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Ultrasonic signal processing methods for detection of defects in composite materials

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Introduction

Ultrasonic technique is one of widely used techniques for nondestructive testing (NDT) of materials [1, 2]. In ultrasonic testing useful information about integrity or geometry of the object under a test is obtained. Measurement configuration often encountered in NDT includes pulse-echo reflection technique. The ultrasonic wave, generated by a piezoelectric transducer propagates through the material and is reflected by defects and back surface of the sample. The signals reflected by defects possess information about defects size and orientation [3]. This method is successfully used in NDT of various materials.

However, ultrasonic NDT of composite materials or multi-layer plastic pipes with intermediate fiber-reinforced layers meets serious problems [4-6]. The experimental investigations of plastic pipe sample with artificial defects have showed that detection of holes in a porous layer and under this layer is complicated [7]. To solve this problem novel measurement and signal processing methods are necessary.

Problems of signal detection

Detection of defects involves many factors, which influence the transmitted ultrasonic signal in the material under investigation. The theory of acoustic propagation in materials shows that the parameters of the backscattered ultrasonic signal depend on many factors main of which are the following:

- ultrasonic signal frequency and bandwidth;
- inspection path and distance;
- position of defects and their size;
- material properties.

The material parameters influence very much detection of defects. NDT of composite materials meets some specific problems caused by a high attenuation of the ultrasonic signal [1]. Attenuation of ultrasonic waves is due to absorption and scattering phenomena. The absorption converts acoustic energy into heat via viscosity, relaxation, heat conduction, elastic hysteresis, etc. The absorbed energy of the acoustic field is irreversibly lost since it is dissipated in the medium. The absorption is essentially independent of grain size, shape and volume.

Scattering converts the energy of the coherent, collimated beam into incoherent, divergent waves. This is result of wave interaction with non-uniformities in the material. The scattering by micro structural components of a material causes serious difficulties in detection of discontinuities, as it reduces the signal to noise ratio (SNR). The scattering from boundaries between small, randomly distributed grains in metals create small ripples in the reflected ultrasonic signals, which in NDT are referred to as grain noise or material noise. The ultrasonic grain noise caused by micro-structural inhomogeneities limit the detection of small cracks, flaws or other defects. The following formula relates some of the variables affecting the SNR [8]:

$$SNR = \sqrt{\frac{16}{\rho c w_x w_y \Delta t}} \frac{A(f_0)}{FOM(f_0)}, \tag{1}$$

where ρ is the material density; c is the sound speed; w_x, w_y are the lateral beam widths at the flaw depth; Δt is the pulse duration; $A(f_0)$ is the flaw scattering amplitude at the center frequency; $FOM(f_0)$ is the noise Figure of Merit at the center frequency.

Compared to metals, composite materials cause additional problems in detection of defects. One example may be detection of defects in multi-layered plastic pipes with fiber-reinforced layer. Similar problem is met in NDT of composite fiber-reinforced aerospace materials. Fiber-reinforced composites possess a high acoustic attenuation and a high structural noise due to scattering of ultrasonic waves by fiber-reinforced layer and due to multiple reflections inside the samples caused by different acoustic impedances of the layers. The named problems show that testing of composite materials requires a special care in frequency selection and signal interpretation. Enhancement of the received ultrasonic signals can be achieved by applying signal processing techniques.

In this paper a review of different signal processing methods for detection of defects in composite materials is presented. The aim of this analysis is to find out an optimal method for testing of composite fiber-reinforced multi-layer materials.

Ultrasonic signal processing methods

For detection and characterization of defects various signal processing techniques are already used. In this paper we shall analyze theses techniques from the point of their suitability for detection of reflected echoes in composite materials with a high attenuation of ultrasonic waves caused by scattering.

The simple signal processing options implemented in hardware and available in many conventional ultrasonic flaw detectors are the following:

- analog filtering;
- transducer damping;
- pulse shaping and smoothing;
- clipping the signal;

- automatic control of amplitude of the signal.

The main tasks which are met in NDT of multi-layer lossy non-uniform materials are the following:

- detection of ultrasonic signals, reflected by defects, which are masked by a structural noise;
- modeling of ultrasonic signals scattered by non-uniform structure of the material, for example, grains in metals;
- improvement of spatial resolution in presence of multiple reflections inside the sample;
- determination of position of the detected inhomogeneities;

Theses tasks are solved applying various linear and non-linear signal processing techniques including signal averaging, auto and cross correlation, convolution, deconvolution, filtering etc. In all these techniques the signal is analyzed in the time domain or in the frequency domain.

