RECONSTRUCTING ULTRASONIC IMAGES AND FLAW DETECTION IN TIME-FREQUENCY DOMAIN BY MATCHING A-SCAN INSPECTIONS

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ABSTRACT

Time-frequency techniques are applied for mixing signals from a material inspected by a multiple sensor detection system. Ultrasonic sensors are located at the perimeter of a rectangular shaped material evaluated in a pulse-echo scheme. The resulting mixed signal becomes a high-resolution time-frequency image of the material. Different kinds of classification techniques can be applied to this image in order to obtain the defects in the material. In this paper, a simulation and experimental evaluation of the proposed approach are presented. Several time-frequency transforms and the fuzzy c-means are used. In the simulations, backscattering of the material grain is modelled by using Gaussian and K distributions with different signal to noise ratio parameters. The validity of the presented method is assessed through the detection and spatial location of artificial defects in a material with a rectangular shape. The performance of the classification technique in discerning defects buried in the backscattering from the material grain microstructure, is also discussed.

1. INTRODUCTION

The significance of combining and separating signals captured by multiple sensor systems has been recognized throughout different studies in diverse areas, such as, ultrasound images [1] and radar [2]. Most of the techniques that have been used such as beamforming and MUSIC are based on uniform linear array signal processing [3].

Another technique that has been applied is data fusion which consists of the association, correlation, and combination of data from single or multiple sources for carrying out identity and position estimation [4]. In the non-destructive evaluation of materials, the main objective of data fusion is to improve information for the decision-making process through the signal mixture of different inspections of a material. One approach consists of mixing decision information from different inspection techniques such as transmission-reception and impact-echo [5].

Signal information mixing has been applied to increase signal bandwidth using a multiple transducer array. It has been explored to complement the non available information regarding a transducer in some frequency bands with information from other transducers. The information lost in some transducer frequency bands can be replaced with information from other transducers [6].

This paper proposes a technique for integrating signal information and detecting defects in a rectangular shaped material evaluated by a multiple sensor system. Signal integration is based on a sensor trace matching approach and time-frequency techniques such as STFT and Choi-Williams transforms [7]. Signal integration can obtain high-resolution time-frequency material images from a small number of material inspections. Applying fuzzy c-means heuristic classification to the time-frequency images enables defect detection. A mathematical model of the proposed method, simulations and experimental results showing its performance are included.

2. MIXING OF SIGNALS

Figure 1 shows a simulation scenario where a rectangular shaped material is evaluated using a multiple sensor system. This area is located in the first quadrant of the coordinated axes. Four vertical aperture sensors and three horizontal aperture sensors can be seen. Two targets located at (150,240) and (210,150), and some diagonal trajectories for signal mixing are also displayed.

Original time domain signals are transformed into time-frequency domain signals by using transforms such as STFT, Wigner-Ville and Choi-Williams. The resulting signals in the time-frequency domain are arranged into two 3D matrices, H_f and V_f ,

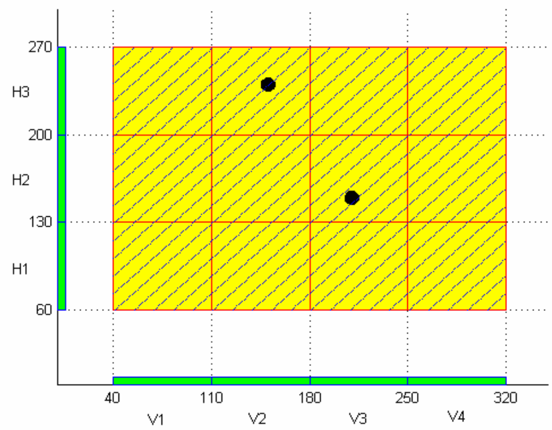

Figure 1. Simulation scenario

$$H_f = \begin{bmatrix} h(1,1,f) & \cdots & h(1,longx,f) \\ & \vdots & \\ h(n,1,f) & \cdots & h(n,longx,f) \end{bmatrix}$$
$$V_f = \begin{bmatrix} v(1,1,f) & \cdots & v(1,longy,f) \\ & \vdots & \\ v(m,1,f) & \cdots & v(m,longy,f) \end{bmatrix} \quad (1)$$

where n is the number of horizontal sensors and m the number of vertical sensors, *longx* is the material length in axis x and *longy* is the material length in axis y. In the time domain, $H(i,j)$ is the horizontal sensor i measurement in the instant j and $V(k,l)$ is the vertical sensor k measurement in the instant l.

