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Advancing Concrete Integrity Using Phased Array Ultrasonic Testing

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Abstract: Assessment of structural condition is essential for ensuring concrete integrity. Phased Array Ultrasonic Testing (PAUT) offers notable advantages for concrete inspection, including electronic beam steering and dynamic focusing; however, its application is challenged by signal attenuation, material heterogeneity, and limited defect resolution. This paper provides a comprehensive overview of PAUT's principles and applications in concrete structures, supported by experimental results and case studies. The study evaluates current limitations and highlights the novelty of advanced signal processing and machine learning integration to enhance defect detectability and improve data interpretation in heterogeneous concrete structures.

Keywords: Concrete; Machine learning; Phased Array Ultrasonic Testing; Signal processing

1. Introduction

Concrete is the primary construction material in civil engineering due to its durability, strength, and cost-effectiveness. When combined with steel reinforcement, it offers excellent mechanical and structural performance over its service life. However, concrete material is prone to defects such as voids, cracks, and delamination, which may weaken the structural durability of buildings and infrastructure[1,2]. These defects can be particularly problematic in harsh conditions. For example, the rusting of reinforcing bars in concrete can weaken structures[3,4], the load-carrying capacity[5], and affect the earthquake resistance[6]. In marine environments, chloride ions can migrate through concrete and cause corrosion[7]. In pre-stressed concrete, corrosion is often found in ducts with voids caused by trapped air pockets, grout bleeding[8], or improper grouting[9–11] . Cracks in concrete can also occur due to various reasons such as external force, rebar corrosion, freeze-thaw cycles, moisture changes, and self-shrinkage. The detection and characterization of these defects are crucial for ensuring safety and longevity. However, determining defects in concrete, particularly those that are internal, is a difficult task.

To resolve these problems, Ultrasonic Testing (UT) can be used to detect defects in concrete. UT is a non-destructive test that uses high-frequency sound waves through the concrete and measures how they travel through the material. Defects such as voids, cracks, and delamination areas can be detected by analyzing the reflected sound waves. UT offers many advantages, including accuracy and precision, flexibility, and versatility. It can also be used to test in a wide range of areas, making it an essential method for verifying the integrity and safety of concrete structures. Moreover, UT can be used to monitor the condition of reinforcing bars and detect early signs of corrosion, allowing for maintenance and repairs. The UT method can increase the concrete structure’s durability, prevent the risk of failure, and improve overall safety. It employs high-frequency sound waves to identify flaws or defects. These sound waves, usually ranging from 0.5 to 15 MHz, are generated by a transducer and travel through the material being tested. When these waves encounter a boundary between different materials or a flaw such as a crack or void, part of the wave energy is reflected to the transducer. By analyzing the time of wave propagation and the amplitude, UT offers valuable insights into the material’s integrity.

Recent advancements in UT methods have significantly enhanced non-destructive evaluation (NDE) techniques for concrete structures, enabling precise detection of internal defects, measurement of thickness, and monitoring of structural integrity. Maack et al.[12,13] provided a comprehensive dataset using low-frequency ultrasonic pulse-echo techniques for concrete specimens, highlighting high precision and repeatability. Xu and Jin[13] combined UT with artificial neural networks to measure reinforcement corrosion and found that moisture significantly impacts ultrasonic velocity. Corrosion in reinforced concrete can also detect by using ultrasonic-guided waves[14,15], and this method showed the effectiveness in identifying top-bar defects and facilitating early maintenance. Another study investigated ultra-high-performance fiber-reinforced concrete (UHPFRC) using an in-situ nonlinear ultrasonic technique, which demonstrated high sensitivity to early-stage damage, while ultrasonic fatigue testing showed the durability of concrete under cyclic loading[15]. Additionally, Terzioglu et al.[16] assessed various NDE techniques for detecting defects of grout in post-tensioned girders and stated that while Ground Penetrating Radar (GPR) identified tendon profiles, Impact Echo (IE) and Ultrasonic Pulse Echo (UPE) were more effective in locating grout defects. These advancements highlight the critical role of ultrasonic testing in ensuring the longevity and safety of concrete infrastructures. Furthermore, Wael Zatarl[17] conducted a study using UPE to evaluate defects in reinforced concrete decks. The study emphasized that these methods could assess the location and the depth of void defects, providing valuable quantitative data for calibrating UPE device images. Nevertheless, such methods have insufficient accuracy in quantitatively measuring internal defects in concrete structures.

PAUT offers several advantages compared to traditional UT methods[18], making it the best option in many applications, particularly for the NDE of concrete structures. The following section reviews the fundamental theory of PAUT, compares its performance with other NDE techniques, and summarizes its applications and optimization strategies for concrete inspection. In general, the electronic control of beam steering and focusing enables flexible inspection, improves the detection capability for internal defects, and allows effective scanning even in structures with limited access or complex geometries.

Higher frequencies theoretically enhance the sensitivity and resolution of PAUT imaging, but attenuation must be considered. Frequencies in the MHz range are typically used for inspecting metals, where wave propagation is less affected. However, for concrete structures, which are more attenuated than metals, a lower-frequency array transducer is essential for effective PAUT imaging. To further enhance the results and obtain better images from PAUT, signal wavelet processing techniques can be utilized. Signal wavelet processing decomposes ultrasonic signals into various frequency components and enables further analysis and processing to improve image quality. This technique allows for noise reduction, enhanced resolution, and improved defect detectability.

