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Adaptive filtering and Fractional Fourier transform for ultrasonic signal processsing and flaw detection

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Abstract— **In this investigation, an adaptive filter algorithm using Fractional Fourier transform (FrFT) has been developed for enhancement of targets in microstructure noise. In particular, the FrFT is introduced as a transformation tool to prepare ultrasonic signals for a more compact support. It also reduces the non-stationarity of signals. Furthermore, a normalized least mean square (NLMS) filter is applied on the transformed signal to suppress the grain noise. In order to evaluate the performance of the algorithm, various experimental ultrasonic data sets are acquired from a large grained specimen with embedded defects. A 5-MHz broadband transducer is utilized for data acquisition. The proposed algorithm is applied to discriminate defects in presence of high grain scattering noise. The experimental study shows that the algorithm greatly reduces grain noise and improves the signal-to-grain-noise ratio by about 12 dB. With the help of FrFT and the NLMS filter, the algorithm successfully identifies defects embedded in grain noise. This type of study can broaden the scope of applying adaptive filter in material evaluation and target detection.**

Keywords– Ultrasonic nondestructive evaluation, Fractional Fourier Transform, adaptive filter

I. INTRODUCTION

In ultrasonic nondestructive evaluation applications, the received ultrasonic signal consists of backscattered echoes from microstructures (i.e., grains) and discontinuities (i.e., flaws) inside the material. To detect flaws, evaluate material or recognize patterns, researchers have put great effort into developing signal processing algorithms to analyze ultrasound echoes. These algorithms include split spectrum processing, discrete cosine transform, chirplet signal decomposition, neural network, discrete wavelet transform, and Hilbert transform to name a few [1-5]. Nevertheless it is still challenging to perform robust flaw discrimination on ultrasonic signals, especially those with echoes from high-density grains.

Adaptive filtering is a classic signal processing approach widely used in system identification, noise cancellation and adaptive prediction [6]. In general, there are two signals utilized in the adaptive system: one is reference signal; another is primary noise. The filter is adaptively updated to exploit the correlation between the primary noise and the noise in the reference signal. Therefore, the noise can be greatly reduced in the reference signal.

It is of great interest to use adaptive filtering system for ultrasonic NDE applications. There have been some efforts in applying adaptive filter on ultrasound signals for material evaluation, target detection and pattern recognition. For example, Y. Zhu et al. discussed the combination of normalized least mean square adaptive filter and constant-false alarm rate (CFAR) in material evaluation [7]. S. Bae et al designed an adaptive IIR filter for noise cancellation in ultrasound NDE signals [8]. Chirplet echo model, a commonly used model in ultrasound applications, has been used in a simulation study of adaptive filtering [9-10]. These studies exhibited the feasibility of applying adaptive filter on ultrasound signals. Ultrasonic NDE application shows its own challenges of how to utilize adaptive filter. To obtain the reference input signal and the primary noise input signal for adaptive filtering, ultrasound signals are carefully acquired to make sure that grain echoes in both ultrasound signals are correlated. In the meantime, grain echoes and flaw echoes are uncorrelated.

Due to the randomness and high density of grains in material, it is important to acquire two ultrasound signals without moving the transducer much so that the correlation of grain echoes can be assured. Meanwhile, since the distance of transducer positions for data acquisitions is very small, the flaw echo will be a part of both signals, which makes adaptive filtering less efficient.

It becomes a significant problem when ultrasound echoes are prolonged in the presence of dispersive wave propagation. It is desirable to compress ultrasound echoes through transformation. Fractional Fourier transform (FrFT), a generalized Fourier transform, could be a good candidate of the transform.

As a generalized Fourier transform, the FrFT has been utilized to analyze non-stationary ultrasonic signals for echo decomposition and parameter estimation [11-16]. FrFT rotates the spectrum of ultrasonic signals in the time-frequency domain. In this investigation, an adaptive filtering algorithm based on Fractional Fourier transform (FrFT) has been developed for enhancing target echoes in ultrasonic NDE. Especially, the FrFT is introduced as a transformation tool to condition ultrasonic signals for a more compact support in adaptive processing. It also reduces the non-stationarity of signals. Furthermore, a normalized least mean square (NLMS) algorithm is used for adaptive filtering on the transformed signals.

The paper is organized as follows: Section II briefly reviews adaptive filter. Section III reviews FrFT and describes the proposed algorithm using the combination of FrFT and adaptive filter. Section IV shows signal processing results using experimental ultrasound data. Section V concludes the discussion.