In the time-frequency domain $H_f(i,j,f)$ is the horizontal sensor i measurement in the instant j at the analyzed frequency f and $V_f(k,l,f)$ is the vertical sensor k measurement in the instant l at the analyzed frequency f $(f=1,.., F)$.

The diagonal lines in Figure 1 represent the trajectories for obtaining mixed signals from the original ones. The illuminated area resulting from the intersection of sensor beams (mixing area) has the following dimensions: $width = n \cdot longt$ and $height = m \cdot longt$, where *longt* is the length covered by one sensor in the material perimeter. In the mixing area it is possible to accommodate a total of $diag = n \cdot m \cdot longt^2 - 1$ inspection diagonals to produce a complete scanning of the material. Therefore, the diagonal mixing trajectories can be defined as follows,

$$B_{tr} = \{(a_{tr}, b_{tr})\} / x_{ini} \le a_{tr} \le x_{end}, y_{ini} \le b_{tr} \le y_{end}, \quad b_{tr} = s \cdot a_{tr} + d_{tr} \quad (tr = 1, \ldots, diag) \quad (2)$$

where B_{tr} defines a set of coordinate pairs (a_{tr}, b_{tr}) corresponding to each one of the *tr* signal mixing trajectories. x_{ini} and x_{end} correspond respectively to the left and right locations of the vertical sensor set, and y_{ini} and y_{end} correspond respectively to the lower and upper locations of the horizontal sensor set. Each mixing trajectory is a diagonal line with slope s and intersects d_{tr} with axis y.

The mixing of signals is achieved using two operations: Signal Matching and Signal Mixing. Signal matching (*MATCH*) consists of matching the original signals from both vertical and horizontal aperture sensors through diagonal mixing trajectories. Each point of a diagonal line maps a signal sample captured by a horizontal sensor and a signal sample captured by a vertical sensor. These samples can correspond to different instants of time in captured signals due to sensor location. *MATCH* operation must be carried out $diag$ times, obtaining $diag$ pairs of vertical and horizontal signal segments which are defined as follows,

In the time domain,

$$Hm_{tr} = H \underset{\mathrm{tr}=1}{\overset{diag}{MATCH}} B_{tr}$$
$$Vm_{tr} = V \underset{\mathrm{tr}=1}{\overset{diag}{MATCH}} B_{tr} \quad (3)$$

In the time-frequency domain,

$$Hm_{f,tr} = H_{f\,(f=1,\ldots,F)} \underset{\mathrm{tr}=1}{\overset{diag}{MATCH}} B_{tr}$$
$$Vm_{f,tr} = V_{f\,(f=1,\ldots,F)} \underset{\mathrm{tr}=1}{\overset{diag}{MATCH}} B_{tr} \quad (4)$$

Segments of signals resulting from the *MATCH* operation are processed by the *MIX* operation to produce a mixed signal. The mixing of signals can be carried out using different operators such as, mean, product, maximum and minimum. It is defined as follows,

In the time domain,

$$Sm_{tr} = \underset{\mathrm{tr}=1}{\overset{diag}{MIX}}(Hm_{tr}, Vm_{tr}) \quad (5)$$

In the time-frequency domain,

$$Sm_{f,tr} = \underset{\mathrm{tr}=1}{\overset{diag}{MIX}}(Hm_{f,tr}, Vm_{f,tr})_{(f=1,\ldots,F)} \quad (6)$$

The described procedure has been applied for the example in Figure 1. The Choi-Williams transform was used with Hamming *(N/10)* time smoothing window, Hamming *(N/4)* frequency smoothing window and kernel width = 1. N is the signal length that varies according to the mixing diagonal length. The product was used as an operator for signal mixing. Defects were simulated with Gaussian modulated pulses. Backscattering from the material grain microstructure was simulated by using a Gaussian distribution with $SNR=0.9$, defined as follows,

$$SNR = \frac{pulse\ envelope\ peak\ value}{noise\ variance} \quad (7)$$

The 58800 pixels, (280x210) image in Figure 2 has been obtained using 3 A-scan inputs of 280 points and 4 A-scan inputs of 210 points. It corresponds to one of the analyzed frequencies in the signal spectrum $(f = 1,...,3)$, the central sensing frequency.

3. DEFECT DETECTION

Heuristic classification using the fuzzy c-means algorithm has been applied to acquire information concerning defect spatial localization. This algorithm finds structures contained within groups of data. These structures are usually classes to which objects from the data are assigned [8]. Classical clustering assigns each object to exactly one class, whereas in fuzzy clustering, the objects are assigned varying degrees of membership to the different classes.