Recent developments in Artificial Intelligence (AI) have significantly enhanced the accuracy and efficiency of data interpretation. Toke[19] and Deepal[20] demonstrated that an Artificial Neural Network (ANN) can enhance the quality prediction and material evaluation. Similarly, Pinku[21] and Sethi[22] presented the potential of applying deep learning and machine learning to improve the prediction and perform pattern recognition.

1.1. Existing review articles and motivation for the present review

Several review articles have examined NDE, Structural Health Monitoring (SHM), UT, and AI applications for infrastructure assessment[23–26]. Previous reviews have provided a systematic review of advanced sensor technologies used in Non-Destructive Test (NDT) and SHM, covering UT, GPR, infrared thermography, acoustic emission, and AI-assisted monitoring systems [27]. Their review offers a broad perspective on sensing technologies and infrastructure monitoring strategies. Furthermore, deep-learning applications in ultrasonic NDE have been reviewed, highlighting developments in automated defect detection, classification, and signal interpretation[28] More recently, machine learning applications in PAUT have been discussed, emphasizing the use of intelligent algorithms for defect characterization and automated analysis[29].

As summarized in Table 1, previous review articles have primarily focused on broad NDE technologies, general UT methods, or AI-assisted inspection frameworks. Although these studies have significantly advanced the understanding of infrastructure assessment, relatively limited attention has been given to the application of PAUT for concrete structures. Furthermore, the integration of PAUT with signal processing techniques such as wavelet-based analysis, image reconstruction, and AI

Table 1: Comparison of existing review articles and the present review

Review article	NDE methods	PAUT	Concrete focus	Signal processing	AI
Mainly focus on NDT techniques[30]	✓	✗	✓	✗	✗
Broad review of sensor technology and SHM[27]	✓	Limited	✓	General discussion	✓
Focus on deep learning[28]	Ultrasonic NDE	Limited	✗	Limited	✓
Focus on machine learning for PAUT[29]	PAUT	✓	Partial	Limited	✓
Present review	✓	✓	✓	✓	✓

classifiers remains insufficiently addressed in the existing review literature.

Therefore, this review aims to provide a comprehensive overview of PAUT for concrete integrity assessment, with particular emphasis on signal processing techniques, imaging enhancement methods, and AI-assisted interpretation approaches. By integrating these topics within a single review, this study seeks to identify current challenges, summarize recent advances, and highlight future research directions for improving defect detection and characterization in concrete structures.

2. Fundamentals of PAUT

2.1. Comparison of other NDE methods

Various NDE techniques have been developed to assess the internal condition of concrete structures, including GPR, IE, UT and PAUT. These methods differ in their physical principles, defect detection capabilities, penetration characteristics, and suitability for complex concrete structures.

GPR utilizes electromagnetic waves to identify changes in dielectric associated with internal defects. Due to its rapid scanning capability and ability to cover large inspection areas, GPR has been widely used for the evaluation of bridge decks, tunnels, and post-tensioned concrete structures[31,32]. Previous studies have shown that GPR can effectively detect water filled voids, chloride-induced corrosion, and grouting deficiencies in prestressing ducts[31,33]. In addition, GPR has demonstrated the ability to distinguish between well-grouted and voided ducts and to differentiate air-filled and water-filled voids based on their reflection characteristics[34]. However, the performance of GPR is strongly influenced by moisture content, reinforcement density, antenna frequency, and data acquisition configuration[33,35]. Furthermore, GPR surveys can be affected by scan spacing, and field conditions, including signal interference and positioning limitations[36]. Consequently, although GPR is highly effective for rapid screening and large-area condition assessment, its capability for detailed defect characterization remains limited in heavily reinforced concrete structures.

IE is an acoustic-based technique that evaluates the frequency response of stress waves generated by a mechanical impact. The method has been extensively applied to detect voids, delamination, thickness variations, and defects associated with concrete[37–41]. Previous investigations have demonstrated that IE can estimate defect location and depth with reasonable accuracy and provide valuable information for structural condition assessment and maintenance planning[38,39]. Nevertheless, the performance of IE is influenced by defect geometry, orientation, and material characteristics. Defect with surfaces perpendicular to the testing surface may be difficult to detect, and error in depth estimation can occur in complex structural configurations[37].

Conventional UT has long been employed for the evaluation of concrete structures because its sensitivity to changes in acoustic properties[42–44]. Techniques such as Ultrasonic Pulse Velocity (UPV), Ultrasonic Pulse Echo (UPE), and ultrasonic tomography have been used to assess concrete quality, estimate material properties, and detect defects including cracks, voids, honeycombing, and delamination[44–46]. UT methods can also be applied to evaluate grout condition in post-tensioned ducts and assess tendon integrity[16]. By analyzing wave velocity, attenuation, travel time, and reflection characteristics, UT provides valuable information regarding internal structural conditions. However, the heterogeneous nature of concrete introduces significant attenuation and scattering, which can complicate signal interpretation. Moreover, conventional UT typically employs single-element transducers, requiring multiple measurements and mechanical repositioning to inspect large areas. Consequently, the resulting information is often localized, limiting defect visualization and reducing inspection efficiency. To overcome these limitations, PAUT offers superior inspection efficiency[47,48], improving defect inspection, and greater flexibility in complex structural geometries[18,47]. Table 2 summarizes the characteristics, advantages, and limitations of principal NDE methods used for concrete evaluation.

