

ADVANCED DAMAGE DETECTION IN REINFORCED CONCRETE APPLYING ACOUSTIC EMISSION, WAVELET TRANSFORM AND SHANNON ENTROPY

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Received: July 08, 2024; Revised: October 16, 2024; Accepted: October 28, 2024

Abstract

Concrete structures are extensively used in infrastructure but are susceptible to deterioration due to external loads, fatigue, and environmental factors. Early damage detection is vital for effective monitoring and failure prevention. Continuous sensor-based health monitoring can extend the design life of these structures. Acoustic Emission (AE) is a promising non-destructive testing technique for assessing damage in concrete, as it captures signals generated by microcrack formation and propagation. AE sensors detect these signals, which can be analyzed using wavelet transform (WT) in the time-frequency domain. Additionally, changes in the Shannon entropy of AE signals can indicate the presence and severity of damage in concrete. This study explores the effectiveness of combining WT and Shannon entropy for detecting damage in concrete structures using AE signals. Concrete specimens were subjected to simulated damage using pencil-lead break (PLB) tests, and the resulting AE signals were recorded. The WT was applied to decompose the AE signals into time-frequency components, facilitating the identification of damage-induced frequency bands. Shannon entropy was then calculated for each decomposed frequency band to measure the randomness or disorder within the signal. The results are expected to show that damage initiation and progression are reflected in changes in the frequency content and entropy of AE signals. An increase in entropy in specific WT frequency bands is anticipated to correlate with the presence and severity of damage in the concrete. This study aims to establish a different method for the localization of damage in concrete using a combination of WT and Shannon entropy analysis of AE signals.

Keywords: Concrete Structure; Health Monitoring; Acoustic Emission; Damage Detection; Wavelet Transform; Shannon Entropy

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DOI: <https://doi.org/10.55766/sujst-2024-05-e05716>

Introduction

Concrete structures are subject to degradation over time due to the effects of mechanical loads, environmental conditions, and other external factors. These influences include the application of stress, exposure to varying weather patterns, and the presence of aggressive substances in the environment, all of which contribute to the progressive deterioration of the material's physical and chemical integrity. Early damage detection is crucial to avoid catastrophic failures. Structural health monitoring (SHM) helps maintain these structures by utilizing data collected through various techniques, which can include periodic inspections with non-destructive testing (NDT) or continuous monitoring with sensors. One popular SHM method for real-time damage assessment in concrete is acoustic emission (AE), which captures sound waves emitted during rapid energy releases from damage events like crack formation or growth. Sensor-based systems gather these waves, facilitating damage localization.

Researchers have investigated multiple techniques for analyzing AE signals in concrete structures. Among the available signal processing methods, wavelet transform (WT) has become popular due to its capability to analyze non-stationary signals—those that change over time (Sengupta *et al.*, 2015). To perform a modal analysis of AE responses, a time-frequency domain analysis is necessary. Initially, following the introduction of WT, researchers employed it for the time-frequency analysis of acoustic signals (Pomponi *et al.*, 2013; Esmailzadeh *et al.*, 2023). WT allows for examining AE signals in both time and frequency domains, aiding in distinguishing actual damage-induced signals from background noise (Breckenridge, 1990). By analyzing the time-frequency features extracted from AE signals using WT, researchers can detect changes in dominant frequencies, energy distribution patterns, and specific frequency components indicative of crack initiation, propagation, and type (Naderpour *et al.*, 2017, Pal *et al.*, 2024). WT helps identify characteristic frequency components associated with damage and analyze their propagation through the concrete, aiding in pinpointing the exact damage location (Ebrahimkhanlou and Salamonea, 2017, Das *et al.*, 2024a). This refined analysis enables early detection of damage progression, allowing for timely intervention and repair. The time-frequency domain analysis of AE signals using WT can be used more effectively also for localizing the damage. A direction towards this was shown through a research conducted in thin plates, where

the researchers used the concept of group velocity through the material and linked the frequency of the group velocity curve to the frequency of the WT data (Jeong and Jang, 2000).

The group velocity is the speed at which wave groups travel through a material. Group velocity varies with frequency, and past research has successfully localized damage using the fundamental mode of group velocity. The primary aim of these studies was to ascertain the group velocity or dispersion behavior of Lamb waves. By analyzing the frequency-group velocity relationship, the corresponding group velocity for a given frequency can be determined (Chui, 1992; Suzuki, 1996). This group velocity can then be multiplied by time to estimate the travel distance, indicating the AE source location. Group velocity has different anti-symmetric (A0, A1) and symmetric (S0, S1) modes (Aggelis, 2011). Most existing research focuses on AE source localization by signal processing in different materials, typically employing fundamental modes (A0, S0) to identify the damage source (Das *et al.*, 2023). However, in the present study on concrete structures, which are considered moderately thick and anisotropic, higher modes of group velocity (A1, S1) have been used for damage localization (Das *et al.*, 2022).