Time delay estimation methods

For detection echoes in noisy signals and estimation of their delay *cross-correlation* method is widely used. In this method the cross-correlation function between the two digital sequences $x_T(nT)$ and $x_E(nT)$, representing the transmitted and echo signals is calculated [9]:

$$x_T(nT) = s(nT) + v(nT)$$
$$x_E(nT) = \alpha \cdot s(nT - D) + n(nT), \qquad (2)$$

where T is the sampling interval, $s(nT)$ is the generated signal, $v(nT)$ and $n(nT)$ are uncorrelated noises, α is the coefficient of estimating signal attenuation, D is the determined delay time. This method is in pulse-echo measurements used.

The correlation of the two sequences is given by:

$$C(kT) = \sum_{n=-\infty}^{+\infty} x_T(nT) x_E(nT + kT). \qquad (3)$$

The statistical expectation of this sequence is:

$$E[C(kT)] = \alpha C_{ss}(kT - D), \qquad (4)$$

where $C_{ss}(kT)$ is the sampled auto-correlation function of the signal $s(t)$. For a finite energy signal equation (4) have a peak for k=k_D. In practice the delay time D can be estimated by finding the peak of the correlation (3).

In NDT applications very often the delay of the signal and distance till defect is found from the peak value of the signal envelope. The envelope of the narrowband signals may be determined using the *Hilbert transform.* [10]. In the case of narrowband signals it is a fast and simple method to estimate small time delays. The Hilbert transform of the reference echo signal $r(t)$ is defined as:

$$\check{r}(t) = \mathrm{H}\{r(t)\} = \frac{1}{\pi}\int_{-\infty}^{\infty} \frac{r(x)}{x-t} dx = h(t) * r(t), \qquad (5)$$

where the integral is a Cauchy Principal Value (CPV); * denotes convolution. The Hilbert kernel is denoted by $h(t) = -\frac{1}{\pi t}$ and the received echo signal is $s(t) = r(t - \theta)$, where θ is the delay time.

The cross correlation between $s(t)$ and $\check{r}(t)$ will not have maximum at the time lag θ but a zero crossing. It is necessity of this method that it is easier to find a zero crossing than a peak in a noisy signal. Assuming that $r(t)$ is narrowband, e.g., its energy is concentrated in frequency intervals B around $\pm f_0$ and that $B\theta$<<1, the cross correlation $R_{s\check{r}}(0)$ can be approximated as

$$R_{sr'}(0) \approx \int_{-f_0 - B/2}^{-f_0 + B/2} e^{j2\pi f\theta} H(f)|R(f)|^2 df \approx -E_r \sin w_0\theta, \qquad (6)$$

where $E_r = \int_{-\infty}^{\infty} r^2(t)dt$ is the energy of $r(t)$ and $w_0 = 2\pi f_0$.

The cross-correlation method is combined with co called method of *digital Windows* [11]. In this method ultrasonic signals are segmented at different depths by partially overlapping windows. The waveforms in each window are cross-correlated to estimate the time-delays. Two time delay estimates from the overlapping windows are used to estimate the axial strain field in a sample under a test.

The time-domain techniques based on application of correlation processing are especially useful in determining the exact time delay between similar, but distorted, noisy signals. However, this technique gives unambiguous results when the signals are distorted and scattered by grains non-uniformities in materials or the echoes are overlapped. The main reason for it is that in this case a structural noise prevails, which partially is correlated with the received signal.

Deconvolution in thin samples

In thin samples the reflected signals are overlapping thus making detection of defects in the sample and accurate measurements impossible. For improvement of spatial resolution various filtering techniques known as the inverse filtering (deconvolution), usually in the frequency domain, are used: homomorphic (cepstrum) processing and parametric identification. For example, the power cepstrum has been proposed for detecting echoes in thin composite materials and noisy seismic signals. These techniques can be used for relatively low signal-to-noise ratios and high echo distortion.

