Postprint of an Ultrasonic Multiscale Attenuation Evaluation Method for Grain Size

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Abstract

The time-scale distribution of ultrasonic energy is obtained using wavelet transform, the distribution law of attenuation coefficient with scale is studied, a weighted ultrasonic multi-scale attenuation coefficient is defined, and an ultrasonic multi-scale attenuation evaluation model for grain size is established by combining an optimal scale combination designed using particle swarm algorithm with its normalized weight allocation strategy. Experiments were conducted on 304 stainless steel, and its attenuation coefficient-scale distribution diagram indicates that ultrasonic waves attenuate rapidly at small scales, reflecting the frequency characteristics of attenuation in highly scattering materials; as the grain size of the specimen increases, the attenuation across the entire scale range is significantly intensified. Experimental results demonstrate that the maximum systematic errors of the velocity method, traditional attenuation method, and the proposed method are +12.57%, +5.85%, and -1.33%, respectively. A validation specimen with an average grain size of 103.5 mm measured by metallographic method was evaluated using the three methods, yielding results of (110.4$±7.8), (98.2±6.6), *and* (101.7±$3.9) mm, respectively. The proposed method not only reduces systematic error, but also effectively suppresses random error through the constant-Q filtering characteristic of wavelet transform.

Full Text

Ultrasonic Evaluation Method for Grain Size Based on Multi-Scale Attenuation

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Abstract

To address the limitations of traditional ultrasonic time-domain attenuation methods for grain size evaluation—namely high sensitivity to noise and low accuracy—this paper proposes an ultrasonic nondestructive evaluation model based on multi-scale attenuation coefficients. Wavelet transformation is employed to obtain the time-scale distribution of ultrasonic energy, enabling analysis of attenuation coefficient distribution across scales. A weighted multi-scale ultrasonic attenuation coefficient is defined, and an optimal scale combination with its normalized weight allocation strategy is designed using particle swarm optimization. This establishes an ultrasonic multi-scale attenuation evaluation model for grain size. Experiments conducted on 304 stainless steel demonstrate that ultrasonic waves attenuate rapidly at small scales, reflecting the frequency characteristics of attenuation in highly scattering materials. As sample grain size increases, attenuation intensifies across the entire scale range. Test results show that the maximum systematic errors for the sound velocity method, traditional attenuation method, and the proposed method are +12.57%, +5.85%, and -1.33%, respectively. For a validation sample with an average grain size of 103.5 mm measured by metallographic analysis, the three methods yield evaluation results of (110.4$\pm$7.8), (98.2$\pm$6.6), and (101.7$\pm$3.9) mm, respectively. The proposed method not only reduces systematic error but also effectively suppresses random error through the constant-Q filtering properties of wavelet transformation.

KEY WORDS grain size, ultrasonic nondestructive evaluation, multi-scale analysis, attenuation coefficient

Introduction

Grain size is a critical parameter characterizing the microstructure of metallic materials, significantly influencing yield strength, plasticity, toughness, fatigue strength, creep strength, and corrosion resistance. The Hall-Petch equation describes the relationship between grain size and yield strength in polycrystalline metals, demonstrating the size-strength effect. For instance, excessive grain growth in the heat-affected zone of austenitic stainless steel welds can lead to insufficient strength, poor corrosion fatigue performance, and crack nucleation under high temperature and cyclic stress, potentially causing fracture accidents. Therefore, effective measurement of metallic material grain size is essential for ensuring the reliability of critical equipment.

Grain size measurement methods can be categorized as destructive or nondestructive. Destructive methods require material damage, such as metallographic analysis and electron backscatter diffraction (EBSD). Metallographic analysis offers intuitive results and high precision but suffers from cumbersome procedures and low efficiency. EBSD does not require etching but demands more stringent polishing sample preparation. Nondestructive methods offer convenience, speed, and no material damage, with primary approaches being eddy current and ultrasonic methods. Eddy current methods suffer from skin effects that only reflect surface or near-surface grain size information and exhibit large nonlinear errors when evaluating grain size through electrical conductivity. Ultrasonic methods, however, can detect internal microstructural characteristics, prompting extensive theoretical and applied research on ultrasonic grain size evaluation.

Ultrasonic grain size evaluation primarily includes backscatter, attenuation, and velocity methods. The backscatter method is based on the positive correlation between average grain size and ultrasonic backscatter coefficients, but backscatter signals are essentially noise signals with limited sensitivity range, restricting measurable grain size ranges. The velocity method evaluates average grain size using velocity differences caused by varying elastic moduli at grain boundaries, though its sensitivity is low for some metallic materials, resulting in large relative errors. The attenuation method is widely applied, as ultrasonic energy attenuation varies when propagating through materials with different average grain sizes. Applications include establishing empirical fitting models using total attenuation coefficients in the time domain or power-function models through attenuation coefficient spectra in the frequency domain. Spectral peak methods are essentially attenuation method variants. However, ultrasonic echo signals are time-varying non-stationary signals, and traditional attenuation methods—whether time- or frequency-domain—lose richer grain size information carried by local frequency spectra and are susceptible to noise interference, affecting evaluation precision and reliability. This study proposes an ultrasonic multi-scale attenuation evaluation method for grain size to improve the effectiveness of nondestructive evaluation of metallic material grain size.

