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Research Article

Effect of Signal Features and Model Variables on Energy-Traced Arrival Time Picking of Acoustic Signals Used for Structural Damage Detection

Sena Tayfur

Ege University, Faculty of Engineering, Department of Civil Engineering, İzmir, Türkiye, sena.tayfur@ege.edu.tr

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ABSTRACT

To monitor damage developments in structures, various structural health monitoring methods based on different principles are used. The common aspect of elastic wave-based methods is to place appropriate sensors on the structure, to detect acoustic wave propagation and to analyze these signals the sensors transformed. The arrival time of these recorded signals to the sensors is the most significant parameter used to determine critical information such as the time and location of the damage. Therefore, the accurate calculation of the arrival time affects the accuracy of the damage detection.

In this study, effects of the signal-to-noise ratio (SNR), sampling frequency, length of the signal, and length of the focal window on determining the arrival time of the signals to the sensors were investigated. For this purpose, an energy-traced arrival time picking approach (Akaike Information Criterion, AIC), which is the frequently used method in the literature, has been applied to a typical acoustic signal originated from a concrete cracking. The results of the study suggest the necessity of noise elimination, the optimum level of data logging and the ratios of focal window lengths for accurate time of arrival detection in the field monitoring of the structures using acoustic methods.

1. Introduction

The location, size, and time of occurrence of the crack, which is the main damage type in concrete structures, can be determined by acoustic-based nondestructive testing methods. The main principle of these methods is propagation of the energy with frequencies that the human ear cannot hear and detection of them by appropriate sensors [1-3].

When the sound waves reach the sensor, the sensor starts to generate an electrical signal and these signals, which contain information about the damage, can be processed and analyzed to obtain information about the damage status of the structure [4, 5]. Some pulses may be lost as the sensor's signal generation depends on the sampling frequency of the recording system. But more importantly, arrival time of the signal to the sensor can be lost here. On the other hand, since the recording system is triggered on the basis that the sensor starts to generate a signal as soon as it detects the pulse exceeding the threshold value, a pre-trigger window is also provided to the system in order not to lose the arrival time. Thus, along with the ambient noise, a set of pulses representing arrival time at the very beginning of the signal is added to the signal form.

The arrival time of the signal at the sensor is one of the two main parameters necessary to determine the location of the damage [6-8]. Since the propagation velocity of the wave, which is the other parameter in this problem, is very high (approximately 2500-3500 m/sec) in the concrete material [9], even microsecond errors in the arrival time calculation cause the damage

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location to be calculated with high margin errors [10]. For this reason, the problem of accurate picking of this arrival time in the pre-trigger window, which is mixed with noise, has been one of the focal points of signal processing studies for structural damage assessment in the literature. For this purpose, different arrival time capturing methods with various approaches have been proposed [11-14]. Among them, Akaike Information Criteria (AIC), which picks the arrival time by tracing the change of signal energy, is the most preferred because it is used for a long time and it works with high reliability [15, 16].

Numerous studies exist in the literature demonstrating the effectiveness of AIC on the signals. Current studies are generally aimed to improve the method by developing it with different approaches and/or automating it during structural monitoring [17-19]. In this study, instead to search the method that captures the arrival time most accurately, the question of how the improvements that can be made on the signal form affect the arrival time estimation has been investigated. First, the most accurate arrival time obtained by filtering the raw signal exposed to ambient noise was investigated. Accordingly, the effect of noise filters with four different approaches, which are frequently encountered in the literature for damage signals, on arrival time detection was investigated. Then, the arrival time obtained from the most successfully filtered signal was then taken as a reference to reveal the effects of the signal length, sampling frequency and AIC focal window length. In this way, the necessity of noise elimination, optimum data logging level and the ratios of focal window lengths were evaluated to determine the accurate arrival time for monitoring the structures.

2. Methodology

Energy released by the damage propagates as acoustic waves with a wide frequency range (kHz-MHz), and these waves can be detected and converted into electrical signals with appropriate sensors placed on or embedded within the structure. Significant information about structural damage can be obtained by statistically evaluating the parameters of these signals and analyzing the signal form with various techniques [4]. To obtain this information, the experimental setup is of great importance as well as the conditions under which the structure is monitored. The settings such as signal length, sampling frequency, pre-triggering window length to be used in the creation of the signal form should be chosen by an expert who can predict what kind of damage sources and what characteristics the signal will come from. On the other hand, these selections should be kept at an optimum level so as not to miss critical information about the signal and not to slow down the system and increase energy consumption.

2.1.Characteristics of acoustic signals

Signals showing the time-dependent voltage values contain important characteristics to determine information as to damage such as its size, type, time of occurrence and location. As seen from Figure 1, which shows a typical acoustic signal recorded from a concrete cracking event, a threshold level is used to highlight the pulses above a certain level. The area of the signal envelope formed by the pulses above the threshold defines the energy of the signal. Parameters such as amplitude, rise time, duration and count are the other characteristics that help determine the size and type of the damage [2].