In the *power cepstrum* method [12] the convolution is represented by the product of their respective Fourier transforms $S(\omega)$ and $H(\omega)$, where $S(\omega)$ and $H(\omega)$ is the Fourier transformed ultrasonic signal and noise. The system response $h(t)$ can be separated from the signal by simply dividing $X(\omega)$ by $S(\omega)$ and taking the inverse transform of it. The inverse Fourier transform is defined of the log-normalized Fourier transform:

$$C(q) = F^{-1}\{\log(F\{x(t)\})\} \qquad (7)$$

where q is called the quefrency and $x(t)$ is the obtained waveform. The low-frequency ripples can be reduced by low-pass liftering:

$$H(\omega) = F\{\exp(F^{-1}\{w(q)C(q)\})\}, \qquad (8)$$

where

$$w(q) = \begin{cases} 1 & \text{for } q > q_c \\ 0 & \text{for } q < q_c \end{cases} \qquad (9)$$

is the cut-off function and q_c is a cut-off quefrency which may be determined for a given measurement system and the material configuration.

Homomorphic deconvolution method enables to reduce the pulse width for imaging of defects in thin laminates of composites[13]. The core idea of this method is to convert the product $S(\omega)H(\omega)$ into a sum by applying a logarithmic function. The complex cepstrum is defined as the inverse Fourier transformation of the log-normalized Fourier transform of the input signal, which is reverted to the time or the quefrency domain.

Characterization of ultrasonic signals backscattered by grainy structure

In the frequency domain processing techniques the power density spectrum of ultrasonic signals is exploited. It is assumed that echoes due to flaws differ in spectral content from the echoes caused by background scattering noise. Otherwise use of these methods is complicated. For detection of the reflected signals in scattering structures the *autoregressive* (AR) cepstrum is used [14, 15]. The autoregressive parameter identification process is closely related to the theory of linear prediction.

Let us assume that the measured grain signal $r(n)$ is an AR process with p parameters, then the predictive value of the sampled grain signal $\hat{r}(n)$ is defined as:

$$r^\wedge(n) = -\sum_{i=1}^{p} a_i r(n-i)\,, \qquad (10)$$

where the a_i refers to the AR coefficients and the p is the order of the AR model.

The normal AR model for the estimate a_i can use p equations and p unknown AR coefficients [15]:

$$\Phi(0,j) + \sum_{i=1}^{p} a_i \Phi(i,j) = 0, \qquad 1 \le j \le p\,, \qquad (11)$$

where the correlation function $\Phi(i,j)$ is

$$\Phi(i,j) = \sum_{n} r(n-i) r(n-j)\,. \qquad (12)$$

The grain discrete transfer function $H(z)$ for a *second-order AR* model can be written as:

$$H(z) = \frac{1}{1 + a_i z^{-1} + a_2 z^{-2}}\,. \qquad (13)$$

The complex poles of the Eq.13 give the resonance frequency of the second-order AR process:

$$f_r = \frac{1}{2\pi T}\tan^{-1}\left(\frac{\sqrt{4a_2 - a_1^2}}{a_1}\right), \qquad (14)$$

where T is the sampling period.

The maximum frequency is not equal to the resonance frequency:

$$f_m = \frac{1}{2\pi T}\cos^{-1}\left(\frac{a_1 a_2 + a_1}{-4a_2}\right). \qquad (15)$$

The resonating frequency can be approximately represented by the frequency of the maximum energy. It can be correlated to the frequency shift inherent to random grain signals.

A closer spectral match can be obtained using a *third-order AR* system:

$$H(z) = \frac{1}{1 + a_i z^{-1} + a_2 z^{-2} + a_3 z^{-3}}\,. \qquad (16)$$

Similar to the second-order AR model the third-order model results in different maximum energy and resonating frequencies. Backscattered echoes from specimens with different grain sizes result in different values for the resonating frequency and AR coefficients. These coefficients can be estimated from the sample data by using existing processing techniques. The second- and third-order autoregressive models are used to evaluate the spectral shift in grain signals by utilizing features such as resonating frequency, maximum energy frequency or AR coefficients. These features are applied to classify grain scattering characteristics.

Detection of defects by Wavelet transform

The *Wavelet Transform* (WT) is a new method of processing transient nonstationary signals simultaneously in time and frequency domains [16, 17]. This method has generated much interest in various applications such as speech coding, pitch detection, image compression, multiresolution analysis and modeling and estimation of multiscale processes. In NDT it was applied for enhancement of detection of defects.