1.1 Multi-Scale Attenuation Evaluation Model

For establishing the evaluation model, assume N samples are used, with the k-th sample having average thickness Hk (k = 1, 2, ···, N). Assuming uniform grain size and orientation distribution along the ultrasonic propagation direction in all modeling samples, metallographic analysis measures their grain sizes, with average grain size denoted as D̄k. Pulse-echo method 采集 s ultrasonic A-scan signals Ak(t). Rectangular windows extract the front-wall echo and first back-wall echo signals, denoted as xk(t) and yk(t), respectively. To explore the optimal fitting form, a traditional time-domain attenuation model is first considered, where the total attenuation coefficient αk is:

$$\alpha_k = \frac{1}{H_k} \ln \left| \frac{x_k(t)}{y_k(t)} \right|$$

Random errors are eliminated through multiple measurements, with S ultrasonic signals acquired for each sample. The total attenuation coefficient from the j-th signal of the k-th sample is αk^j, yielding the average total attenuation coefficient:

$$\bar{\alpha}_k = \frac{1}{S} \sum_{j=1}^{S} \alpha_k^j$$

Least squares fitting of $\bar{\alpha}$k and D̄k is performed. If basis functions $\{\phi_1, \phi_2, \cdots, \phi\ \}$ yield minimum fitting error, they are termed optimal basis functions and serve as the foundation for the multi-scale attenuation evaluation model. Since traditional time-domain attenuation models reflect the direct relationship between grain size and ultrasonic attenuation, their fitting form provides a reference for the multi-scale model.

Next, continuous wavelet transform is applied to xk(t) and yk(t) using a mother wavelet , yielding wavelet coefficient matrices Xk(a,b) and Yk(a,b):

$$X_k(a,b) = \frac{1}{\sqrt{a}} \int_R x_k(t) \psi^* \left(\frac{t-b}{a} \right) dt$$
$$Y_k(a,b) = \frac{1}{\sqrt{a}} \int_R y_k(t) \psi^* \left(\frac{t-b}{a} \right) dt$$

where a is the scale factor, b is the translation factor, and , forms the wavelet function family. In continuous wavelet transform, a takes consecutive positive integers for M decomposition levels. The i-th row of the wavelet coefficient matrix represents the wavelet component at scale a . The attenuation coefficient α , for the k-th sample at scale a is defined as:

$$\alpha_{a_i,k} = \frac{1}{H_k} \ln \left| \frac{X_k(a_i,b)}{Y_k(a_i,b)} \right|$$

Assuming m representative scales {â$_1$, â$_2$, ···, â } are selected, attenuation coefficients at these scales are extracted and weighted to define the multi-scale attenuation coefficient:

$$\alpha_k^{multi} = \sum_{r=1}^{m} w_r \alpha_{\hat{a}r,k}$$

where w = [w_1, w_2, ···, w] is the normalized weight vector satisfying w = 1. All samples use the same representative scales and weights. Multiple measurements yield attenuation coefficients $\hat{\alpha}$, for each representative scale, from which average attenuation coefficients at each scale are calculated. The key to constructing the multi-scale attenuation coefficient with highest fitting precision lies in selecting representative scales {â } and corresponding normalized weights w.

This work modifies particle swarm optimization to design optimal scale combinations and weight allocation strategies:

1. Initially assume all M scales are representative (m = M), with normalized weight vector w derived from original weight vector W. The algorithm aims to drive weights of non-representative scales to zero.
2. For Q particles, the q-th particle' s position represents an M-dimensional original weight vector Wq = [Wq_1, Wq_2, ···, Wq] , and velocity is vq = [vq_1, vq_2, ···, vq] . Position and velocity update functions are:

$$v_q(T+1) = \Omega v_q(T) + c_1 r_1 (p_q - W_q(T)) + c_2 r_2 (p_g - W_q(T))$$
$$W_q(T+1) = W_q(T) + v_q(T+1)$$

where Ω is the inertia coefficient, c_1 and c_2 are cognitive and social learning factors, r_1 and r_2 are random numbers in [0,1], p_q is the individual best solution, p_g is the global best solution, and v_{max} is the maximum velocity. If any component of Wq becomes negative after updating, it is set to zero, ensuring only representative scales retain non-zero weights.