Table 2: Comparison of NDE methods for concrete assessment

Method	Principle	Advantages	Limitations	Typical defects detected
GPR	Electromagnetic wave reflection	Rapid scanning, large-area coverage	Sensitive to reinforcement density, moisture variation, and antenna resolution	Voids, corrosion, grout deficiencies
IE	Stress-wave frequency analysis	Effective for depth estimation and defect assessment	Limited imaging capability and defect characterization	Voids, delamination, thickness variations
Conventional UT	Analysis of ultrasonic wave propagation and reflection	Sensitive to internal defects, material condition information	Limited coverage and visualization	Cracks, voids, honeycombing, delamination, grout defects
PAUT	Electronically steered, focused ultrasonic array	High-resolution imaging, improved coverage, accurate localization	Higher equipment cost and data-processing complexity	Voids, cracks, grout deficiencies

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2.2. Basic theory of PAUT

PAUT is a sophisticated non-destructive testing technique, increasingly applied to evaluating the integrity of concrete structures. Unlike traditional methods, PAUT uses multiple ultrasonic elements and delayed electronic signals (Figure 1) to generate a signal and direct, focus, and steer it electronically. By applying time delays to the signals emitted by each transducer element, the ultrasonic beam can be electronically steered to various angles[49]. This approach directs the inspection beam without physically moving the probe. It also uses time delays to focus the ultrasonic beam at specific depths within the material. This improves the detection and sizing of defects by concentrating on the signal energy at a particular point. The phased array system can electronically scan the beam across the test object. This rapid scanning capability increases inspection speed and coverage compared to conventional single-element ultrasonic testing. This capability allows for detailed concrete scanning, offering enhanced detection of flaws such as cracks, voids, delamination, and corrosion without invasive measures.

PAUT's flexibility in adapting to different concrete conditions and its ability to provide accurate, real-time imaging make it invaluable in ensuring structural integrity assessments, making guidelines for conducting repairs, and extending the lifespan of concrete infrastructure. PAUT of concrete commonly uses a frequency range of 50 to 200 kHz, influenced by variables such as aggregate composition and pore pattern, which impact the ultrasonic wave scattering and energy loss. However, low-frequency ultrasound testing presents various practical and technical challenges, including the need for probes with a larger diameter compared to those used in conventional ultrasound testing. Consequently, the longitudinal wave sound beam becomes nearly non-directional. Additionally, significant shear and surface waves occur, interfering with the PAUT results. Ultrasonic waves propagate more efficiently in uniform materials, whereas in air they are largely reflected. This principle is essential for detecting micro-cracks within the material. Analyzing changes in acoustic characteristic parameters during ultrasonic wave propagation can detect internal defects in materials, such as pulse wave velocity, time of flight, attenuation, and amplitude. (1) Pulse wave velocity: the speed of ultrasonic waves in a material depends on the propagation medium, with denser materials allowing for faster wave propagation. (2) Time of flight: it refers to the duration for an ultrasonic wave to pass through the material and bounce back to the transducer after encountering a defect or boundary. If the wave encounters a boundary (like the back wall of the material) or a defect (such as a crack or void), it will reflect toward the transducer. (3) Attenuation: the phenomenon of gradual loss of energy as an ultrasonic wave propagates through a material, which affects the amplitude of the received signal. Ultrasonic waves with higher frequencies attenuate more rapidly than those with lower frequencies. This is because higher-frequency waves are more capable of scattering and absorption. (4) Amplitude: a measure of the strength of the ultrasonic wave that is reflected to the transducer from a defect or boundary within the material. A higher amplitude indicates a stronger reflection, while a lower amplitude indicates a weaker reflection.

2.3. Application of PAUT

The application of ultrasonic methods for non-destructive testing in civil engineering significantly differs from their use in metal testing. In concrete, the heterogeneous composition contributes to significant sound reduction caused by absorption and scattering. Conventional ultrasonic testing methods, especially those utilizing higher frequencies, often fail to detect internal defects such as cracks and delamination effectively. Consequently, ultrasound frequencies lower than 200 kHz, corresponding to wavelengths over 2 cm, are typically required. Yoshikazu Ohara et al[50] discussed the development of a low-frequency (LF) phased array transducer designed for NDT of concrete structures. The research showed the

