A TRUE WIENER FILTER IMPLEMENTATION FOR IMPROVING SIGNAL TO NOISE AND RESOLUTION IN ACOUSTIC IMAGES

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INTRODUCTION

The use of ultrasonic imaging for the detection of flaws is a common non-destructive evaluation (NDE) technique. However, like most imaging techniques, ultrasonic images are degraded by blurring due to practical limitations of the ultrasound system. Consequently, while detection of a flaw may be simple, the characterization of the flaw may be quite difficult. In addition, even the detection of flaws may be challenging because of the presence of correlated noise. Correlated spatial noise is generally the result of inherent structure present in the material and could be more appropriately referred to as 'unwanted signal'. However, since this is the most dominant image feature which restricts the ability to detect low reflectivity flaws, this unwanted signal will be referred to as 'noise'.

Signal processing techniques can be used to reduce the blurring effects of the system and to enhance the flaw signal in the presence of the noise. Based on the data acquisition method, there are several different forms of the ultrasound data which can be processed. For example, a full 3-D set of waveform data can be processed both temporally and spatially. In addition, C-scan images created from the waveform data can be processed using image processing techniques. Although full 3-D waveform processing offers the most potential for improving flaw characterization and detectability, it was decided that this work focus on C-scan image processing. The motivation for pursuing this path is based on the growing popularity of C-scan ultrasonic imaging as a practical inspection technique among many members of the NDE community. In particular, this work has focused on the development of a true Wiener filter for processing C-scan images.

THE WIENER FILTER

The 2D Wiener filter is a well known image processing technique which can be used to improve both the resolution and the signal-to-noise (SNR) ratio of a particular object in an image. A brief overview of the 2D Wiener filter is presented below. For a more detailed description the reader can refer to any of the many image processing books (See for example Chapter 8 of Jain [1]). In the formulation of the Wiener filter it is assumed that the observed (or degraded) image \( g(x,y) \), can be described by the equation given below:

\[
g(x,y) = f(x,y) \ast h(x,y) + n(x,y)
\]

(1)
where $f(x,y)$ represents the ideal (or original) image, $h(x,y)$ is the point spread function (the inherent blurring of the ultrasound imaging system in our case) and $n(x,y)$ is additive noise. The symbol "*" is used here to denote linear convolution. In the development of the Wiener filter it is assumed that the noise is uncorrelated with the signal. Given this model, the Wiener filter is the optimal linear processing technique for minimizing, in the statistical sense, the mean square error between the restored image and the ideal image [1]. The frequency response of the Wiener filter can be expressed as:

$$R(u,v) = \left[ \frac{H(u,v)^*}{|H(u,v)|^2 + S_n(u,v)/S_f(u,v)} \right] G(u,v)$$  \hspace{1cm} (2)

where:

- $R(u,v) = $ Fourier Transform of the Restored Image.
- $H(u,v) = $ Fourier Transform of the Point Spread Function.
- $S_n(u,v) = $ Power Spectral Density of the Noise.
- $G(u,v) = $ Fourier Transform of the Observed Image.

In most practical implementations of the Wiener filter, the ratio $S_n(u,v)/S_f(u,v)$ is replaced by a frequency independent constant (referred to as $K$). When the filter is implemented with this constant, the reconstructed image is suboptimal in the mean square sense discussed earlier. There are several problems associated with the suboptimal Wiener filter. First, a standard method for determining the constant $K$ does not exist. In most cases, the constant is determined experimentally. Usually the constant is varied until an acceptable restoration is obtained. Occasionally, an acceptable restoration is determined from qualitative methods such as visual appearance of the restored image.

In addition to the problem of determining the value of the constant, there are problems associated with the performance of the filter. Depending on the value of the constant the filter can actually amplify frequency components associated with the noise. Figure 1 graphically shows this problem for the simple 1D case. Figure 1a shows the spectrum of an ideal flaw signal. Figures 1b and 1c shows the spectrum of the noise and the resulting spectrum of the degraded image, respectively. Figure 2 shows the spectra of several different restorations using different values of the constant. It is clear that the amount of noise present in the spectrum of the reconstructed image is strongly related to the value of the constant used in the restoration. Clearly the restored spectrum can differ significantly from the ideal spectrum depending on the value of the constant.