II. Review of Adaptive Filter

In an adaptive filtering system, the filter output, $y(n)$, can be written as

$$y(n) = W^T(n)X(n) = \sum_{i=0}^{L-1} w_i(n)\; x(n-i) \tag{1}$$

where L is the length of filter

$W(n) = [w_0(n) \;\; w_1(n) \;\; \ldots \;\; w_{L-1}(n)]^T$ is the filter coefficients.

and $X(n) = [x(n) \;\; x(n-1) \;\; \ldots \;\; x(n-L+1)]^T$ is the filter input.

Figure 1 shows the general block diagram of an adaptive filtering system.

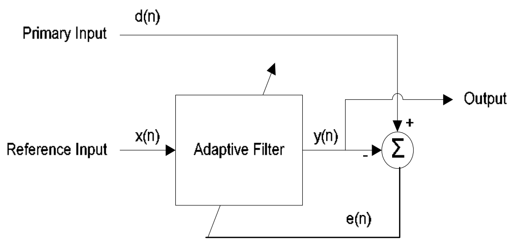

Figure 1. General block diagram of adaptive filter

The cost function, $J(n)$, (i.e., the mean square error function) can be written as

$$\begin{aligned} J(n) &= E\left[e^2(n)\right] \\ &= E\left[d^2(n)\right] - 2W^T(n)E\left[X(n)\,d(n)\right] \\ &\quad + W^T(n)E\left[X(n)\,X^T(n)\right]W(n) \end{aligned} \tag{2}$$

where $d(n)$ is the primary input; $x(n)$ is the filter input

$y(n)$ is the filter output; $e(n)$ is the error signal.

There are different approaches to update the filter coefficients, $W(n)$, such that the cost function $J(n)$ can be minimized[6].

$$\frac{\partial J(n)}{\partial W^T(n)} = 0 \tag{3}$$

A normalized least mean square (NLMS) filter, a commonly used adaptive filter, is chosen in this study. The filter coefficients $W(n)$ are updated following the equations below [9-10].

$$W(n+1) = W(n) + \frac{\delta}{p(n)}\, e(n)X(n) \tag{4}$$

where δ denotes a value to adjust the learning rate

$p(n)$ denotes the estimated signal power;

$$p(n) = \zeta\, p(n-1) + (1-\zeta)x^2(n) \tag{5}$$

where ζ is the forgetting factor of $p(n)$.

III. Reveiew of FrFT

For a given signal, $f(t)$, its FrFt is given by

$$F^{\alpha}(k) = \frac{e^{-i\left(\frac{\pi}{4}-\frac{\pi\alpha}{4}\right)}}{\left(2\pi\left|\sin\frac{\pi\alpha}{2}\right|\right)^{\frac{1}{2}}} e^{\frac{1}{2}ik^2\cot\frac{\pi\alpha}{2}} \int_{-\infty}^{\infty} e^{\left(-i\frac{kt}{\sin\frac{\pi\alpha}{2}} + \frac{1}{2}it^2\cot\frac{\pi\alpha}{2}\right)} f(t)\,dt \tag{6}$$

where α is the transform order of FrFT

k is the variable in transform domain.

It can be proved that the transform order, α, changing from 0 to 4, is equivalent to the change of spectrum rotation angle from 0 to 2π.

The Kurtosis value in Fractional transform domain [3] can be used as the metric of searching an optimal transform order for an ultrasonic signal.

Let's consider an ultrasonic chirp echo, which can represent a broad range of ultrasonic NDE signals.

$$\begin{aligned} f_{\Theta}(t) = \beta \exp\; (&-\alpha_1(t-\tau)^2 \\ &+ i\,2\pi f_c(t-\tau) + i\theta + i\;\alpha_2\,(t-\tau)^2\,) \end{aligned} \tag{7}$$

where τ is the time-of-arrival, f_c is the center frequency, β is the amplitude, α_1 is the bandwidth factor, α_2 is the chirp-rate, and θ is the phase.

It has been shown that FrFT can compress chirp echoes. Under certain conditions, the FrFT of signal could be transformed to a delta function [3]. It is a desirable property of introducing FrFT for the preprocessing of ultrasonic echoes.

IV. Experimental Study and Results

In order to evaluate the performance of the algorithm, various experimental ultrasonic data sets are acquired from a large grained specimen with embedded defects (i.e., flat-bottom holes). A 5 MHz broadband transducer is utilized for data acquisition and the sampling at the rate of 100 MHz. The proposed algorithm is applied to discriminate defects in presence of high grain scattering noise.