The Wavelet Transform decomposes signal $s(t)$ in a sum of elementary contributions called wavelets. The WT is the correlation between the signal and a set of basic wavelets. The daughter wavelets $\psi_{a,b}(t)$ are generated from the mother wavelet $\psi(t)$ by dilation and shift operations. The WT expansion coefficients $X_{WT}(a,b)$ of the signal $s(t)$ are given by:

$$X_{WT}(a,b) = \int_{-\infty}^{\infty} s(t)\psi^*_{a,b}(t)dt\,, \qquad (17)$$

where

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right). \qquad (18)$$

The Fourier transform of the daughter wavelet $\psi_{a,b}(t)$ is given by:

$$\psi_{a,b}(f) = \sqrt{a}\psi(af)\cdot e^{-j2\pi fb} \qquad (19)$$

where $\psi(f)$ represents the Fourier transform of the mother wavelet. This equation shows the important concept that a dilation t/a in the time domain is equivalent to a frequency change of af.

If the variables a and b are limited to integer values, then the *Wavelet Transform* becomes the *discrete wavelet transform* (DWT) [18]:

$$\psi_{m,n}(t) = 2^{-m/2}\psi(2^{-m}t - n)\,, \quad m,n \in \mathrm{Z}, \qquad (20)$$

where $\psi_{m,n}(t)$ constitute an orthonormals functions family. The discrete wavelet transform of analogue temporal signal is given by:

$$X_{DWT}(m,n) = \int_{-\infty}^{\infty} s(t)\psi^*_{m,n}(t)dt\,. \qquad (21)$$

The Wavelet Transform was applied to improve ultrasonic flaw detection in noisy signals. The WT is the most recent technique for processing signals with time-varying spectra. This method uses scaling in the time domain to scale a single function in the frequency domain.

The mother wavelet function is used to extract details and information in the time and the frequency domains from the transient signal under analysis.

Detection of defects in grainy materials

A very promising signal processing technique in nondestructive testing of composite materials has been named as *split spectrum processing* (SSP) [19-27]. The SSP technique enables to improve flaw detection in materials in which the coarse microstructure produces broadband noise of large amplitude, which masks useful signals. This method eliminates the need for multiple measurements and offers the possibility to obtain frequency diverse signal sets without recollecting data. SSP consists of two main steps illustrated in Fig.1. [19]:

- the received signal is transformed into a time-frequency representation by means of a filter bank;
- the received signal is processed by a nonlinear operation.

The Gaussian bandpass filters of different center frequencies but constant bandwidht are used to split the spectrum of the received signal into several frequency bands [20]. To these splitted time-domain signals the inverse Fourier is applied. For further processing of the signals the various SSP algorithms have been developed.

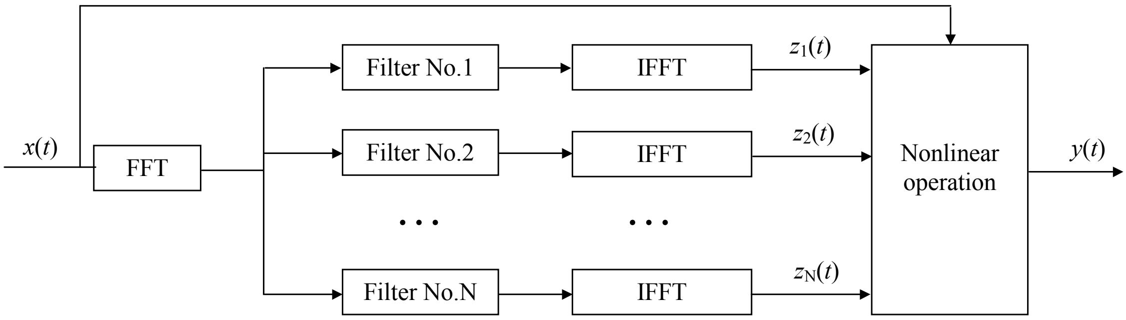

Fig.1. **Signal processing technique with Split Spectrum Processing (SSP). (FFT – fast Fourier transform, IFFT – inverse fast Fourier transform)**