Beyond traditional AE parameters, Shannon entropy, an information theory concept, measures the unpredictability or randomness within a signal. It has been used to understand energy distribution in wavelet coefficients and fatigue damage in various materials. Changes in Shannon entropy can indicate the presence and severity of damage. An increase in entropy suggests higher randomness or disorder in the signal, potentially due to microcrack formation and propagation (Piotrkowski *et al.*, 2009). By calculating the entropy of the entire AE signal or its decomposed components (e.g., through wavelet transform), researchers can assess changes in randomness associated with damage initiation and progression (Yang *et al.*, 2016; Das *et al.*, 2024b). Studies have demonstrated Shannon entropy's potential for identifying damage signatures within complex signals in various materials. Concrete structures under stress produce AE signals that are inherently non-stationary, meaning their statistical properties change over time. Shannon entropy is particularly well-suited to handling these non-stationary signals, as it doesn't assume constant statistical characteristics. This makes it a reliable tool for tracking the evolving damage process in real time (Chen *et al.*, 2016; Zhang *et al.*, 2022). In summary, Shannon entropy is particularly suitable

for analyzing AE signals in concrete due to its ability to capture signal complexity, its sensitivity to micro-damage, and its effectiveness in handling non-stationary data. These characteristics make it ideal for detecting and localizing damage in the heterogeneous and complex nature of concrete.

While both WT and Shannon entropy have been individually explored for damage detection, limited research has examined their combined application in AE-based SHM for concrete structures. By decomposing the AE signal using WT and analyzing entropy within each frequency band, a more comprehensive understanding of damage characteristics within the concrete structure can be achieved. Combining wavelet transform with Shannon entropy offers valuable insights into the damage characteristics of concrete structures. The wavelet transform offers a detailed view of AE signals in both time and frequency domains, while Shannon entropy quantifies the complexity of these signals, making them a powerful combination for detecting and localizing structural damage. Together, they provide greater sensitivity to transient events and better accuracy in damage localization. This research extends existing knowledge by exploring the potential of using higher group velocity modes for AE source determination in moderately thick concrete slabs in a controlled laboratory setting. Data collected from a single AE sensor placed at different locations on the slab will be used for this purpose. Subsequently, investigations will focus on the values of Shannon entropy along with the entropy-frequency plots for accurate damage detection in concrete structures.

Methodology

Experimental Setup

An experiment was conducted on concrete slabs with dimensions 1200 mm × 750 mm × 41 mm and 1200 mm × 750 mm × 50 mm, resulting in slabs of different thicknesses. The samples were made using M-20 concrete. M-20 is a nominal mix grade of concrete, commonly used in construction, with a compressive strength of 20 MPa after 28 days of curing. The proportion of materials for an M-20 mix typically follows a ratio of 1:1.5:3 for cement: sand: coarse aggregate with a water-cement ratio of 0.5 (IS 456: 2000, IS 10262:2009). The samples were cast and then cured, where the concrete surface was continuously kept wet for 28 days to maintain moisture, ensuring proper hydration of cement and

adequate strength development by placing them inside the water reservoir by using the ponding method. The experiment involved an acoustic emission (AE) setup within the lab. Data was captured using an R6D sensor, which can detect frequency responses from 35 to 100 kHz. R6D sensor has high sensitivity to high-frequency signals, which can easily capture microcracks and fracture even in concrete structures (Das *et al.*, 2024b). For data collection, the sensor was placed at the exact center of the upper surface of the 41 mm thick slab. Simulated damage on the top surface was induced using pencil-lead-breaks (PLB) of 0.5 mm and 2 mm thicknesses at various points positioned 50 mm from the sensor, as shown in Figure 1. AE waves are high-frequency stress waves. When a pencil lead is broken on the surface of the material, high-frequency stress waves are generated during actual crack initiation or propagation, making it an ideal test signal. Hence, it possesses the ability to mimic real damage mechanisms in materials (Hsu and Fr, 1981). Additionally, the 50 mm thick slab, was marked as four equal quadrants, with the sensor located at the center of the respective quadrants and subsequently, the PLB was done on each of the quadrants, as shown in Figure 2.

The structure's surface undergoes local deformation due to the applied pressure, leading to a sudden release of accumulated stress, which generates acoustic waves. These waves are transmitted as signals to the pre-amplifier and then to the acquisition system. The AE data acquisition system, manufactured by Physical Acoustic Corporation (PAC), USA, is equipped with 8 channels for simultaneous AE signal capture. During data collection, the preamplifier gain was carefully calibrated to 40 dB to ensure optimal reliability and signal integrity. The experimental setup simulated damage initiation by applying pressure with a mechanical lead pencil until it broke, creating a controlled and replicable environment for analysis. Figure 3 shows the acquisition system, which uses the AEwin interface for user interaction. The collected data are then extracted for analysis. AEwin offers various tools for extracting AE parametric data. The sensor-generated signals undergo amplification and filtering, where the voltage is increased to an optimal level for measurement, and integrated filters within the instrumentation define the usable frequency range while attenuating extraneous low-frequency noise.