Two ultrasonic data sets are used in the NLMS filter, one for the reference input, another is for primary input. FrFT is used to preprocess both data sets with the optimal transform order of the reference input. Figure 2 shows the original ultrasonic experimental data and its FrFT with the transform order, α=0.04, corresponds to the highest Kurtosis value in the transform domain. From Figure 2, the FrFT signal shows compact support with less dispersion. The FrFT signal is used as a reference input signal in the NLMS adaptive filtering system.

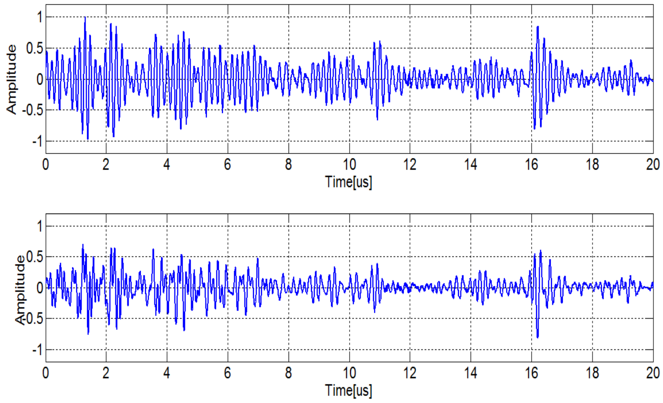

Figure 2. a) Ultrasonic experimental signal
b) FrFT of the signal in (a) with the transform order 0.04, which corresponds to the highest Kurtosis value in the transform domain.

In the follow-up NLMS filter, the parameters of filter are listed below: $\delta = 0.013$, $\zeta = 0.99$ and $L = 5$.

To clearly show the improvement in the signal-to-grain-noise ratio (SQNR), the magnitudes of reference input, primary input and the filter output are used in Figure 3. It shows that there is about 12 dB improvement in the SQNR. In addition, the time-frequency representations of the input and output signals for NLMS filter are shown in Figure 4. The time-frequency (TF) representation of the reference input signal shows that the target echo (around 16 us) is embedded and difficult to detect. After the combinational process of FrFT and adaptive filtering, the TF representation of the filter output signal clearly shows the detected flaw.

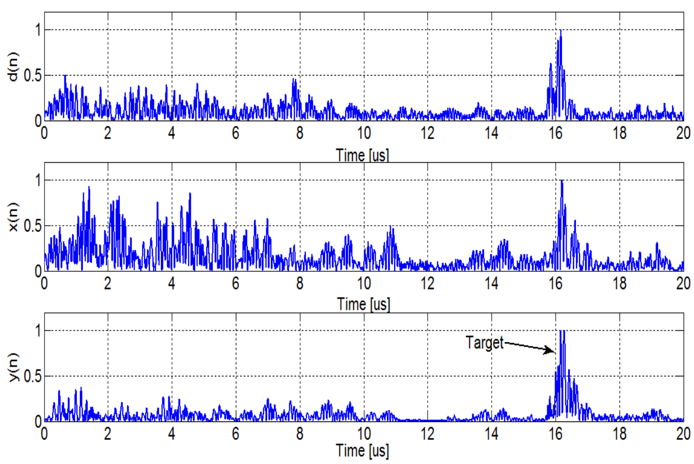

Figure 3. From top to down:
a) The primary signal of NLMS filter
b) The reference input signal of NLMS filter
c) The output signal of NLMS filter

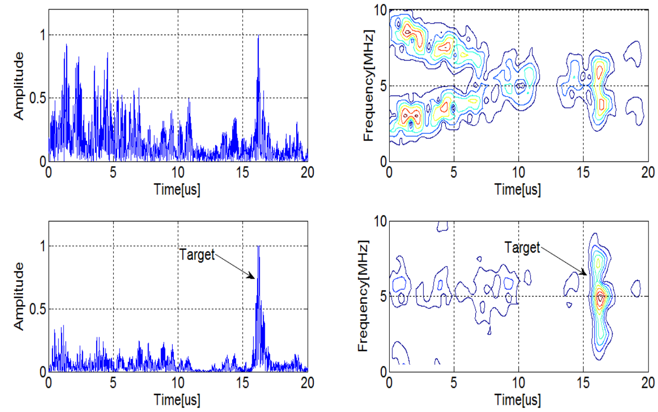

Figure 4. From top to down:
a) The reference input signal of NLMS filter (left) and its chirplet time-frequency representation(right)
b) The output signal of NLMS filter(left) and its chirplet time-frequency representation(right)

V. Conclusion

In this study, an adaptive filtering algorithm using Fractional Fourier transform (FrFT) is developed for ultrasonic signal processing. The experimental study shows that the proposed algorithm greatly reduces grain noise and identifies defects in complex materials successfully. This type of study can have a broad range of applications in interference cancellation, signal classification and flaw detection.