One of the first representations of signals in the time-frequency domain is known as the *Gabor decomposition* [21]. The time signal $r(t)$ is decomposed into a two-variable function $R(\tau, \omega)$ according to the equation:

$$R(\tau,\omega) = \frac{1}{2\pi}(2\pi\sigma^2)^{-1/4}\int_{-\infty}^{\infty} e^{-(t-\tau)^2/4\sigma^2} e^{-i\omega(t-\tau)} r(t)dt \quad (22)$$

The function $R(\tau, \omega)$ is the convolution of the received signal $r(t)$ with the Gaussian wavelet $h(t)$ given by:

$$h(t) = \frac{1}{2\pi}(2\pi\sigma^2)^{-1/4} e^{-t^2/4\sigma^2} e^{i\omega t}. \quad (23)$$

Since convolution in the time domain is equivalent to multiplication in the frequency domain, the decomposition of the signals $r_j(t)$ can be expressed as:

$$r_j(t) = \frac{1}{\sqrt{2}}(2\pi/\sigma)^{3/4} R(t,\omega_j). \quad (24)$$

where ω_j is the center frequency of the filters. The optimization processing in the Gabor decomposition is a non-linear processing of the function $R(t, \omega)$ for each time t. A practical application of the Gabor decomposition is limited to analysis of short high frequency signals, whose decomposition involve wavelets of broad envelope and a large number of cycles.

In *geometric mean* method the filter signals $z_i(t)$ i=1,2,...M can be formed as a vector $z(t)=(z_1(t), z_2(t),... z_M(t))^T$, where M is the number of filters and T denotes the transpose [22]. With increasing time this vector carves out a trajectory in the filter signal space, which is dependent on the number of filters and the filter parameters.

The output signal $y(t)$ of "filtering" process using geometric mean (GM) algorithm can be expressed as:

$$[y(t)]^M = \prod_{k=1}^{M} |z_k(t)|. \quad (25)$$

This algorithm is based on heuristic arguments and not on any detailed model of the signal or noise.

The *polarity thresholding* (PT) algorithm is based on the principle that at time instants where the flaw signal is present, the corresponding SSP data set will not exhibit any polarity reversal since the flaw signal will dominate the grain noise [25,26]. If the data set contains only grain noise, which possesses a zero mean value, then it is likely that the data will exhibit polarity reversal. By setting the amplitude of the processed signal to zero at time instants, the grain noise can be reduced significantly. The PT output can be expressed as

$$y_{PT} = \begin{cases} r(t_k) & \text{if } r_i(t_k) > 0 \text{ or } r_i(t_k) < 0 \\ & \text{for all } i = 1,2,..., N \\ 0 & \text{otherwise} \end{cases} \quad (26)$$

where t_k are discrete time instants with k=1,2,...,M.

The geometric mean and polarity thresholding algorithms mainly are based on the phase characteristics of noise free filtered signals and not on any noise model. Therefore it is very difficult to predict how the algorithms will perform for a given certain noise distribution. That is a serious limitation of these methods.

A new multi-step technique was proposed which combines the *group delay moving entropy* and the SSP technique for improved detection of complex multiple targets in ultrasonic applications [23, 24]. This method is designed to iteratively detect the most dominant target present in the received signal and subsequently eliminate it using a time domain window centered at the target location. The multiple target problems can be formulated as [23]

$$s_P(t) = \sum_{i=1}^{P} a_i \delta(t - T_i), \quad (27)$$

where P is the total number of targets, a_i and T_i are the amplitude and the location parameters of the ith target. The group delay of the target signal can be calculated from the phase

$$\phi_P(f) = -\left\{ \tan^{-1} \frac{\sum_{i=1}^{P} a_i \sin 2\pi f T_i}{\sum_{i=1}^{P} a_i \cos 2\pi f T_i} \right\} \quad (28)$$

using

$$v_P(f) = -\frac{1}{2\pi} \frac{d\phi_P(f)}{df}. \quad (29)$$

The group delay for multiple targets is not a constant. To identify the optimal frequency region the group delay entropy was proposed [24]:

$$I_k = -\sum_{m=1}^{M} f_k(m) \log_2 f_k(m), \quad \frac{M}{2} \le k \le \frac{(N-M)}{2}, \quad (30)$$

where k is the frequency index, N is the total number of data points in the discrete Fourier transform, M is the width of the moving window as well as the number of quantization levels for the group delay values, f_k is the probability density function of the group delay. The group delay moving entropy method can be used effectively to select the optimal frequency region for split spectrum processing when detecting such targets. This technique has the potential for improving detection of defects in composites, multilayer materials, etc.

