine will be principal axes.

Th for N observations, we will have a matrix of $N \times P$ size which is given by:

$$e = [e_1 \; e_2 \; e_3 \; .... \; e_N] \tag{3}$$

The average signal is defined by:

$$\psi = \frac{1}{N}\sum_{m=1}^{N} e_m \tag{4}$$

For each element, we calculate the difference:

$$\phi_i = e_i - \psi \tag{5}$$

The computation of covariance matrix is:

$$C = \frac{1}{N}\sum_{m=1}^{N}\phi_m \phi_m^T = \frac{1}{N} A \times A^T \tag{6}$$

with : $A = [\phi_1 \; \phi_2 \; \phi_3 \; .... \; \phi_N]$.

However, the determination of the eigen vectors of covariance matrix will require an excessive calculation, the size of this matrix is (P $\times$P). if v_i is the eigen vector of $A \times A^T$, its eigenvalues are:

$$A^T A v_i = \mu_i v_i \tag{7}$$

Then the eigen vectors of C are calculated by:

$$u_i = A v_i \tag{8}$$

Finally, the principal component of each signal e_i is given by:

$$w_k = u_k^T \times (e_i - \psi) \tag{9}$$

The vector w_k represents the new parameters completely decorreled and optimized for classification.

IV. SUPPORT VECTORS MACHINES (SVM)

The SVM are a new class of training algorithm introduced by V Vapnik. The principle of this algorithm is based on the structural risk minimization (SRM) [3]. The SVM carry out the model of recognition for of two-classes problems by determining the hyperplane of separation with the maximum distance to the narrowest points of the positioning of formation. These points are called *the vectors of support.* If the data are not linearly separable in the input space, one can apply a non-linear transformation.

In this section, we will present from a mathematical point of view, only the model applied in this study, as the case where the data are linearly separable.

A. Principle

Let us suppose initially that if the sample (xi, yi), I = 1.....,n (where y1 = ±1 gives the class of each example) is linearly separable, then there is an hyperplane such as:

$$f(x) = w.x + b. \tag{10}$$

Moreover, we want that this hyperplane has the maximum of separation of the margin with regard to two classes. Specifically, this amounts finding an hyperplane H:

$$H : y = w.x - b = 0. \tag{11}$$

And two hyperplanes H1 and H2 which are parallel whose distances are equal:

$$H_1 : y = w.x + b = -1 \tag{12}$$

$$H_1 : y = w.x + b = 1 \tag{13}$$

With the condition that there is not reference mark between H1 and H2 and the distance between H1 and H2 is maximized.

For any plan of separation H corresponding to H1 and H2, we can always standardize the vector W of coefficients so that H1 is

$y = w.x - b = +1$ et H_2 soit $y = w.x - b = -1$. (14)

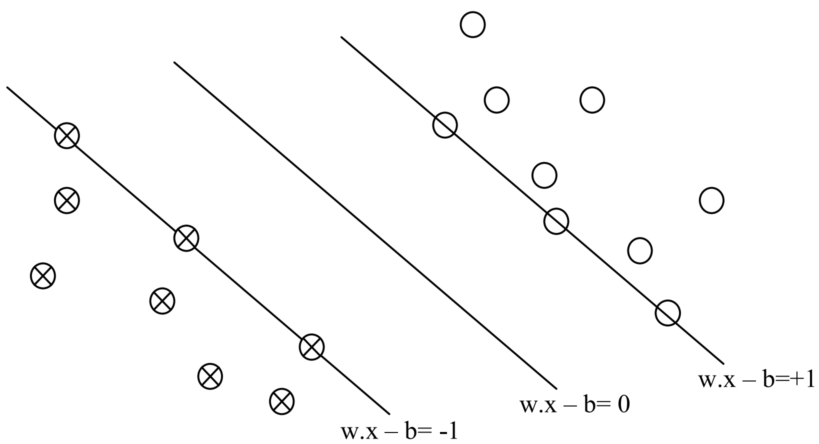


Fig. 2 The optimal separating hyperplane is located at the medium of the two classes

By maximizing the distance between H1 and H2, there will be some positive examples on negative H1 and some negative examples on H2. These examples are the support vectors which take part in the definition of the hyperplane of separation, and other examples can be withdrawn and/or moved in order to do not cross the plans H1 and H2.