References

[1] E. Oruklu and J. Saniie, "Ultrasonic flaw detection using discrete wavelet transform for NDE applications," *Ultrasonics Symposium, 2004 IEEE* , vol.2, no., pp.1054,1057 Vol.2, 23-27 Aug. 2004 doi: 10.1109/ULTSYM.2004.1417956

[2] Y. Lu, E. Oruklu and J. Saniie, "Chirplet signal and Empirical Mode Decompositions of ultrasonic signals for echo detection and estimation," *Journal of Signal and Information Processing*, Vol. 4 No. 2, 2013, pp. 149-157. doi: 10.4236/jsip.2013.42022.

[3] Y. Lu, A. Kasaeifard, E. Oruklu, and J. Saniie, "Fractional Fourier Transform for ultrasonic Chirplet signal decomposition," *Advances in Acoustics and Vibration*, vol. 2012, Article ID 480473, 13 pages, 2012. doi:10.1155/2012/480473

[4] Y. Lu, R. Demirli, G.Cardoso, and J. Saniie, "A successive parameter estimation algorithm for chirplet signal decomposition," *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, vol. 53, pp. 2121–2131, November 2006.

[5] G. Cardoso, and J. Saniie, " Ultrasonic data compression via parameter estimation," *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, vol. 52, pp. 313- 325, November 2005.

[6] D. G. Manolakis, V. K. Ingle, and S. M. Kogon, "Statistical and adaptive signal processing: spectral estimation, signal modeling, adaptive filtering, and array processing", ISBN:1580536107, Artech House, 2005.

[7] Y. Zhu, and J. Weight "Ultrasonic nondestructive evaluation of highly scattering materials using adaptive filtering and detection," *IEEE Transaction on Ultrasonics, Ferroelectrics, and Frequency Control*, vol. 41, pp. 26–33, January 1994.

[8] S. Bae, J. Kim, I. Udpa and S. S. Udpa, “A new adaptive grain noise cancellation filtering technique,” *Review of Progress in Quantitative Nondestructive Evaluation*, vol. 17, pp. 759-765, 1998.

[9] D. Monroe, I. S. Ahn, and Y. Lu, "Adaptive filtering and target detection for ultrasonic backscattered signal," *The Proceedings of IEEE Electro/Information Technology Conference 2010* pp. 20-22 May 2010.

[10] C. Brady, J. Arbona, I. S. Ahn and Y. Lu, "FPGA-based adaptive noise cancellation for ultrasonic NDE application," *The Proceedings of IEEE Electro/Information Technology Conference 2012* pp. 6-8 May 2012.

[11] A. S. Amein, and J. J. Soraghan, “The fractional Fourier transform and its application to high resolution SAR imaging,” *IEEE Proceedings of Geoscience and Remote Sensing* pp. 5174-5177, 2007.

[12] M. Barbu, E. J. Kaminsky, and R. E. Trahan, “Fractional Fourier transform for sonar signal processing,” *IEEE Proceedings of OCEANS,* pp. 1630-1635, 2005.

[13] I. S. Yetik, and A. Nehorai, “Beamforming using the fractional Fourier transform,” *IEEE Transaction on Signal Processing*, vol. 51, pp. 1663-1668, June 2003.

[14] S. Karako-Eilon, A. Yeredor, and D. Mendlovic, “Blind source separation based on the fractional Fourier transform,” *Proceedings of 4th In ternational Sy mposium on Independent Component Analysis and Blind Signal Separation,* pp. 615-620, 2003.

[15] A. T. Catherall, and D. P. Williams, “High resolution spectrograms using a component optimized short-term fractional Fourier transform,” *Signal Processing*, ISSN: 0165-1684, vol. 53, pp. 1591-1596, 2010.

[16] M. Bennett, S. McLaughlin, T. Anderson, and N. McDicken, “Filtering of chirped ultrasound echo signals with the fractional Fourier transform,” *IEEE Proceedings of Ultrasonic Symposium*, vol. 1, pp. 2036- 2040, September 2004.

[17] L. Stankovic, T. Alieva, and M. J. Bastiaans, “Time-frequency signal analysis based on the windowed fractional Fourier transform,” *Signal Processing*, ISSN: 0165-1684, vol. 83, pp. 2459-2468, 2003

[18] Y. Lu, A. Kasaeifrad, E. Oruklu, and J. Saniie, “Performance evaluation of fractional Fourier transform(FrFT) for time-frequency analysis of ultrasonic signals in NDE applications,” *IEEE Proceedings of Ultrasonic Symposium*, October 2010.