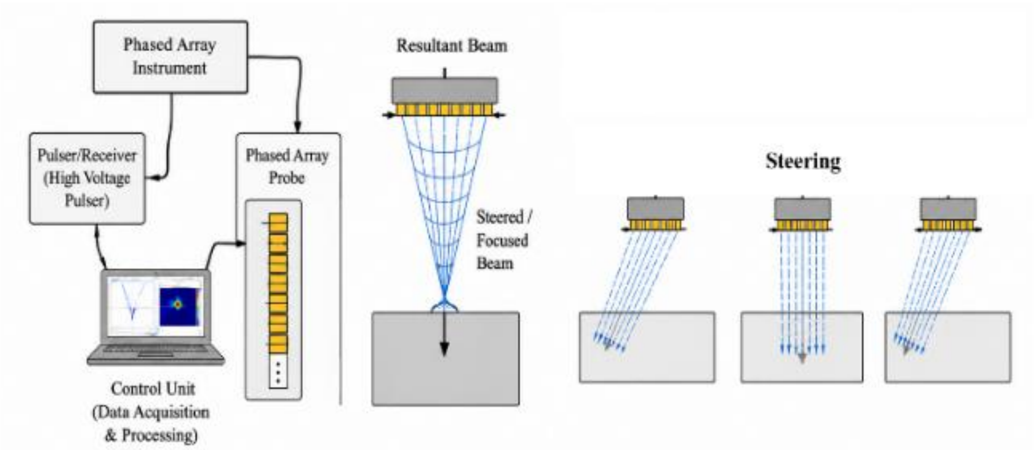

Fig. 1: Beam focusing and steering in PAUT

effectiveness of the LF phased array transducer for imaging internal defects in concrete structures. However, while LF enhances detectability, it results in lower spatial resolution, which may limit the accurate characterization of small defects. To further address wave distortion and signal loss, several studies[47,51,52] integrated advanced imaging into low-frequency ultrasonic imaging, such as Total Focusing Method (TFM), Diffusion Attenuation Compensation Method (DACM), and Solid Directivity Correction Method (SDCM). These methods improved the signal-to-noise ratio (SNR) and significantly enhanced defect detection accuracy and resolution, especially for defects at large deflection angles or distances. However, the effectiveness of these techniques depends on material properties, which may vary significantly between concrete specimens.

O. Paris, C. Poidevin, J.M. Rambach, and G. Nahas[47,53] investigated the application of PAUT for inspecting concrete structures, particularly in nuclear power plants. The research utilized the potential of PAUT and Synthetic Aperture Focusing Technique (SAFT) and succeeded in improving inspection accuracy by enhancing SNR and resolution. Jialun Zhang, Lin Liu, and Lixin Li[54] explored the application of PAUT for identifying internal defects in concrete structures. PAUT allows for dynamic adjustment of the sound beam's focus and angle, enabling detailed imaging and precise detection of internal defects in concrete structures. Its advantages include continuous scanning capability, clear imaging, and the ability to identify various types of defects. PAUT was also used for detecting interfacial debonding in Concrete-Filled Steel Tube (CFST) structures, with a specific focus on its application to the Shenzhen SEG building. The findings indicated that the method proves successful in determining the debonding area and measuring its size.

2.4. Optimization of PAUT

To optimize PAUT in concrete, it is essential to overcome the unique challenges caused by the material's heterogeneous and attenuated nature. Frequency is a critical factor in PAUT due to its balancing the trade-offs between penetration depth, resolution, material attenuation, and the specific characteristics of the defects and material being inspected. Lower frequencies penetrate deeper into the material but have lower resolution. They are useful for inspecting thicker sections of concrete. Higher frequencies provide better resolution but have less penetration depth, making them suitable for detecting smaller defects near the surface. Higher frequencies can sometimes result in lower SNR due to scattering effects and reduced signal quality in concrete. Optimizing the frequency helps maintain a good SNR, which is crucial for accurate defect detection and characterization. Proper surface preparation is also crucial, ensuring the concrete surface is smooth and adequately coupled with a suitable gel to enhance signal transmission. Moreover, utilizes advanced signal processing techniques, such as filtering and averaging, to reduce noise and improve the signal-to-noise ratio. To reduce Gaussian noise, which is characterized by random, normally distributed amplitude fluctuations and other random noise in the signal, an Adaptive Least Mean Square (ALMS) filter was suggested[55]. By combining a low-pass filter (LPF), a high-pass filter (HPF), and a band-pass filter (BPF), the ALMS filter reduces noise while preserving defect-related signal characteristics. Further signal processing approaches, such as the wavelet transform, are presented in the next section.

Machine learning and deep learning have significant potential to optimize PAUT by enhancing data interpretation, improving defect detection accuracy, and automating analysis processes. Conventional PAUT methods rely heavily on manual interpretation of complex signal data, making the process time-consuming and susceptible to human error. Machine learning models[24], such as support vector machine and random forest classifiers, can be trained on feature extraction of PAUT signals to identify patterns associated with different defect types and anomalies. Deep learning approaches, particularly Deep Convolutional Neural Networks (DCNN), further advance this capability by automatically extracting features from processed PAUT signals, enabling more accurate defect localization and classification[55]. Additionally, integrating machine learning and deep learning can reduce the reliance on traditional signal processing techniques, improving the speed and efficiency of defect detection in concrete and other materials[56,57].

Focusing is also important in PAUT because it directly affects beam energy concentration, SNR, and spatial resolution, all of which are essential for accurate defect

Table 3: Summary of studies on PAUT optimization

Optimization strategy	Reported improvement
Wave transmission sequence (full matrix capture, plane waves, Hadamard)[59]	Hadamard improved SNR by 9 dB compared to full matrix capture, plane waves
Focal law optimization[60]	Increased the acoustic energy and significantly improved the focusing performance
Optimized sensor position and defect depth[61]	The echo amplitude increased significantly
Coded excitation (Golay)[58]	SNR increased from 11.1 dB to 16.4 dB
Adaptive filtering + DCNN [55]	Mean square error reduced to 0,0938, and classification accuracy reached 97%

