ADAPTIVE EXTRACTION OF RESONANCES IN ACOUSTIC BACKSCATTER FROM ELASTIC TARGETS

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ABSTRACT

A new approach for identifying the presence of resonance in the acoustic backscatter from unknown elastic targets by isolating the resonance part from the specular contribution is developed. The method allows for characterization of both the time history and time-scale of the resonant contribution of the target directly from the acoustic backscatter. An adaptive transversal filter structure is used to estimate the specular part of the backscatter and consequently the error signal would provide an estimate of the resonance part. This scheme does not require any underlying model assumption about the elastic return and further can be applied to targets of unknown geometry and thickness. The adaptation rule is based upon fast Recursive Least Squares (RLS) learning. Test results on acoustic data are presented which indicate the effectiveness of the proposed approach.

1. INTRODUCTION

The problem of underwater target detection and classification from acoustic backscatter is the central focus of this paper. It has been shown [1]-[3] that at certain frequencies the acoustic backscatter from elastic targets exhibits certain resonance behavior which closely relates to the physical properties of the target such as dimension, thickness and composition. Several techniques [4]-[7] have been developed to characterize the resonance phenomena in acoustical backscatter from spherical or cylindrical thin shells. A joint time-frequency examination of the impulse response of a thin spherical shell is investigated in [4] using the Wigner-Ville distribution. This time-frequency representation provides localization of the signal energy along both the time and frequency axis. In [5] Wilbur and Kargl applied a wavelet transform to detect the resonance corresponding to the mid-frequency enhancement of a thin spherical shell submerged in water and surrounded by biologics. It is shown, in the simulation results in [5], that the mid-frequency enhancement corresponding to the lowest order symmetric Lamb mode [1] can be identified through the wavelet decomposition in the acoustic return from a thin spherical shell surrounded by biologics.

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The purpose of this paper is to develop a new adaptive approach for isolating the resonant response from the acoustic backscatter of a submerged elastic target of unknown shape. The approach allows for resonance extraction directly from backscattered data. Although resonance extraction has been studied and developed extensively for spherical shells, large aspect ratio cylindrical shells and cylinders with spherical end caps [6],[7], the problem is difficult when applied to an elastic target of arbitrary geometry for which the poles of the resonances are not known *a priori*. This is especially true when the specular and resonant returns overlap in both the time and frequency domains. The method in this paper is general in the sense that it does not require generation of the impulse response or the transfer function and can be applied to a target of unknown geometry and thickness. An adaptive transversal filter structure is used to estimate the specular part of the backscatter and extract the hidden resonance characteristics of the elastic objects. The estimate of the specular part is provided at the output of the system and consequently the error signal extracts the resonant part. The adaptation rule is based upon the RLS learning. The adaptive processor is applied to both the time domain and time-scale representations of the acoustic backscatter from a submerged elastic target whose shape is that of a tapered, notched cylinder with flattened ends and rivets. Adaptive separation on the signal time-history is applied to narrow-beam data while wavelet separartion is applied to broad-beam data. The results are then compared to those collected for a non-target concrete chunk of a size similar to that of the target.

2. ACOUSTIC RESONANCE CHARACTERIZATION

The theory of acoustic resonance scattering from submerged elastic shells has received considerable attention [1]-[3]. The acoustic scattering response from thin shells can be divided into three frequency bands of interest : the low frequency band, which is defined as the region for which the acoustic wavelength, λ , is less than the shell thickness, h; high frequency band which is defined as the region for which λ exceeds the radius,a, of the target; and the mid-frequency band of operation defined as $h<\lambda<a$. The mid-frequency band has been of particular interest in the characterization of small elastic targets [1]-[3]. This band is dominated by the specular reflection and the lowest order

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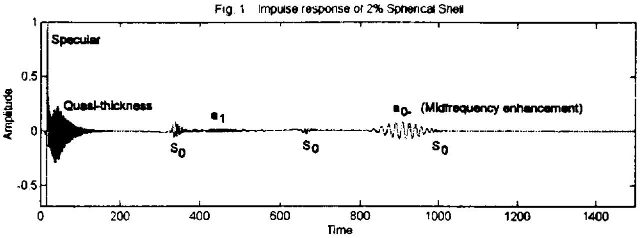
symmetric, s_0, and anti-symmetric,a_0, Lamb modes which propagate on the shell. The resonant backscatter attributed to the s_0 and a_0 Lamb modes have been found to offer viable signature clues for identifying submerged elastic targets [2],[3]. However, identification of the elastic response associated with the mid-frequency region is non-trivial, especially for targets of arbitrary geometry. That is, the resonant return can be difficult to isolate from the specular component and is often buried in the noise. When the target parameters are not known *a priori* a large time-bandwidth product (TB) may be sent to sufficiently excite the resonant modes. However, the specular and resonant responses in the acoustic backscatter may overlap both temporally and spectrally. This, coupled with other factors in a real target detection environment, such as sensitivity of the sensors to the environmental and operating conditions, non-repeatability of the target signatures, competing clutter objects having similar response as the actual targets and lack of *a priori* information about the actual targets, create a complex signal processing problem.