Let us recall that in the case of two dimensions, the distance from a point (x0, y0) to a line:

$$Ax+By+C=0 \text{ is : } \frac{|Ax_0 + By_0 + C|}{\sqrt{A^2 + B^2}} \tag{15}$$

In the same way, the distance from a point on H1 with H:

$$w.x - b = 0 \text{ and : } \frac{|w.x - b|}{\|w\|} = \frac{1}{\|w\|} \tag{16}$$

and the distances between H1 and H2 is $\frac{2}{\|w\|}$.

Thus, in order to maximize the distance, it is necessary to reduce to the minimum $\|w\| = w^T w$ with the conditions that there is no reference mark between H1 and H2:

$$w.x - b \geq +1, \quad si \ \ yi = +1; \tag{17}$$

$$w.x - b \leq -1, \quad si \ \ yi = -1; \tag{18}$$

These two conditions (17) and (18) can be combined in yi (**w.x** - b) ≥1. Thus, this problem can be formulated like:

for $yi(w.x_i - b) \geq 1$

$$\min \quad \frac{1}{2} w^T w$$

It is a problem of convex programming quadratic (in w and b), in a convex unit presenting of the multipliers of

Lagrange $\alpha_1, \alpha_2, \ldots, \alpha_N \geq 0$, we have *the Lagrangian* following:

$$L(w,b,\alpha) = \frac{1}{2} w^T w - \sum_{i=1}^{N} \alpha_i y_i (w.x_i - b) + \sum_{i=1}^{N} \alpha_i \quad (19)$$

V. Experiments

We carried out some tests with an ultrasonic focused transducer of 10MHz on several pieces containing of known defects to provide a data bank of several echoes (112 signals) representing the various types of defects.

A. Proposed Algorithms

The developed algorithms are schematized in the following figure:

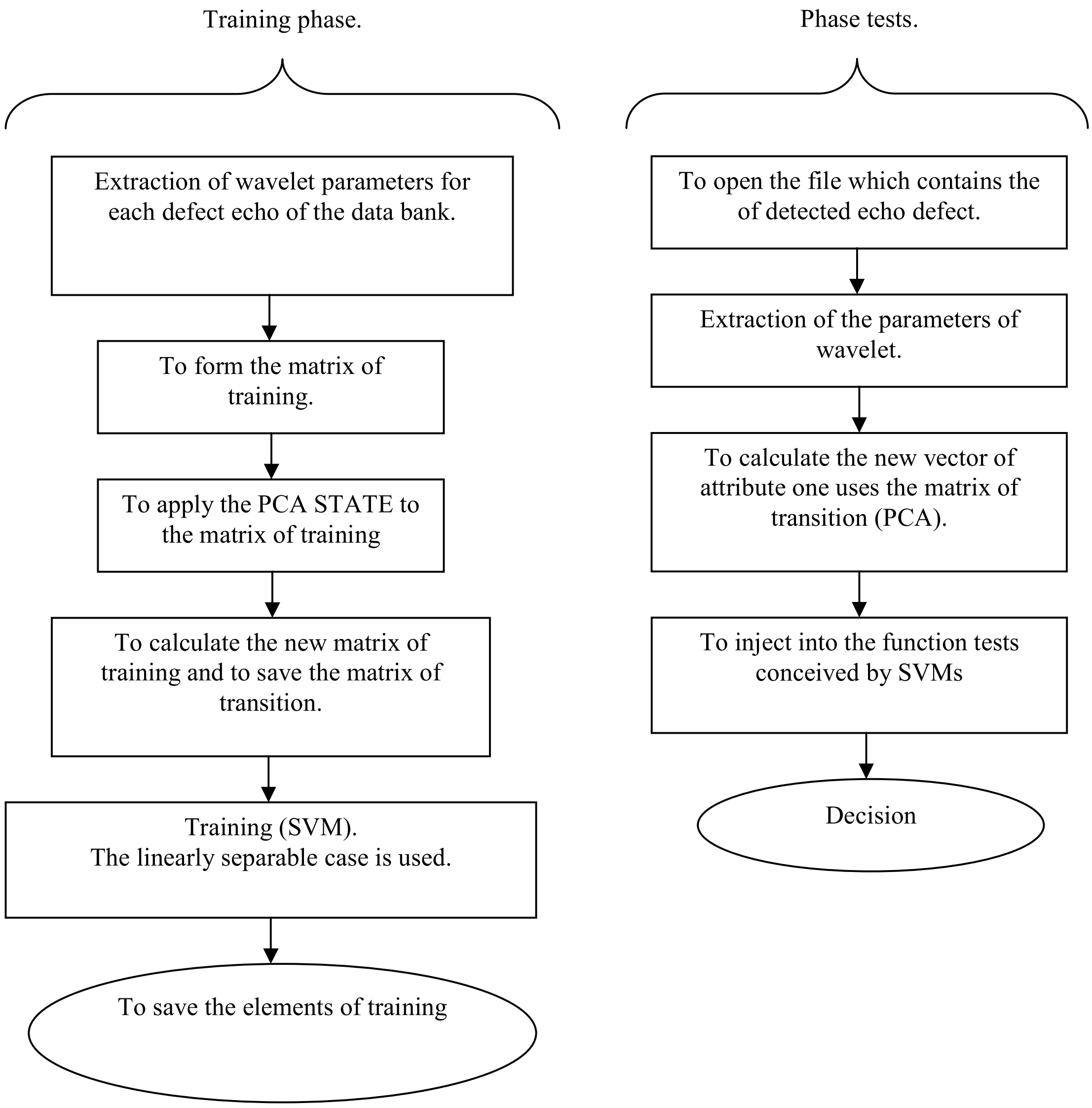


Fig. 3 The proposed algorithm

B. Extraction of Wavelets Parameters

Analyses processed on examples of defect echoes detected in metallic components, showed clearly that these waveforms can be described by pertinent features allowing weld defects classification. After pertinent features extraction, it is normally useful to elaborate a recognition procedure (identification) of the detected defect type. This defect identification in the inspected components will be a criteria to assess their fitness for use.

The normalised signal of defect echo is characterised by wavelets coefficients which are the successive continuation of the approximation coefficients (ca_i) and details coefficients (cd_i) where i is the level of calculation : ca_9, cd_9, cd_8, ...,cd_1 calculated by the algorithm of decomposition of S.MALLAT at level 9 using the DAUBECHIES window of order 2. As an example, we have taken at 128 sampling points a defect signal of 10 MHZ mid-frequency sampled at 51,2 MHz. Then, it was normalized to 1 MHz by interpolation of 10, so we have obtained 1280 samples and we wish to calculate their DWT coefficients. Fig (4) shows the defect signal and Fig (5) show the representation of 512 samples of DWT coefficients.

The last 256 samples constituting the coefficients of the DWT at level 1 (sample 257 up to 512) characterising the signal in the frequency band [π / 2, π] rad/s which corresponds to the range from 128MHz until 256MHz, these samples do not contain any information, because the signal does not have any spectral component in this interval. Coefficients of DWT at level 2 (sample 129 up to 256) characterising the signal in the frequency band [π / 4, π / 2] rad/s which corresponds to the range from 64MHz until 128MHz. Coefficients of DWT at level 3 (sample 65 up to 128) characterising the signal in the frequency band [π / 8, π / 4] rad/s which corresponds to the range from 32MHz until 64MHz. Coefficients DWT at level 4 (sample 33 up to 64) characterise the signal in the frequency band [π / 16, π / 8] rad/s which corresponds to the range from 16MHz until 32MHz. The significant part of the energy of the signal appears in DWT coefficients at level 5 (sample 16 up to 32), characterise the signal in the frequency band [π / 32, π / 16] rad/s which corresponds to the range from 8MHz until 16MHz. The relatively broad peak negative appearing in the coefficients of the DWT at level 6 corresponds at the low frequencies in the signal, including the envelope of the signal. We can easily see that the 512 samples of the ultrasonic signal can be characterised by the first 64 samples of the DWT, because the contribution of the remaining samples is negligible. Therefore the coefficients of the DWT computed from level 1, 2 and 3 can be eliminated without any loss of information. It is necessary to note that Polikar et al. have used, in theirs paper [4], the half of samples (128 on a signal sampled at 256). In this work, we propose a classification on the signal useful part solely. Indeed, we have used the first 64 coefficients which contain frequency components characterising the defect echo.

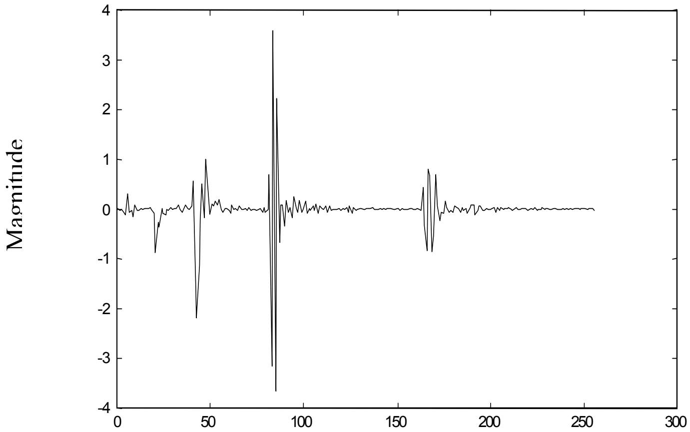
The experimental results obtained are illustrated by the Fig (4) and (5) as an example by the layout of the echoes and their wavelets transformed.

