ULTRASONIC SIGNAL PROCESSING AND PATTERN RECOGNITION IN EVALUATING THE MICROSTRUCTURE OF MATERIALS

BY

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This thesis is dedicated to the author's parents and his Motherland.

T.W.
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ABSTRACT

The need for refined signal processing techniques to analyze the microstructure of materials using ultrasonic backscattered echoes has been long recognized. This thesis focuses on the analysis and development of signal processing technique for microstructure evaluation based on attenuation estimation, resonating frequency extraction and frequency shift evaluation. Existing conventional techniques are incapable of characterizing the microstructure of the materials because the backscattered signal consists of interfering multiple echoes with random amplitude and phase corresponding to highly complex scatterers. Thus, the development of effective techniques for imaging and evaluating the microstructure of the materials remains a challenging scientific and practical concern.

The ultrasonic backscattered signal is treated as a random process, and a statistical model is developed that describes the backscattered signal as a function of physical parameters such as attenuation and frequency shift. This work has shown that it is feasible to characterize materials with different grain sizes by analyzing the backscattered grain signal. Grain size characterization has been achieved by measuring the attenuation coefficient using two equivalent approaches, namely, temporal (time) and spatial (ensemble) averaging for smoothing the backscattered signal. Statistical analysis and experimental results suggest that the accuracy of the estimated attenuation coefficients using time averaging is very close to ensemble averaging. The choice of scanning steps for spatial averaging and window length for temporal averaging is critical to the effectiveness of the smoothing operation. The effectiveness of the averaging schemes is found to be less than 50% due to a high degree of correlation between successive measurements. Experimental studies were performed using steel samples and it was found that the estimated
attenuation coefficients is position-dependent such that its value decreases as the ultrasonic beam penetrates the specimen.

Signal processing techniques in frequency domain based on existing signal theories for characterizing the behavior of backscattered signals have been examined. In particular, the spectral shift effects of backscattered grain signals is evaluated through moment analysis and homomorphic processing. The performance of homomorphic processing technique is limited by the random nature of the backscattered signals. The power spectrum centroids of the ultrasonic wavelet can be extracted from random backscattered signals by using the homomorphic processing technique with less than 2% error. Different short-pass lifters essential in homomorphic wavelet recovery system are evaluated, and the criterion for the best achievable performance is discussed. As an alternative method, linear predictive analysis is used for spectral smoothing and for extracting features from the random grain signals. A third-order linear predictive model is used to describe grain signals with different center frequencies. Parameters of the linear predictive model (autoregressive coefficients) have been used as a feature vector for the pattern recognition and classification of grain signals. When the frequency difference is more than 0.5 MHz (10% of center frequency), the probability of correct classification is found to be as much as 90%.
CHAPTER I

INTRODUCTION

The research reported in this thesis is concerned with applying various signal processing techniques to analyze ultrasonic grain signals. The intent of the research is to extract information contained in the broadband grain signal, which consists of multiple interfering echoes with random amplitude and phase corresponding to highly complex grain structures. The specified goal of this thesis is the development of a pattern recognition system that utilizes the inherent properties of grain signal such as the attenuation coefficient and frequency shift phenomenon. This thesis presents the development and analysis for grain size estimation using ultrasound with the above stated goal in mind.

1.1 Importance of Grains in Materials

During the transition of a vapor, solution, or melt into a solid state, a crystal forms when a seed is present [1]. The grains may form by crystallization from the melt or by recrystallization during heat treatment, as in metal, or they may be brought together by pressure and sintering, as in ceramic. Most solids are polycrystalline in nature because nucleation occurs at many points; that is, many grains are formed during the solidification process, and as the solidification rate varies, the grain size will be varied. A typical grain photo micrograph is shown in Figure 1.1. As shown in this figure, these grains in general are of various shapes and sizes, filling all space within the boundaries of the medium.

† Numbers in brackets refer to numbered references in the bibliography.
Figure 1.1. Photomicrograph of Steel Showing the Grain Structure (Magnification 400). Heat Treatment Condition: Open Fire Anneal at 1600°F for Four Hours after the Stable Temperature had been Achieved. Then, Remove from Furnace and Air Cool Sample.
Many of the properties inherent in materials are closely related to the grain size (D), grain shape (elongated, flattened, equiaxed or mixture), grain orientation (random or preferred), quality of grain boundaries (presence or absence of voids or inclusion), and proportion of chemical constituents [2]. For example, the creep rate of equiaxed fine grained "MgO" at high temperatures and low stresses is proportional to $D^{-2}$ [1]. Hence, a large grain size would be desirable to reduce the creep rate. On the other hand, because the fracture stress of many polycrystalline materials, which are brittle, is proportional to $D^{-1}$, we might desire a small grain size for certain purposes. The magnetic properties of the materials can also be affected by the variation of grain size; one example [3] is that the magnetomechanical acoustic emission (MAE) and the magnetic Barkausen effect noise for nickel samples are decreased with an increasing grain size. Orientation of the grain can also be very important since many properties of single crystals are highly anisotropic. In another words, even when only a single type of crystal is presented, the materials may still be inhomogeneous if the grains are randomly oriented. The boundaries between the grains reveal regions of imperfect crystallinity and are the weakest area of the structure which makes them susceptible to chemical attack and etching.

1.2 Ultrasonic Grain Size Characterization

The importance of grain size estimation as a means of determining the structural and mechanical properties of materials, as well as for controlling the manufacturing tolerances during the fabrication of metal and ceramic parts, has been long recognized. Among the various methods for microstructure (i.e., grain) evaluation of materials, the utilization of the ultrasonic backscattered signal has been proven to be a simple and efficient method of nondestructive testing. Two major
ultrasonic microstructure evaluation techniques have been proposed in recent years and have met with reasonable success [4, 5, 6]: 1) techniques based on attenuation measurements, and 2) techniques based on scattering measurements.

In polycrystalline materials, the attenuation of an ultrasonic wave is primarily caused by scattering from the grain boundaries. The backscattered pressure field at the measurement position is the superposition of the pressure field from all scatterers [7]. The signal originating from the scatterers at location \( r_i \) depends on a set of transfer functions. First, the ultrasonic impulse that reaches the scatterer is the result of an impulse delta voltage applied to the transducer. On its way to \( r_i \) the ultrasonic impulse undergoes a change due to the absorption and the scattering of the medium. Both effects depend on the location of the scatterer \( r_i \), path of propagation, and the frequency. The sound wave impulse is then scattered according to certain functions between the wave frequency and the size of the scatterer. A typical example of a backscattered signal is shown in Figure 1.2. This measurement of the signal was accomplished by using a Gamma type transducer manufactured by K-B Aerotech with approximately a 5 MHz center frequency and 3-dB bandwidth of approximately 1.5 MHz. The signal, which was sampled at 100 MHz with 8-bits of resolution, has the duration of about 20\( \mu \)s, representing the scattering characteristics in the region between 0.40 to 2.75 inches from the front surface of the steel sample. As shown in this figure, this signal consists of interfering multiple echoes with random amplitudes and phases, which correspond to a highly complex grain pattern.

When an ultrasonic burst of sound travels through an inhomogeneous material, its amplitude is attenuated as a function of the frequency and position. In general, the attenuation is caused by hysteresis loss (absorption loss), which is a true loss created by the inelastic behavior of the materials, and scattering loss...
Figure 1.2: The Backscattered Grain Signal of the Specimen with Average Grain Size of 50 μm, Measured by Using 5 MHz Aero-tech Gamma Transducer.
associated with the characteristics of the grain and phase boundaries (acoustic impedance discontinuities). Usually, grain scattering at ultrasonic frequencies is so large relative to the hysteresis loss that the latter can be ignored.

Common ultrasonic microstructure evaluation is based on a comparison of attenuation measurements of specimens with unknown grain sizes to specimens with known grain sizes. This is accomplished either by direct wave transmission using two transducers, or by pulsing the oscillator and measuring the amplitude of the echoes as they return from the far end of the specimen to the single transducer as shown in Figure 1.3 and Figure 1.4.

Microstructure evaluation techniques based on ultrasonic attenuation measurements have some practical limitations [8,9]: i) perfect coupling between the transducer and the sample is difficult, ii) a flat and parallel surface is required in order to avoid complex corrections, and iii) since the attenuation coefficient represents an average value over the total sound path, local variation can greatly alter the attenuation coefficient and can not be effectively evaluated.

An alternate method of evaluating the grain size can be achieved by using the measurements of the backscattered signal. This method is based on the principle that an ultrasonic wave travelling through a medium is subject to scattering and absorption losses. Therefore, characterizing the backscattered signal amplitude yields information related to the average grain size of the specimen. By utilizing various averaging techniques (spatial, directional and frequency), one can enhance the SNR ratio and quantitatively obtain the attenuation coefficient. In general, grain size characterization using backscattered signals requires significant computing time and memory storage and it may necessitate the correction for diffractive and refractive losses. In spite of these limitations, the analysis and processing of
Figure 1.3. Ultrasonic through Transmission Method
Figure 1.4. Ultrasonic Pulse Echo Method
the backscattered signal is potentially useful in assessing grain size distribution and the degree of inhomogeneity in the materials.

1.3 Brief Introduction to the Research

This thesis is an investigation of the application of signal processing techniques, building upon previous work, and introducing the performance evaluation and a new grain signal processing approach — spectral shift — with sufficient mathematical analysis and experimental results to demonstrate the feasibility of time and ensemble averaging as well as the spectral shift approach. Understanding the grain signature will enable us not only to classify grains but also to detect flaw echoes which can be severely masked by the presence of grain echoes. An efficient method of estimating grain parameters will result in the formation of diagnostic feature vectors (i.e., grain signatures) that can be used for the design of grain classifiers and classification.

The performance evaluation of time and ensemble averaging was based on the assumption that the grain signal is attenuated as the time proceeds, and the multiple scattering and absorption are neglected. The backscattered grain signal is represented by a mathematical model based on the ultrasonic wavelet and grain characteristic function. The expected value of the grain signal was found to be related to the attenuation coefficient and the attenuation coefficients were related to the position of the ultrasonic wave traveling path. The position-dependent attenuation coefficients were extracted by averaging techniques, and the measurements efficiency was evaluated through the information criterion. The grain size identification was accomplished by comparing the position-dependent attenuation coefficients obtained through choosing the suitable window for curves fitting processing. The possible causes for position-dependent attenuation coefficients were
also discussed. The variance of the averaged signal as well as the correlation effects related to the measurement efficiency were examined in details through the experimental measurements and signal processing procedure.

The spectral shift analysis was based on the fact that the ultrasonic wave traveling through solids is subject to energy loss due to scattering and absorption. In the Rayleigh scattering region, both scattering and absorption are functions of frequency and grain size distribution. The grain scattering results in an upward shift in the expected frequency of a broadband ultrasonic wave, while the attenuation effect influences the frequency shift in a downward direction. These opposing phenomena can be utilized for grain size evaluation. In this investigation, the spectral shift quantization technique using homomorphic processing and moment analysis was examined. Computer simulation and experimental results obtained from the steel samples with different grain sizes support the feasibility of using a spectral quantization technique for estimating grain size.

1.4 Thesis Outline

Beginning in the late 1940’s, extensive studies have been carried out and reported on concerning grain signal analysis. Chapter II provides a survey of the available literature with an emphasis focused on work concerned with the analysis of ultrasonic backscattered grain signals.

In order to provide suitable samples for experiments, the sample selection and preparation works are reported in Chapter III. In this chapter, the type of steel samples and heat treatment conditions are selected based on the literature suggestions. The intercept grain size estimation method from micrographs and the instruments used in this investigation are also introduced.
The mathematical representation of the backscattered grain signal and the concepts that are introductory to the rest of the thesis are presented in Chapter IV. In particular, the amplitude histogram of the backscattered grain signal construction, the mathematical derivations of the amplitude distribution, as well as the effect of the attenuation, are included.

In order to evaluate the performance of time and ensemble averaging techniques, a detailed statistical analysis on the extracting attenuation coefficients utilizing averaging techniques are given in Chapter V. Further discussion about the efficiency and consistency of attenuation estimation in terms of individual measurements using various scanning areas and different smoothed windows are presented in this chapter.

The use of homomorphic processing on the analysis of backscattered grain signals is the subject of Chapter VI. The investigation of the reliability and accuracy of this cepstral analysis method was carried out by computer simulation. In this chapter, moment analysis was used as a performance measure to evaluate the effectiveness of homomorphic processing. The by-products of these studies are obtained a relationship between the spectral shift phenomenon and the average grain size. Experimental results obtained from steel samples with different grain sizes as well as the discussion of the feasibility for analysis methods have also been included.

The linear predictive (LP) analysis technique is a powerful technique which has been used extensively in speech signal processing and seismic data analysis. Chapter VII discusses the feasibility of using linear predictive analysis on grain signal analysis. This chapter covers linear spectrum matching, the linear resonating
frequency estimator, and the linear distance classifier design problem. The performance evaluation of linear predictive analysis is applied to computer simulated grain data. The feature vectors of the simulated grain signals with different center frequency are formed by linear predictive coefficients. The corrected classification probability achieved by these feature vectors is more than 90%. The detailed presentation of pattern recognition are included in this chapter. Finally, a summary of research achievements and conclusions have been presented in Chapter VIII, along with the suggestions for future research.
CHAPTER II

LITERATURE REVIEW

Understanding the historical development of techniques for evaluating the statistical properties of scatterers (grains) is important and necessary for studying this difficult subject. This task is a formidable one since many relevant papers in a wide variety of journals have been published since the early 1940s. This chapter contains a general overview of available literature and highlights the merits of individual works. The papers briefly reviewed here are those most relevant to the topic of interest.

2.1 Energy Losses of Ultrasonic Wave in Polycrystalline Materials

Many papers have been published that deal with the energy losses of an ultrasonic wave propagated through polycrystalline materials. One of the earliest discussions was carried on by Mason and McSkimin in the late 40s [10,11]. In their discussions, measurements made in a frequency region from 2 to 15 MHz indicated that a scattering loss was the principal source of attenuation and that this loss was proportional to the grain volume and the fourth powers of the frequency in agreement with Rayleigh's calculation for the scattering of sound by an obstacle. Further calculations of scattering factors for cubic and hexagonal metal were made that showed that scattering is determined by the anisotropy of elastic constants. Two different factors were obtained: one for shear waves and one for longitudinal. They used high frequency longitudinal (dilatational) and transverse (shear) sound waves which were passed through polycrystalline materials. Three
distinct scattering regions, based on the comparison of the scattering centers, were found. Mason and McSkimin developed the expression for ultrasonic attenuation of the longitudinal and shear waves.

The scattering regions were described as:

(1) Rayleigh region \((\frac{\lambda}{D} > 1)\): the region in which grain size is small compared to the wavelength of the ultrasound. In this region losses are due to the Rayleigh fourth power scattering law and are proportional to the grain volume. It was shown in this region that attenuation can be represented by the equation

\[ A = B_1 f + B_2 f^4 \]  

(2.1)

where \(A\) is the attenuation in nepers per centimeter and \(B_1\) and \(B_2\) are constants. This indicated that attenuation contains a hysteresis term proportional to the frequency and a fourth power scattering term. For longitudinal and shear waves, the \(B_2\) constant varies from \(3.74 \times 10^{-30}\) neper/cm/Hz to \(50.2 \times 10^{-30}\) neper/cm/Hz under the conditions 0.23-mm grain size of aluminum rod [10].

(2) Stochastic region \((\lambda \approx D)\): the region of scattering in which the wavelength is comparable to the mean grain diameter. The scattering coefficient is proportional to the mean grain diameter and to the second power of frequency.

(3) Diffusion region \((\lambda \ll \frac{D}{f})\): the region in which the mean grain diameter is greater than the wavelength. In Mason and McSkimin's experiments, they noticed that, as frequency increases, the loss of the larger grain size materials becomes less than that for smaller grain size materials, and at high frequencies the relative loss is nearly inversely proportional to the grain size.
Among these three regions of scattering, the present concern is with the evaluation of weak scattering which falls in the Rayleigh scattering regions. The theory of Rayleigh scattering analysis by Mason and McSkimin [11] was calculated for a condition in which the distance between scattering centers is much greater than the mean diameters of these centers. The grains in polycrystalline materials, however, are tightly packed, and the distance between their centers is roughly equal to the grain diameters. Nevertheless, in spite of structural differences, the study of grains in solids that refers to Rayleigh scattering equations is the closest equivalent for our signal processing purposes.

As the wavelength of an acoustical wave becomes less than the grain size, the Rayleigh type of scattering loss gradually becomes a diffusion type of wave propagation similar to the mechanism for heat transfer. A rough estimate of diffusion losses proposed by Mason and McSkimin [11], was made as follows: The receiving crystal is very directional and hence all that will be picked up are waves that are normal to the surface when the frequency is so high that the wavelength is small compared to grain size; the loss is caused by reflection between grains and by the change in direction caused by these reflections. These two losses, since they are both caused by reflections, are comparable, hence, we can calculate the losses by reflection at normal incidence, and assume the change in direction loss is of the same order of magnitude. If the wave goes from one grain to another at normal incidence across the boundary, one part is transmitted and the other reflected. Since the amount lost by reflection is small, the transmitted part is in terms of pressure.

\[ P = P_0(1 - R_1) = P_0e^{-R_1} \]  \hspace{1cm} (2.2)

where \( R_1 \) is the reflection coefficient. For \( n \) such reflections in a length \( l \), the terminal pressure becomes:

\[ P = P_0e^{-(R_1 + \ldots + R_n)} = P_0e^{nR} \]  \hspace{1cm} (2.3)
where $\overline{R}$ is the average reflection coefficient. Now, if the average particle diameter is $D$, then $nD = l$, or $n = \frac{l}{D}$ where $l$ is the total path length. Hence

$$P = P_0 e^{-\frac{\overline{R}l}{D}}$$

(2.4)

and the loss should be inversely proportional to the grain diameter for a diffusion process.