The fuzzy c-means uses the following definitions. The first definition is the Euclidean distance between two objects o_i and o_j. In this application one object is a pixel in the image and there are 3 features $(S=3)$ describing each object. These features are the values of spatial coordinate x, coordinate y and the spectrum value corresponding to one analyzed frequency f at one point of a mixing diagonal trajectory tr.

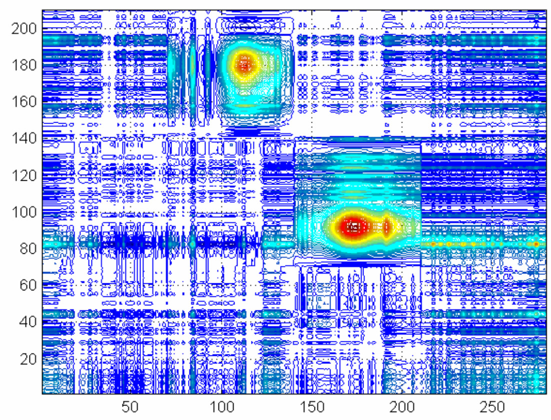

Figure 2. Simulated time-frequency material image by central frequency (cf)

Firstly, the fuzzy c-means initializes the membership values. μ_{ik} is the membership value of the k^{th} object o_k to the i^{th} cluster and $\sum_{i=1}^{c}\mu_{ik}=1,\ \mu_{ik}\in[0,1]$, $i=1,\ldots,c$; $k=1,\ldots,K$.

Calculate the cluster centroids as follows,

$$v_i=\frac{\sum_{k=1}^{K}(\mu_{ik})^m\cdot o_k}{\sum_{k=1}^{K}(\mu_{ik})^m}, \tag{8}$$

m = determines the degree of fuzziness of the process

Calculate the new membership values μ_{ik}^{new} using v_i as follows,

$$\mu_{ik}^{new}=\frac{1}{\sum_{j=1}^{c}\left(\frac{\|v_i-o_k\|}{\|v_j-o_k\|}\right)^{\frac{2}{m-1}}} \tag{9}$$

If $\|\mu_{ik}^{new}-\mu\|>\varepsilon$, it replaces μ by μ^{new} and finally, recalculate the new centroids until the algorithm converges.

The fuzzy-c means is applied to the F images produced during signal mixing, obtaining a number of centroids for each image. The maximum spectrum value centroid is selected from each image and the selected centroids are averaged to provide the coordinates for the estimated defect localization. These coordinates are defined using the following expressions,

$$xde=\frac{1}{F}\sum_{f=1}^{F}xd_f;\qquad yde=\frac{1}{F}\sum_{f=1}^{F}yd_f \tag{10}$$

where xd_f is coordinate x for a selected centroid of an image corresponding to analyzed frequency f, and yd_f is coordinate y for a selected centroid of an image corresponding to analyzed frequency f. In the eventuality of detecting a number of defects, a number of the highest spectrum value centroids are selected in order to obtain the coordinates of the defects.

4. RESULTS

Several simulations were conducted, modelling defects with Gaussian, Hamming and Hanning modulated pulses; Gaussian modulated pulses were shown to offer the best results. The unity slope was the best value for diagonal mixing trajectories. Simulations were carried out in a scenario using the configuration in Figure 1. A defect was located in position (150,240) which was simulated with a Gaussian modulated pulse with 5 MHz central frequency, 40 MHz sampled and 2 MHz bandwidth.

A total of 19,200 simulations were carried out, consisting of 384 groups with 50 simulations in each one. Each group was characterized according to the following parameters: a) Time-frequency transform (PWV: Pseudo Wigner-Ville, SPWV: Smoothed Pseudo Wigner-Ville, CW: Choi-Williams, ESPEC: Spectrogram, STFT: Short Time Fourier Transform, WVLT: Wavelet). b) Signal mixing operator (Product, Mean). c) Noise type (Gaussian, K type with α=0.5, 1, 3). Furthermore, simulations were made in two modalities: employing or not employing a matched filter as the signal preprocessing operation, and taking the values from the pulse as the filter coefficients.

In time-frequency transforms the following parameters were used: Hamming (*N/10*) time smoothing window, Hamming (*N/4*) frequency smoothing window. *N* is the signal length as explained earlier. A kernel width = 1 was used in the Choi-Williams transform and the Morlet function was used in the Wavelet transform.

Some of the simulation results of defect detection are given in Figure 3 corresponding to K type noise with α=0.5. The criterion for the clustering quality used for defect detection was the partition coefficient which performed better than the partition entropy and the proportion exponent. The value of fuzziness degree was 1.2. Figure 3 shows the Euclidean distance obtained from the difference between the estimated defect position and the real defect position for various SNR.