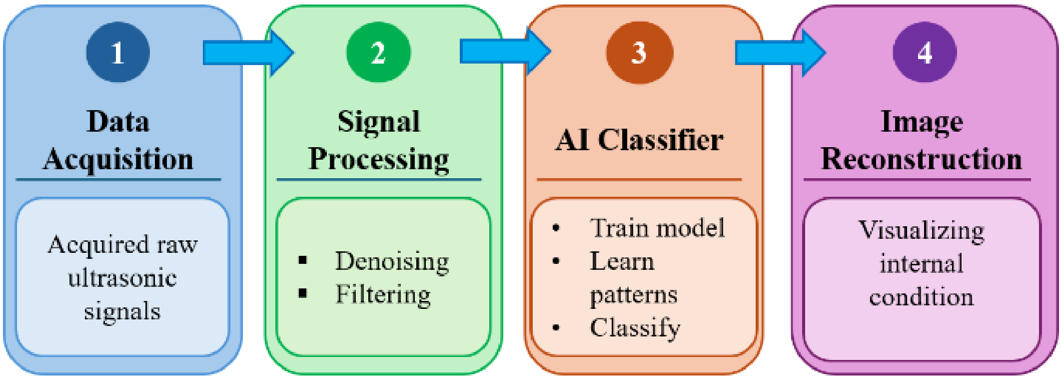

Fig. 2: General framework of defect detection based on ultrasonic signals

classification and imaging. Therefore, proper adjustment of steering angles and focus point based on the inspection geometry and expected defect locations enhances echo amplitude and improves detection contrast. Viktor Feller[58] discussed innovations in using a phased array with dry contact probes for testing concrete components. The study focused on using low-frequency ultrasonic phased arrays with shear wave probes to control the sound field's directivity during measurements. The results showed the effectiveness of point source synthesis in optimizing probe array designs, particularly in suppressing side lobes and enhancing signal concentration. The research also highlighted the utilization of coded transmission signals, such as Golay coding, to enhance the signal-to-noise ratio, which resulted in better performance than traditional rectangular pulses. Table 3 summarizes several studies investigating different approaches to PAUT optimization.

3. Defect detection based on signal

Ultrasonic signals obtained from concrete structures are inherently non-stationary and contain information in both the time and frequency domains. Figure 2 illustrates the general framework of ultrasonic signals-based defect detection. Raw ultrasonic signals are first acquired and then processed through denoising and filtering techniques to improve signal quality. Then analyzed by an Artificial Intelligence (AI) method for defect classification. Finally, image reconstruction techniques are applied to visualize the internal condition of the structure and localize potential defects.

3.1. Signal filtering

Signal filtering is an important process in signal processing that involves removing unwanted components or noise from a signal to enhance its quality and extract useful information[62) [29,30]. In the context of ultrasonic testing and other non-destructive evaluation methods, signal filtering is indispensable for improving the clarity and accuracy of the detected signals. Figure 3 presents a schematic illustration of the effect of signal filtering on ultrasonic signals. In the raw signal, defect-related reflections are partially masked by noise and unwanted signals. After filtering, noise is suppressed, and the defect-scattering response becomes more distinguishable, resulting in improved signal interpretation and defect detectability.

For instance, researchers employed Chebyshev's filtering[63] to enhance the SNR of defect-scattering signals. By selecting filter parameters, the researchers were able to remove unwanted noise components while preserving the integrity of the defect signals, thereby improving the accuracy of the defect detection process. M. Moles, L. Wesley, and T. Sinclair[63] discussed advancements in accurately sizing defects using ultrasonic phased array technology combined with digital signal processing techniques. Traditional ultrasonic sizing methods,

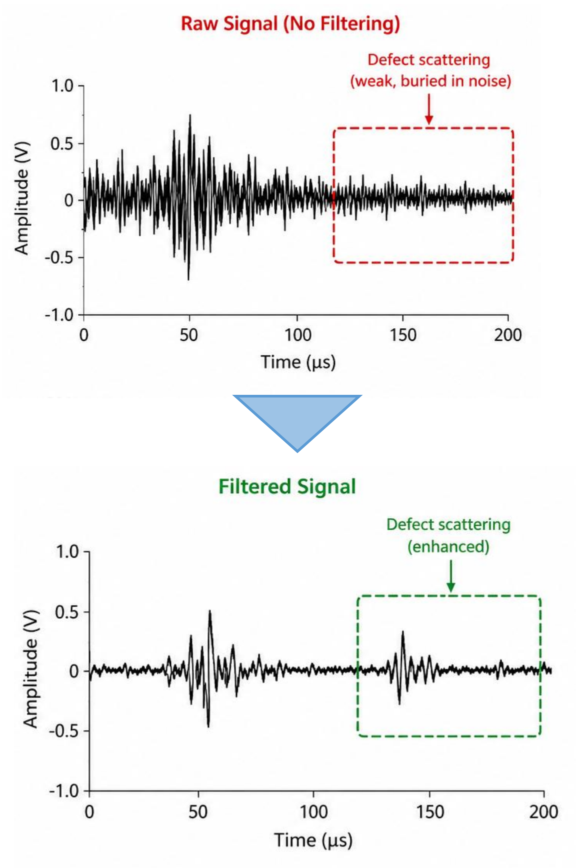

Fig. 3: Schematic representation of filtering effects

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including simple amplitude-based techniques and Time-Of-Flight Diffraction (TOFD), have limitations in accuracy due to factors like pulse length and operator interpretation. This study proposed an innovative approach using Weiner filtering and autoregressive spectral extrapolation to improve ultrasonic signals' time resolution and accuracy. Furthermore, Weifeng Yang[64] introduced a novel denoising method with a detailed study of electrical noise in PAUT. The study provided a detailed evaluation of electrical noise in PAUT systems and presented an effective denoising method that enhances the accuracy and reliability of ultrasonic testing, especially in materials with high acoustic energy loss like composites.