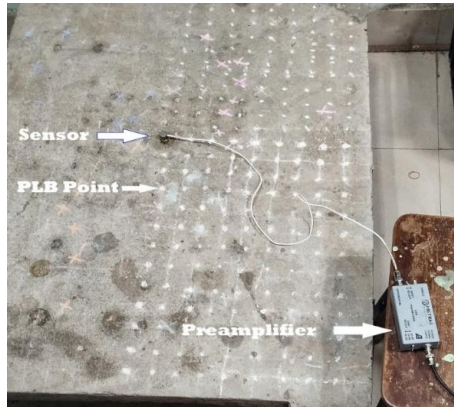
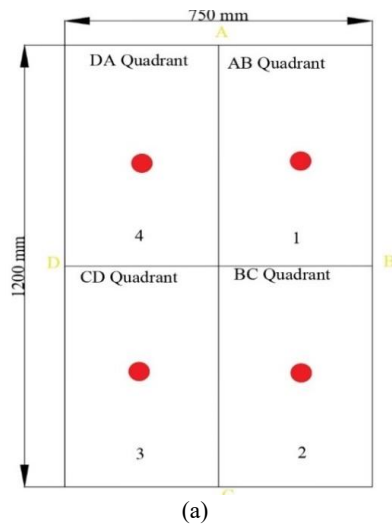


Figure 1. Position of the sensor and different PLB points Slab Specimen



	(SIP1)44	(SIP1)43	(SIP1)42	(SIP1)41	(PIQ1)41	(PIQ1)42	(PIQ1)43	(PIQ1)44
	(SIP1)34	(SIP1)33	(SIP1)32	(SIP1)31	(PIQ1)31	(PIQ1)32	(PIQ1)33	(PIQ1)34
	(SIP1)24	(SIP1)23	(SIP1)22	(SIP1)21	(PIQ1)21	(PIQ1)22	(PIQ1)23	(PIQ1)24
	(SIP1)14	(SIP1)13	(SIP1)12	(SIP1)11	(PIQ1)11	(PIQ1)12	(PIQ1)13	(PIQ1)14
	(SI)4	(SI)3	(SI)2	(SI)1	(QI)1	(QI)2	(QI)3	(QI)4
	(RIS1)14	(RIS1)13	(RIS1)12	(RIS1)11	(QIR1)11	(QIR1)12	(QIR1)13	(QIR1)14
	(RIS1)24	(RIS1)23	(RIS1)22	(RIS1)21	(QIR1)21	(QIR1)22	(QIR1)23	(QIR1)24
	(RIS1)34	(RIS1)33	(RIS1)32	(RIS1)31	(QIR1)31	(QIR1)32	(QIR1)33	(QIR1)34
	(RIS1)44	(RIS1)43	(RIS1)42	(RIS1)41	(QIR1)41	(QIR1)42	(QIR1)43	(QIR1)44

(b)

Figure 2. Different lead-break points on the sample (a) sensor placed at different quadrants and (b) points of PLB for a single quadrant

Wavelet Transform

The captured AE data within the system are gathered for subsequent analysis, as depicted in Figure 3. This analysis is conducted using software that is available for free, and tailored for WT study. The Gabor function is selected for this study using AGU-Vallen software. While other wavelets meeting the tolerability condition could be considered, the Gabor wavelet is preferred due to its ability to offer the most precise time-frequency solution (Ji and Yan, 2017). The Gabor wavelet is widely preferred for time-frequency analysis due to its ability to offer precise localization in both the time and frequency domains. This characteristic arises from its Gaussian-modulated sinusoidal function, making it ideal for analyzing non-stationary signals where both time and frequency details are crucial. It has been shown to outperform other methods, particularly in applications like image processing and seismic signal interpretation, because of its effective multi-resolution capabilities (Shen and Bai, 2006). The mathematical expression for the Gabor wavelet is as follows:

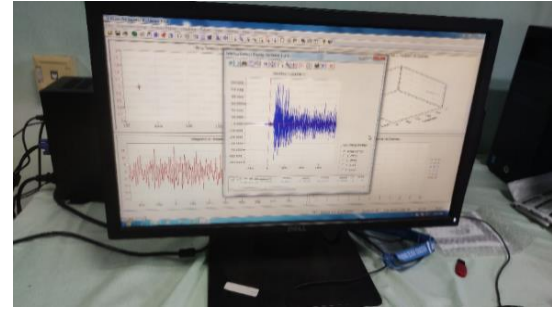


Figure 3. AE responses collected through the system (AEwin interface)

$$\psi_g(t) = \frac{1}{\sqrt[4]{\pi}} \sqrt{\frac{\omega_0}{\gamma}} \exp \left[-\frac{(\frac{\omega_0}{\gamma})^2}{2} t^2 \right] \exp(i\omega_0 t) \quad (1)$$

and its Fourier Transform is

$$\hat{\psi}_g(\omega) = \frac{\sqrt{2\pi}}{\sqrt[4]{\pi}} \sqrt{\frac{\gamma}{\omega_0}} \exp \left[-\frac{(\frac{\gamma}{\omega_0})^2}{2} (\omega - \omega_0)^2 \right] \quad (2)$$

Where, ω_0 and γ are the constants (positive values). The Gabor function is generally measured as a Gaussian window function centered at $t = 0$ and its Fourier transform (FT) centered at $\omega = \omega_0$.

The function $\psi_g\left(\frac{t-b}{a}\right)$ is centered on $t = b$ and its FT is centered about $\omega = \frac{\omega_0}{a}$. The WT $Wf(a, b)$ using Gabor wavelet hence denote the time-frequency component of the function $f(t)$ around $t = b$ and $\omega = \frac{\omega_0}{a}$.

Shannon Entropy

Afterwards the WT test, the time-frequency data is then considered for further study. Shannon Entropy is subsequently computed using the specified equations;

$$W P_a = \sum_{b=1}^N wp(a, b) \quad (3)$$

$$p_{a,b} = wp(a, b) / W P_a \quad (4)$$

$$Entropy(a) = -\sum_{b=1}^N p_{a,b} \times \log_2 p_{a,b} \quad (5)$$

The Shannon Entropy of the wavelet coefficients is limited by;

$$0 \leq Entropy(a) \leq \log_2 N \quad (6)$$

Where $Entropy(a)$ denotes the wavelet entropy corresponding to the scale a ; a denotes the scale index (frequency interval related with a); b denotes the time shifting; N is the number of wavelet coefficients in time series.

Results and Discussion

Using Wavelet Transform Technique

The experimental data undergoes wavelet transform (WT) analysis to establish a time-frequency relationship, revealing varying WT extents across different time and frequency intervals. This time-frequency domain statistics is then utilized to localize acoustic emission (AE) sources through group velocity analysis. Dispersion curves are subsequently generated, with typical P-wave and S-wave velocities for concrete set at 3400 m/sec and 2200 m/sec respectively, considering a sample thickness of 41 mm (Mirgal, 2020).

Within the dispersion curve setup screen depicted in Figure 4, the "Show Curves" option can be found. Specifically, the "A1 and S1 modes" option is selected for analysis. The response data obtained from various directions relative to the source undergoes WT. A 2D color contour plot illustrating WT coefficients is produced, where

the color scale employs a linear gradient. Regions shaded in red indicate the highest WT magnitudes, while pink denotes areas of minimal or zero magnitude. Additionally, the group velocity plot is superimposed onto the same WT diagram by adjusting the distance parameter accordingly,

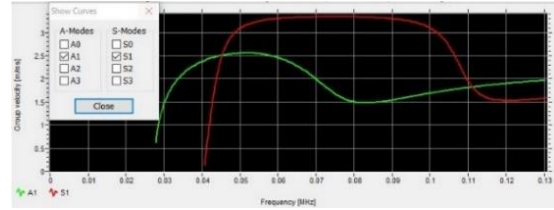


Figure 4. Dispersion curves for a concrete slab of 41 mm thickness

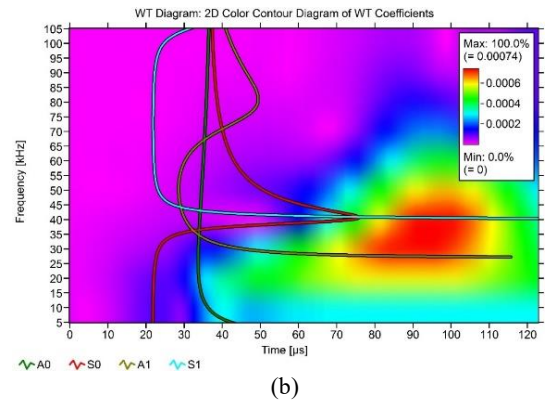
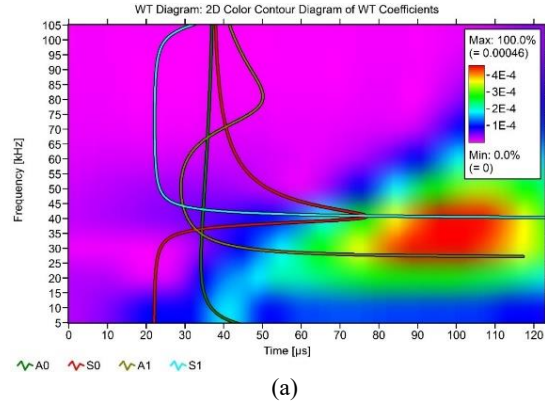