Figure 1 shows the impulse response for a steel spherical shell where the ratio of the shell thickness to outer radius is 2%. This impulse response exhibits several prominent parts which are associated with different scattering phenomena [1]-[3]. The leading spike is associated with the specular reflection (direct geometrically reflected return) on the outer surface of the shell. This is followed by a decaying sequence which is partly attributed to the first order symmetric Lamb wave (s_1) and partly due to the transmitted bulk waves undergoing multiple reflections between shell surfaces. This contribution is in the high frequency region and is sometimes referred to as the "quasi-thickness resonance"[3]. The echoes labelled by s_0 and a_1 are associated with the lowest symmetric Lamb wave and the first order supersonic anti-symmetric Lamb wave, respectively. The mid-frequency enhancement corresponds to those prominent oscillations designated by a_{0-} which are attributed to the subsonic branch of the lowest order anti-symmetric leaky Lamb mode. In the frequency domain for those frequencies where this mode is excited, a resonance phenomenon is caused. These resonances are closely related to the surface waves circumnavigating around the shell [1]. The high-Q resonance is often buried inside a wide-band spectrum associated with the specular part. The center frequency of this Gaussian type spectral envelope is inversely proportional to the shell diameter and thickness.

The time-scale representation for the 2% shell, using five cycle cosine modulated Gaussian wavelets, form a ridge along all dilations associated with the specular reflection [5]. The contribution attributed to the first return from the subsonic branch of the lowest order anti-symmetric Lamb wave occurs in regular time intervals that are localized in scale. This midfrequency enhancement region moves to smaller scales with decreasing shell thickness.

In the next section a new approach for characterizing the presence of resonance in the acoustic backscatter from a target of unknown geometry is introduced. This method uses an adaptive filter structure to isolate the resonance part from the specular contribution in either time domain or time-scale representation.

Fig. 1 Impulse response of 2% Spherical Shell



3. ADAPTIVE SIGNAL SEPARATION

The structure of the adaptive system used for separating the hidden resonance in the acoustic backscatter is shown in Figure 2. The reference input to the adaptive system is the incident waveform while the desired signal is the backscattered. In this way, the adaptive system produces an output which is the estimate of the specular part and the error signal would provide an estimate of the resonance part. There are two principal ideas behind the development of this structure: (1) the specular part of the acoustic backscatter is more correlated with the incident than the resonance (elastic) part, and (2) there is always a time delay between the onset of the specular part and that of the resonance part. Thus, provided that the learning is fast enough, during this period of time the adaptive system produces an output which is an accurate estimate of the specular part. Since the system has infinite memory and further the specular part is more correlated with the input (incident) the system continues to provide a good estimate of the specular part even after the resonance has appeared. As a result, the error signal provides an estimate of the resonance part of the backscattered. Note that the delay Δ is provided to account for the actual delay between the incident and the backscattered.

If the adaptive system is of moving average (MA) type with tap weights denoted by $w_i(n)$'s for $\forall\ i \in [0,N-1]$, and $n \in [0,P-1]$ where N and P respectively represent the filter order and the number of points in the signal, then the output of the filter at time n is the weighted sum of the N present and past input samples $x(k)$'s, $k \in [n,n-N+1]$, weighted by the associated tap weight, $w_k(n-1)$. In vector form the expression for the output y(n) is given by

$$y(n)=\mathbf{W}^t(n-1)\,\mathbf{X}(n) \tag{1}$$

where $\mathbf{X}(n)$ and $\mathbf{W}(n-1)$ represent the input and weight vectors, respectively i.e.

$$\mathbf{W}(n-1) = [w_0(n-1)\ w_1(n-1) \ldots\ w_{N-1}(n-1)]^t \tag{2a}$$

and

$$\mathbf{X}(n) = [x(n)\ x(n-1) \ldots\ x(n-N+1)]^t \tag{2b}$$

As can be observed from (1), the output at time n i.e. y(n) is estimated using the weights at time (n-1). Now, using the current sample of the desired signal, d(n), the weights can be updated using a weight adaptation rule for transversal filter