Mason and McSkimin's works first developed the quantitative relationship between the average grain diameter and the attenuation coefficient, although their derivation was based on some impractical assumptions or limitations. As summarized later by E. P. Papadakis [2,4]: The early work on grain scattering by Mason and McSkimin was an attempt to adapt the formula of Rayleigh to scattering by grains in a metal. Two concepts were introduced by Mason and McSkimin; the idea that the number of scatterers was inversely proportional to the average grain volume and the idea that the mean-square fractional variation of the modulus of a grain with azimuth and declination could express the elastic difference between the grain as an inhomogeneity and all the other grains as a medium in which the one scatterers. The first concept is still used, but the second has been modified considerably in the more exact formulations of the grain scattering theory made more recently. An acknowledged shortcoming of the early theory was its failure to account for mode conversion.

Including the mode conversion in solids, Merkulov [12] developed the mathematical expression for the Rayleigh scattering attenuation coefficient in hexagonal and cubic metals. For longitudinal and shear waves, the attenuation expressions of a cubic crystal in nepers/(unit length) become [2]:

$$\alpha_l = \frac{8\pi^3 \mu^2 V f^4}{375 \rho^2 v_l^3} \left( \frac{2}{v_l^5} + \frac{3}{v_l^3} \right)$$

(2.5)
\[ \alpha_t = \frac{2\pi^3 \mu^2 V f^4}{125 \rho^2 v_l^3} \left( \frac{2}{v_l^5} + \frac{3}{v_t^5} \right) \]  

(2.6)

with \( \mu = C_{11} - C_{12} - 2C_{44} \), where the \( C_{ij} \) are elastic constants of the single cubic crystallite, \( V \) is the average crystalline volume, \( f \) is the frequency of the sound wave, \( v_l \) is the longitudinal velocity, and \( v_t \) is the shear (transverse) velocity, and \( \rho \) is the medium density. The two terms in brackets indicate the scattering contribution from mode conversion (which was ignored by Mason and McSkimin). The second term in brackets is the dominating term, since shear wave velocity is smaller than longitudinal wave velocity. According to Merkulov, this accounted for the 30 dB difference in the attenuation they measured from that which was derived by Mason’s estimate for longitudinal wave.

Similarly, attenuation for hexagonal crystals becomes [2]:

\[ \alpha_t = \frac{4\pi^3 V f^4}{450 \rho^2 v_l^3} \left( \frac{a_1}{v_l^5} + \frac{b_1}{v_t^5} \right) \]  

(2.7)

\[ \alpha_t = \frac{4\pi^3 V f^4}{450 \rho^2 v_t^2} \left( \frac{a_2}{v_l^5} + \frac{b_2}{v_t^5} \right) \]  

(2.8)

with

\[ a_1 = \frac{88}{15} \gamma^2 + 40 \alpha^2 + 96 \eta^2 + \frac{80}{3} \alpha \gamma + \frac{128}{3} \gamma \eta + \frac{320}{3} \alpha \eta \]  

(2.9)

\[ b_1 = \frac{82}{15} \gamma^2 + 30 \alpha^2 + \frac{272}{3} \eta^2 + 30 \alpha \gamma + \frac{112}{3} \gamma \eta + 80 \alpha \eta \]  

(2.10)

\[ a_2 = \frac{41}{15} \gamma^2 + 15 \alpha^2 + \frac{136}{3} \eta^2 + 10 \alpha \gamma + \frac{56}{3} \gamma \eta + 40 \alpha \eta \]  

(2.11)

\[ b_2 = \frac{8}{5} \gamma^2 + 28 \eta^2 + 8 \gamma \eta \]  

(2.12)

where

\[ \gamma = C_{11} + C_{33} - 2(C_{13} + 2C_{44}) \]  

(2.13)

\[ \alpha = C_{13} - C_{12} \]  

(2.14)
\[ \eta = C_{44} + \frac{(C_{12} - C_{11})}{2} \]  

(2.15)

Inspection of Equations. 2.5, 2.6, 2.7 and 2.8 reveal that both transverse and longitudinal scattering losses are dependent on the third power of grain diameter (i.e., grain volume) and the fourth power of frequency, which is the essential result of Mason and McSkimin's efforts.

For the mathematical expression in the stochastic scattering region, the attenuation coefficients of hexagonal and cubic crystallites were [2];

Cubic:

\[ \alpha_l = \frac{16\pi^2 \mu^2 D f^2}{525\nu_l^6 \rho^2} \]  

(2.16)

\[ \alpha_t = \frac{4\pi^2 \mu^2 D f^2}{210\nu_l^6 \rho^2} \]  

(2.17)

Hexagonal:

\[ \alpha_l = \frac{16\pi^2 D f^2 \alpha_3}{1575\nu_l^6 \rho^2} \]  

(2.18)

with

\[ \alpha_3 = 7\gamma^2 + 35\alpha^2 + 140\eta^2 + 140\alpha\eta + 30\eta\gamma + 60\eta\gamma \]  

(2.19)

where \( \alpha, \eta, \gamma \) is defined in Equations. 2.13, 2.14, 2.15. No \( \alpha_t \) was given in literatures. Equations 2.16, 2.17, 2.18 indicate that the transverse and longitudinal scattering are of lower sensitivity to the grain diameter (related to the form of the first order) and the frequency (related to the form of the second order). An equivalent theoretical analysis was performed by Bhatia [13] which was slightly more general, and indeed reduced to those presented by Merkulov when certain conditions were satisfied.
In a diffusive scattering region ultrasonic propagation begins to interact with the individual crystalline (i.e., geometric scattering). Due to the anisotropy of wave velocity in crystallines [14], the velocity of an ultrasonic wave must show a discontinuity in magnitude and direction at the intercrystalline boundaries with a considerable scattering energy, so the attenuation becomes:

\[ \alpha = \frac{R}{D} + Cf \]  

(2.20)

where \( R \) is the average effective reflection coefficient for the wave at the intercrystalline boundaries. No provision has been made in the theory to account for mode conversion at the intercrystalline boundaries.

2.2 Ultrasonic Prediction of Grain Size Distribution

In late 50s and early of 60s, Papadakis was concentrating on the ultrasonic application of grain size estimation [2,15]. In one of his works [2], he pointed out that, in Mason and McSkimin derivations, it was assumed that the spread in grain diameters is so small that the n-th rooted average of all the n-th powers of the grain diameter \( D \) over the grain size distribution are equal to the median grain diameter \( D_0 \). In another work [15], Papadakis introduced the expressions of attenuation coefficients which are proportional to \( Tf^4 \) where \( T \) is equal to \( \frac{4}{3} \pi (R^6)_{av}/(R^3)_{av} \); although \( T \) has the dimensions of volume, it is not equal to the average grain volume itself. Because of its dependence on an average of high powers of the grain radius \( R \), \( T \) is strongly dependent upon the breadth and shape of grain size distribution.

In Papadakis’s work [15], quantitative agreement was obtained between the scattering theory and experiments in ultrasonic attenuation measurements on several polycrystalline metals. Merkulou’s theory was used in both Rayleigh and
Stochastic scattering regions. Papadakis was able to show that in the Rayleigh region, Merkulou's theory was good for both longitudinal and shear waves; in the Stochastic region, it underestimates the longitudinal wave attenuation. The reason for this, Papadakis thought, might be the lack of a term for mode conversion in the expression for stochastic attenuation. Mode conversion contributes to the longitudinal wave attenuation a great deal (about 80% of the total in the Rayleigh region) while it contributes only a little to shear wave attenuation (about 20% ). In the interpretation of attenuation data, his work has shown that the theory and experiments agree within experimental error.

In some of Papadakis's other works [16,17], he presented a matrix inversion procedure for the computation of grain size distribution of a solid volume from the image-size distribution on the photomicrograph of its surface. It was shown that the distribution must be finite (or zero) for extremely small grains and must have a decreasing tail for very large grains. Distribution may be monotonic decreasing from a grain radius $R = 0$ to $R \to \infty$ or it may have one or more local maxima. A broad range of distributions were discussed in his works. The reliability of the procedure was checked by applying it to image distribution derived from simple hypothetical grain size distributions. The matrix inversion replicated the hypothetical distribution within 20% of their values at all points.

Another useful point of Papadakis's work is the discussion of ultrasonic diffraction loss and phase change in anisotropic materials. He said [18]: In the use of piezoelectric transducers for generating and receiving ultrasonic waves for the measurements of the elastic and inelastic properties of materials, the diffraction is important, since it adds to the attenuation appreciably while raising the velocity slightly. In general, for a given size of transducers, the diffraction loss between a given pair of echoes will be higher at the lower frequencies. When the frequency
dependence of the attenuation is important (i.e., most of the time), the dependence in the raw data may be masked by the diffraction loss. An example was given in his works [18] to illustrate the masking to which he referred.

2.3 Signal Processing of the Backscattered Grain Signal

One of the earliest works on grain size estimation using backscattered ultrasonic grain signals was performed by Beecham [19]. This work used the amplitude variation of the received signal to describe grain size distribution within the metal. In addition, Beecham was able to improve the accuracy of his results by averaging the statistical characteristics from each independent measurement. Independent measurements can be obtained by:

1. varying the position of the transducer,
2. increasing the pulse duration,
3. changing the carrier frequency.

Aldridge [20] confirmed Beecham’s results and concluded that; when ultrasound is radiated from a transducer into metal having a uniform grain size and freedom from major defects, the sound scattered back from the grain boundaries to the transducer has characteristics not only of the acoustic mismatch at the grain boundaries, but of the grain size and shape. If the transducer is moved so that the volume being insonified is changing, then the scatter received by the transducer is also changing and the transducer output can be statistically processed to yield distribution of scatter amplitudes, which can then be used as a measure of mean grain size. Fay [21] demonstrated that the decay of backscattered echoes as a function of depth was related to the grain size of the metal. He further demonstrated
that this relationship could be used to monitor changes in the average grain size from one steel billet to another. Fay also suggested a technique which estimates scattering and attenuation coefficients from the backscattered signal [21] based on the uniform average grain size and distribution along the entire sound path, as well as single scattering assumptions. These assumptions require that the scattering be weak due either to small impedance changed at the grain boundaries or the use of ultrasound which has a wavelength that is long compared to average size.

Goebbel et al. [22, 23] altered and refined Fay's techniques to more accurately determine the amplitude of the backscattered echoes with respect to depth by utilizing various averaging techniques, namely, spatial, directional, and frequency averaging. They determined that for a given backscattered signal as a function of time or function of propagation path, the signal is the result of reflections at all grain boundaries. The amplitude modulated signal (i.e., grain signal) has a frequency spectrum quite similar to that of the wavelet spectrum; therefore, it is coherent to the signal by reflection at grain boundaries. To make this noise signal to an incoherent, stochastic one, it is necessary to vary the interference patterns while keeping useful information invariant (at least in approximation); then, one can improve the signal-to-noise ratio to such an extent that grain size estimation becomes feasible.

Saniie and Bilgutay [24] later demonstrated various grain size characterization techniques which will able to extract parameters from the backscattered signal related to frequency-dependent attenuation coefficients. Histogram analysis for the backscattered grain signal amplitude was presented. Cepstral analysis of ultrasonic grain size characterization was introduced which seemed to achieve a certain success. Spectral analysis, as well as time domain and moment analysis have also
been successfully investigated by Saniie and Bilgutay; and it is this work which has served as a basis for the topic of discussion in this dissertation.

The works done by O'Donnell and Miller [26,27] used the broadband backscatter technique to obtain a frequency dependence scattering coefficient over a continuous range of frequencies from a collection of scatterers. In their work, the backscattered coefficient is defined as a scattering cross section from a normalized volume of the sample. Their work confirmed that the magnitude of the frequency-dependent backscattered coefficient is closely related to the physical properties of scatterers. Ueda and Ozawa [28,29] discussed the incoherent scattering problem from a different point of the view. They analyzed and presented the scattering expression for a case in which the correlation length of the medium is much smaller than the wavelength and the beamwidth. They concluded that the scattering coefficient is proportional to the fourth order of frequency and the third order of the scattering cross section (i.e., Rayleigh scattering).

The paper by Carletor and Muratore [25] demonstrated that ultrasonic NDE methods can be used for evaluating the internal structure of concrete and related materials. They found that the amount of energy penetrating into the concrete followed a linear inverse dependence on frequency, and concluded that it was possible to establish both maximum penetration and spatial resolution of ultrasonic analysis. For better performance they suggested using depth-dependent deconvolution to compensate for signal spectral characteristics.

Recently, since fiber-reinforced composites have found increasing use as structural materials, more attention has been directed toward the unique problem encountered in ultrasonic scattering from inhomogeneous, anisotropic and often layered composites [30]. Fiber-reinforced composites are densely packed with scatterers in the form of fibers and interfaces. Scattered signals from the composites
contain more diffraction and interference than metal, due to geometric periodicities. These factors greatly increase difficulty in analyzing the signal of scattering and little has been done to evaluate it. An earlier work on the ultrasonic evaluation of composites was conducted by Bar-Cohen and Crane [31]. They noted in their experiments that maximum backscattered energy occurs over a small angular range on either side of normal incidence to the fiber axis; that is, reflection of the ultrasonic beam occurs only when the incident beam is approximately at right angles to the axis of the individual fibers within a particular layer. Therefore, they concluded that the backscattered acoustic field of a composite can be utilized to determine both gross fiber orientation and small misalignments of fiber bundles in a specific ply. If the backscattered acoustic field is sampled in a rastered pattern across a composite plate, it is then possible to image or map the intralamellar cracks associated with plies failure. Although it is not the primary concern of this work to characterize composites ultrasonically, current developed signal processing schemes will pave the way toward evaluating such complex structures nondestructively.
3.1 Introduction

For experimental studies, specimens were needed in which the physical parameters of the materials (crystal shape, elastic constants, sound velocities, etc.) remained constants, while the grain sizes of the specimens have been considerably changed. This would allow accurate interpretations of ultrasonic measurements resulting from the grain size variations.

In this study steel samples were used for ultrasonic microstructure evaluation. The literature survey [32, 33] indicated that steels are manufactured having coarse or fine grained depending on their chemical constituents. Fine-grained steels are deoxidized with aluminum, which contains fine aluminum nitride particles that restrain austenite grain growth. On the other hand, coarse-grained steels are generally deoxidized with silicon, which does not produce particle dispersions effective in inhibiting austenite grain growth. The effect of grain growth as a function of temperature for both coarse and fine-grained steel is shown in Figure 3.1 [32]. Figure 3.1 shows that coarse-grained steels coarsen gradually with an increasing austenitizing temperature; but, fine-grained steels show no grain growth until a relatively high austenitizing temperature is reached. Keeping this principle in mind, type 1018 coarse-grained silicon-killed steel blocks were used in experiments to obtain the various grain sizes.
Figure 3.1. Austenite Grain Size as a Function of Austenitizing Temperature for Coarse-grained and Fine-grained steel
3.2 Sample Preparation

Steel type 1018 blocks, which are commonly used for industrial applications, have been chosen for this study. Metallurgical characteristics of this kind of specimen are not presented here; however, this information is available from many sources (for example, the book by Kruss [32]). The steel blocks initially had an average grain size of about 14μm and heat treatment was performed to achieve various grain sizes.

Sample preparations were accomplished by heat treating type 1018 steel blocks with dimensions 4 x 4 x 10 inches at different temperatures in order to obtain a broad range of grain sizes. Empirically, it was found that the grain size will not change significantly with heat treatment of up to 1600°F. When the heat treatment temperature reached 1700°F and 2000°F, the grain size in the steel blocks changed from 14μm to 25μm and 50μm, respectively. The steel blocks were kept at temperatures of 1700°F and 2000°F for a period of roughly 4 hours after stable temperatures had been reached. Upon completion of the heat treatment process, the steel blocks were removed from the furnace and cooled in open air.

Small segments of the cooled samples were polished and etched in an oxygen acid solution in order to prepare the surface for estimating grain size. Micrographs of the heat treated samples were taken at a magnification of 400. These micrographs were shown in Figure 3.2-3.4. A comparison of these figures displays significant changes in grain size caused by the heat treatment. In addition, inspection of these micrographs reveals a significant randomness in grain size, shape and orientation.
Figure 3.2. Micrograph Result of Steel Type 1018. (Average Grain Size 14μm.)
Figure 3.3. Micrograph Result of Steel Type 1018. Heat Treated at 1700°F and Average Grain Size 24 μm.
Figure 3.4. Micrograph Result of Steel Type 1018 Heat Treated at 2000°F and Average Grain Size 50 μm
3.3 Grain Size Estimation from Micrographs

A method for grain size estimation from micrographs that is popular and certainly simple is the intercept method. In the intercept method of grain size analysis a count is made of the number of grain boundaries intersected by a test line. This method provides an average intercept length which can be converted to an ASTM (American Society for Testing and Materials) grain size number. The advantages of the intercept method are its simple interpretation and its computational efficiency [34]. In this study, the grain sizes are represented by an average linear intercept $\bar{L}$ which is,

$$\bar{L} = \frac{C}{MN} \quad (3.1)$$

where $N$ is the number of intersections, $C$ is the length of the intercepting line, and $M$ is the magnification. In general, the average grain size $\bar{D}$ is linearly related to $\bar{L}$, but the exact value of the proportionality constants depends on the grain shape [34]. In this study, in order to avoid ambiguity, the average linear intercept is used to represent the grain size. In addition, the ASTM grain size number was approximated using the following relations:

$$g_e = -10.0 + 6.64 \log_{10}\left[\frac{1}{\bar{L}}\right] \quad (3.2)$$

where $\bar{L}$ is in centimeter. The above expressions for the mean linear intercept and ASTM grain size number were applied to the micrographs of steel and those heat treated at $1700^\circ F$ (steel-1700) and $2000^\circ F$ (steel-2000) and results are shown in Table 3.1.
Table 3.1. Grain Sizes Corresponding to the Type 1018 Steel Samples.