![Fig. 1. Simple spectra for 1D pseudo-Wiener filtering example. (a) Spectrum of Ideal Flaw. (b) Spectrum of Noise. (c) Spectrum of Degraded signal.](image-url)
TRUE WIENER FILTERING: SIMULATIONS

In spite of all of the problems associated with pseudo-Wiener filtering, it is commonly used in practice because most users of the filter believe that it is too difficult to estimate the spectra of the signal and the noise. Although obtaining good estimates of the signal is a non-trivial problem, we have determined that good estimates of the power spectrum of the noise can be obtained using autoregressive estimates instead of the more commonly used periodogram estimates. In order to understand the effect that the noise estimate has on the quality of the restored image, an implementation of the true Wiener filter was examined using periodogram estimates of the noise. A 2-D periodogram spectral estimate is obtained by taking the squared magnitude of the Fourier transform of the spatial signal. For a Gaussian random process a spectral estimate determined in this manner has a variance at each sample frequency directly proportional to the squared amplitude of the true spectrum at that frequency [2].

In order to evaluate the effects of the noise estimate on the filter's performance a simulated image was generated. Use of a simulated image eliminated all of the other variables which affect the performance of the filter in practical applications (i.e., point spread function estimate, estimate of the signal spectrum and the linearity assumption). A simulated image was created containing a simple 5 x 5 pixel flaw buried in additive colored noise. The colored noise was created by passing white noise through an 11th order autoregressive process. Two different colored noise buffers were created in this manner. One was used with the simulated flaw and the other was used to generate the periodogram estimate of the noise. The simulated image containing the flaw will be referred to as image A and the one containing only noise will be called image B. The quality of the reconstructed images was determined by calculating a signal-to-noise ratio given by,

\[
\text{SNR} = 20\log_{10} \frac{u_s}{\sigma_n} 
\]

where \(u_s\) is the mean pixel value over the signal region and \(\sigma_n\) is the standard deviation of the noise.

The original simulated image has a SNR of 8.5 dB and is shown in Fig. 3. The results of processing the data using a single periodogram estimate is shown in Fig. 4. The white box in the image indicates the true position of the flaw. The SNR of the processed image is 10.4 dB. Although the SNR has increased by almost 2 dB, it is clear that there are several high amplitude artifacts in the image. In fact,
several of these artifacts could be erroneously interpreted as flaws. Since all of the variables in the Wiener filter are known except the noise, it is clear that the large number of false positive flaws must be a result of the poor estimate of the noise power spectrum. Consequently, one would assume that a more accurate estimate could be obtained using an average of several periodograms. Figure 5 shows the result of Wiener filtering using a spectral estimate obtained by averaging over five periodograms. Notice that the absolute number of false positives have decreased although several of them still remain. Furthermore, the SNR has increased from 10.42 dB to 13.49 dB in going from the single periodogram estimate to the multi-periodogram averaged estimate. It is apparent that the SNR of the restored image will improve if we average over a larger number of periodogram estimates. However, this is not practical because in real applications the number of known flawless regions available to obtain the periodogram estimates of the noise will be limited.

A spectral estimation technique based on autoregressive modelling has been shown to produce better estimates than simple periodograms in certain applications [3,4]. For this method an ultrasound image of the grain noise is modelled by an autoregressive process as given by the expression below.

\[ n(m,n) = - \sum_{k=0}^{M} \sum_{l=0}^{N} a(k,l)n(m-k,n-l) + \eta(m,n) \text{ for } (k,l) \neq (0,0) \] (4)

The expression above defines a MxN order strictly causal autoregressive progress. Basically it is assumed that the pixel at position \((m,n)\) is a linear combination of the 'past' pixels plus a random component \(\eta(m,n)\). If we assume that the \((0,0)\) position of the image is located in the upper left corner, then the term 'past' refers to those pixels in the northwest quadrant of the image with respect to \((m,n)\). Given this model an estimate of the power spectrum can be obtained [4],

\[ P(u,v) = \frac{\beta^2}{1 + \sum_{k=0}^{M} \sum_{l=0}^{N} a(k,l)e^{-j(2\pi uk + 2\pi vl)}}^2 \] (5)
where $\beta^2$ is the variance of the random process $\eta(m,n)$.

An autoregressive spectral estimate of the noise was obtained using image B. Then image A was Wiener filtered using this estimate. The result is shown in figure 6. The SNR of the restored image is 14.8 dB and there are only a few potentially false flaws in the image.