Among the available filtering approaches, low-pass, band-pass, adaptive, and wavelet-based filtering techniques are the most employed in ultrasonic NDE. Each method offers distinct advantages depending on the signal characteristics, noise, and inspection objectives.

3.1.1. Low-pass filtering

Low-pass filtering allows low-frequency components of a signal to pass while attenuating high-frequency noise. In ultrasonic concrete inspection, high-frequency noise may originate from electronic interference, coupling variations, and wave scattering caused by aggregates and material heterogeneity[65]. Therefore, low-pass filters are commonly employed to improve signal quality, enhance the signal-to-noise ratio (SNR), and facilitate the identification of dominant reflections associated with internal defects[66,67]. Studies have shown that filtering techniques can significantly improve the visibility of defect echoes and the quality of ultrasonic images in concrete structures. However, excessive low-pass filtering may suppress high-frequency information associated with small defects, leading to reduced spatial resolution and decreased sensitivity to fine discontinuities.

3.1.2. Band-pass filtering

Band-pass filtering allows signals within a specified frequency range to pass while attenuating both low-frequency and high-frequency noise components. In ultrasonic concrete inspection, band-pass filters are commonly employed to isolate the frequency content associated with ultrasonic wave propagation and defect reflections while suppressing electronic noise, low-frequency drift, and scattering-related disturbances[68]. By retaining only the frequency band of interest, band-pass filtering can improve the signal-to-noise ratio (SNR), enhance defect visibility, and improve the quality of ultrasonic images. Recent studies on ultrasonic concrete imaging have demonstrated that band-pass filtering effectively improves the detectability of internal defects and can provide superior image quality when combined with a reconstruction algorithm such as SAFT[69,70]. However, improper selection of the passband may result in the loss of useful defect information or insufficient noise suppression. Therefore, the filter parameter should be carefully selected according to the transducer frequency and inspection requirements[71,72].

3.1.3. Adaptive filtering

Adaptive filtering is a signal-processing technique that automatically adjusts its filter parameters according to the characteristics of the input signal and surrounding noise environment. Unlike fixed low-pass or band-pass filters, adaptive filters continuously update their response to suppress noise while preserving useful ultrasonic information[73]. This capability is particularly valuable in concrete inspection, where ultrasonic signals are strongly affected by material heterogeneity, aggregate scattering, coupling variations, and environmental interference. Early research reported that adaptive beamforming and adaptive array processing can effectively suppress noise, enhance defect echoes, and improve imaging resolution in ultrasonic array inspection, thereby increasing the reliability of defect detection and characterization[74]. More recently, adaptive signal processing has been integrated into phased array testing imaging algorithms. An adaptive amplitude-phase fusion framework that combines adaptive phase-entropy weighting and phase-amplitude interaction was proposed[75]. Their results demonstrated enhanced SNR, improved defect boundary, and a more accurate image of internal defects in precast concrete.

3.1.4. Wavelet denoising

Another filter that is also widely used is wavelet denoising. This filtering offers several advantages over traditional filtering methods, especially for certain types of signals and applications. Wavelet-based denoising provides a time-frequency representation of the signal[76,77], allowing for adaptive filtering that can target specific features or noise patterns within the signal[76,78]. This is especially beneficial for non-stationary signals, where the frequency content changes over time. Wavelet transforms decompose a signal into components based on shifted and scaled versions of a mother wavelet function[79,80].

Previous studies have demonstrated that wavelet denoising effectively improves SNR, enhances the clarity of defect-related reflections, and facilitates more accurate characterization of cracks and other internal defects in concrete[77,81,82]. Furthermore, Wavelet Packet Transform (WPT) methods have been successfully applied to reconstruct useful frequency-band information approaches such as Convolutional Neural Network (CNN), have achieved high accuracy in automated concrete defect recognition and classification[78].

In ultrasonic imaging and signal enhancement, two main wavelet transform types are commonly used: (1) Continuous Wavelet Transform (CWT). Provides a highly redundant representation of the signal with continuous scaling and shifting. It is useful for detailed analysis of signal characteristics at various scales and locations; (2) Discrete Wavelet Transform (DWT). Offers more efficient representation by using discrete scaling and shifting steps, often implemented through multi-resolution analysis (MRA), suitable for filtering and denoising applications.

CWT has been applied to the analysis of frequency-dependent velocities in concrete[83]. In this study, multiple wavelet families constructed the time-frequency distributions of ultrasonic pulses, and the analysis evaluated velocity variations with frequency for both transverse and longitudinal waves. The experimental dataset consisted of 14 concrete specimens with five different mix designs, demonstrating the capability of CWT to decompose and analyze waves propagating in heterogeneous materials. The results indicated that CWT is particularly effective for overcoming challenges related to attenuation and material heterogeneity, providing a clearer understanding of the concrete microstructure and its damage condition. In contrast, DWT is more commonly used for signal denoising and feature enhancement[84]. Takashi Nagamatsu[85] studied the use of Parasitic Discrete Wavelet Transform (P-DWT) for early detection of anomalies in the rotating machinery of the fast-breeder reactor Monju. In this study, the diagnostic system integrated P-DWT and designed customized mother wavelets to closely resemble real anomaly signals. This parasitic filtering enabled the enhancement of the weak diagnostic component while suppressing noise, therefore improving detection sensitivity in environments with challenging signal conditions.