<table>
<thead>
<tr>
<th>Sample</th>
<th>Grain Size (µm) (intercept method)</th>
<th>Grain Size Number (ASTM)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SS</td>
<td>14</td>
<td>9</td>
</tr>
<tr>
<td>SS-1700</td>
<td>25</td>
<td>7</td>
</tr>
<tr>
<td>SS-2000</td>
<td>50</td>
<td>5</td>
</tr>
</tbody>
</table>
3.4 Instrumentation

Experimental studies were conducted at the Ultrasonic Information Processing Laboratory (UIPL) at Illinois Institute of Technology. The currently used data acquisition system block diagram of UIPL is shown in Figure 3.5. This system consists of an IBM-AT personal computer with the necessary interfacing modules and programmable, high speed digitizer (TEK7612D). The major components of the system are the ultrasonic pulser, transmitting/receiving piezoelectric transducer, wide band amplifier, a two-dimensional scanner and the central processing computer HP-9836 with its supporting peripherals.

The main function of the IBM-AT computer is to monitor the transducer's position; control the step motors of the scanner for different scanning areas and different distance between the successive measurements; program the high speed digitizer for a sampling rate, number of samples, mode of triggering and sensitivity adjustment; display the data, and relay it directly or after some preprocessing (e.g., rectifying, averaging) to the central processing units (HP-9836).

The ultrasonic scanning system consists of a mechanical assembly which can move the ultrasonic transducer in X and Y directions within the precision of a few microns. Step motors coupled with controlling modules are used to drive the scanner in X and Y directions, which allows for automatic scanning of the samples and reconstructing their acoustical images. The high speed programmable digitizer TEK7612D provides a dual channel analog-to-digital converter (ADC) with a maximum sampling rate of 200 MHz. It also records the data in an ultrafast response memory with an 8-bit resolution ADC and the ideal signal-to-noise ratio of 49.8 dB.
Figure 3.5. Data Acquisition System Diagram in Ultrasonic Information Processing Laboratory of IIT
The central processing units consist of a HP-9836 multi-user computer, disc drive (HP7912), graphic plotter (HP7470A), and a HP thinkjet printer. These facilities are used for digital signal processing. A local network provides additional supported computational facilities from the university academic computing center, which contains VAX11/780, VAX11/750 and UNIX systems along with many other pieces of equipment necessary for computing, displaying, and producing high quality output, such as graphic terminals and laserprinters, and disc and tape storage facilities.

3.5 Experimental Procedure

The experimental measurements were acquired by pulsing the transducer with a electrical pulse on the order of a few nanoseconds wide (the pulse duration and amplitude are adjustable). The power spectrum of the pulser is broad enough to cover the transducer spectrum almost uniformly. The reflected echo is amplified by a RF receiver. A range gate enables the selection of a particular segment of the reflected signal for processing. All measurements were made by the immersion technique and data was taken in the far field of transducer. A Gamma type transducer, made by Aero-tech, which has a center frequency of about 5 MHz and 3 dB bandwidth of approximately 1.5 MHz, and a Panametric type transducer with a center frequency of about 6.22 MHz and 3 dB bandwidth of 2.75 MHz, were used for experiments. These transducers have a high sensitivity that allows the detection of echoes from a greater depth in the sample.

The specimens were placed in the 3 x 5 x 1.5 foot water tank and the transducer was attached to the frame driven by step motors along the X-Y scanning direction. The IBM-AT computer was used to control the scanning process and
data acquisition, as well as data storage process. A HP-9836 multi-user computer and graphic plotter (HP-7470A) were used for analyzing and displaying the obtained data. All of the data were sampled at 100 MHz and contained 2048 data points. The adjustment of the high speed programmable digitizer for sampling intervals and the length of data string may be set manually or by remote control through the IBM-AT computer. After the data were stored in the IBM-AT, they could be transmitted to the HP-9836 central processing units. The final stage analysis and display were performed in an HP-9836 computer and its supporting equipment.
CHAPTER IV

MODEL OF GRAIN SIGNAL

4.1 Introduction

The ultrasonic wave traveling through solids is subject to energy losses due to scattering and absorption. The intensity of scattering is a nonexplicit function of the average grain diameter, ultrasonic wavelength, inherent anisotropic character of the individual grains, and the random orientation of the crystallites \([2, 12, 13]\). In all scattering processes, changes in the amplitude, phase, velocity, frequency, or direction of the incident wave are caused by a spatial non-uniformity in the medium of propagation. As a matter of fact, the scattered energy (mainly caused by acoustical impedance discontinuity of grain boundaries) propagates in all directions in a random fashion. In the pulse echo mode operation dealt with case, we are interested in evaluating the backscattered grain signal (defined as the scattering signal of 180° relative to the direction of transmission). The backscattered grain signal at the measurement position is the superposition of echoes returned from many scatterers \([7]\). The signal originating from the scatterer at location \(r_i\) depends on a set of transfer functions. First, the ultrasonic impulse that reaches the scatterer is the result of an impulse delta voltage applied to the transducer. On its way to \(r_i\), the ultrasonic impulse undergoes a change due to the absorption and the scattering of the medium. Both effects depend on the location of the scatterer \(r_i\), path of propagation, and the frequency. The sound wave impulse is then scattered according to certain functions between the wave frequency and the size of the scatterers. The backscattered echoes toward the transducer is
governed by the same phenomenon as the propagation from the transducer. A typical backscattered grain signal consists of interfering multiple echoes with random amplitude and phase, which correspond to a highly complex grain pattern.

4.2 Heuristic Model of Backscattered Signal

Let us assume that the received signal is due to a larger number of statistically independent scattering centers in which the sound wavelength is significantly larger than the size of the scatterers (i.e., Rayleigh region, which is our main interest and its situation is applicable to most practical cases). Furthermore, it is assumed that the scatterers (i.e., grains) are located in the farfield of the transducer, and the incident wave is a pulsed plane wave propagating into the bulk materials. The beam spreading over a small range within the materials is considered to be insignificant, and the beamwidth is assumed to be much larger than the grain size. Under these assumptions, the backscattered signal is dominated by the sum of echoes reflected from randomly distributed incoherent scatterers [35, 36].

The received signal at time \( \tau \) is the results from which the scattering occurs in the materials at a distance of \( \frac{u \tau}{2} \), where \( u \) is the propagation velocity of sound (shear or longitudinal) in the medium. Since the scatterers (i.e., grains) are stationary, the amplitude of a detected signal at a fixed time after transmission of a pulse will be constant for fixed transducer position and frequency. This detected signal \( r(t) \) can be segmented into time intervals \( r_j(t) \) corresponding to fixed spatial intervals (i.e., \( \Delta d = d_{j+1} - d_j \)) within the sample (for clarity, see Figure 4.1) [24].

\[
r(t) = \sum_{j=1}^{q} r_j(t) \tag{4.1}
\]
Figure 4.1. A Sample under Ultrasonic Testing for Grain Size Estimation Using Backscattered Echoes with a Typical Backscattered Grain Signal Corresponding to Region $j$ and $j+1$. 
where \( r_j(t) \) represents the signal correspond to the jth region and \( q \) is the number of regions, region \( j \) should typically corresponding to a segment of the sample that does not exhibit strong isolated reflector nor show any influence by the front and back surfaces. In addition, the segment size should be much larger than the average grain size \( \bar{D} \). As shown in Figure 4.2, for a given \( j \), the measured backscattered echoes form a composite signal which may be modeled as:

\[
    r_j(t) = \sum_{k=1}^{N_j} A_{kj} < u_j(t - \tau_{kj}) >, \quad j = 1, 2, 3, \ldots, q
\]

with

\[
0 < \tau_{k1} < \frac{2d_1}{v}, \quad \text{for } j = 1
\]

\[
\frac{2d_{j-1}}{v} < \tau_{kj} < \frac{2d_j}{v}, \quad \text{for } j > 1
\]

where \( A_{kj}, \tau_{kj}, \) and \( N_j \) are random variables representing the intensity, position, and the number of scatterers within the region \( j \). The term \( < u_j(t) > \) is the expected ultrasonic wavelet within the j-th region of the sample. A typical ultrasonic wavelet is shown in Figure 4.3. This wavelet has a Gaussian shape spectrum that occupies 2.5 MHz bandwidth. In general, the echo \( < u_j(t) > \) can be approximately as a time-limited RF echo with Gaussian envelope:

\[
    u_j(t) = \rho_j e^{-\frac{t^2}{2\sigma^2}} \cos f_j t
\]

The spectrum of \( < u_j(t) > \) is

\[
    < U_j(f) > \approx \rho_j e^{-\frac{(f-f_j)^2}{2}} ; \quad f \geq 0
\]

where the conditions

\[
    f_j \geq f_i; \quad \rho_j \geq \rho_i ; \quad \text{when } i > j > 1
\]
Figure 4.2. Segmented Model of the Backscattered Grain Signal.
Figure 4.3. A Typical Ultrasonic Wavelet.
generally hold. The relationship among the mean wavelet due to the effect of frequency-dependent attenuation in different regions can be represented as [24,37]:

\[< U_{j+1}(f) >= e^{-\left(\alpha_j(f)+i\beta(f)\right)\Delta d} < U_j(f) >\]  

(4.6)

where

\[\Delta d = 2(d_j - d_{j-1})\]

\[\beta(f) = \frac{2\pi f}{v}, \quad i = \sqrt{-1}\]

The term \(\alpha_j(f)\) is the attenuation coefficient due to scattering and absorption and \(U_j(f)\) is the Fourier transform of the mean ultrasonic wavelet. It is appropriate to point out that Equation 4.3 by no means corresponds to the individual grain size or its exact position in the propagation path. However, this is a heuristic model of the composite characteristics of the received signal, which inherently contains information related to the acoustical characteristics of that given region, and can also display the effectiveness of various digital signal processing techniques in calculating the grain size of materials. Upon estimation of the mean ultrasonic wavelet, it is possible to find the frequency-dependent attenuation coefficient.

\[\alpha_j(f) = \frac{|\log | < U_j(f) > | - \log | < U_{j+1}(f) > ||}{2\Delta d}\]  

(4.7)

4.3 Statistical Model of Grain Signal

The measured grain backscattered echo is a composite signal corresponding to many reflected echoes with random amplitude and arrival time. In general, the attenuation term may either be involved in the mean wavelet term or in the term that represents the scattering effects of the grain scattering cross section. If the attenuation was involved in the mean wavelet term, we have the model of the grain
signal presented in the previous section. This model can be used to estimate the frequency-dependent attenuation coefficient through Equation 4.7. However, since we are interested in performing the statistical evaluation of ultrasonic backscattered signals in time domain, the attenuation is represented as a single parameter and its effect is included in the term representing the grain scattering cross section. As shown in Figure 4.4, in a given range cell, the random scatterers can be represented by delta functions, and the grain characteristic function by the sum of these delta functions:

\[ g(t) = \sum_{k=1}^{M} A_k \delta(t - \tau_k) \]  

(4.8)

where the range cell at time \( t \) represents a small time interval of size \( 2\varepsilon \),

\[ t - \varepsilon < \tau_k < t + \varepsilon, \quad \forall \ k \]  

(4.9)

Note that \( M \) is a random variable and represents the total number of scatterers within the range cell. The term \( A_k \) is defined as:

\[ A_k = \sigma_{sk} e^{-\alpha \tau_k} \]  

(4.10)

where \( \sigma_{sk} \) is a random variable related to the grain scattering cross section and \( e^{-\alpha \tau_k} \) is the result of attenuation, which depends on the position of the scatterers within the range cell. It is important to point out that although both the scattering coefficient \( \sigma_{sk} \) and the attenuation coefficient \( \alpha \) are functions of frequency, this is omitted in the above equation in order to simplify the mathematical representation.

Based on the properties of linear system theory, the measured signal is:

\[ r(t) = u(t) * g(t) = \sum_{k=1}^{M} A_k u(t - \tau_k) \]  

(4.11)
Figure 4.4. A Range Cell Configuration
where \( u(t) \) is the basic ultrasonic wavelet as shown in Figure 4.3. Without loss of generality, we make the assumption that the wavelet has Gaussian envelope,

\[
u(t) = e^{-\gamma t^2} e^{j\omega t}
\]

(4.12)

where \( \omega \) is the center frequency, and \( \gamma \) is a constant representing the width of the wavelet in time.

Using Equation 4.12, the grain signal corresponding to range cell centered about time \( t \) becomes:

\[
r(t) = \sum_{k=1}^{M} \sigma_{sk} e^{-\alpha \tau_k} e^{j\omega (t-\tau_k)} e^{-\gamma (t-\tau_k)^2}
\]

(4.13)

For \( \epsilon \) on the order of a period and \( t \gg \epsilon \) (far-field region), \( e^{-\alpha \tau_k} \approx e^{-\alpha t} \) and Equation 4.13 will simplify to:

\[
r(t) = e^{-\alpha t} \sum_{k=1}^{M} \sigma_{sk} e^{j\phi_k} \ ; \ \phi_k = (t-\tau_k)\omega
\]

(4.14)

Note that the random phase, \( \phi_k \), is governed by the random arrival time of echoes and is considered to be uniformly distributed from 0 to \( 2\pi \). Let's define

\[
Re^{j\theta} = \sum_{k=1}^{M} \sigma_{sk} e^{j\phi_k}
\]

(4.15)

Then,

\[
r(t) = Re^{j\theta} e^{-\alpha t}
\]

(4.16)

As shown in Figure 4.5 [38], the term \( Re^{j\theta} \) given in Equation 4.15 can be resolved to \( X \) and \( Y \) components:

\[
X = \sum_{k=1}^{M} X_k = \sum_{k=1}^{M} \sigma_{sk} \cos \phi_k
\]

(4.17)
Figure 4.5. A Random Phasor Sum in the Complex Plane[49]
In practice, the number of scatterers under the illumination of the transducer is very large and they are considered to be independent and identically distributed (i.i.d). Therefore, according to central limit theorem, for large $M$, $X$ and $Y$ are normally distributed. The mean of random variable $X$ and $Y$ is:

$$E[X] = E[E[\sum_{i=1}^{M} \sigma_{s_k} \cos \phi_k]]$$

(4.19)

$$E[Y] = E[E[\sum_{i=1}^{M} \sigma_{s_k} \sin \phi_k]]$$

(4.20)

Since the random variables $M$, and $\sigma_{s_k}$ and $\phi_k$ are considered to be independent, and $\phi_k$ is uniformly distributed over the range $(0,2\pi)$, the expected value of the random variables $X$ and $Y$ are zero. The variances of $X$ and $Y$ are [38]:

$$\sigma_X^2 = \sigma_Y^2 = \frac{1}{2} E[M] \cdot E[\sigma_{s_k}^2] = \sigma^2.$$  

(4.21)

Furthermore, it can be proven that $X$ and $Y$ are uncorrelated:

$$E[XY] = E[X] \cdot E[Y] = 0.$$  

(4.22)

Although from theoretical points of view [66], the two random variables are marginally normal and may not imply the jointly normal even for the mutually independent cases. For practical application, the strictly mathematical conditions may not be necessary to hold. Therefore, we can assume the joint probability density of $X$ and $Y$ are jointly normal and can be represented as:

$$f_{XY}(x, y) = f_X(x)f_Y(y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right).$$

(4.23)
The distribution of the amplitude of the backscattered grain signal, \( f_R(r) \), can be achieved by using the following relationships [38]:

\[
X = R \cos \theta \tag{4.24}
\]

\[
Y = R \sin \theta \tag{4.25}
\]

\[
f_R(r) = \int_0^{2\pi} f_{R\theta}(r, \theta) d\theta \tag{4.26}
\]

and that is:

\[
f_R(r) = \frac{2r}{\eta} e^{-\frac{r^2}{\eta}} \tag{4.27}
\]

where

\[
\eta = E[M] \cdot E[\sigma^2_s]. \tag{4.28}
\]

Equation 4.27 is referred to as the Rayleigh probability density function in the literature. Actually, John William Strutt Rayleigh [62] actually derived this distribution function differently and certainly without the use of the probability theory method. This function has the desirable characteristic that it can be defined by one parameter \( \eta \). The mean, second moment, and the variance of this distribution in terms of \( \eta \) are:

\[
E[r] = \frac{\sqrt{\pi \eta}}{2}, \quad E[r^2] = \eta, \quad \sigma_r^2 = [1 - \frac{\pi}{4}]\eta. \tag{4.29}
\]

The validity of this theoretical derivation is examined experimentally based on the amplitude histogram of the backscattered grain signal from steel samples (type 1018) of different grain sizes. Prior to constructing this histogram, the grain signal was filtered by an envelope detector and normalized by removing the effect of attenuation. Figure 4.6 shows the histogram of the grain signal backscattered from two different steel samples with grain sizes of 14\( \mu m \) and 50\( \mu m \). As shown in
Figure 4.6. Amplitude Histogram of Grain Signals, a) Steel, and b) Steel-2000
this figure, the histograms (solid line) fit the Rayleigh probability density function (dash line) very closely. These results represent a sample of many observations of similar behavior. It should be noted that although our experimental results show a close fit to Rayleigh distribution, in practice, this may not always be the case for scattering properties of various microstructures of materials. A similar study has been carried out on radar clutter [45, 46], and a broad range of probability density functions of scattering cross sections have been reported.