Figure 5. WT for flexural AE response on points (a) 100 mm from sensor and (b) 158 mm from sensor due to simulated AE source with superimposed anti-symmetric (A0, A1) and symmetric (S0, S1) modes after converting group velocity to time

Upon scrutinizing the experimental specimen, it is observed that the fundamental symmetric and anti-symmetric modes (S0 and A0) do not intersect with the regions of highest WT magnitude in the contour diagram. In contrast, the higher symmetric (S1) and anti-symmetric (A1) modes do coincide with these high magnitude regions (see Figure 5), particularly at points corresponding to the lead-break. From the frequency at which the maximum WT coefficient is found in Figure 5, for different curves the group velocity values could be obtained from Figure 4. This group velocity, multiplied by the time at which the maximum WT coefficient occurs, the distance at which the PLB was done, could be found.

The information presented in Table 1 outlines the maximum WT coefficients along with their corresponding group velocities and the respective times at which these maximum coefficients are reached at specific points in different directions. The distance from the source to the damaged location (0.5 mm pencil) is computed by multiplying the time when the maximum WT coefficient is attained by the group velocity. For most observations recorded at various locations using the S1 curve, the percentage of error is within acceptable limits. It is noteworthy that in most cases, the higher modes of the symmetric curve (S1) have demonstrated more accurate predictions of the source location. The S1 group velocity curve provides more reliable data for damage localization in concrete structures due to its higher sensitivity to defects, lower dispersion, and reduced susceptibility to noise and boundary

conditions. These observations were true for PLBs using both 0.5 mm and 2 mm thick pencils (Table 2). For the data obtained from different locations with the sensor in the center of the slab with a 2 mm pencil-lead break, the results are found to be within the limits. In Table 2, these results have been shown. However, it has been observed from the data obtained from the 2 mm thick pencil-lead break that the error percentage of source prediction is slightly high for most of the observations. Again, the higher modes of the symmetric curve (S1) have demonstrated better predictions of the source location. Moreover, the wavelet coefficients are slightly high using a 2 mm thick pencil.

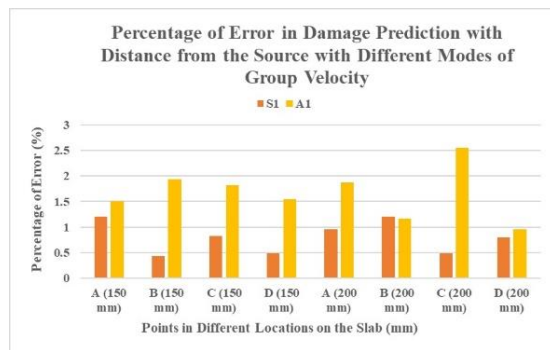
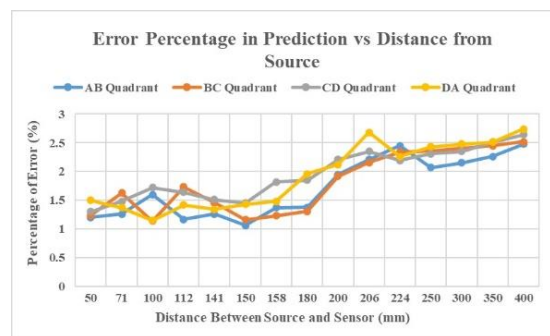
Table 3 shows the data obtained by placing the sensor at the center of each quadrant of the 50 mm thick slab with a 0.5 mm thick pencil. Here point (P1Q1)11 is a representative point on each quadrant as shown in Figure 2. These results also show similar trends as found before (Table 1). Hence, we could say that this method is very useful in finding the damage location in slabs of different thicknesses and by using different loading conditions, which are different thicknesses of pencil in our study. Figure 6 shows the percentage of error in predicting damage with distance from the source with different modes of group velocity on the 41 mm slab with 0.5 mm thick pencil. This is true for both slabs with different thicknesses. On the other hand, for pencils of different thicknesses, the percentage of error is within the limits in different locations of the slab (Figure 7). In Figure 7, the results for 0.5 mm PLB are shown.