The other method of signal processing is called the *optimal detector* (OD) [26]. The optimal detector minimizes the number of decision errors during detection of a known transient in additive Gaussian noise. To obtain the OD the multidimensional hypothesis problem is formulated

$$\begin{aligned} H_1 &: \quad r(n) = s_0 + v(n) \quad \text{transient present} \\ H_0 &: \quad r(n) = v(n) \quad \text{no transient} \end{aligned} \quad (31)$$

where $s_0=s(n_0)$ denotes the prototype vector. To minimize the number of decision errors, one should decide signal when the inequality

$$s_0^T \sum{}^{-1} r - (s_0^T \sum{}^{-1} s_0)/2 > \ln[P(H_0)/P(H_1)] \quad (32)$$

is satisfied and $P(H_k)$ denotes the probability of hypothesis H_k. The left-hand side is referred to as "the test statistic" and the right-hand side as "the optimal threshold". The optimal detector method has been used for echo detection in large-grained materials. The limitation of this method is presumption that a Gaussian stochastic process can approximate the clutter noise.

The split spectrum processing (SSP) method can be combined with *neural networks* (NN) approach [27, 28]. SSP is used to create frequency-diverse signal features, and NN is used to discriminate flaw echoes from the undesired grain echoes. If the elements of the vector

$$x(t) = (x_1(t), x_2(t), ..., x_M(t))^T \quad (33)$$

correspond to samples from a received ultrasonic signal; they can be fed into multilayer perceptron neural network (Fig.2) [27]. The input net_k to the k^{th} neuron is a linear combination of the delayed samples, e.g. $net_k = w_k^T - \theta_k$, where w_k is the so-called weight vector and θ_k the threshold. The input net_k can be interpreted as the output from a linear finite impulse response (FIR) filter where the weights correspond to the tap coefficients. The structure in Fig.2 can be interpreted as a linear filter bank followed by a memoryless nonlinearity.

The neural network can be trained and adapt to a particular application. It was trained to process ultrasonic signals to output zero when there was only noise in the delay line and to one if there was a transient. The goal of the learning process is to define values for the weighting coefficients of all neural connections in the net for a practical problem. This method can be used for ultrasonic flaw detection in a situation where the flaw echo is highly masked by grain scattering echoes.

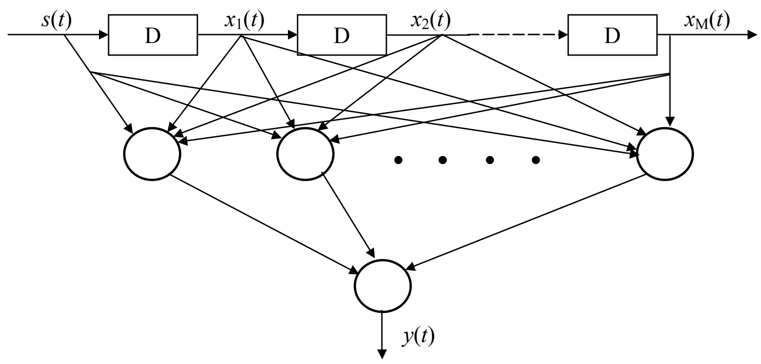

Fig.2. **Signal processing technique using a multilayer perceptron Neural Network (NN).**

Discussions

The described ultrasonic signals processing methods are used in different areas of nondestructive testing of materials. Each method can solve some problems and at the same time possesses various limitations. For NDT of composite materials with a high attenuation, structural noise and scattering of ultrasonic signal novel signal processing methods are necessary. In order to determine most optimal way for development of new processing techniques the known methods should be compared and analyzed.

Transform-domain ultrasonic signal processing techniques were developed to determine the defects in thin composite materials. In all these methods broadband ultrasonic signals are used, which are analyzed in the time or frequency domains. These signals are usually or time-limited or band-limited. The time-domain processing techniques can be confusing when the signals are distorted or the echoes are overlapped. The frequency-domain processing techniques are not suitable when the defects are close to the surfaces or the echoes are overlapped.