One of the objectives of evaluating the backscattered signal is to extract the attenuation coefficient. Equation 4.26 indicates that the measured signal, $r(t)$, has a random pattern and attenuation can only be obtained by performing some sort of averaging. Using Equations 4.27 and 4.28, the expected value of the amplitude of the backscattered signal will result in:

$$E[r(t)] = \frac{e^{-\alpha t}}{2} \sqrt{E(M) \cdot E(\sigma^2)} \pi = C_1 \cdot e^{-\alpha t} \tag{4.30}$$

Inspection of Equation 4.30 reveals that the expected grain signal is attenuated exponentially as a function of time and the intensity is proportional to the grain scattering cross section. Based on the above equations, the attenuation coefficient can be obtained by ensemble averaging of the grain signals at a given time. In general, a better estimate of the attenuation coefficient can be obtained by estimating $E[r(t)]$ through ensemble averaging at many different times and applying linear regression after logarithmic transformation. The overall system of estimating the attenuation coefficient is shown in Figure 4.7. The key to the accuracy of estimating the measurement is the effectiveness of the averaging operation. In the following chapters, a mathematical analysis of two techniques—spatial and temporal—for obtaining the expected value of the grain signal is presented along
Figure 4.7. System Block Diagram for Attenuation Measurements
with the discussion of the effectiveness of the average operation and the comparison of these two equivalent approaches. One of the objectives of this part of the work is to evaluate grain echoes using a single A-scan rather than to average multiple measurements obtained by changing the position, orientation, or frequency of the transducer [22, 23]. The single A-scan is more practical and efficient for ultrasonic testing [24]. In fact, in some situations, the geometry of the object interferes with or prohibits the use of multiple measurements. Furthermore, if the penetration of the ultrasonic energy is position–or orientation–dependent, an assessment of this variation is necessary and must be compensated prior to averaging. Finally, and most importantly, the use of a single measurement reveals information confined to a smaller region of the sample relative to the average of multiple measurements, which displays integrated information pertaining to a broader region of the sample.
5.1 Introduction

Insonification of the microstructure of materials results in a backscattered signal consisting of multiple interfering echoes with random amplitudes and phases. Information pertaining to grain-scattering cross section and grain size distribution is an inherent property of the backscattered signal. The importance of grain size estimation has long been recognized in examining many inherent mechanical properties such as strength and toughness [39,40], and the magnetic properties of some materials [41,42]. Among the various methods for evaluating the microstructure of materials, the utilization of the ultrasonic backscattered signal has been proven to be a simple and efficient method of nondestructive testing. Most studies dealing with ultrasonic microstructure evaluation are based on comparison of the attenuation coefficient of specimens with unknown grain sizes to specimens with known grain sizes under similar experimental conditions. The attenuation measurement is generally accomplished either by comparing the front and back surface echoes of a specimen of known thickness using the pulse-echo mode, or by comparing the intensity of the pulse through the unknown specimen with that of the calibrated specimen using the transmission mode. The backscattered grain echoes are random signals which bear information related to the attenuation properties of the materials. The variation of attenuation as a function of position represents statistical changes in the scattering cross section and absorption properties of grains. Some earlier research efforts have been directed at characterizing the statistical relationships between the energy of the ultrasonic propagation wave and the local
variation of the scatterers. Beechman [19] was able to demonstrate that the attenuation of backscattered echoes with depth is related to the average grain size of the specimen. Aldridge [20] confirmed Beechman's results and concluded that, the distribution of grain-scattering cross section can be obtained through multiple measurements of non-overlapping scattering regions. Fay [21] and Goebbels et al. [5, 22, 23] further improved this idea to more accurately determine the expected amplitude of the backscattered echoes with respect to depth by utilizing various averaging techniques, namely, spatial, directional and frequency averaging. Saniie and Bilgutay [24] demonstrated various grain size characterization techniques that extract parameters from the backscattered signal related to the frequency-dependent attenuation coefficient.

In this chapter, a statistical comparison of the time averaging method accomplished using a single A-scan and ensemble averaging, which requires multiple measurements obtained by changing the position of the transducer, is presented. The backscattered grain signal is represented by a mathematical model that is proposed in previous chapter and is used for obtaining the ultrasonic attenuation coefficient. Correlation effects on the performance of attenuation estimation and the local variation of attenuation coefficients are discussed. Finally, both ensemble and time averaging are implemented for characterizing the grain size in steel samples.

5.2 Grain Attenuation

When an ultrasonic burst of sound travels through an inhomogeneous materials, its amplitude is attenuated as:

\[ A = A_0 e^{-\int_0^Z \alpha(z_f)dz} \]  

(5.1)
where $A_0$ is the initial amplitude, $A$ is the amplitude at the given position $z$ corresponding to time $t$, and $\alpha(z, f)$ is the position and frequency-dependent attenuation coefficient. If materials exhibit homogeneous properties as a function of position $z$, the above equation can be simplified to:

$$A = A_0 e^{-\alpha(f)z} \tag{5.2}$$

where $\alpha(z, f) = \alpha(f)$. In general, The attenuation coefficient has two major causes:

$$\alpha(f) = \alpha_a(f) + \alpha_s(f) \tag{5.3}$$

where the term $\alpha_a(f)$ is a hysteresis loss caused mainly by the inelastic behavior of the materials, and the term $\alpha_s(f)$ is a scattering loss mainly associated with the characteristics of grain and phase boundaries (acoustical impedance discontinuities). In many practical situations, grain-scattering loss at ultrasonic frequencies is so large relative to the hysteresis loss that the latter is negligible. The scattering formulas have been studied and classified into distinct scattering regions according to the ratio of the sound wavelength $\lambda$ to the mean grain diameter $\bar{D}$ [7, 10, 13]. The functions are tabulated in Table 5.1.

In this study, experiments were conducted in the Rayleigh scattering region. Details concerning the scattering constants (i.e., the constants $a_1$, $a_2$, $a_3$ as shown in Table 5.1) for both cubic and hexagonal grains can be found in the paper by Papadakis [2,7]. Among the three scattering regions, the Rayleigh scattering region ($\lambda \gg \bar{D}$) exhibits the most sensitivity to the frequency and grain size distribution. In addition, the multiple scattering is considered to be negligible, which simplifies the localization of scatterers and their scattering properties.

With the assumptions and the derivations made in Chapter 4, the amplitude of the received grain signal is of the Rayleigh probability density function. The
Table 5.1. Scattering Coefficients as Function of Grain Diameter and Frequency.

<table>
<thead>
<tr>
<th>Scattering Region</th>
<th>Scattering Functions</th>
<th>Relationships</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rayleigh</td>
<td>$C_1 D^3 f^4$</td>
<td>$\lambda \gg D$</td>
</tr>
<tr>
<td>Stochastic</td>
<td>$C_2 D f^2$</td>
<td>$\lambda \approx D$</td>
</tr>
<tr>
<td>Diffusive</td>
<td>$C_3 / D$</td>
<td>$\lambda \ll D$</td>
</tr>
</tbody>
</table>
expected value of the grain signal has an attenuation factor, and it can be extracted by performing some sort of average.

\[
E[r(t)] = \frac{e^{-at}}{2} \sqrt{E(M) \cdot E(\sigma_s^2) \pi} = C_1 \cdot e^{-at}.
\] (5.4)

Inspection of Equation 5.4 reveals that the expected grain signal is attenuated exponentially as a function of time and the intensity is proportional to the grain-scattering cross section. Based on the above equations, the attenuation coefficient can be obtained from the ensemble average of the grain signals at a given time. In the following sections we present the mathematical analysis of two averaging techniques - spatial and temporal - for obtaining the expected value of the grain signal.

5.3 Spatial Averaging

Spatial averaging is a method for characterizing attenuation as a function of position. This can be accomplished by scanning the specimen and averaging the rectified backscattered signals. Let's assume that averaging of \( N \) measurements at \( N \) different positions of the specimen is performed,

\[
\langle r(t) \rangle = \frac{1}{N} \sum_{i=1}^{N} \hat{r}_i e^{-at}
\] (5.5)

where \( \hat{r}_i e^{-at} \) is the rectified backscattered signal measured at a given position \( i \). In general, for homogeneous materials, the signal amplitude is wide-sense stationary which implies:

\[
E[\hat{r}_i] = m
\] (5.6)

\[
E[\hat{r}_i \hat{r}_j] = R_s(k) \quad \forall k = |i - j|
\] (5.7)
Except for the scaling factor, $m$, Equation 5.5 is an unbiased estimator of attenuation:

$$E[(r(t))] = me^{-at}. \quad (5.8)$$

Furthermore, using Equations 5.6-5.8, the variance of $(r(t))$ can be determined,

$$\sigma^2_{(r(t))} = e^{-2at}\frac{\sigma^2_{\tau}}{N} + e^{-2at}\frac{1}{N^2} \sum_{k=1}^{N-1} \{2(N-k)(R_s(k) - m^2)\}. \quad (5.9)$$

If the spacing between measurements is large, the ensemble measurements will be uncorrelated. Hence,

$$R_s(k) = n^2, \quad k \neq 0 \quad (5.10)$$

and

$$\sigma^2_{(r(t))} = e^{-2at}\frac{\sigma^2_{\tau}}{N}. \quad (5.11)$$

In the above equation, as $(N \to \infty)$, the term $\sigma^2_{(r(t))} \to 0$. This is the condition for obtaining a consistent estimate of $(r(t))$. In practice, the ensemble measurements are not necessarily uncorrelated ($R_s(k) \neq m^2$) and, consequently, the effective number of independent averagings is expected to be less than the actual value of $N$.

### 5.4 Time Averaging

Another practical approach to ensemble averaging is time domain averaging. The grain signal is a stochastic process in which randomness is inherent to any single measurement. The temporal fluctuations contain equivalent information to the random spatial fluctuations; therefore, it is appropriate to determine the statistical parameters (e.g., mean and variance) of the process from a single measurement, which is far more practical than using multiple measurements. This
approach is valid when using stationary random processes in which time averages are identical to their ensemble averages (i.e., ergodic process[66]).

Time averaging is accomplished by averaging samples of the rectified grain signal taken at time \( t + \Delta t, \ldots, t + N \Delta t \), such that,

\[
\overline{r(t)} = \frac{1}{N} \sum_{i=1}^{N} \hat{r}_i e^{-\alpha(t+i\Delta t)} \tag{5.12}
\]

where \( \hat{r}_i \) is the amplitude of unattenuated signal corresponding to given time \( t+i\Delta t \). In the above equation, the sum represents averaging of \( N \) random variables weighted by \( e^{-\alpha \Delta t} \). The \( \hat{r}_i \) is a stationary random process and the expected value of Equation 5.12 becomes:

\[
E[\overline{r(t)}] = \frac{e^{-\alpha t}}{N} m \sum_{i=1}^{N} e^{-\alpha i \Delta t} \tag{5.13}
\]

where \( m = E[\hat{r}_i] \). Let's assume the integration period, \( T \), is equal to \( N \Delta t \), and the term \( T \) remains constant as \( N \to \infty \). Then, Equation 5.13 is simplified to:

\[
E[\overline{r(t)}] = e^{-\alpha t} (E[\hat{r}]) \cdot \frac{1 - e^{-\alpha T}}{\alpha T}. \tag{5.14}
\]

Once \( T \) is defined, the term \( \frac{1 - e^{-\alpha T}}{\alpha T} \) becomes a known constant. Similar to spatial averaging, time domain integration of the amplitude signal is equal to the attenuation factor, \( e^{-\alpha t} \), multiplied by a constant (Equation 5.14). Therefore, time averaging (Equation 5.12) is an unbiased estimator of the attenuation. The accuracy of the estimation is highly dependent on the value of \( \frac{\sigma^2}{\overline{r(t)}} \).

Let's define the temporal autocorrelation of the sampled signal as,

\[
R_t(|i - j|) = E[\hat{r}_i \hat{r}_j] \tag{5.15}
\]
then, the second moment of \( \overline{r(t)} \) can be represented in terms of the autocorrelation functions:

\[
E[\overline{r(t)}^2] = \frac{1}{N^2} E[\sum_{i=1}^{N} \sum_{j=1}^{N} r_i r_j] = \frac{e^{-2\alpha t}}{N^2} Z^T R \cdot Z
\]  

(5.16)

where,

\[Z = (e^{-\alpha \Delta t}, \ldots, e^{-\alpha N \Delta t})^T\]

and

\[
R = \begin{pmatrix}
R(0) & R(1) & R(2) & \ldots & R(N-1) \\
R(1) & R(0) & R(1) & \ldots & R(N-2) \\
R(2) & R(1) & R(0) & \ldots & R(N-3) \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
R(N-1) & R(N-2) & R(N-3) & \ldots & R(0)
\end{pmatrix}
\]

so,

\[
E(\overline{r(t)}^2) = \frac{e^{-2\alpha t}}{N^2} \{R(0) \sum_{i=1}^{N} e^{-2\alpha i \Delta t} + \sum_{i=1}^{N} \sum_{j=1}^{N} e^{-\alpha(i+j) \Delta t} R(|i-j|)\}
\]

(5.17)

The variance of \( \overline{r(t)} \) is:

\[
\sigma^2_{\overline{r(t)}} = \frac{e^{-2\alpha t}}{N^2} \cdot \left( \sum_{i=1}^{N} e^{-2\alpha i \Delta t} \right) + \sum_{i=1}^{N} \sum_{j=1}^{N} e^{-\alpha(i+j) \Delta t} (R(|i - j|) - E^2[r_i])
\]

(5.18)

define

\[R(|i - j|) - (E[r_i])^2 = \sigma^2_{\overline{r_i}}(k)
\]

(5.19)
Consider the second sum;

\[
\sum_{i=1}^{N} \sum_{j=1}^{N} e^{-\alpha(i+j)\Delta t} \sigma_{\epsilon o}^2(|i - j|)
\]

\[
= 2 \sum_{k=1}^{N-1} \sum_{i=1}^{k} e^{-\alpha(N-k+2i)\Delta t} \sigma_{\epsilon o}^2(N - k)
\]

\[
= \sum_{k=1}^{N} \sigma_{\epsilon o}^2(N - k)e^{-\alpha(N-k)\Delta t} \sum_{i=1}^{k} e^{-2\alpha i\Delta t}
\]

\[
= \frac{2e^{-2\alpha\Delta t}}{(1 - e^{-2\alpha\Delta t})} \sum_{j=1}^{N-1} \sigma_{\epsilon o}^2(j)[e^{-\alpha j\Delta t} - e^{-2\alpha N\Delta t + j\Delta t}]
\]

so the variance;

\[
\sigma_r^2 = \frac{e^{-2\alpha t}}{N^2} \cdot \left\{ \sigma_{\epsilon o}^2 \sum_{i=1}^{N} e^{-2\alpha i\Delta t}
\right\}
\]

\[
+ \sum_{i=1}^{N} \sum_{j=1}^{N} e^{-\alpha(i+j)\Delta t}(R_i(|i - j|) - m^2)
\]

where \(\sigma_{\epsilon o}^2\) is the variance of \(\epsilon_i\). Let's define,

\[
\sigma_{\epsilon o}^2(k) = R_i(|i - j|) - m^2.
\]

Hence, the variance can be rewritten as:

\[
\sigma_r^2 = \frac{e^{-2\alpha t}}{N^2} \cdot \left\{ \sigma_{\epsilon o}^2 \sum_{i=1}^{N} e^{-2\alpha i\Delta t}
\right\}
\]

\[
+ \frac{2e^{-2\alpha\Delta t}}{1 - e^{-2\alpha\Delta t}} \sum_{k=1}^{N-1} \sigma_{\epsilon o}^2(k)(e^{-\alpha k\Delta t} - e^{-2\alpha N\Delta t + k\Delta t\alpha})
\]  

(5.23)

If the sample values are uncorrelated, the term \(\sigma_{\epsilon o}^2\) becomes zero for all \(k\).

Under this condition, the variance of the estimation simplifies to:

\[
\sigma_r^2 = \frac{\sigma_{\epsilon o}^2}{N} \cdot \frac{e^{-2\alpha t}(1 - e^{-2\alpha T})}{2\alpha T}.
\]

(5.24)
If \( N \to \infty \), and \( \frac{\sigma^2}{r(t)} \to 0 \) then the estimation becomes consistent. It is important to point out that for a small value of \( \alpha T \), the mean and variance associated with temporal averaging becomes identical to spatial averaging. This equality is only true with conditions of ergodicity, stationarity, and when using uncorrelated observations. As with spatial averaging, the effective number of time averages is less than the actual value of \( N \) when the sampled values of the signal are correlated. Furthermore, the accuracy or reliability of time averaging is highly dependent on the choice of \( T \). From an analytical point of view, the larger the value of \( T \), the better the estimate can be. But when \( T \) is assigned a large value, signal attenuation becomes significant, causing poor signal-to-noise ratio, which will introduce error in the estimation.

5.5 Temporal and Spatial Averaging Results

The object of this work is to evaluate the grain size variation in solids when other physical parameters (e.g., crystal shape, elastic constants, density, and velocities) remain constant. These assumptions allow us to accurately interpret the measurements resulting from the grain size variation. In this study, Type 1018 steel blocks (4\( \times \)4\( \times \)10 inches) were heat treated for four hours to obtain various grain sizes. Type 1018 steel sample has an average grain size of 14\( \mu \)m prior to heat treatment and the grain size increases to 24\( \mu \)m and 50\( \mu \)m with heat treatment at 1700\( ^{\circ} \)F and 2000\( ^{\circ} \)F, respectively.