Table 1. Maximum WT Coefficients Corresponding to Frequency, Group Velocity and Calculated Distance from Source for PLB Locations (0.5 mm thick pencil on 41 mm thick slab)

Distance from Source (mm) (1)	Mode (2)	Line of PLB (3)	Time when Max WT co-efficient obtained (micro sec) (4)	Group Vel. (mm/micro sec) (5)	Dist. identified (mm) (4×5)	Error (%) in predicted distance	Max WT co-efficient
150	S1	A	94.28	1.61	151.8	1.2	0.092875
		B	83.23	1.81	150.64	0.43	0.024556
		C	92.15	1.64	151.24	0.82	0.071752
		D	98.51	1.53	150.72	0.48	0.000455
	A1	A	68.89	2.21	152.25	1.5	0.034171
		B	73.54	2.08	152.9	1.93	0.016124
		C	75.24	2.03	152.73	1.82	0.024856
		D	55.59	2.74	152.33	1.55	0.009253
200	S1	A	84.28	2.39	201.9	0.95	0.024875
		B	93.23	2.17	202.4	1.20	0.089556
		C	89.25	2.23	199.03	0.48	0.054125
		D	101.51	1.95	198.4	0.80	0.011455
	A1	A	92.19	2.21	203.74	1.87	0.037871
		B	82.24	2.46	202.31	1.16	0.057824
		C	94.61	2.06	194.89	2.55	0.044521
		D	95.23	2.08	198.08	0.96	0.014953

Table 2. Maximum WT coefficients corresponding to frequency, group velocity, and calculated distance from source for different PLB locations (2 mm thick pencil on 41 mm thick slab)

Distance from Source (mm) (1)	Mode (2)	Line of PLB (3)	Time when Max WT co-efficient obtained (micro sec) (4)	Group Vel. (mm/micro sec) (5)	Dist. identified (mm) (4×5)	Error (%) in predicted distance	Max WT co-efficient
50	S1	A	63.28	0.81	51.26	2.51	0.211286
		B	63.95	0.80	51.70	3.40	0.251257
		C	64.51	0.80	51.6	3.20	0.315487
		D	67.51	0.77	51.98	3.97	0.421785
	A1	A	57.89	0.84	48.63	2.74	0.251152
		B	60.24	0.86	51.81	3.61	0.352145
		C	58.35	0.84	49.32	1.36	0.457891
		D	55.23	0.87	48.05	3.90	0.801254
100	S1	A	83.28	1.23	102.77	2.77	0.703286
		B	78.23	1.30	102.13	2.13	0.827123
		C	82.64	1.18	97.15	2.85	0.785123
		D	88.51	1.09	97.13	2.87	0.901487
	A1	A	70.32	1.43	103.56	3.56	0.414397
		B	73.28	1.40	103.59	3.59	0.696189
		C	69.19	1.40	96.87	3.13	0.751245
		D	76.31	1.34	102.49	2.49	0.808271

**Figure 6. Percentage of Error in Predicting Damage with Distance from the Source with Different Modes of Group Velocity****Figure 7. Percentage of Error in Predicting the Damage Location of Different Locations of the 41 mm Thick Slab**

Using Shannon Entropy

Cumulative entropy values are computed for each simulated damage location by summing all entropy values. It has been observed that as the distance from the sensor to PLB point increases, cumulative entropy decreases, which is attributed to signal attenuation over distance. This trend holds true for both the 41 mm and 50 mm thick slabs (Table 4), with minimal variation between them. The peak in the entropy-frequency curve occurs at the frequency corresponding to the maximum WT coefficient, as indicated in Figure 8. This frequency, associated with the peak WT coefficient, helps determine the group velocity and ultimately identifies the location of the damage. Therefore, the Shannon entropy diagram or values enable the localization of damage within the structure. Concrete is a heterogeneous material with multiple phases, including aggregates, cement paste, and voids, which generate highly complex AE signals during damage events like cracking or debonding. Shannon entropy excels at capturing the level of uncertainty or disorder in these signals. As the micro-cracking or damage intensifies, AE signals become more random, increasing the entropy values, which makes it an excellent measure for monitoring damage progression.

Table 3. Group Velocity for Calculating Distance from Source for different PLB locations (0.5 mm PLB on 50 mm thick slab)

Point/ Distance from source (mm)	Mode	Point on the Quadra nt	Time of Max WT coefficient obtained (micro sec) (1)	Group Velocity (m/ms) (2)	Distance identified (1×2) (mm)	Percentage of error (%) in terms of distance from source	Maximum WT coefficient
(P1Q1) (71)	S1	AB	75.01	0.97	72.76	2.48	0.002458
		BC	75.19	0.96	72.18	1.67	0.002148
		CD	74.52	0.98	73.14	3.01	0.001456
		DA	77.62	0.89	69.08	2.70	0.003157
	A1	AB	73.92	0.92	68.01	4.22	0.002698
		BC	72.23	1.00	72.23	1.73	0.001985
		CD	73.21	0.99	72.64	2.30	0.002478
		DA	74.01	0.92	68.09	4.10	0.003169
(Q2R2)21 (112)	S1	AB	83.28	1.35	112.43	0.38	0.011287
		BC	84.97	1.31	111.31	0.62	0.003298
		CD	83.21	1.32	109.84	1.92	0.003514
		DA	85.12	1.29	109.80	1.96	0.002725
	A1	AB	84.23	1.31	110.34	1.48	0.001392
		BC	87.11	1.28	111.50	0.45	0.003146
		CD	88.21	1.24	109.38	2.33	0.002147
		DA	86.35	1.30	112.26	0.23	0.032254