As shown in Table 4, conventional filtering techniques such as low-pass and band-pass filters are computationally efficient and effective for removing specific frequency components. However, their fixed frequency-domain operation limits their ability to process non-stationary ultrasonic signals in concrete inspection.

Adaptive filtering offers greater flexibility but requires additional computational resources and parameter optimization. Among the reviewed techniques, wavelet denoising techniques have proven to be powerful tools for signal enhancement, particularly in the field of ultrasonic testing and non-destructive evaluation. Wavelet analysis enables the extraction of subtle signal features that are often masked by noise. Furthermore, the integration of wavelet filtering with advanced digital signal processing techniques, as demonstrated in several recent studies, continues to improve the detection sensitivity of UT.

3.2. AI-based defect classification

AI has emerged as a powerful tool for interpreting ultrasonic ins for interpreting ultrasonic inspection data and improving defect characterization in concrete structures. Conventional ultrasonic analysis often relies on manual interpretation of signal amplitudes, wave arrival time, and reconstructed images, which can be time-consuming and highly dependent on operator expertise. The integration of AI techniques enables automated analysis of complex ultrasonic data, improving inspection efficiency, consistency, and reliability. Recent studies have highlighted the importance of machine learning and deep learning for ultrasonic NDE, particularly for defect detection, characterization, and imaging application[86–88].

Machine learning algorithms are typically applied after signal pre-processing. Statistical features, frequency-domain parameters, wavelet coefficients, and image descriptors can be extracted from ultrasonic signals and subsequently used as inputs for classification models. Common machine learning methods include Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), k-Nearest Neighbors (k-NN), and Artificial Neural Network (ANN). These algorithms have demonstrated the ability to classify cracks, voids, delamination, and other internal defects[57,87,89–94]. Furthermore, Cacciola M. et al.[94] proposed an extension of the Takagi-Sugeno fuzzy inference system [TS-FIS] framework based on prototypical fuzzy similarity (PFS) for defect detection in concrete.

Among conventional machine learning approaches, ANN have received considerable attention because of their capability to model complex nonlinear patterns in ultrasonic signals. Their ability to learn from experimental data enables the identification of subtle signal variations

Table 4: Summary of signal filtering methods

Filtering technique	Principle	Advantages	Limitations
Low-pass filter	Retains low-frequency components	Simple implementation	May remove high-frequency information associated with small defects
Band-pass filter	Preserves a selected frequency band	Improves SNR	Required careful selection of cutoff frequencies
Adaptive filter	Dynamically adjusts filter parameters	Effective in non-stationary environments	Higher computational complexity and dependence on parameter selection
Wavelet denoising	Decomposes signal into multiple scales and removes noise	Excellent time-frequency localization	Performance depends on wavelet selection, decomposition level

that may not be evident through traditional analytical methods. Previous studies have demonstrated that ANN-based approaches can improve prediction accuracy and enhance the interpretation of ultrasonic inspection results[93,95,96]. Moreover, Lee S. and Popovics J.S.[95] applied Physics-Informed Neural Networks (PINNs) to facilitate accurate material property characterization and defect identification.

Recent advances in deep learning have further enhanced ultrasonic defect detection and characterization. Convolutional Neural Network (CNN) can automatically learn discriminative features directly from ultrasonic signals or reconstructed images without requiring extensive manual feature engineering. Deep learning methods have been applied to various NDE, including signal preprocessing, defect detection, defect characterization, and automated image interpretation[97–99].

In PAUT, AI techniques have become increasingly important because of the complexity of data. Recent studies have reported successful applications of machine learning for PAUT image enhancement, defect detection, defect characterization, and automated interpretation[86,87,100,101]. Machine learning-assisted PAUT has demonstrated the potential to improve defect localization and enhance inspection consistency.

3.3. Imaging methods

The imaging method for wavelet signals involves using wavelet transform techniques to analyze and visualize signals in a way that captures both time and frequency information. The integration of wavelet signal analysis with advanced imaging algorithms has significantly enhanced the capability of NDE to visualize and interpret internal structure conditions. Figure 4 presents a schematic illustration of the ultrasonic image reconstruction process. Multiple A-scan signals acquired from different transducer positions are combined using reconstruction algorithms to generate a two-dimensional image of the inspected region. The reconstructed image provides spatial information regarding the location and geometry of internal reflectors, enabling improved visualization and characterization of defects.