The experimental grain signal measurements were accomplished using a Gamma type transducer manufactured by K-B Aerotech with approximately a 5-MHz center frequency and 3-dB bandwidth of approximately 1.5 MHz. The RF signal was sampled at 100 MHz with 8-bit resolution. All measurements were carried out
using an immersion technique with the specimens being placed in the far fields of the transducer. The transducer aperture is 0.5 inch and, therefore, significant spacing between measurements is required for obtaining uncorrelated data. The scanning area is square-shaped, covered by a 16x16 grid. Figure 5.1 shows spatial averaging results corresponding to various scanning areas: 0.5x0.5, 0.75x0.75, 1.0x1.0, and 2.0x2.0 inches. All measurements clearly display the effect of attenuation in the signal. It should be noted that there is more variation in the rate of decay in data corresponding to smaller scan areas (e.g., 0.5x0.5 inches) than the larger areas (e.g., 2.0x2.0 inches). This is due to the higher degree of correlation between measurements when using a small area of scanning. For different grain size samples, the attenuation coefficient was estimated using the procedure described earlier in Figure 4.7. The grain signal used for estimating the attenuation coefficient represents scattering characteristics in the region between 0.40 and 2.75 inches from the front surface of the specimen. Consistent estimates of attenuation coefficients (i.e., ±5% variation) are obtained within a 2.0x2.0-inch scanning area.

A comparison of ensemble averaging results corresponding to samples of various grain sizes is shown in Figure 5.2. The four measurements shown in this figure were obtained under identical experimental conditions (i.e., the position of transducer with respect to samples, the angle of incident beam, and the pulser, receiver and digitizer adjustments) using ensemble averaging of 2 x 2-inch scanning area of specimen covered by 16 x 16 grids. The top three traces represent the ensemble averaging of backscattered signals corresponding to different grain sizes. The lower trace is the system noise level in the absence of the grain signal. The duration of the signals are 20μs while the starting points are 3.5μs away from the front surface echoes. These signals provide information corresponding to a region between 0.40 to 2.75 inches inside the steel samples. As evident from Figure 5.2, the samples with larger grain sizes scatter echoes of larger intensity compared to
Figure 5.1. Comparison of the Backscattered Grain Signals Using Different Scanning Area for Spatial Averaging
Figure 5.2. Spatial Averaging of Backscattered Ultrasonic Signals from Steel Samples with Different Grain Sizes
Table 5.2. Estimated Attenuation Coefficients for Different Grain Sizes.

<table>
<thead>
<tr>
<th>Steel</th>
<th>Heat-Treated Temp. (°F)</th>
<th>Estimated Grain Size (μm)</th>
<th>Estimated Attenu. Coeff. (db/cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Steel</td>
<td></td>
<td>14</td>
<td>0.6226</td>
</tr>
<tr>
<td>Steel-1700</td>
<td>1700</td>
<td>24</td>
<td>0.8252</td>
</tr>
<tr>
<td>Steel-2000</td>
<td>2000</td>
<td>50</td>
<td>1.139</td>
</tr>
</tbody>
</table>
samples of smaller grain sizes. In general, the intensity of the backscattered signal can be correlated with the grain size, although, one must be aware that this intensity is highly dependent on the geometry of the specimen and the beam angle of incidence. Furthermore, all three traces of the grain signals display attenuation effects. The estimates of the attenuation coefficients in the steel samples obtained using spatial averaging is presented in Table 5.2. The attenuation coefficients are estimated by utilizing the entire 2048 data points and applying the steps involved in the model shown in Figure 4.7.

Through extensive experimentation and evaluation of the backscattered grain signal, we have observed that the attenuation coefficient is position-dependent, which creates ambiguity in the interpretation of the results. An experimental evaluation of this problem is discussed later. Nevertheless, the graphical results shown in Figure 5.2 and the numerical values presented in Table 5.2 indicate the feasibility and potential of attenuation measurement as a method for nondestructive grain size characterization.

A similar study has been performed using temporal averaging. As discussed in the theoretical section, the number of samples and sampling intervals are essential in obtaining consistent averaging results. To evaluate temporal averaging performance, window lengths between 64 to 512 samples were examined. Experimental results of the time averaging using different window sizes are shown in Figure 5.3. It should be noted that with temporal averaging there is significant variation in the rate of decay corresponding to smaller window sizes. Estimating the attenuation coefficient using temporal averaging based on the methods shown in Figure 4.7 appears to be consistent to within ±10%. These observations suggest that temporal averaging is a good substitute for spatial averaging. For the steel specimens examined, results of spatial and temporal averaging have been very similar. An
Figure 5.3. Temporal Averaging of Ultrasonic Signal Using Different Window Length
example is shown in Figure 5.4. In general, using a single A-scan is more practical and efficient for ultrasonic testing. In fact, in some situations, the geometry of the object interferes with or prohibits the use of multiple measurements. Furthermore, if the penetration of ultrasonic energy is position- or orientation-dependent, an assessment of this variation is necessary and must be compensated for prior to averaging. Finally, and most importantly, the use of a single measurement reveals information confined to a smaller region of the sample relative to the average of multiple measurements which displays integrated information pertaining to a broader region of the sample.

5.6 Correlation Effects

As discussed earlier, for both temporal and spatial averaging, correlation among repeated measurements plays an important role in the effectiveness of the smoothing process. This fact can be confirmed by the basic principles of information theory [44]. The average mutual information between measurement \( X \) and measurement \( Y \) is given by,

\[
I(X;Y) = H(X) - H(X|Y)
\]

where \( H(X) \) is the average self information (entropy) of measurement \( X \), and \( H(X|Y) \) is the conditional information of measurement \( X \) when measurement \( Y \) has already been carried out. If measurement \( X \) is independent of measurement \( Y \), then, the average mutual information \( I(X;Y) = 0 \), and conditional entropy \( H(X|Y) \) for measurement \( X \) given measurement \( Y \) is equal to the information provided by measurement \( X \). In order to illustrate the measurement performance
Figure 5.4. A Comparison of Spatial Averaging and Temporal Averaging
in terms of the self-information provided by the individual measurement, we introduce the effective number of independent measurements $N_e$, defined as:

$$N_e = \frac{\text{Variance at the averager input}}{\text{Variance at the averager output}}$$

(4.26)

If all measurements are independent, $N_e = N$, then, the effect of the averager is to reduce the variance of the random averaging signal by a factor of $N$. If all measurements are completely correlated, then $N_e = 1$, and there is no reduction in the variance of the random averaging signal.

The correlation properties and the effective number, $N_e$, of the measured signals were examined. The estimated effective number, $N_e$, for both temporal and ensemble averaging is presented in Tables 5.3 and 5.4. In Table 5.3, the effective number was computed by using Equation 5.29, and the results were normalized by the actual number of measurements. We note that the normalized effective number of measurements becomes larger as the scanning area increases. This suggests that there is less correlation among grain signals if they are measured at positions farther apart. Similar conclusions can be reached in measurements involving temporal averaging. Table 5.4 shows the normalized effective number of measurements corresponding to different window lengths. As the integration time increases, the performance of averaging improves and the normalized effective number increases. It must be noted that since a high correlation exists between the successive sample values of the grain signal, the effective number is significantly smaller than the total number of sample values as shown in Table 5.4.

An evaluation of the autocorrelation (Equation 5.15) and the ensemble correlation (Equation 5.10) is shown in Figure 5.5. This figure supports the principle
Table 5.3. Performance of Spatial Averaging.

<table>
<thead>
<tr>
<th>Scanning Area</th>
<th>0.5 x 0.5 inches</th>
<th>0.75 x 0.75 inches</th>
<th>1.0 x 1.0 inches</th>
<th>2.0 x 2.0 inches</th>
<th>2.0 x 8.0 inches</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual N</td>
<td>256</td>
<td>256</td>
<td>256</td>
<td>256</td>
<td>1024</td>
</tr>
<tr>
<td>Var.(0.145)</td>
<td>0.017</td>
<td>0.015</td>
<td>0.006</td>
<td>0.002</td>
<td>0.0003</td>
</tr>
<tr>
<td>Effective N</td>
<td>8.6</td>
<td>9.6</td>
<td>24.5</td>
<td>58.5</td>
<td>437.7</td>
</tr>
<tr>
<td>Normalized Effective N</td>
<td>3%</td>
<td>4%</td>
<td>10%</td>
<td>22%</td>
<td>44%</td>
</tr>
<tr>
<td>Window Size (Actual N)</td>
<td>128</td>
<td>256</td>
<td>384</td>
<td>512</td>
<td></td>
</tr>
<tr>
<td>------------------------</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td></td>
</tr>
<tr>
<td>Var(0.145)</td>
<td>0.021</td>
<td>0.0032</td>
<td>0.0018</td>
<td>0.0011</td>
<td></td>
</tr>
<tr>
<td>Effective N</td>
<td>6.8</td>
<td>45.2</td>
<td>77.9</td>
<td>134.5</td>
<td></td>
</tr>
<tr>
<td>Normalized Effective N</td>
<td>5%</td>
<td>18%</td>
<td>21%</td>
<td>20%</td>
<td></td>
</tr>
</tbody>
</table>
Figure 5.5. Comparison of Temporal and Ensemble Correlation Functions
of ergodicity, since a great degree of similarity exists between the pattern of autocorrelation and ensemble correlation. Furthermore, both autocorrelation and ensemble correlation values are high for a small shift in position (e.g., within 0.1 inches), although beyond 0.2 inches the correlation drops as much as 80%. The correlation for data collected at positions farther apart fluctuates around 20%, which implies that the ratio of $N_f/N$ will not reach the ideal value of unity. Regardless of the low value for $N_f/N$, one can conclude that a spacing larger than 0.1 inches is desirable between sequential measurements. In fact, this condition was satisfied in the spatial averaging of a 2 x 2-inch area scanned using a 16 x 16 grid. For this situation, $N_f/N$ is about 25% which is far less than unity.

5.7 Grain Signal Attenuation Behavior

In the process of estimating the attenuation coefficient, we have observed that attenuation is position-dependent. The rate of decay of grain signal is initially large and drops as time proceeds. This suggests that the attenuation characteristic is not a simple exponential decay process at all, although such a model seems to be widely used.

Position-dependent attenuation cannot be related to the possible existence of multiple scattering since all the measurements are carried out in the Rayleigh scattering region where multiple reflections are generally negligible. There is no clear explanation for the existence of position-dependent attenuation, and this cannot be related to the variation in grain size with position since the steel samples used are homogeneous. There are reports [47,48] that suggest that the rate of decay of the backscattered signal is initially dominated by scattering effects, but with depth the effects of absorption become more dominant, which is less severe.
Another possible cause of position-dependent attenuation can be related to the diffraction property of the ultrasonic beam. Nevertheless, from a practical point of view, the estimation of the attenuation coefficient must be confined to a known region in order to more meaningfully characterize the grain size based on the presence of decay in the backscattered signal.

The experiments for examining the position-dependent attenuation coefficient were based on spatial averaging since it performs slightly better than time averaging. In order to evaluate the position-dependent attenuation coefficient, the attenuation coefficient was estimated using a data window which corresponds to a 0.6-inch segment of the specimen. This window was applied to the traces shown in Figure 5.2, and was shifted through the entire signal. The estimated attenuation coefficients via position of the window are shown in Figure 5.6. In the beginning of the estimate it is evident that the heat-treated steel sample with the smaller grain size (steel-1700) shows higher attenuation coefficient than the larger grain size sample (steel-2000). However, the attenuation of steel-1700 becomes less than the attenuation of steel-2000 at a later position. This inconsistent behavior in the estimation of the attenuation coefficients may be caused by inadequate data size, or by the high degree of variation in the characteristics of grain-scattering. A consistent estimate can be obtained by using larger window size. For example, Figure 5.7 shows the results when using data window size corresponding to 1.2 inches of the sample. In this figure, the sample with the larger grain size shows higher attenuation compared to the sample with the smaller grain size. All three samples exhibit a change in the rate of attenuation as a function of position. Further inspection of this figure reveals that, although the estimation at the starting position shows higher attenuation for the larger grain sample, this may not be the case at a later position (i.e., deeper in the sample). This behavior can be influenced by the microstructure of the material, as well as the transducer beamwidth, center
frequency and bandwidth, and the size of the estimation window. Therefore, it is important that this technique be carefully evaluated prior to its utilization in routine nondestructive testing.
Figure 5.6: Estimated Position-Dependent Attenuation Coefficient of Steel Sample Using 0.6 inch (1.5 cm) Window
Figure 5.1: Estimated Position Dependent Attenuation Coefficient of Steel Sample Using 1.2 inch (3.0 cm) Window
6.1 Introduction

A model for the grain signal with reasonable accuracy consists of a convolution of components representing the contributions of the measuring system impulse response (basic ultrasonic wavelet) and the grain scattering function. In order to quantitatively and effectively evaluate the inherent properties of the microstructure of the materials, it is desirable to isolate these two components. Conventional deconvolutions are performed by means of inverse filtering or optimum zero-lag Wiener filtering, which suffers from the limitation that either the shape of the ultrasonic wavelet must be known or the assumption must be made that the wavelet is minimum-phase [51, 52]. The homomorphic deconvolution, a procedure for separating the components of grain signal, is based on the approach of nonlinear filtering of signals which have been combined in a nonadditive fashion. Homomorphic processing offers the considerable advantage that no prior assumption about the nature of the ultrasonic wavelet or the impulse response of the transmission path need to be made. The ultrasonic wavelet that is recovered by homomorphic deconvolution is of importance in studies of regional attenuation and frequency dispersion in the backscattered grain signal spectrum.

This chapter contains an evaluation of the techniques, homomorphic processing and moment analysis. These techniques are capable of estimating frequency shift resulting from grain scattering and attenuation in the power spectrum. Both
computer simulated data and experimental measurements are used for evaluating the performance of these techniques.

A model for the expected amplitude of the backscattered signal, $A_b$, corresponding to a given position $z$, is [70]:

$$A_b = A_o \alpha_s(z, f) e^{-\int_0^z \alpha(z, f) dz} \quad (6.1)$$

where $A_o$ is the initial amplitude, $\alpha_s(z, f)$ is the position and frequency-dependent scattering coefficient and $\alpha(z, f)$ is the overall attenuation coefficient. If materials exhibit homogeneous properties as a function of position $z$, then, Equation 6.1 can be simplified to:

$$A_b = A_o \alpha_s(f) e^{-\alpha(f)z} \quad (6.2)$$

where $\alpha(z, f) = \alpha(f)$ and $\alpha_s(z, f) = \alpha_s(f)$. Note that the attenuation coefficient $\alpha(f)$ is caused by the scattering coefficient $\alpha_s(f)$ and absorption $\alpha_a(f)$:

$$\alpha(f) = \alpha_a(f) + \alpha_s(f) \quad (6.3)$$

In general, grain scattering losses are large compared to absorption losses. The scattering coefficient has been classified based on the ratio of sound wavelength, $\lambda$, to the mean grain diameter, $D$ [17]. For the situation where $\lambda > D$ (Rayleigh scattering region) the scattering coefficient varies with the average volume of the grain ($D^3$) and the fourth power of ultrasonic wave frequency, while absorption is increased linearly with the frequency. Hence, the attenuation coefficients can be represented in terms of grain size and frequency:

$$\alpha(f) = a_1 f + a_2 D^3 f^4 \quad (6.4)$$

where $a_1$ is the absorption constant, $a_2$ is the scattering constant, and $f$ is the wave frequency. Note that, for the scattering region in which the wavelength is
of the same order as the grain diameter (Stochastic region), or is larger than the grain diameter (Diffusion region), the scattering coefficient is far less sensitive to the grain size or to the frequency [2].

The overall $a_s$ behavior as a function of the normalized grain diameter ($\frac{D}{\lambda}$) is shown in Figure 6.1 [50, 71]. Among the three scattering regions, Rayleigh scattering is of primary concern where multiple reflections between grain boundaries are negligible and $a_s(f)$ shows high sensitivity to the grain size variation. In the Rayleigh scattering region, high frequency components are backscattered with large intensity compared to low frequency components. Consequently, this situation results in an upward shift in the expected frequency of the power spectrum of broadband echoes. In fact, the frequency upward shift behavior can be verified, and results are presented in the experimental section. Since the degree of the spectral shift is grain size dependent, an estimate of upward shift can be used for grain size characterization. Furthermore, inspection of Equation 6.1 reveals that, the term $e^{-a(f)x}$ influences the frequency shift in a downward direction. The downward shift is dependent on the position of the scatterers relative to the transmitting/receiving transducer. Therefore, a family of curves, as shown in Figure 6.2 for different positions of scatterers, must be considered for frequency shift evaluation. The two opposing phenomena (i.e., upward shift due to scattering and downward shift caused by attenuation) can be utilized to our advantage for grain size evaluation. Estimating frequency shift can only be achieved from random patterns of grain echoes, and this is a challenging task. Nevertheless, techniques such as homomorphic processing and moment analysis can be used to quantize the frequency shift in the power spectrum in order to perform correlation studies between the estimated frequency shift and the variation existing in the material's microstructure.
Figure 6.1. The Overall Scattering Behavior as a Function of the Normalized Grain Diameter ($\frac{D}{\lambda}$)
Figure 6.2. The Attenuation Behavior as a Function of the Frequency and Position.
6.2 Spectral Analysis

The grain signal (see Equation 4.2) from a given region of the specimen (e.g., j-th region) can be modeled as a convolution of the mean ultrasonic wavelet, \(< u_j(t) >\), and grain characteristic function, \(g_j(t)\):

\[
r_j(t) = < u_j(t) > * g_j(t)
\]  
(6.5)

where

\[
g_j(t) = \sum_{k=1}^{N_j} A_{kj} \delta(t - \tau_{kj}) \]  
(6.6)

The term \(< u_j(t) >\) represents the mean shape of the echo (i.e., impulse response of the transducer or wavelet) within the j-th region of the sample. The shape of this function is governed by transfer functions of the ultrasonic pulser, transmitting and receiving transducers, amplifier, and the variable propagation path characteristics. Since the measuring system characteristics are fixed, any change in the ultrasonic wavelet is indicative of the acoustical properties of the propagation path. In the above equations, the random variable \(N_j\) represents the number of scatterers in the j-th region, the random variable \(A_{kj}\) represents the scattering cross section of grains caused by the quality of grain boundaries, shape, size and the proportionality of chemical constituents [2]. The random variable \(\tau_{kj}\) represents the random position of the grain scattering centers in the j-th region of the specimen.