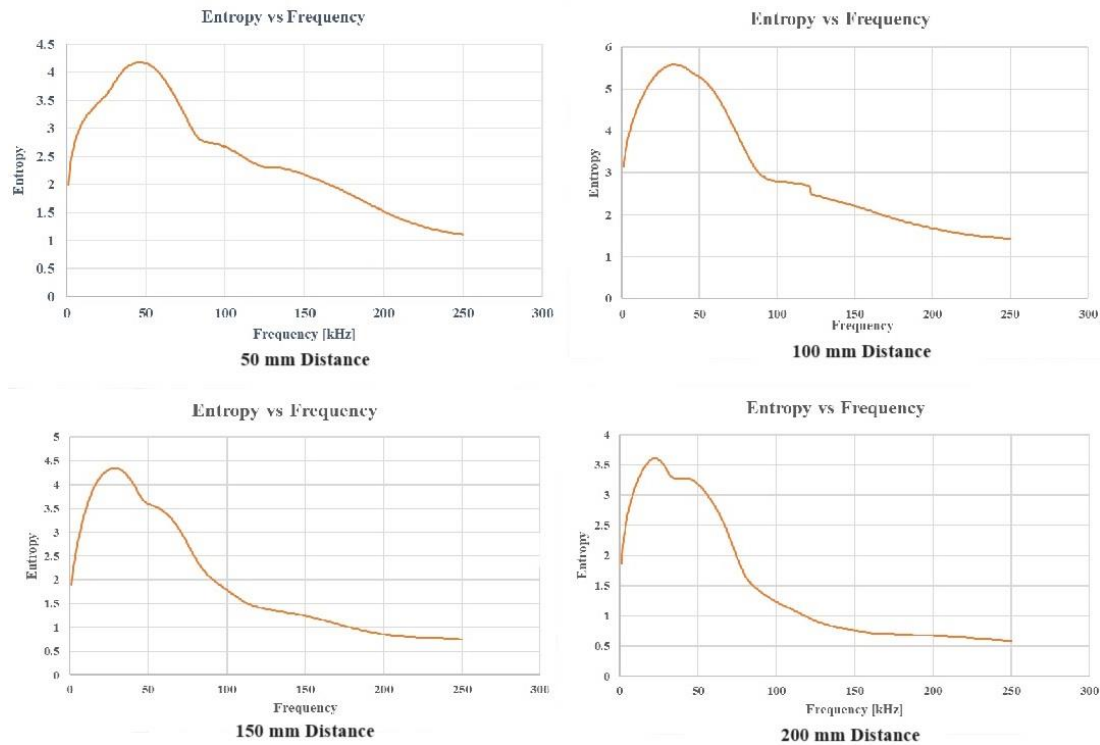
**Figure 8. Entropy-Frequency curve on different points of the 41 mm thick slab (0.5 mm PLB)**

Figure 9 displays frequency entropy curves for a point on the 50 mm thick slab and the corresponding WT diagram. The peak of the Frequency-Entropy curve occurs when the WT diagram shows its maximum frequency. Table 5 details the changes in cumulative entropy values across different distances. Additionally, in

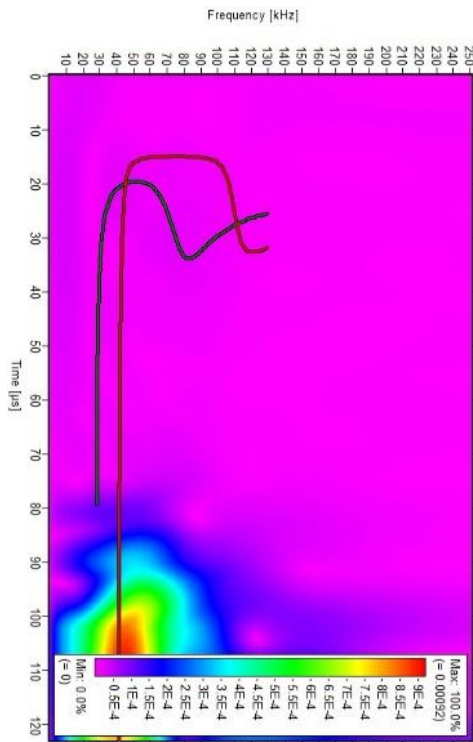
a previous section investigating lead thickness of 2 mm, it was found that maximum WT coefficients were higher compared to data obtained using a 0.5 mm thick lead. Consequently, cumulative entropy is also higher, reflecting increased disorder in the slab when simulating cracks with thicker lead.