In different curves “SNR vs. distance”, was observed that as the SNR increases, the estimated defect localization for different signal mixing operators moves nearer towards the real defect localization. In general, the matched filter improved the defect localization for higher SNR (1, 1.2), but deteriorates for lower SNR (0.6, 0.8). However, with both operators (product and mean), the utilization of a matched filter makes the detection process converge more quickly.

In general, the procedure displaying a more consistent behaviour in simulations was the Pseudo Wigner-Ville transform with a matched filter preprocessing operation and the product as the mixing operator. In addition, bilinear transforms (PWV, SPWV, CW) have produced better results than the linear transforms (STFT, WVLT, ESPEC).

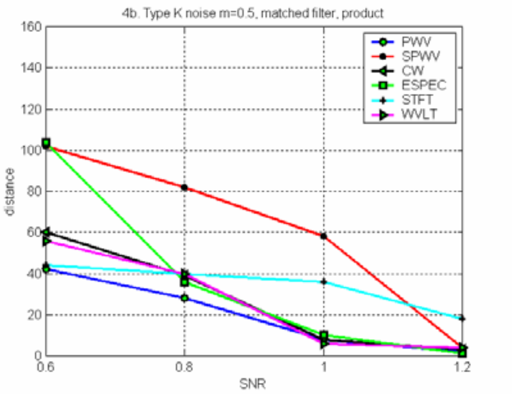

Figure 3. Noise K type with α =0.5 simulation results

For the detection of various defects, a group of specific simulations was conducted, revealing that the identification of close defects is restricted by the duration of the simulated pulses, which can be related to the shape of the defect.

A real experiment with a 0.15x0.25x0.005 m. duraluminium probe was made. The used equipment was: Ultrasonic card IPR-100 of Physical Acoustics, 5 MHz transducer MSWQC5 KBA of Krautkramer and Tektronix TDS3012 oscilloscope for digitalizing. The numbers of horizontal and vertical measurements were 49 and 29 A-Scans with 2320 and 3920 samples respectively, see Figure 4. Sampling frequency was 50 MHz. The time-frequency image from mixing of vertical and horizontal inspections, corresponding to the central frequency (5 MHz) is overwritten with yellow lines on Figure 4. It was obtained by using the Pseudo Wigner-Ville transform and the product as signal mixing operator. The three defects (2 holes and 1 crack) in material can be seen properly detected.

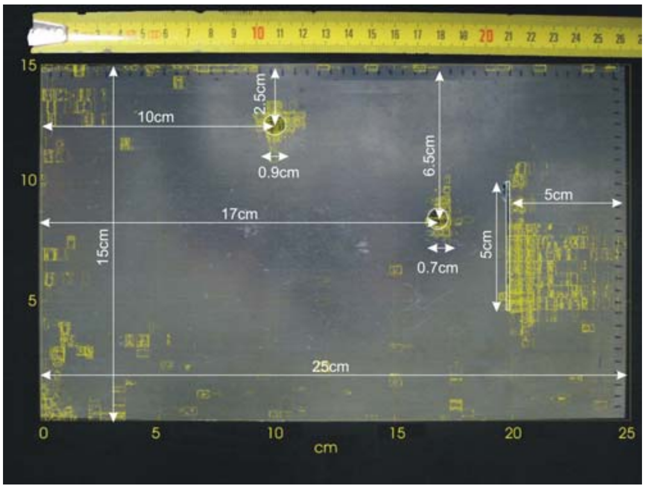

Figure 4.Testing material photograph and time-frequency image

Two problems have arisen in real measurements that did not appear in the simulations, the first one is the multiple reflections due to the pulse-echo inspection scheme and the second one is hidden defects by other defects found first in the ultrasonic beam trajectory. The first problem is fixed by using redundant information of the different plane inspections with the minimum signal mixing operator. For fixing the second problem various mixing operators can be applied to the original signals to locate the defects.

5. CONCLUSIONS

The main results of this paper are listed below.

A new technique in time-frequency domain has been proposed for achieving high resolution images from the mixing of signals detected by multiple sensor systems.

A detection procedure based on the fuzzy c-means classification algorithm, based on the use of time-frequency images, has been proposed.

By mixing inspections from different planes, some problems such as multiple reflections and hidden defects can be fixed.

The proposed method has been evaluated using several time-frequency techniques in simulations and a real experiment, finding that the Wigner-Ville transform performs better in defect spatial localization.

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