3. After position updating and zeroing, normalization yields wq. Combined with average attenuation coefficients at all scales, the average multi-scale attenuation coefficient for each sample is calculated via Eq. (6). Least squares fitting with optimal basis functions {ϕ_1, ϕ_2, ···, ϕ *} yields fitted values Dk. The fitness value is the 2-norm of residuals between fitted and actual values:

$$F = \sqrt{\sum_{k=1}^{N} (D_k - \bar{D}_k)^2}$$

Searching for minimum fitness yields the optimal scale combination {â *} and normalized weights w.* The average multi-scale attenuation coefficient is then calculated, and the final multi-scale attenuation evaluation model is established via least squares fitting:

$$\tilde{D} = d_0 + d_1\phi_1^*(\alpha^{multi}) + \cdots + d_n\phi_n^*(\alpha^{multi})$$

where d_0, d_1, ···, d are fitting coefficients corresponding to the optimal basis. Note that different materials require calibration of their optimal scale combinations, weights, and fitting coefficients.

1.2 Sample Preparation and Pre-processing

Grade 06Cr19Ni10 304 stainless steel was selected for experiments. Stainless steel rods (25 mm diameter) were cut into 6 blanks (15 mm height) using wire electrical discharge machining. Solid solution treatments were performed using a 1610BL high-temperature furnace according to specifications in to create gradient grain size distributions. All samples underwent stress relief annealing. After heat treatment, samples were ground and thickness measured with a screw micrometer (results in), where D represents metallographically measured average grain size and E denotes relative measurement error.

Ultrasonic A-scan signals were acquired using immersion pulse-echo method, with 20 signal groups per sample. As shown in [Figure 1: see original paper], the acquisition system comprises a six-degree-of-freedom motion platform, Olympus 5072PR pulser/receiver, 10 MHz V312-SU immersion longitudinal wave transducer, and ADLink PCIe-9852 high-speed digital acquisition card.

After ultrasonic data collection, samples were destructively sectioned for metallographic analysis. Three random detection surfaces per sample were selected for cutting, mounting, grinding, and polishing. An etchant of 20% HF + 10% HNO_3 + 70% H_2O was applied for 20 minutes. DM4000M metallographic microscope captured 5 random fields per surface. Representative metallographic images are shown in [Figure 2: see original paper].

2.1 Establishment of Multi-Scale Attenuation Evaluation Model

For each k-th sample (k = 1, 2, ···, 6), dual gates were applied to 20 acquired ultrasonic signals to extract front-wall and back-wall echoes using rectangular windows. [Figure 3: see original paper] shows a raw ultrasonic signal and extracted echoes for Sample No.2.

Average grain size D̄k and relative error were measured via metallographic analysis using the intercept method with measurement grids (results in). Average total attenuation coefficient $\bar{\alpha}$k was calculated using Eqs. (1) and (2). [Figure 4: see original paper] displays the scatter plot of $\bar{\alpha}$k versus D̄k for all 6 samples, showing points clustered near a straight line. Thus, the optimal basis functions are {1, $\bar{\alpha}$k}, yielding the traditional attenuation evaluation model via least squares:

$$\tilde{D}(\bar{\alpha}_k) = -57.355 + 1.585\bar{\alpha}_k$$

where D has units of mm and $\bar{\alpha}$k has units of $\mathrm{Np \cdot m^{-1}}$.

According to Eqs. (3) and (4), Haar wavelet decomposition with 128 levels was applied to front-wall echo xk(t) and back-wall echo yk(t), obtaining coefficient matrices Xk(a,b) and Yk(a,b). The time-scale distributions for Sample No.2 are visualized via wavelet scale spectrograms in [Figure 5: see original paper]. Attenuation coefficients at each scale were calculated using Eq. (5) and averaged across 20 signal groups, producing the mean attenuation coefficient spectrogram in [Figure 6: see original paper].

[Figure 6: see original paper] shows that for a given sample, attenuation coefficients are larger at small scales, while for a given scale, attenuation coefficients are smaller for larger grain sizes. This indicates rapid ultrasonic attenuation at small scales, reflecting the frequency characteristics of high scattering materials where high-frequency components attenuate more. As grain size increases, attenuation intensifies across all scales, demonstrating positive correlation between attenuation coefficients at different scales and grain size.