Table 4. Cumulative entropy values in different locations of PLB for 41 mm and 50 mm thick slab

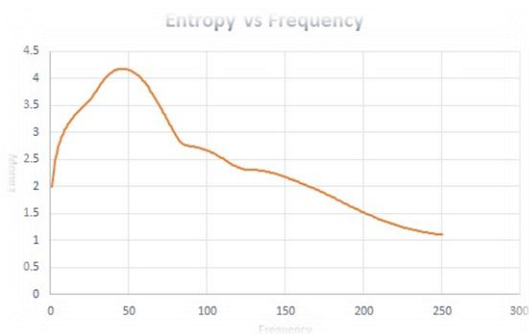
Cumulative Entropy		Distance of PLB point concerning the Sensor (mm)
For 41 mm thick slab	For 50 mm thick slab	
632.1	617.1	50
593.3	522.2	100
508.7	488.5	150
459.4	379.5	200
392.6	352.4	250
322.7	314.6	300

Table 5. Cumulative entropy values in different locations of PLB using 0.5 mm thick lead and 2 mm thick lead for 50 mm thick slab

Cumulative Entropy		Distance of PLB point concerning the Sensor (mm)
Using 0.5 mm thick lead	Using 2.0 mm thick lead	
617.1	953.2	50
522.2	877.2	100
488.5	752.4	150
379.5	622.4	200
352.4	587.5	250
314.6	554.3	300



(a)



(b)

Figure 9. AE data representation after WT in a point 50 mm away from the sensor, (a) 2D color contour, (b) Entropy-Frequency curve

Conclusions

Localization using higher modes of group velocity curves indicates their prominence in thicker plates. In concrete slabs, fundamental group velocity modes fail to accurately predict damage locations because their curves do not intersect with the highest magnitude zones in the wavelet transform (WT) diagram during time-frequency domain analysis of acoustic emission (AE) waveforms. Conversely, experimental findings demonstrate that higher modes, specifically S1 and A1, more accurately pinpoint damage locations, and intersecting sections with maximum values in the WT contour map. Notably, the symmetric higher mode curve (S1) consistently yields more precise results with lower percentage error compared to the A1 mode across different points on the samples. The S1 group velocity curve provides more reliable data for damage localization in concrete structures due to its higher sensitivity to defects, lower dispersion, and reduced susceptibility to noise and boundary conditions. Thus, wavelet analysis exhibits significant potential for precise source localization in concrete structures.

Shannon entropy, representing the energy distribution of wavelet coefficients, holds promise in detecting damage in concrete materials. In this study, simulated Acoustic Emission (AE) signals were used to evaluate Shannon Entropy's effectiveness in localizing damage. Notably, the Entropy-Frequency curve peaks align with locations of simulated damage, corresponding to red-colored zones in the two-dimensional color contour of the Wavelet Transform (WT). Damage location precision is facilitated by plotting Shannon Entropy against its corresponding frequency, identifying point damage at the peak frequency denoted by the red zone in the WT color contour diagram. Furthermore, cumulative Shannon Entropy decreases with

increasing distance from the sensor to the PLB location, offering insight into the damage location through comparison of cumulative entropy values across different locations.

Wavelet transform decomposes the AE signals into various time-frequency components, providing detailed information about the nature of the signal. Shannon entropy then quantifies the complexity of these components, making it easier to detect anomalous patterns that indicate damage. Moreover, by applying both methods across different sensors or locations on a structure, the spatial distribution of entropy values can be used to localize the damage. Areas with higher entropy correspond to regions with more complex AE signals, typically near the damaged zone. Additionally, wavelet transform is effective in filtering out noise from the AE signals, while Shannon entropy helps to further differentiate between normal operation and damage events. This combination improves the accuracy of damage detection and localization, even in the presence of background noise.

While periodic data collection may present challenges for health monitoring, continuous data accumulation over time enables ongoing assessment. Improvements in precision of sample casting, inclusion of additional AE parameters, variation in sample dimensions, consideration of lower-grade concrete within higher-grade samples due to construction constraints, and adoption of diverse loading techniques can enhance test accuracy and broaden dataset applicability for result prediction. Additionally, exploring alternative types of Wavelet Transforms, such as the Morlet Wavelet, with collected test data can further assess method suitability.

Acknowledgement

The experiment was conducted in the Structural Health Monitoring lab of the National Institute of Technology Durgapur. The casting of slabs was done in the Concrete Technology Lab of the Department of Civil Engineering, Dr. B. C. Roy Engineering College Durgapur.

Soumyadip Das: Material Collection, Casting, Testing & Data Collection, Analysis, Reporting.
Aloke Kumar Datta: Conceptualization & Review.
Pijush Topdar : Conceptualization & Review.
Sanjay Sengupta : Conceptualization & Review.

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