The spectrum of the measured data corresponding to the j-th region can be obtained by Fourier transforming Equation 6.5:

\[
R_j(f) = G_j(f) < U_j(f) >
\]  
(6.7)
where

\[ G_j(f) = \sum_{k=1}^{N_j} A_{kj} e^{-2\pi if\tau_{kj}} \]  

(6.8)

The grain transfer function \( G_j(f) \) has a complicated form consisting of random amplitudes and phases corresponding to highly complex grain structures. This function modulates and distorts the magnitude spectrum of the wavelet, \( < U_j(f) > \), which results in the change of the frequency contents. Since the spectral distortion bears information related to the unknown physical characteristics of the specimen such as grain sizes, it is possible to classify the samples with different grain sizes by quantitatively evaluating the spectral appearance.

The term \( R_j(f) \) consists of random patterns and an estimation of \( < U_j(f) > \) from \( R_j(f) \) and can only be achieved by performing some sort of smoothing operation. For example, measuring many signals and performing ensemble averaging of the power spectra can result in an estimation of the power spectrum of the wavelet. Ensemble averaging is an effective method but not practical. Therefore, any alternative method which is capable of smoothing of \( R_j(f) \) with reasonable accuracy is always desirable.

The frequency spectrum of the ultrasonic wavelet can be extracted from the measured signal through homomorphic processing [24]. The homomorphic wavelet recovery system is shown in Figure 6.3. As shown in this figure, the magnitude spectrum of the grain signal is obtained by Fourier transforming the backscattered signal. The logarithmic operator is used for converting the multiplicative relationship between the wavelet and the grain impulse response to the additive relationship. The inverse Fourier transformation results in the grain signal power cepstrum, \( \hat{r}_j(t) \). The wavelet power cepstrum generally has a time width that is
Figure 6.3. Homomorphic Wavelet Recovery System.
narrower than that of the grain impulse response. Therefore, when a shortpass window (i.e., shortpass lifter) of a duration equivalent to the echo duration is applied to the grain signal power cepstrum, the power cepstrum of the wavelet can be recovered. Finally, the Fourier transform of the wavelet’s power cepstrum will result in a Log spectrum and when an exponential operation is performed at this stage, it generates the magnitude spectrum of the ultrasonic wavelet. The recovered magnitude spectrum of the wavelet can be used to estimate frequency shift for grain size characterization. Note that a challenge aspect of the homomorphic wavelet recovering system is the design of the shortpass lifter. An evaluation of such a design is presented in the computer simulation section.

A comparison of the regional estimate of an ultrasonic wavelet results in an estimation of frequency-dependent attenuation. For example, from knowledge of an ultrasonic wavelet corresponding to two successive regions of the specimen separated by $\Delta d$, the frequency-dependent attenuation coefficient can be estimated [24]:

$$\alpha_j(f) = \frac{\log|<U_j(f)>| - \log|<U_{j+1}(f)>|}{\Delta d}$$

(6.9)

An alternative method is moment analysis, which is simple to implement and has the potential to characterize the presence of a frequency shift in an ultrasonic backscattered signal is moment analysis [38]. A generalized definition for moments is given:

$$\bar{M}_{KL} = \frac{\int_0^\infty f^K |R_j(f)|^L df}{\int_0^\infty |R_j(f)|^L df}$$

(6.10)

Due to the integrating operation which is inherent to moment estimation, the contribution of the random pattern of the power spectrum to moment values is less noticeable compared to the effect of a frequency shift. A confirmation of this statement has been evaluated using extensive computer simulation (results
are presented later). When \( L = 1 \) and \( K \) is a positive integer, then \( \overline{M_{1K}} \) is the \( K \)th moments of the magnitude spectrum according to the common definition of moments. In general, \( K \) and \( L \) can be any real number. The usefulness of the above equation becomes apparent only if the moment results show enough correlation to an unknown physical characteristic such as the grain size. For the special case in which \( K = 1 \) and \( L = 2 \),

\[
\overline{M_{12}} = \frac{\int_0^\infty f |R_j(f)|^2 df}{\int_0^\infty |R_j(f)|^2 df}
\]  

(6.11)

the \( \overline{M_{12}} \) is referred to as the power spectrum centroids. In one earlier study [6], the examination of the moment values (\( K=1, 2, 3, \) and \( L=1, 2, 3, 4 \)) revealed that no specific feature in the magnitude spectrum (e.g., a forbidden band of frequency or an enlarged frequency component) existed. Therefore, no unusual value has been observed (either very large or very small) for the moments of a higher order of weighing. In addition, a noticeable correlation has been found to exist among moments corresponding to different values of \( K \) and \( L \). Hence, it becomes evident, for our present studies, that one moment (e.g., power spectrum centroids) is adequate for quantizing the magnitude spectrum.

### 6.3 Computer Simulation

The object of computer simulation is to reproduce grain signals with the same behavior of random multiple interfering echoes and frequency content as the measured grain signal. Then the simulated grain signal can be utilized to examine the effectiveness and sensitivity of homomorphic processing. The grain signal is simulated by superimposing multiple echoes with random positions and random amplitudes. It is assumed that the mean ultrasonic wavelets are Gaussian in shape with center frequencies 4, 4.5 and 5 MHz and 3 dB bandwidths of 1.25, 1.5 and
1.70 MHz, respectively. The entire generated signal is made up of 2048 points with a 100 MHz sampling rate. It is also assumed that about 512 random echoes will be detected by the transducer in the duration of 20 μs of the backscattered signal. To depict the intensity of the detected echoes, a random number generator with a Rayleigh probability distribution is used. In addition, a uniformly distributed random number generator is used for determining the position of the scatterers.

The Rayleigh distributed random number generator was formed by applying the following procedures. Two successive uniformly distributed random number between (0,1) had been generated from the standard uniformly distributed random generator, called \( u \) and \( v \). Then, through the mathematical expressions below [57]:

\[
s_{n-1} = \sigma \sqrt{-2 \log u \cos 2\pi v + \mu} \quad (6.12)
\]

\[
s_n = \sigma \sqrt{-2 \log u \sin 2\pi v + \mu} \quad (6.13)
\]

The uniformly distributed between (0,1) random numbers \( u \) and \( v \) had been transferred to the uncorrelated Gaussian distributed numbers \( s_n \) and \( s_{n-1} \) with the mean \( \mu \) and the standard deviation \( \sigma \) [57]. In this transformation process, the Gaussian distribution assumed to have mean \( \mu = 0 \) and standard deviation \( \sigma = 1 \). Finally, the Rayleigh distributed random number was obtained by taking the square root of \( s_{n-1}^2 + s_n^2 \). The uniformly distributed random number generator was obtained by multiplicative congruential procedure [57] and its mathematical derivation is omitted for space limitation.

In the computer simulation of the grain signal process, there are three sets of data generated (using different sets of random numbers), each of them has a different center and bandwidth (see Figure 6.4a, 6.5a, 6.6a). The grain signal has
Figure 6.4. Computer Simulated Grain Signal; a) Spectrum of a 4 MHz Center Frequency Wavelet, b) Grain Signal Generated by 4 MHz Wavelet, and c) Spectrum of Recovered Wavelet from the Grain Signal b)
Figure 6.5. Computer Simulated Grain Signal; a) Spectrum of a 4.5 MHz Center Frequency Wavelet, b) Grain Signal Generated by 4.5 MHz Wavelet, and c) Spectrum of Recovered Wavelet from the Grain Signal b)
Computer Simulated Grain Signal; a) Spectrum of a 5 MHz Center Frequency Wavelet, b) Grain Signal Generated by 5 MHz Wavelet, and c) Sum of Recovered Wavelet from the Grain Signal b)
been obtained by a convolution of the grain characteristic function \( g_j(t) \) and the ultrasonic wavelet \( < u_j(t) > \). The simulation of the backscattered echoes has produced signals very similar in terms of their random nature and frequency shift to that of actual grain signals. The uniqueness of each data set, which coincides with the randomness of different measurements of the same materials, is easily observed (Figure 6.4b, 6.5b, 6.6b). Homomorphic processing is applied to grain signals in order to obtain the basic ultrasonic wavelet. The spectra of the simulated grain signals were passed through the logarithmic operator to convert the multiplicative relation between the mean echo wavelet and the grain characteristic function to the additive relation:

\[
\log|R_j(f)| = \log|< U_j(f) > | + \log|G_j(f)|
\]  

(6.14)

The cepstra of the simulated grain signals were obtained using an inverse Fourier transform of Equation 6.14. The length of the shortpass lifter was 64 sample points corresponding in time to about 0.64\( \mu \)s. The shortpass lifter was applied to the cepstrum of the grain signals, and the wavelets corresponding to the original echoes were recovered (see Figure 6.4c, 6.5c, 6.6c). The entire homomorphic signal processing procedures for grain signals are presented in Figure 6.7 and Figure 6.8.

For the purpose of evaluating the sensitivity of homomorphic processing techniques, we have compared the three sets of data with their respective center frequencies: 4, 4.5 and 5 MHz. Moment estimation of the spectrum from different data sets specifies the frequency shift as discussed earlier. The power spectrum centroids defined in Equation 6.11 are calculated and presented in Table 6.1. The differences in the moment estimation of the spectra show a clear sensitivity to the changing center frequency of the wavelet, but some error must be anticipated due to the random patterns of the spectrum of each data set. As we noted, there
Figure 6.7. Homomorphic Processing of 4 MHz Grain Signal; a) Echo with the Center Frequency 4.0 MHz and Bandwidth 1.25 MHz, b) Power Cepstrum of the Grain Signal, c) Simulated Grain Signal, d) Power Spectrum of the Grain Signal, e) Power Spectrum of the Echo, and f) Recovered Spectrum of the Echo
Figure 6.8. Homomorphic Processing of 5 MHz Grain Signal; a) Echo with the Center Frequency 5.0 MHz and Bandwidth 1.70 MHz, b) Power Cepstrum of the Grain Signal, c) Simulated Grain Signal, d) Power Spectrum of the Grain Signal, e) Power Spectrum of the Echo, and f) Recovered Spectrum of the Echo.
are some variations in recovered wavelets and the power spectrum centroids; however, a number of studies reveal that such variations are small. In fact, Table 6.1 shows that the quantitative errors are less than 2%. It should be noted that the choice of length for the shortpass lifter is essential for obtaining a good estimate. A short duration of the shortpass lifter will truncate information at the cepstrum domain, and consequently, the recovered wavelet will have a broad band spectrum. On the other hand, a long duration of the shortpass lifter will introduce spurious information in the cepstrum domain which may distort the recovered wavelet.

6.4 Discussion of Shortpass Lifter

The most important step in the homomorphic wavelet recovery system is the design of time windows (shortpass lifter) in cepstrum domain. The word "lifter," came from descriptions by Bogert et al. [53] in 1963 and is the paraphrased term according to a syllabic interchange rule for the word "filter," which stands for the filter in cepstrum domain. The basic function of the shortpass lifter is to filter out the effects of grain characteristic function so as to make the wavelet recovery possible. However, since the short pass lifter behavior is analogous to the low pass filter, the choices of the shape and duration of the shortpass lifter (time-pass) are the key parameters to decide the performance of the homomorphic wavelet recovery system. Hence, it is necessary to discuss the choice of relevant parameters of the shortpass lifter so that the best performance can be achieved.

It has been observed that the amplitude of the cepstrum of the grain signal varies appreciably with time. In particular, the amplitude of the cepstrum segment corresponding to the wavelet is generally much larger than that of the rest of segments corresponding to the grains. Therefore, information in the neighbourhood of the biggest peak area is our primary concern. A comparison of the
Figure 6.9. The Magnitude Cepstrum of the Computer Simulated Data in Logarithmic Scale; a) The Magnitude Cepstrum of the Wavelet, b) The Magnitude Cepstrum of the Grain Signal
Table 6.1. Summary of Frequency Shift.

<table>
<thead>
<tr>
<th>Sample</th>
<th>Signals</th>
<th>Centroids</th>
</tr>
</thead>
<tbody>
<tr>
<td>Steel</td>
<td>Back Echo</td>
<td>5.94 MHz</td>
</tr>
<tr>
<td>Steel</td>
<td>Grain Signal</td>
<td>7.02 MHz</td>
</tr>
<tr>
<td>Steel</td>
<td>Recovered Wavelet</td>
<td>7.03 MHz</td>
</tr>
<tr>
<td>Steel-2000</td>
<td>Back Echo</td>
<td>4.54 MHz</td>
</tr>
<tr>
<td>Steel-2000</td>
<td>Grain Signal</td>
<td>6.67 MHz</td>
</tr>
<tr>
<td>Steel-2000</td>
<td>Recovered Wavelet</td>
<td>6.62 MHz</td>
</tr>
</tbody>
</table>
wavelet power cepstrum and grain signal power cepstrum is shown in Figure 6.9. Inspection of this figure reveals that a window of short duration to extract the information in the neighbourhood of the biggest peak and eliminate the rest of the random variation caused by the scattering resulted from the microstructure of the materials. However, longer duration of the shortpass lifters will introduce spurious information in the cepstrum and the recovered wavelet will have a narrower bandwidth than the original one, while the shorter duration of the shortpass lifters will truncate the necessary information for wavelet recovery, and the bandwidth of the recovered wavelet will be larger than the original one [54].

Accurate wavelet recovery is important in the attenuation and frequency shift estimation and any minor distortion of the spectrum of the recovered wavelet can result in significant errors in estimation. Figure 6.10 displays the recovered magnitude spectrum of the same echo using different durations of rectangular shortpass lifter. The center frequency of the ultrasonic wavelet is 20 MHz, and the bandwidth of the wavelet is 10 MHz. The Figure 6.10a shows the spectrum of recovered wavelet when the duration of the shortpass lifter was 64 sample points. As we noted, since the duration of the shortpass lifter is slightly longer than the wavelet duration, the recovered wavelet spectrum displays spurious patterns due to grain characteristics. Figure 6.10b shows the spectrum of the recovered wavelet when the duration of the shortpass lifter was 32 sample points. Clearly, the shortpass lifter eliminates the effect of grain characteristic function and results in a smoothed, recovered spectrum. Figure 6.10c shows the spectrum of the recovered wavelet when the duration of the shortpass lifter is 16 sample points, and Figure 6.10d shows the spectrum of the recovered wavelet when the duration of the shortpass lifter is 8 sample points, which is far narrower than the actual echo. It must be noted that when the duration of the shortpass lifter is too short, the bandwidth of the recovered wavelet will affect the estimate of power spectrum centroids. In fact,
Figure 6.10. Effects of the Durations of the Rectangular Shortpass Lifter. 

(a) 64 Sample Points, (b) 32 Sample Points, (c) 16 Sample Points, and (d) 8 Sample Points. This signal has a center frequency of 20 MHz and the bandwidth of 10 MHz.
Figure 6.10. (continued)
Figure 6.10d shows that when the duration of the shortpass lifter was 8 points, the bandwidth of the recovered wavelet was enlarged by about 20%.

Based on extensive computer simulation, it can be concluded that the best choice of the duration of the shortpass lifter should be the same as the duration of the actual wavelet in time, which is inversely proportional to the signal bandwidth. A comparison of wavelets with different bandwidths and their cepstra in logarithmic scale are shown in Figure 6.11. This figure demonstrates that for the best performance of the homomorphic wavelet recovery system, the duration of the shortpass lifter should vary inversely with the signal bandwidth. In another words, the multiplication of the duration of the shortpass lifter (sampling points) and the bandwidth of the wavelet (MHz) should be constant.

It is important to point out when a window is applied to data, the spectrum of the original signal is distorted by the characteristics of the window. The rectangular window used in this study is simple to implement and its effect is easy to evaluate. However, other types of windows may perform satisfactorily for the homomorphic wavelet recovery system. As an alternative, the Gaussian type window was examined in this study. Figure 6.12a shows the results of the applying the Gaussian type window to the cepstrum of the signal. Similar to rectangular window, the timewidth of the Gaussian window is an important factor for obtaining an accurately recovered wavelet. If the timewidth of the Gaussian window is wider than the expected wavelet duration, the recovered wavelet begins to be influenced by the grain characteristics. If the timewidth of the Gaussian window smaller than the expected wavelet duration, the bandwidth of the recovered wavelet becomes broader, which will ruin the accuracy of estimates of the power spectrum centroids. Generally speaking, the best choice of the timewidth of the Gaussian window must be close to the duration of the wavelet. Figures 6.12b, 6.12c, 6.12d
Figure 6.11. The Shortpass Lifters with Different Timewidth Associate with the Different Timewidth (or Bandwidth) Wavelets, a) 1.5 MHz Bandwidth Wavelet, b) 2.0 MHz Bandwidth Wavelet, c) 2.5 MHz Bandwidth Wavelet and d) 3.0 MHz Bandwidth Wavelet, and (1) is the Wavelet, (2) is the Magnitude Spectrum for the Wavelet, and (3) is the Power Cepstrum for Wavelet
Figure 6.11. (continued)
show the recovered magnitude spectra of the echoes using Gaussian windows with
different timewidths. Clearly, the choice of the timewidth of window dictates the
quality of the estimates.