In our study, we take only the first 64 points of the DWT.

C. Optimization of Wavelets Parameters

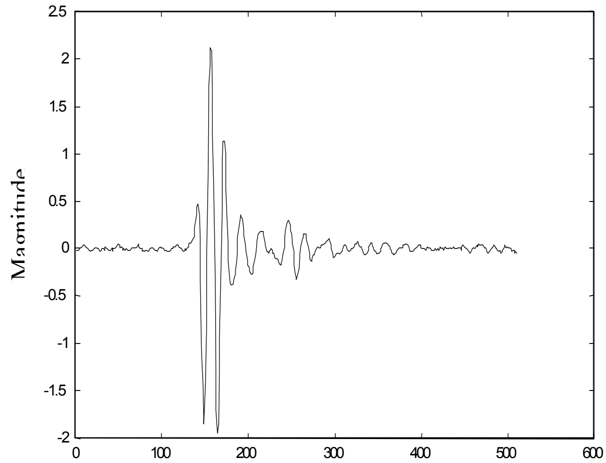
With each example, we take the first 64 points of the vector of decomposition and we build a matrix of $P \times N$ such as P represents the number of example and N the 64 parameters of wavelets. From this matrix, we get 50 examples: 25 planar defects and 25 volumic defects, and then we build one other matrix of 50×64 : it is the training matrix.

For the optimization of this matrix, we apply PCA algorithm and we obtain a training matrix of $50 \text{ x } 7$. Therefore, it can be noted that the number of parameters is reduced to 7 instead of 64.



DWT Coefficients Signal

Fig. 4 Echo of defect



Signal samples

Fig. 5 DWT coefficients

D. Training and Classification

In this work, we applied the linearly separable case. After achieving the training matrix transition, we present to the classification network 50 examples with their exits desired output. After converging, we save training data (the hyperplanes) for test stage.

As test stage, we carried out tests with 112 signal echoes of various types, we reached a rate of good decision of **98.21%** with a deviation of **1.79%**.

VI. CONCLUSION

Our objective is to carry out a robust means allowing the identification of the defects type which can arise in a material to inspect. We applied classification algorithms in order to identify defect echoes and recognize defect type.. The results obtained are considered to be satisfactory and show that the selected parameters are quite representative of the echo of defect. The use of SVM as classification method gave good results. These results can be enhanced if we enrich the data bank of defects with various dimensions and various positions. However, the use of the PCA enabled us to reduce the size of the vector of attribute and to optimize it to have more precision. We can conclude that this method enabled us to establish a reliable classifier for the discrimination of the types of detected defects and gives results better than the methods of the ANN realized in [1].

REFERENCES

[1] R. Drai, M. Khelil and A. Benchaala "Time-frequency and wavelet transform applied to selected problems in ultrasonics NDE ".NDT & E International Volume 35, Issue 8, Décembre 2002, Pages 567-572.
[2] A.sophian & G.tian & D.taylor & J.rudlin A "feature extraction technique based on pricipal component analysis for pulsed Eddy current NDT". NDT&E international 36 (2003) 37-41.
[3] Olivier bousquet "Introduction aux Support Vector machine"(SVM). Orsay, 15 Novembre 2001
[4] R. Polikar & T. Taylor & L. Udpa & S Udpa "frequency invariant classification of ultrasonic weld inspection signals." IEEE transactions on ultrasonics, ferroelectrics, and frequency control. Vol. 45, may1998.
[5] Drai R, Khelil M & Benchaala A, "Elaboration of some signal processing algorithms in ultrasonic techniques : Application to materials NDT.". ULTRASONICS, VOL.38 (1-8) 2000, pp.503-507
[6] Burrus, C.S., Gopinath, R.A. & Guo, H. "Introducing to wavelets and wavelet transformation", Prentice-Hall, 1998
[7] Mallat, S., "*A Theory for Multiresolution Signal Processing: The Wavelet Representation,*" IEEE Transactions on Pattern Analysis and Machine Intelligence, July 1989, Vol. 11, pp 674-693.
[8] Rashmi, M., Bilgutay N. M. and Kagan Kaya, O. *"Detection of ultrasonic anomaly signals using wavelet decomposition."* Materials evaluation (Nov. 1997), 1274-1279.