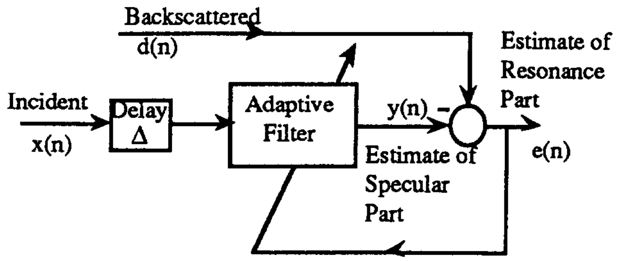


Figure 2. Adaptive Structure for Estimation of Resonance Part.

structures [8]. The weight updating equations using the RLS scheme are given in order as [8]:

$$\mathbf{K}(n) = \frac{\mathbf{P}(n\text{-}1)\mathbf{X}(n)}{\mu + \mathbf{X}^t(n)\ \mathbf{P}(n\text{-}1)\ \mathbf{X}(n)} \tag{3a}$$

$$e(n) = d(n) - y(n) = d(n) - \hat{\mathbf{W}}^t(n\text{-}1)\ \mathbf{X}(n) \tag{3b}$$

$$\hat{\mathbf{W}}(n) = \hat{\mathbf{W}}(n\text{-}1) + \mathbf{K}(n)\ e(n) \tag{3c}$$

$$\mathbf{P}(n) = \mu^{-1}\left[\ \mathbf{I} - \mathbf{K}(n)\ \mathbf{X}^t(n)\ \right]\mathbf{P}(n\text{-}1) \tag{3d}$$

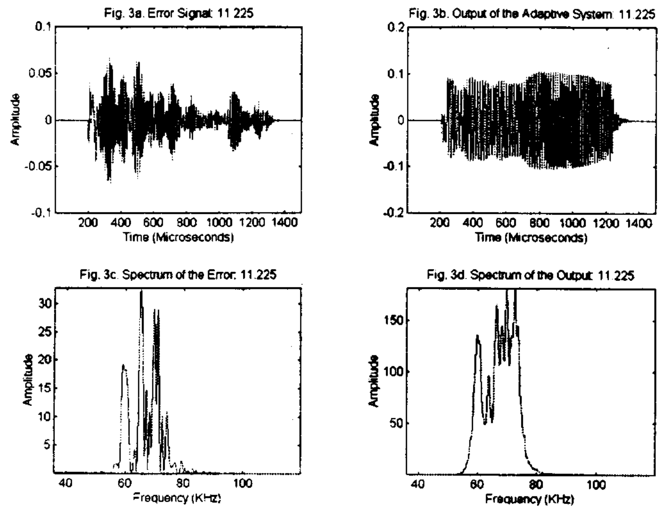
where $\hat{\mathbf{W}}$ is the estimate of the weight vector $\mathbf{W}$; e(n) is the estimation error (resonant part); $\mathbf{K}(n)$ is the gain vector; $\mathbf{P}(n)$ is the inverse of the input data covariance matrix and μ is the "forgetting factor" which determines the memory ($M = 1/(1-\mu)$) of the adaptation process and $0<\mu\leq 1$. Generally, for stationary processes μ is chosen to be unity (i.e.infinite memory) which corresponds to standard LS solution. Note that in our application we require infinite memory in order to provide a consistent estimate of the specular component even though the acoustic backscatter is a non-stationary process. The process starts with a set of initial values namely $\mathbf{P}(0)=\delta^{-1}\ \mathbf{I}$ and $\hat{\mathbf{W}}(0)=\mathbf{0}$ where δ is a small quantity [8]. For large sequences the choices of the initial conditions do not impact the performance of the RLS scheme.

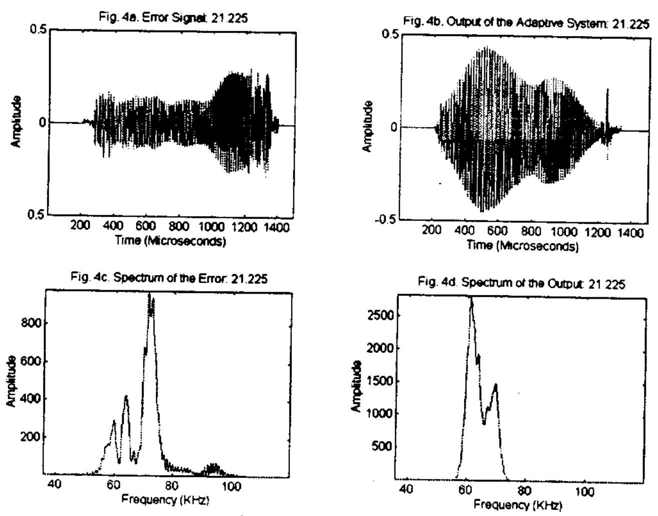
For wavelet separation, time-scale representations for the transmitted pulse and the acoustic backscatter are generated by convolving these signals with scaled five cycle cosine modulated Gaussian; the collection of which act as a bank of filters which span the frequency range under investigation. Resonance characterization at each scale is then performed using an adaptive system with a structure similar to that in Figure 2. In this case, the reference and the desired inputs to this filter are the results of the respective convolutions. The wavelet estimator maintains the same two principle assumptions as before. Given these criteria, the adaptive system output produces the specular part of the signal wavelet transform and the residual yields an estimate of the resonant part of the wavelet transform.