Both rectangular and Gaussian windows are capable of recovering the wavelet
with reasonable accuracy. The results reported here indicate that the rectangular
window performs slightly better compared to the Gaussian window (in terms of
power spectrum centroids estimates of the wavelet). To examine the possible
explanations, it has been understood that, in the region where the power cepstrum
of wavelet is very small (60 db below its maximum value), the cepstrum of grain
characteristics is at least 30 db higher than the cepstrum of the wavelet. The
rectangular window will eliminate the grain characteristics information completely,
while the Gaussian window is not capable of total elimination (for clarity, refer
to Figure 6.9). Consequently, the recovered wavelet using the rectangular window
has less grain information than the wavelet obtained using the Gaussian window.

6.5 Experimental Results and Discussion

The experiments were conducted using a Panametrics transducer with 6.224
MHz center frequency and 3-dB bandwidth of 2.75 MHz. Two specimens examined
in this study were steel blocks type 1018. One steel block has an average grain size
of 14\(\mu\)m. The other block was heat-treated at a temperature of 2000°F and the
average grain size of the sample grew to 50 \(\mu\)m. The specimens were placed at the
far fields of the transducer and the ultrasonic measurements were performed using
the immersion testing technique. The transducer impulse response, which serves
as the reference ultrasonic wavelet for the comparison of the upward and down-
ward shift in spectrum, was measured using the front surface echo of the specimen
Figure 6.12. Effects of the Duration of the Gaussian Shortpass Lifter; a) 1.35 $\mu$s, b) 0.45 $\mu$s, c) 0.25 $\mu$s, and d) 0.13 $\mu$s. This Signal has a Center Frequency of 5 MHz and 2.5 MHz Bandwidth.
(see Figure 6.13). The grain signal shown in Figure 6.14a with a 20μs duration contains the information corresponding to grain scattering within the region of 1 cm to 7 cm of the steel specimen. It must be noted that inherent in any grain signal is an upward shift in frequency due to scattering, and a downward shift caused by an attenuation effect. In all measured grain signals, we have observed that the upward shift in the frequency is far more dominating than the downward shift. In order to assess the degree of downward shift caused by the microstructures of materials, the backsurface echo was measured (see Figure 6.14b). The result shown in Figure 6.14b displays the downward shift effect introduced by attenuation since the echo is backscattered from the far end flat surface of the specimen (no scattering effect). Figure 6.15 shows the measured grain signal spectrum and its wavelet recovered through homomorphic processing. The estimated power spectrum centroids for the transducer impulse response, recovered grain signal wavelet, and the backsurface echo are 6.22 MHz, 7.02 MHz, and 5.94 MHz, respectively. These results demonstrate the existence of an upward frequency shift due to scattering and a downward frequency shift due to attenuation. The degree of frequency shift can be correlated to the inherent properties of the grain scattering.

Similar experimental measurements were conducted using the heat-treated steel sample (steel-2000). Figure 6.16 shows the backscattered grain signal and the backsurface echo of the steel-2000 specimen. The spectra of the grain signal and the recovered wavelet are shown in Figure 6.17. The estimated power spectrum centroids for the recovered wavelet and the backsurface echo are 6.62 MHz and 4.54 MHz, respectively. Comparison of the power spectrum centroids from the grain signals using "steel" and "steel-2000" indicate that the difference in frequency shift is relatively small, although "steel" has a much smaller grain size than that of the "steel-2000" specimen. The lack of a significant frequency shift may be accounted for since the ultrasonic wavelength is about 1000μm, and \( \frac{\lambda}{D} \) for both specimens
Figure 6.13. The Transducer Impulse Response and Its Amplitude Spectrum
Figure 6.14. Experimental Measurements from the Steel Sample. a) the Grain Signal, and b) the Backsurface Echo
Figure 6.15. A Comparison of the Measured Grain Signal Spectrum and the Recovered Wavelet Spectrum from the Steel Sample, a) Actually Grain Signal Spectrum, and b) the Recovered Wavelet Spectrum
Figure 6.16. Experimental Measurements from the Steel-2000 Sample, a) the Grain Signal, and b) the Backsurface Echo
Figure 6.17. A Comparison of the Measured Grain Signal Spectrum and the Recovered Wavelet Spectrum from the Steel-2000 Sample, a) Grain Signal Spectrum, and b) the Recovered Wavelet Spectrum
is so small (steel: $\frac{D}{X} = 0.014$; steel-2000: $\frac{D}{X} = 0.050$) that they fall into the lower and insensitive portion of the Rayleigh scattering region (for clarity, refer to Figure 6.1). Furthermore, the measuring transducer has a limited bandwidth and filters out the desirable frequency shift caused by grain scattering, which can also account for an insignificant frequency shift.
CHAPTER VII

LINEAR PREDICTIVE ANALYSIS OF ULTRASONIC GRAIN SIGNAL

7.1 Introduction

The common approach to estimation of the power spectral density (PSD) or simply the spectrum of discretely sampled deterministic and stochastic processes is based on the periodogram technique that makes use of the Fast Fourier Transform (FFT). This approach to spectrum analysis is computationally efficient and produces reasonably good results for a large class of signals. In spite of these advantages, there are several performance limitations inherent in this approach. One of them is so-called "leakage" into the sidelobes, which obscures and distorts other spectral responses that are present. In fact, weak signal spectral response can be masked by higher sidelobes from stronger spectral response [56]. A suitable smoothing window can reduce the sidelobe leakage, but always at the expense of less resolution. Another limitation is that of the frequency resolution, i.e., the ability to distinguish the spectral response of two signals. These two performance limitations of the Fast Fourier Transform are particularly severe when analyzing short data strings.

In an attempt to alleviate the limitation inherent in the FFT approach, many alternative spectral estimation procedures have been proposed in recent years. Among all of these proposed procedures, the linear predictive technique, also known as the maximum entropy method (MEM) of spectral estimation, is known to provide improved frequency resolution over short data string [59]. In this chapter, the linear predictive analysis is presented for spectra estimation.
Furthermore, computer-simulated data are examined using the linear predictive analysis, and the linear distance classifier is designed for grain size classification. Finally, conclusions and recommendations are given at the end of this chapter.

7.2 Linear Spectrum Matching

The autoregressive (AR) or autoregressive moving average (ARMA) techniques have been extensively applied to speech processing [58, 59], and recently, to seismic and radar signal processing [72]. The autoregressive parameter identification process is closely related to the theory of linear prediction.

Assume the measured grain signal \( s(n) \) is an AR(p) process with ‘p’ parameter, then the predictive value of the sampled grain signal \( \hat{s}(n) \) is defined as:

\[
\hat{s}(n) = -a_1s(n - 1) - a_2s(n - 2) - \ldots - a_ps(n - p)
\]  

(7.1)

or

\[
\hat{s}(n) = -\sum_{i=1}^{p} a_is(n - i)
\]  

(7.2)

where the \( a_i \) is referred to autoregression coefficients, the ‘p’ is the order of the AR model. Then, any error between the actual value \( s(n) \) and the predicted value \( \hat{s}(n) \) can be given by:

\[
e(n) = s(n) - \hat{s}(n) = s(n)(1 + \sum_{i=1}^{p} a_i\delta(n - i))
\]  

(7.3)

The term \( e(n) \) is also known as the residual. The energy of the residual is:

\[
E_n = \sum_n e^2(n) = \sum_n (s(n) - \hat{s}(n))^2 = \sum_n [s(n) + \sum_{i=1}^{p} a_is(n - i)]^2
\]  

(7.4)
In order to obtain the $a_j$ such that $E_n$ will be minimized, we took the derivation with respect to $a_j$ and set it equal to zero:

$$\frac{\partial E_n}{\partial a_j} = 0; \quad 1 \leq j \leq p,$$

(7.5)

Which can result in

$$\sum_n s(n)s(n-j) + \sum_{i=1}^p a_i \sum_n s(n-i)s(n-j) = 0$$

(7.6)

or

$$\Phi(0,j) + \sum_{i=1}^p a_i \Phi(i,j) = 0, \quad 1 \leq j \leq p$$

(7.7)

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

$$\Phi(i,j) = \sum_n s(n-i)s(n-j)$$

(7.8)

In the literature, Equation 7.7 is known as the normal equation and can be used for solving $a_j$ since there are "p" equations and "p" unknowns. The optimal linear predictive signal $\hat{s}(n)$ can be obtained by estimating $a_j$ through the least square method.

If the signal $s(n)$ is assumed to be a sample of a random process, then the error $e(n)$ is a random signal. In the least squares method, we minimize the expected value of the square of the error. Thus

$$E = E(e^2(n)) = E(s(n)) + \sum_{k=1}^p a_k s_{n-k})^2$$

(7.9)

Applying the same procedure for minimum error (describing in Equations 7.4-7.6), we obtain a similar type of equation for solving $a_j$;

$$\sum_{k=1}^p a_k E(s(n-k)s(n-i)) = -E(s(n)s(n-i)); \quad 1 \leq i \leq p$$

(7.10)
Equation 7.10 becomes identical to Equation 7.7 based on the assumption that the grain signal is an ergodic process. If the signal is an AR process, then the optimum linear predictor parameters are the AR parameters. The AR coefficients can be estimated from the sample data by using existing processing techniques such as auto-correlation, auto-covariance, and the lattice method, etc. When the signal is not an AR process, but an AR model is used, the number of linear predictive parameters of the optimal predictor is generally infinite. Theoretically, as the number of the predictor parameters increases, the error will decrease. A low guess for model order results in a highly smoothed spectral estimate, and high order introduces spurious detail into the spectrum. Therefore, choosing the order of the model becomes a key problem in linear predictive analysis. Figure 7.1 shows a typical linear predictive spectral match process for a grain signal. Because the coefficients of an AR model are capable of characterizing the power spectrum of the grain signal, these coefficients are used for the smoothing grain signal spectrum. Figure 7.2 shows the lower order of the linear predictive spectrum match. As shown in this figure, the lower order of the AR process highly smooths the randomness of the grain signal spectrum such that it might lose some detailed information pertaining to the spectrum. Figure 7.3 and Figure 7.4 shows a higher order of the linear predictive spectrum match process. This figure was obtained by applying the higher order of the AR model to the signal of Figure 7.2 used. As demonstrated in Figure 7.3 and Figure 7.4, the higher order of the AR process introduced some spurious details in the spectrum such that it will cause difficulty in classifying them. Although the autoregressive spectrum match has some limitations involving the degrading effects of observation noise, spurious peaks and some anomalous effects which occur when the data are dominated by sinusoidal components [56], the linear predictive spectrum match is a simple and efficient approach for the study of the overall behavior of the composite signal such as grain backscattered echoes in frequency domain.
Figure 7.1. A 35-pole Linear Prediction Model of a Grain Signal
Figure 7.2. A 10-pole Linear Prediction Model of a Grain Signal
Figure 7.3. A 100-pole Linear Predictive Model of a Grain Signal
Figure 7.4. A 150-pole Linear Predictive Model of a Grain Signal
Let's discuss the linear spectral matching methods in detail. If the assumed autoregressive model is a reasonable model for the data, then the AR power spectral density estimate based on Equation 7.3 may be written as:

$$S(z) = \frac{E(z)}{1 + \sum_{i=1}^{p} a_i z^{-i}}$$ (7.11)

where $S(z)$ and $E(z)$ are z-transforms for signal $s(n)$ and error sequence $e(n)$, respectively. For above expression Equation 7.11 is normally evaluated along the unit circle, $z = \exp(j\omega \Delta t)$ for $-\frac{\pi}{\Delta t} \leq \omega \leq \frac{\pi}{\Delta t}$ and $\Delta t$ is the sampling interval. Often the driving process $e(n)$ is assumed to be a white-noise sequence of zero mean and variance $\sigma^2$ [56]. The power spectrum density of the noise is then $\sigma^2 \Delta t$. Here, we included the $\Delta t$ factor in the expression for power spectral density of the noise such that, when evaluating the $S(z)$ over the unit circle, the integral over $-\frac{\pi}{\Delta t} \leq \omega \leq \frac{\pi}{\Delta t}$ yields the true power of an analog signal.

$$S(\omega) = \frac{\sigma^2 \Delta t}{|1 + \sum_{k=1}^{p} a_k e^{jk\omega}|^2} = \frac{E(\omega)}{|1 + \sum_{k=1}^{p} a_k e^{jk\omega}|^2}$$ (7.12)

Furthermore, let's denote:

$$A(e^{j\omega}) = 1 + \sum_{k=1}^{p} a_k e^{jk\omega}$$ (7.13)

$$S(\omega) = |H(e^{j\omega})|^2$$ (7.14)

then, the all-pole transfer function can be represented as:

$$H(e^{j\omega}) = \frac{G}{A(e^{j\omega})}$$ (7.15)

such that

$$\sigma^2 \Delta t = G^2$$ (7.16)
Equation 7.15 implies that, when the signal $S(\omega)$ is being modeled by Equation 7.12, the error power spectrum $E(\omega)$ is being modeled by a flat spectrum whose power spectrum density is equal to $G^2$. This means that, the actual error signal $e(n)$ is approximated by a signal that has flat spectrum such as a unit impulse, white noise or any other signal with a flat spectrum over the interesting regions. $-\frac{\pi}{\Delta f} \leq \omega \leq \frac{\pi}{\Delta f}$. In literatures [58, 59], the filter $A(e^{j\omega})$ is known as a "whitening filter," since it attempts to produce an output signal $e(n)$ that has a white spectrum.

Since the grain scattering process can be assumed as the wide sense stationary process; using Equation 7.8, the autocorrelation function $R(k)$ is defined as:

$$R(k) = \phi(k) = \sum_n s(n)s(n - k)$$  \hspace{1cm} (7.17)

then,

$$E = \sum_n e^2(n)$$

$$= \sum_n [s^2(n) + 2s(n) \sum_{k=1}^p a_k s(n - k) + \sum_{k=1}^p \sum_{i=1}^p a_ka_is(n - k)s(n - i)]$$

$$= R(0) + 2 \sum_{k=1}^p a_k R(k) + \sum_{k=1}^p \sum_{i=1}^p a_ka_iR(k - i)$$  \hspace{1cm} (7.18)

Substitute the Equation 7.7 into above equation, then,

$$R(j) + \sum_{i=1}^p a_i R(i - j) = 0$$  \hspace{1cm} (7.19)

Hence, Equation 7.18 reduced to,

$$E = R(0) + \sum_{k=1}^p a_k R(k)$$  \hspace{1cm} (7.20)
Let the input driving process to the all pole filter \( H(e^{j\omega}) \) be an impulse or unit sample at \( n = 0 \), i.e., \( u(n) = \delta(n) \), then according to Equation 7.2,

\[
    h(n) = - \sum_{k=1}^{p} a_k h(n - k) + G\delta(n)
\]  

(7.21)

Define the autocorrelation process for the input driving signal as

\[
    \hat{R}(k) = \sum_{n} h(n)h(n - k)
\]  

(7.22)

then, from Equation 7.19, we have

\[
    \hat{R}(i) = - \sum_{k=1}^{p} a_k \hat{R}(i - k), \quad 1 \leq |i| \leq \infty
\]  

(7.23)

specially,

\[
    \hat{R}(0) = - \sum_{k=1}^{p} a_k \hat{R}(k) + G^2
\]  

(7.24)

If the condition that the total energy in \( h_n \) equals the total energy in \( e(n) \) was met, we must have,

\[
    R(0) + \sum_{k=1}^{p} a_k R(k) = \hat{R}(0) + \sum_{k=1}^{p} a_k \hat{R}(k) = G^2
\]  

(7.25)

That is,

\[
    \hat{R}(0) = R(0), \quad G^2 = R(0) + \sum_{k=1}^{p} a_k R(k)
\]  

(7.26)

where \( G^2 \) is the total energy in the input \( G\delta(n = 0) \), or, we can say \( G^2 \) is the energy of the residual. In the autocorrelation method [59],

\[ G^2 = \alpha \]

where \( \alpha \) is the common notation for the energy of the residual in most computer-implemented program libraries.
7.3 Linear Resonating Frequency Estimator

During the implementation process, it was observed that, the linear predictive method provides the estimated smoothed version signal power spectrum. Although it gives fairly good spectral match results, the order of the filter changes the spectrum shape dramatically as shown in Figure 7.5. The linear predictive spectrum matches the signal spectrum much more closely in the regions of large signal energy (i.e., near the spectrum peaks) than near the regions of low signal energy (i.e., near the spectrum valleys). These observations suggest that, the order “p” of the linear predictive analysis can effectively control the degree of smoothness of the resulting spectrum. However, for the real time processing, the lower order of autoregressive process is of special interest and is always preferable. In spite of the highly smoothed spectrum, the second order or third order linear prediction model, somehow, can efficiently estimate the center frequency or so called resonating frequency, which can be approximately equal to the system resonating frequency (maximum energy occurred frequency). This provides an additional useful result that can be used for the classification technique [58]. That is, the feature vectors used in the pattern recognition process can be simply formed by the linear predictive coefficients.