TRUE WIENER FILTERING: REAL DATA

The results of true Wiener filtering of the simulated data were encouraging and provided a great deal of insight into the effects of the estimate of the noise on restoration quality. Consequently, it was decided to try this approach on a real ultrasound image. Applying the filter to real data required an estimate of the point spread function (PSF) of the system. In some practical applications images of small signals have been used as estimates of the PSF. In order to determine whether this approach was practical for ultrasound images, we acquired a 50 Mhz f/3 C-scan image of a 1951 USAF line-pair resolution target sandwiched between two pieces of sapphire [5]. Sapphire was used because it is essentially an acoustically noiseless medium. An image of a small delamination was chosen as the PSF estimate. The ultrasonic image of a section of the target is shown in figure 7a. The image after the application of a pseudo-Wiener filter is shown in figure 7b. It is clear that the resolution has improved significantly. In particular notice the improvement in the 79 $\mu$m wide lines (outlined by the white box in figure 7a). In the original image the horizontal and vertical lines are indistinguishable. But after filtering, the three lines are readily apparent in the restored image. The very low acoustic noise produced by the single crystal sapphire target material permitted the pseudo filter to closely resemble a real Wiener filter.

The experiments with the sapphire target convinced us that a small flaw in a C-scan image could be used effectively as a PSF estimate. However, most materials of interest have significantly more acoustic noise than sapphire. Consequently, the next step was to evaluate the filter on a real image containing material noise. A titanium block was fabricated containing 4 sets of flat bottom holes (FBH). The sizes ranged from #1 FBH (.0015") to # 4 FBH (.060"). The center of the block contained a single #1 FBH hole. The image of this hole served as an estimate of the spatial point spread function. A gated peak detector C-scan image was acquired by scanning the block with a 20 Mhz f/7
transducer. The section of the image containing the #1 holes is shown in figure 8. The section shown is 256 x 256 pixels with a resolution of .0015". It is clear that all nine of the #1 holes are not resolved. An estimate of the spectrum of the noise was determined using a 256 x 256 region of the image located between the #3 holes and the #2 holes. The region of image used to estimate the noise is shown in figure 9. Although the amplitude of the noise is small, there is a significant amount present. Therefore, this image gives us a good environment in which to test the resolving capabilities of the true Wiener filter.
The results of using the Wiener filter with a periodogram estimate of the noise spectrum is shown in figure 10. The result using a first order autoregressive estimate is shown figure 11. The difference in resolution and signal to noise between the two restorations is clearly apparent. In the restoration using the autoregressive estimate we can clearly see the presence of the nine holes. By increasing the order of the autoregressive model we can improve the resolution further. In each case the estimate of the spectrum of the signal was determined from a small circle with an 11 pixel diameter. This corresponded to the approximate size of a #1 hole (.00156" or 10.4 pixels). However, improvements in resolutions were also obtained when the signal spectrum was estimated from 7,9,13, and 15 pixel diameter holes.

![Fig. 8. F7 20MHz image of #1 holes in Titanium.](image)

![Fig. 9. F7 20 MHz image of flawless region of Titanium block](image)
CONCLUSIONS

It has been demonstrated that good estimates of the noise spectrum can be obtained using autoregressive modelling. The estimates perform significantly better than traditional periodogram estimates. In addition, using simulated data, we demonstrated the effects of the accuracy of the noise spectral estimate on the restoration quality. Finally, we showed in both the sapphire target and the titanium test piece that images of small flaws can be used as good estimates of the point spread function.

Estimation of the noise spectrum is only half of the problem. True Wiener filtering also requires an estimate of the signal spectrum. Of course this problem is slightly more difficult than the noise estimation problem because the signal can be of any size and shape. However, in most cases constraints can be applied to the size and shape of the signal. Under such constraints it may be possible to develop good estimates of a spectrum which would be representative of the set of signals which meet these constraints. Preliminary studies have shown that improvements in resolution and further increases in signal-to-noise can be obtained using such estimates. This work will be presented at a later time.

REFERENCES

4. J.S. Lim, Two Dimensional Signal and Image Processing (Prentice Hall), 1990
5. The Sapphire resolution target courtesy of A. M. Glasser, Dept. of Materials Science, UC Berkeley and J. Wade Garrett Auxiliary Power Division, Phoenix AZ