The modified particle swarm optimization algorithm searched for optimal scale combinations and normalized weights. For the q-th particle, initial position (original weight vector Wq(0)) followed uniform distribution [1, 5] across 128 components (assuming all scales representative). Initial velocity vq(0) followed uniform distribution [0, 0.05] with maximum velocity v_{max} = 0.05. Following literature [20], inertia coefficient $\Omega = 0.729$, cognitive factor $c_1 = 1.494$, and social factor $c_2 = 1.494$. After searching, the global best solution p_g retained non-zero original weights only at scales 1, 2, and 49, which normalized to 0.028, 0.087, and 0.885, respectively. These three scales form the optimal combination, yielding the best fitting performance. Substituting into Eq. (6):

$$\alpha_k^{multi} = 0.028\alpha_{1,k} + 0.087\alpha_{2,k} + 0.885\alpha_{49,k}$$

Average multi-scale attenuation coefficients were calculated for all 6 samples. Least squares fitting with optimal basis {1, α_k^{multi}} and average grain size Dk produced the multi-scale attenuation evaluation model:

$$\tilde{D}(\alpha_k^{multi}) = -110.021 + 2.281\alpha_k^{multi}$$

where D has units of mm and α_k^{multi} has units of $\mathrm{Np \cdot m^{-1}}$. [Figure 7: see original paper] shows this model, demonstrating stronger linearity between average multi-scale attenuation coefficient and average grain size compared to [Figure 4: see original paper], with reduced deviation from the fitted line.

2.2 Effectiveness Analysis

To validate the proposed method, it was compared against the traditional velocity method from literature [13] and traditional time-domain attenuation method from literature [15]. Experimental data yielded the longitudinal wave velocity evaluation model:

$$\tilde{D}(V_L) = 2282.255 - 0.376V_L$$

where V_L has units of $\mathrm{m \cdot s^{-1}}$.

[Figure 8: see original paper] compares evaluation results and error bands for the three methods relative to metallographic measurements. Detailed performance data are provided in , where D represents evaluation results from the velocity, attenuation, and proposed models, and E denotes relative errors versus metallographic measurements. The velocity and traditional attenuation models show large fluctuations relative to the 45° line with wide error bands, while the proposed model exhibits smaller fluctuations and narrower error bands, approaching the metallographic measurement error band level.

Using metallographic values from as ground truth, the maximum systematic errors (relative errors) are +12.57% for the velocity method, +5.85% for traditional attenuation, and -1.33% for the proposed method. Regarding fitting precision, the 2-norm of residuals between estimated and true values is 12.995 and 8.235 for the first two models, respectively, but only 2.544 for the proposed model. The velocity method shows low sensitivity for 304 stainless steel with significant nonlinear error, while traditional attenuation only considers time-domain information without frequency-domain correction. Comparing 3σ error bands, random error significantly impacts the velocity method due to difficult echo front identification and poor anti-interference capability. Its impact decreases for traditional attenuation and becomes negligible for the proposed model, with Sample No.5' s error band reducing from $±$9.0 mm and $±$5.7 mm to $±$2.7 mm.

To verify practical performance, a validation sample was prepared using the method in Section 1.2. A 25 mm diameter, 15 mm long 304 stainless steel sample was heat-treated at 1070°C for 8 hours, water-quenched, and stress-relief annealed. Metallographic measurement per GB/T 6394-2002 yielded an average grain size of 103.5 mm with 2.89% relative error. Multi-scale analysis of 20 acquired ultrasonic A-scan signals produced nondestructive evaluation results of (110.4$±7.8), (98.2±6.6), and (101.7±$3.9) mm using the three methods, respectively.

In summary, the proposed model significantly improves evaluation precision, effectively reducing systematic error and suppressing random error. Theoretical analysis attributes this to: (1) comprehensive utilization of time-frequency domain information through wavelet transform to examine attenuation characteristics across scales, combined with particle swarm optimization for scale selection and weight allocation, yielding a multi-scale attenuation coefficient strongly correlated with grain size and reducing systematic error; (2) exploitation of wavelet transform' s constant-Q filtering properties, where large scales contain fewer low-frequency components with strong anti-high-frequency-noise capability, while small scales contain more high-frequency components with concentrated energy across the bandwidth, making noise impact insignificant. The combined anti-noise capability across scales effectively suppresses random error. Multi-scale signal analysis reveals richer grain size information, improving nondestructive evaluation precision. Future research will incorporate diffraction-induced attenuation terms for curved surfaces to enhance practical applicability.

Conclusions

1. Analyzing limitations of traditional ultrasonic attenuation methods for metallic material grain size evaluation, this work proposes a novel multi-scale attenuation coefficient concept that comprehensively utilizes ultrasonic attenuation characteristics across scales for nondestructive grain size evaluation, leveraging the advantages of strong anti-interference at large scales and high energy at small scales.
2. Based on multi-scale attenuation coefficients, particle swarm optimization designs optimal scale combinations and normalized weight allocation strategies, establishing an ultrasonic multi-scale attenuation evaluation model that effectively suppresses fitting errors.
3. Experiments on 304 stainless steel samples demonstrate that compared with traditional ultrasonic velocity and attenuation methods, the proposed method offers smaller systematic errors and narrower error bands. This method can be extended to nondestructive grain size evaluation of other metallic materials.

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Note: Figure translations are in progress. See original paper for figures.