From the basic linear predictive method, the system function of a second order AR model can be written as [58, 60]:

\[
H(z) = \frac{1}{1 - a_1 z^{-1} - a_2 z^{-2}}
\]

(7.27)

In another words;

\[
H(z) = \frac{1}{1 - 2rcos(\omega_1) z^{-1} + r^2 z^{-2}}
\]

(7.28)
Figure 7.5. A 3-pole Linear Predictive Model of a Grain Signal
where
\[ r^2 = -a_2, \quad \omega_1 = \cos^{-1}\left(\frac{a_1}{2\sqrt{a_2}}\right) \]

and
\[ a_1 = \frac{R(0)R(1) - R(1)R(2)}{R^2(0) - R^2(1)} \]  \hspace{1cm} (7.29)
\[ a_2 = \frac{R(0)R(2) - R^2(1)}{R^2(0) - R^2(1)} \]  \hspace{1cm} (7.30)

Here, the terms \( R(0), R(1), R(2) \) are defined in Equation 7.16. The frequency \( \omega_1 \) was named as the resonating frequency of the second order AR process. However, from another point of view, the power spectrum of the second-order model is given by:
\[ |H(\omega)|^2 = H(z)H(\frac{1}{z}) \bigg|_{z=e^{j\omega}} \]  \hspace{1cm} (7.31)

The maximum value is found by differentiating the Equation 7.31 with respect to \( \omega_1 \), and set it to zero; i.e.,
\[ \frac{\partial|H(\omega)|^2}{\partial \omega} = \frac{\partial}{\partial \omega} \left[ \frac{1}{1 - a_1 e^{-j\omega} - a_2 e^{-2j\omega}} \right] \frac{1}{1 - a_1 e^{j\omega} - a_2 e^{2j\omega}} \]
\[ = \frac{\partial}{\partial \omega} \left[ \frac{1}{1 + a_1^2 + a_2^2 + 2(a_1a_2 - a_1^2)\cos\omega - 2a_2\cos2\omega} \right] = 0 \]  \hspace{1cm} (7.32)

Hence,
\[ (a_1a_2 - a_1^2)\sin\omega = 2a_2\sin2\omega = 4a_2\sin\omega\cos\omega \]  \hspace{1cm} (7.33)
\[ \omega^* = \cos^{-1}\left(\frac{a_1a_2 - a_1^2}{4a_2}\right) \]  \hspace{1cm} (7.34)

Apparently, the \( \omega^* \) is not equal to \( \omega_1 \) \([60]\); the difference between the maximum energy at the frequency \( \omega^* \) and the resonating frequency \( \omega_1 \) is:
\[ |\omega_1 - \omega^*| = \left|\cos^{-1}\left[\frac{1}{8a_2\sqrt{a_2}}[a_1^2(a_1 - a_2) - \sqrt{(4a_2 - a_1^2)(16a_2^2 - a_1^2(a_2 - a_1)^2)}]\right]\right| \]  \hspace{1cm} (7.37)
The Equation 7.37 can be evaluated numerically using a digital computer. Nevertheless, the difference between $\omega_1$ and $\omega^*$ is small (see Figure 7.6), and the resonating frequency of the second order AR system can approximately represent the frequency of the maximum energy. Also, the resonating frequency $\omega_1$ and the difference of these two frequencies can be possibly correlated to some properties inherent in the second-order system, which is useful for extracting information from the random grain signals.

A closer spectrum evaluation can be obtained using the third order autoregressive system:

$$H(z) = \frac{1}{A(z)} = \frac{1}{1 + a_1 z^{-1} + a_2 z^{-2} + a_3 z^{-3}}$$ (7.38)

Similar to second order model, the poles of the system are used in order to obtain the resonating frequency. Consider the polynomial

$$z^3 + a_1 z^2 + a_2 z + a_3 = 0$$ (7.39)

To find the roots for Equation 7.39, let

$$x = z + \frac{a_1}{3}$$

then,

$$x^3 + (a_2 - \frac{a_1^2}{3}) x + a_3 - \frac{a_1 a_2}{3} + \frac{2a_1^3}{27} = 0$$ (7.40)

Furthermore, let

$$p = a_2 - \frac{a_1^2}{3}$$

and

$$q = a_3 - \frac{a_1 a_2}{3} + \frac{2a_1^3}{27}$$
Figure 7.6. Spectral Match Between Gaussian Spectrum and Second Order AR Model in Logarithmic Scale
Then, Equation 7.40 becomes:

\[ x^3 + px + q = 0 \]  

(7.41)

Let

\[ \Delta = \left(\frac{q}{2}\right)^2 + \left(\frac{p}{3}\right)^3 \]  

(7.42)

then, if \( \Delta > 0 \), the roots for Equation 7.41 will be one real root, and a pair of the complex conjugate roots. If \( \Delta = 0 \), Equation 7.41 have three real roots and if \( \Delta < 0 \), Equation 7.41 will have three different real roots [61]. The general expressions for the roots of Equation 7.41 are:

\[ x_1 = 3\sqrt[3]{-\frac{q}{2} + \sqrt{\Delta}} + 3\sqrt[3]{-\frac{q}{2} - \sqrt{\Delta}} \]  

(7.43)

\[ x_2 = \frac{-1 + i\sqrt{3}}{2} 3\sqrt[3]{\frac{q}{2} + \sqrt{\Delta}} + \frac{-1 - i\sqrt{3}}{2} 3\sqrt[3]{\frac{q}{2} - \sqrt{\Delta}} \]  

(7.44)

\[ x_3 = \frac{-1 - i\sqrt{3}}{2} 3\sqrt[3]{\frac{q}{2} + \sqrt{\Delta}} + \frac{-1 + i\sqrt{3}}{2} 3\sqrt[3]{\frac{q}{2} - \sqrt{\Delta}} \]  

(7.45)

Alternatively, expressing the roots in the trigonometric expressions will result in:

\[ x_1 = 2\sqrt[3]{r}\cos\theta \]  

(7.46)

\[ x_2 = 2\sqrt[3]{r}\cos(\theta + 120^\circ) \]  

(7.47)

\[ x_3 = 2\sqrt[3]{r}\cos(\theta + 240^\circ) \]  

(7.48)

where,

\[ r = \sqrt{-\left(\frac{p}{3}\right)^3}, \quad \theta = \frac{1}{3}\cos^{-1}\left(-\frac{q}{2r}\right) \]  

(7.49)

Finally, the poles of the third order system will be:

\[ z_1 = 2\sqrt[3]{r}\cos\theta - \frac{a_1}{3} \]  

(7.50)
Strictly speaking, Equations 7.46-7.52 are only valid for $\frac{a_2^2}{3} > a_2$ case [61]. Under this condition, $\theta$ is the resonating frequency. It is important to point out the resonating frequency may coincide with the position of maximum energy. In addition, the resonating frequency is an index that can be used for spectral evaluation.

### 7.4 Linear Predictive Distance Classifier Evaluating

A useful pattern recognition method is to use the autoregressive coefficients obtained by linear predictive analysis to form the feature vector so that the distance classifier can be designed. It is our intention to apply the AR model to the grain signal for discrimination and pattern recognition. The earlier study in Chapter 6 showed grain scattering influencing the content of the spectrum density. Therefore, for specimens with different grain size, the linear predictive analysis yields different linear predictive coefficients. Those coefficients can be correlated to the grain size, or possibly, to the grain size distribution.

In order to classify the specimens with different grain sizes, a classifier based on the linear predictive parameters as a feature vector must be defined. A common classifier is the Euclidean distance measure $D(a, b)$ between two sets of linear predictive parameters $a$ and $b$ as [63, 64]:

$$D_{AB} = \sqrt{\sum_{i=1}^{p} (a_i - b_i)^2} \quad (7.53)$$

where $p$ is the order of the AR process decided by prior conditions and $a_i$ and $b_i$ are the relevant linear predictive coefficients. Here, we have made the assumption that,
both systems for describing the grain signals are of the same order; if it happens not in same order, the choice of \( p \) should be the largest one. The computer simulations were used for evaluating the third order linear predictive model for the grain signals with different grain sizes. They were based on the principle that the spectra of the backscattered signals with different grain sizes are different; especially, the ultrasonic wavelet has a different center frequency. Therefore, by generating the grain signals with different center frequencies, the backscattered signals from the specimens with different grain sizes can be simulated. Detailed discussion about the simulated grain signal process can be found in the previous chapter.

The distance classifier is used in this study, and this classifier measures the distance between two sets of linear predictive parameters. It is formed by the Euclidean distance, and the decision is made based on the nearest neighbour rule. The cluster centers are formed by using five sets of data for each cluster center. Each set of data contains 2048 sample points. The training pattern classifier process was accomplished by using the linear predictive model that has the order of three, and the autocorrelation method was used in order to find the autoregressive coefficients of the data string. These 5 sets of autoregressive coefficients were used to compute their arithmetic average to form the cluster centers. Furthermore, the Euclidean distance between the autoregressive coefficients of the specimen and the cluster center were computed and consequently, the specimens were classified according to the nearest neighbourhood rule.

Table 7.1 presents the classification results using the third order linear predictive model for the grain signals with a center frequency of 4 MHz. As noted, the three-dimensional feature vector can effectively describe the grain signal so that the classification results are nearly perfect. Table 7.2, and Table 7.3 present the
Table 7.1. Minimum Distance Classification on 4 MHz Grain Signals.

<table>
<thead>
<tr>
<th>Data Sets</th>
<th>4 MHz</th>
<th>4.5 MHz</th>
<th>5 MHz</th>
<th>Decision</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.782</td>
<td>1.542</td>
<td>3.517</td>
<td>4.0 MHz</td>
</tr>
<tr>
<td>2</td>
<td>1.079</td>
<td>1.862</td>
<td>3.837</td>
<td>4.0 MHz</td>
</tr>
<tr>
<td>3</td>
<td>0.324</td>
<td>0.035</td>
<td>2.911</td>
<td>4.0 MHz</td>
</tr>
<tr>
<td>4</td>
<td>0.477</td>
<td>0.475</td>
<td>2.449</td>
<td>4.5 MHz</td>
</tr>
<tr>
<td>5</td>
<td>0.781</td>
<td>1.540</td>
<td>3.516</td>
<td>4.0 MHz</td>
</tr>
<tr>
<td>6</td>
<td>0.392</td>
<td>0.536</td>
<td>2.368</td>
<td>4.0 MHz</td>
</tr>
<tr>
<td>7</td>
<td>1.256</td>
<td>1.815</td>
<td>3.307</td>
<td>4.0 MHz</td>
</tr>
<tr>
<td>8</td>
<td>0.301</td>
<td>0.613</td>
<td>2.275</td>
<td>4.0 MHz</td>
</tr>
<tr>
<td>9</td>
<td>0.324</td>
<td>0.927</td>
<td>2.891</td>
<td>4.0 MHz</td>
</tr>
<tr>
<td>Data Sets</td>
<td>4 MHz</td>
<td>4.5 MHz</td>
<td>5 MHz</td>
<td>Decision</td>
</tr>
<tr>
<td>-----------</td>
<td>-------</td>
<td>---------</td>
<td>-------</td>
<td>----------</td>
</tr>
<tr>
<td>1</td>
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<td>1.939</td>
<td>4.5 MHz</td>
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<tr>
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<td>0.262</td>
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</tr>
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<tr>
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<tr>
<td>9</td>
<td>1.054</td>
<td>0.180</td>
<td>4.5 MHz</td>
<td></td>
</tr>
</tbody>
</table>
Table 7.3. Minimum Distance Classification on 5 MHz Grain Signals.

<table>
<thead>
<tr>
<th>Data Sets</th>
<th>4 MHz</th>
<th>4.5 MHz</th>
<th>5 MHz</th>
<th>Decision</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
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<td>2.063</td>
<td>0.088</td>
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<td>2</td>
<td>2.884</td>
<td>2.046</td>
<td>0.071</td>
<td>5.0 MHz</td>
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<tr>
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<td>1.984</td>
<td>0.009</td>
<td>5.0 MHz</td>
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<tr>
<td>4</td>
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<td>2.049</td>
<td>0.074</td>
<td>5.0 MHz</td>
</tr>
<tr>
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<td>1.983</td>
<td>0.087</td>
<td>5.0 MHz</td>
</tr>
<tr>
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<td>0.133</td>
<td>5.0 MHz</td>
</tr>
<tr>
<td>7</td>
<td>2.317</td>
<td>1.475</td>
<td>0.500</td>
<td>5.0 MHz</td>
</tr>
<tr>
<td>8</td>
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<td>0.272</td>
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<tr>
<td>9</td>
<td>2.811</td>
<td>1.965</td>
<td>0.098</td>
<td>5.0 MHz</td>
</tr>
</tbody>
</table>
classification results for the grain signals with the center frequency of 4.5 and 5 MHz. Inspection of these three tables reveals that the feature vector formed by the linear predictive coefficients can effectively characterize the frequency difference of the grain signals since the correct classification outcomes are better than 90%. The graphic representations of the classification process using the autoregressive coefficients are shown in Figure 7.6 and Figure 7.7. From these graphs similar conclusions can be obtained.

In summary, the third order linear predictive model can be used to describe and recognize the grain signals with different center frequencies. When the frequency difference is more than 0.5 MHz, the probability of correct classification can be as much as 90%.
Figure 7.7. Scatter Plot of Features \((a_1, a_2)\) Describing Three Different Grain Signal Power Spectra (\(\Delta\) for 4 MHz class, x for 4.5 MHz class and \(\bullet\) for 5 MHz class)
Figure 7.8. Scatter Plot of Features \((a_1, a_3)\) Describing Three Different Grain Signal Power Spectra (\(\triangle\) for 4 MHz class, x for 4.5 MHz class and \(\bullet\) for 5 MHz class)
For the past several decades, there has been significant research in the area of ultrasound toward evaluating the scattering and attenuation properties of materials, although little has been done to develop and utilize modern signal processing techniques. This thesis has been concerned with the development and analysis of statistical signal processing techniques in the evaluation of the microstructure of materials using ultrasound; specifically, processing methods in both time and frequency are considered in characterizing ultrasonic backscattered grain signals. In order to pursue the proposed experimental studies on grain signal analysis, specimens with different grain sizes are required. These specimens were obtained from type 1018 coarse-grained, and silicon-killed steel samples that had been heat-treated at different temperatures. The grain sizes and the ASTM grain numbers were obtained from micrographs using the intercept method.

Ultrasonic backscattered echoes were treated as a random process, and a statistical model was developed that describes the backscattered signal as a function of physical parameters such as attenuation and frequency shift. This report has shown that it is feasible to characterize materials with different grain sizes by analyzing the backscattered signal. The mathematical expression for the amplitude of the backscattered grain signal was derived and the results show that the amplitude of backscattered grain signal is Rayleigh distributed, and the expected value of the amplitude of backscattered signal is related to the attenuation coefficients. The histogram reconstructions were based on experimental data that were measured from specimens with different grain sizes. The mathematical conclusion
that the amplitude of backscattered signal is Rayleigh distributed is confirmed by
the reconstructed histograms through the analysis of experimental data. Grain
size characterization has been achieved by measuring the attenuation coefficient
using two equivalent approaches, namely temporal (time) and spatial (ensemble)
averaging for smoothing the backscattered grain signal. Statistical analysis and
experimental results suggest that the accuracy of the estimated attenuation co-
efficient using time averaging is very close to ensemble averaging. The choice of
scanning steps for spatial averaging and window length for temporal averaging is
critical in the effectiveness of the smoothing operation. Experimental studies were
performed using steel samples with different grain sizes, and it was observed that
the estimated attenuation coefficient was position-dependent, such that its value
decreases as the ultrasonic beam penetrates the specimen. Therefore, the use of a
position-dependent attenuation coefficient for grain size characterization must be
confined to a fixed region of the specimen.

In the experiments enacted during this investigation, the effectiveness of the
averaging schemes was found to be less than 50% due to a high degree of correlation
between successive measurements. It is important to point out that the smoothing
procedure does not need to be carried out using ensemble or time averaging. In
practice, a lowpass filter with a proper cutoff frequency is capable of generating
similar results. Indeed, the proposed time averaging technique is a lowpass filtering
process which is simple to implement and provides information confined to a small
region of the materials.

An upward frequency shift due to scattering and a downward frequency shift
due to attenuation exist in ultrasonic backscattered grain signal. The degree of
frequency shift can be correlated to the inherent properties of grain scattering.
Homomorphic processing and moment analysis are effective techniques in estimating this frequency shift in order to evaluate the microstructure of materials. The performance of the homomorphic processing technique is limited by the random nature of the backscattered signals. Using homomorphic processing, the power spectrum centroids of the ultrasonic wavelet can be extracted from the backscattered signal with less than 2% error. The choice of shortpass lifter is critical to the performance of the homomorphic processing. Through extensive computer simulations, it has been found that the rectangular shaped shortpass lifter has better performance than the Gaussian shortpass lifter. Furthermore, it should be understood that for the best achievable performance of the homomorphic wavelet recovery system, the duration of the shortpass lifter must be close to the timewidth of the wavelet. Finally, experimental results for spectral evaluation using steel samples with various grain sizes are presented. These results suggest the feasibility of using the homomorphic processing and moment analysis for grain size characterization.

As an alternative spectral evaluation method, linear predictive analysis is used for spectral smoothing and extracting features from random grain signals. A third-order linear predictive model is applied to computer simulated grain signals with different center frequencies. Autoregressive coefficients have been used to describe and recognize the grain signals, and pattern recognition and classification have been carried out for grain size estimation. When the frequency difference is more than 0.5 MHz (10% of center frequency), the probability of correct classification was found to be as much as 90%.
BIBLIOGRAPHY


[34] J. E. Hilliard, "Grain Size Estimation by the Intercept Method," Northwestern University, Department of Materials Science and Materials Research Center (internal report), Nov. 1963.