The TFM[102,103] was used as a high-resolution ultrasonic

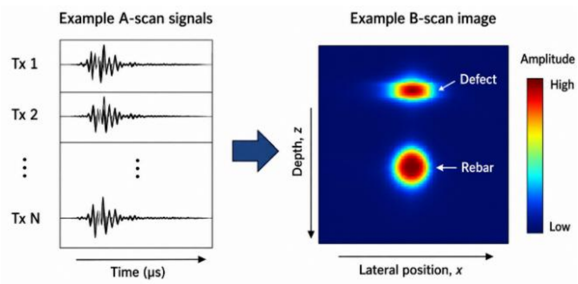

Fig. 4: Schematic illustration of ultrasonic image reconstruction from multiple A-scan signals

imaging method for detecting damage in concrete structures. The study overcame the concrete natural characteristics, such as severe signal scattering due to diverse internal acoustic interfaces and attenuation by coarse aggregates. The authors proposed an optimization method combining TFM with advanced signal processing algorithms to enhance detection resolution and SNR. The combined application of TFM, time reversal (TR), and phase coherence imaging (PCI) algorithms, along with digital filtering, significantly improves the resolution and accuracy of ultrasonic imaging in concrete structures.

Another widely used reconstruction approach is SAFT. SAFT is an image reconstruction method that improves ultrasonic image quality by synthetically increasing the effective aperture of the transducer through the coherent summation of signals acquired from multiple scan positions. These discontinuities make SAFT particularly suitable for locating cracks, voids, and delamination in concrete structures[104,105]. The application of the wavelet transform and SAFT for detecting and sizing flaws in ultrasonic images has been investigated[106]. By integrating wavelet transform for noise reduction and SAFT for enhanced imaging, the authors proposed a method that significantly improved the accuracy and reliability of flaw detection and characterization. Compared with conventional pulse-echo imaging, SAFT provides clearer images and improved defect localization while maintaining relatively low computational requirements

In addition to SAFT, inverse-scattering-based imaging methods have been developed to provide more detailed characterization of internal defects. One of the techniques is the Kirchhoff Linearized Inverse Scattering Method (K-LISM), which reconstructs the geometry and location of internal reflectors by utilizing scattered ultrasonic wavefields. Because K-LSIM accounts for wave-scattering mechanisms, it can provide more detailed representations of defect boundaries and material interfaces than conventional reconstruction methods. The combined application of the K-LISM and P-DWT has been investigated for the early detection and visualization of reinforcing-bar (rebar) corrosion in concrete structures [107]. By integrating K-LISM and P-DWT, the researchers achieved high-resolution imaging of the steel-concrete interface, enabling the identification of corrosion before it becomes visible.

As demonstrated in recent studies, such integrated imaging frameworks improve both accuracy and visual interpretability[108], leading to an intelligent diagnostic system of automated defect recognition and material health evaluation. In general, the imaging methods discussed above show varying performance in terms of resolution, computational requirements, and suitability for concrete inspection. The TFM provides high-resolution imaging and is effective for detecting small defects, but it requires high computational resources and can be affected by strong scattering in heterogeneous materials. The SAFT improves image clarity with lower computational cost, although its resolution may be lower than that of TFM. Meanwhile, K-LSIM enables detailed reconstruction of defect geometry and reflector locations through inverse-scattering analysis, making it highly suitable for defect characterization in heterogeneous materials. Therefore, selecting an appropriate imaging method depends on the inspection objective and the complexity of wave propagation in concrete.

4. Challenges and recommendations

PAUT has become a widely recognized technique in NDT for various materials, notably metals. However, its application in concrete presents unique challenges that interfere with its effectiveness and widespread utilization. Concrete is a composite material with varying densities and compositions, including aggregates, cement paste, and voids. This heterogeneity scatters ultrasonic waves, making it difficult to obtain clear and accurate images. Concrete significantly attenuates ultrasonic waves, especially at higher frequencies. This attenuation reduces the signal strength and penetration depth, limiting the ability to detect deep defects. Furthermore, the complex wave patterns and potential for multiple reflections demand advanced signal processing and analysis techniques to accurately identify and characterize defects. In the future, advancements in PAUT technology and methodologies offer promising solutions to overcome these challenges. Signal processing techniques, including wavelet-based analysis and filtering methods, can reduce noise and separate important information related to defect signals from scattered wave components. Imaging methods, such as advanced reconstruction algorithms, help improve image resolution and depth penetration. Future research should focus on developing computationally efficient reconstruction algorithms that can provide high-resolution imaging while enabling practical field implementation. Furthermore, the integration of advanced computational models and machine learning algorithms can assist in better interpreting complex data[109–111], thereby enhancing the accuracy and reliability of PAUT in concrete. However, future studies are needed to establish large-scale benchmark datasets, improve model generalization suitable for infrastructure application.

5. Conclusions

1) PAUT represents a significant advancement in the NDE of concrete structures. By utilizing multiple ultrasonic elements and electronic time delays, PAUT enables high-resolution imaging for the detection and characterization of internal defects such as voids, cracks, corrosion, and delamination.
2) The application of PAUT in concrete confronts notable challenges due to the material's heterogeneity, which causes wave attenuation and scattering. Future research should focus on optimizing the array and probe configuration to improve beam focusing and penetration depth. In addition, the development of adaptive signal processing algorithms and denoising techniques is promising to improve image resolution and depth penetration. Emphasis on real-time analysis, automated defect assessment, large-scale field validation, and robust machine learning integration will be essential to improve the reliability of defect detection.
3) The future of PAUT in concrete testing is promising, offering real-time defect imaging and improved inspection efficiency, while also enabling effective testing in difficult-to-access regions and structures with complex or asymmetrical geometries. As research progresses, PAUT is expected to become a valuable tool for modern concrete evaluation.

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