The complex cepstrum domain analysis is used to decompose superimposed signals due to multiple echoes or multi-path effects. However, the power cepstrum method was not suitable for signal-to-noise ratios below 18 dB [28].

The Wavelet transform is one of the latest techniques to emerge for processing signals with non-stationary spectral components [14]. The signal analysis using the Wavelet transform is faster than the Fourier transform analysis. Its application seems to be attractive for ultrasonic data processing, especially for detection of defects in grainy materials.

The autoregressive cepstrum model is also often used to detect defects in grainy materials. The mean scatterer spacing can be resolved only when the correlation length of the propagating ultrasonic pulse is shorter than the spacing between individual scatterers. The effective resolution of the received echo imposes a limitation on the smallest resolvable scatterer spacing, while the model order limits the largest detectable scatterer spacing [17].

The split-spectrum processing technique has been established as an effective method of achieving flaw enhancement and grain noise suppression. Several algorithms of the SSP have been proposed. However, these algorithms are not robust since they are sensitive to certain parameter values, e.g., the number of filters in the filter bank and the parameters of the filters. It is not clear how to utilize the information available in an optimal way or even how to define optimality. In addition, wider use of SSP has been limited by the long processing time necessary for the signal decomposition.

The named limitations of different signal processing methods show a need for novel processing algorithms. One possible way is combination of different methods in order to achieve better results in detection of defects [21, 26, and 30].

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R.Kažys, D.Pagodinas

Ultragarsinių signalų apdorojimo metodai kompozitinių medžiagų defektų nustatymui

Reziumė

Vis plačiau naudojant įvairių konstrukcijų gaminius iš polimerinių medžiagų (plastmasių) kyla akivaizdus tokių medžiagų diagnostikos poreikis, pritaikant šiuolaikinius tyrimų metodus, taip pat ir ultragarsinius. Specifinės daugiasluoksnių polimerinių medžiagų mechaninės savybės apsprendžia ultragarsinių tyrimo metodų panaudojimo specifiką bei šių tyrimų skirtumus, lyginant su metalinių konstrukcijų defektoskopija. Daugiasluoksnėse polimerinėse medžiagose pasireiškia didesnis akustinių signalų slopinimas, sąlygojamas šių signalų sugėrimo tiriamoje medžiagoje bei išsklaidymo nuo daugiasluoksnės struktūros nehomogeniškumų. Tuo pačiu sumažėja santykis signalas/triukšmas, išryškėja medžiagos struktūriniai triukšmai. Todėl daugelis šiuo metu metalinių konstrukcijų defektoskopijoje taikomų ultragarsinių signalų apdorojimo metodų netinka polimerinių medžiagų tyrimams.

Šiame straipsnyje apžvelgiami dabartiniu metu defektoskopijoje paplitę akustinių signalų apdorojimo metodai, pateikiami signalų apdorojimo algoritmai, aprašomos šių metodų taikymo sritys ir įvertinamos jų taikymo daugiasluoksnių polimerinių medžiagų defektų nustatymui galimybės. Konstatuota, kad dėl specifinių polimerinių medžiagų savybių tiesiogiai netinka nei vienas išnagrinėtų metodų. Nurodoma, kad gali būti perspektyvu panaudoti kelių metodų kompoziciją, sukuriant naują akustinių signalų apdorojimo metodą.

R.Kažys, D. Pagodinas

Ultrasonic signal processing methods for detection of defects in composite materials

Abstract

Determining the defects in multi-layered plastic pipes with fiber-reinforced layer is a common problem in many fields: fiber-reinforced composites have the high acoustic attenuation and high structure noise resulted from in homogeneity; fiber-reinforced layer characterized by scattering of ultrasonic beam; all layers have different acoustic impedance et al. Named problems show that the composite materials testing require special care in frequency selection and signal interpretation. Enhancement of the received ultrasonic signals can be achieved by applying signal processing techniques.

In this paper application of different signal processing methods for detection of defects in composite materials is analyzed. The aim of this analysis is optimal method to testing of composite materials to searching. The limitations of different signal processing methods condition the new processing algorithms to create. For this purpose can be used composition of different methods to best result of defects detection to achieve. To solve the specific problems can be compare the results of computer simulation of different signal processing methods and chose the best method.

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