4. TEST RESULTS

The adaptive estimation method was applied to the data obtained from a submerged elastic target and an irregularly shaped concrete chunk of similar size. The elastic target had the form of a tapered, notched cylinder with flattened ends and rivets and an aspect ratio of 4 to 1. The incident signal was a wide-band linear FM with a time-bandwidth product of TB=20. The signal was set to sweep over the mid-frequency band. The target was insonified by a narrow-beam on the order of the cylinder radius. The returns from each object were collected over 360^o in 5^o increments to produce 72 data records of differing aspect angle per object. Note that 0^o corresponds to broad-side incidence. The measurements were performed under controlled operating and environmental conditions. The adaptive system had 32 tap weights and the initial conditions were $\mathbf{P}(0)=5000\ \mathbf{I}$ and $\mathbf{W}(0)=\mathbf{0}$. The signal estimation was completed only after one pass over all the samples of the backscattered signal. Figures 3a-d and 4a-d give the respective outputs of the adaptive system and the error signals together with their spectra for 225^o aspect angle, for the target and non-target. As can be seen in these results, for the elastic target the output of the adaptive system, which provides the estimate of the specular part, has a broad-band spectrum while the error signal which provides an estimate of the resonant part generally contains one or more narrow-band components. For the non-target anomaly, however, both the error and output signals were relatively wide-band. Based upon this criterion, over 89% of the cases were correctly identified. The remaining cases were not clearly distinguishable owing to the sensitivity of the adaptive system to strong subsequent specular returns whose onsets arise too quickly for the weights to converge.

In the second set of experiments the entire object was insonified for both the target and cement chunk. Broad-beam insonification increased the number of subsequent specular returns. Time-scale representations of the transmitted and backscattered responses were computed. Specular and resonant separation at each scale was performed using the adaptive estimator. Figure 5 gives the estimate of the resonant part for the respective returns from the elastic target and the cement chunk where the time origin for each scale is set to follow the slope of the linear FM transmit signal in the time-scale plane. The processed target data yielded a more localized concentration than did the processed returns from the cement chunk. The outputs for two data runs comprising different data sets was applied to an automated testing algorithm. Decision criteria for automated classification was based on one look and one feature. The wavelet components were integrated over scale along the linear FM slope and normalized and the ratio between resonant and specular parts was computed. Both runs comprised broadbeam data from 0° to 360° in 10° increments and the cement chunk at arbitrary angles. Using a single feature of the peak-to-width ratio for the processed curves, 84% correct classification was obtained from a simple threshold detector. The results verify the important conclusion that the adaptive estimation scheme is capable of identifying narrow-band phenomena present in the returns collected from targets and non-targets without requiring an underlying model for the returns.





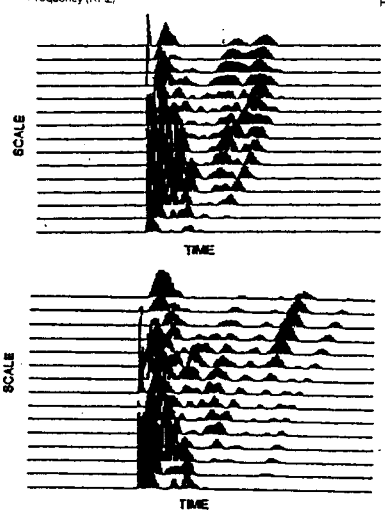


Figure 5. Resonant part of the CWT for the acoustic return: a) Elastic target b) Cement Chunk.

5. CONCLUSIONS

The development of an adaptive system for detection of underwater targets from acoustic backscatter was presented in this paper. The adaptive processing was shown to be an effective method for detecting the presence of submerged elastic targets both in time domain as well as time-scale representation. A unique aspect of this method is that no underlying model assumption is made about the elastic return. The adaptive system is trained to provide an estimate of the specular part which is highly correlated with the incident input. This enables the extraction of the resonant component at the error signal. The test results for an elastic target and a non-target (concrete chunk) were obtained which showed the success of this scheme in isolating narrow-band phenomenon which discriminates the targets from non-targets.

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