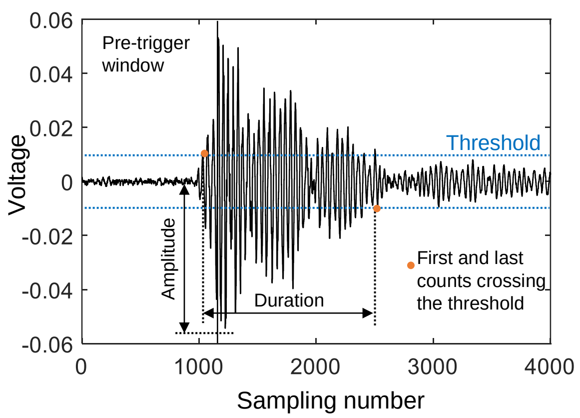

Figure 1. Characteristics of an acoustic signal

On the other hand, arrival time differences between the sensors are used to calculate the location of a damage (Figure 2). If the locations of the damage and ith sensor's, the origination time of the damage, and the arrival time of the signal are defined as (x, y, z), (x_i, y_i, z_i), to and t_i, respectively, distance between the sensor and the damage (D_i) can be calculated using wave velocity of V_p by Equations 1 and 2 [20]. Solution of the system involving i equations supplies the intersection point of the hyperbolas, which is the source location.

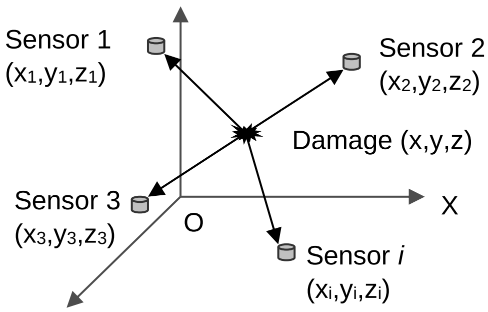

Figure 2. Principle of AE source localization

Sample equation;

$$D_i = V_P(t_i - t_o) \tag{1}$$

$$D_i = \sqrt{(x_i - x)^2 + (y_i - y)^2 + (z_i - z)^2} \tag{2}$$

While the system is recording, when the sensor captures the pulse exceeding the threshold, it also creates the pre-trigger window, and the length of this window can be determined depending on the signal length. The arrival time of the signal, which is used to determine the location of the damage, is also included in this window.

2.2.Energy-traced picking of signal arrival time

Since the system records data with a certain sampling frequency during the monitoring of the structure, arrival time of the signal can be missed, and it has to be calculated correctly for accurate localization of the damage. Since the propagation velocity of the wave in concrete is very high (~2500-3500 m/sec), even the incorrect calculation of the arrival time in the order of microseconds causes high errors in localization procedure. Akaike Information Criteria (AIC) is a statistical method frequently used for picking the arrival time between the noise and the actual signal data in the time history by tracing the energy changes in the signal [15]. For this, first, the AIC function is calculated using Equation 3 in the region where the average of the values of the voltages in the ten groups of the signal is more than four times of the previous group. Then a second focal window is opened with reference to the moment when the AIC function reaches the minimum. After the same process is repeated in the second window, the minimum AIC occurrence moment in the second window defines the arrival time of the signal to the sensor [12].

$$\mathrm{AIC}\{k\} = k.\log\{G,[1,k]\}\} + (N-k).\log\{G,[k+1,N]\}\} \tag{3}$$

where k is the number of the focal signal window, G is the amplitude of the related time and N is the total voltage number within the window.

2.3.Signal-to-noise ratio (SNR)

Electrical or mechanical background noises, which are clearly visible in the pre-triggering window, also interfere with the damage-related signal form. Signal-to-noise ratio (SNR), is defined as the ratio of signal power to the noise power [21-24] and it can be calculated in dB by Equation 4.

$$\mathrm{SNR(dB)} = 20\log_{10}\frac{P_s(w_2)}{P_g(w_1)} \tag{4}$$

where P_s ve P_g are the mean powers of the damage signal and the noise within the windows w_2 and w_1, respectively. Windows w_1 and w_2 are selected according to signal and pre-triggering window lengths. Accordingly, the higher SNR of a signal, the better it suppresses noise. Therefore, the intensity of the noise also affects the correct capturing of the arrival time. The SNR of the signal can be increased by various noise filtering techniques [24, 25].

3. Processing and Arrival Time Picking of an Acoustic Signal

3.1.Details of the tested model

In this study, signal S1 arisen from a crack activity originated in a reinforced concrete beam under flexure test was used to investigate the effects of the signal features and model variables on picking arrival time (Figure 3). The beam was produced from a concrete having cylinder compressive strength of 30 MPa and was in sizes of 235x25x15 cm. It was reinforced with two Ø8 mm longitudinal rebars at the bottom and top of the section and Ø8 mm stirrups with spacing of 10 cm were placed to strengthen shear capacity of the beam. During loading, the beam was monitored using eight piezoelectric sensors having resonance frequency of 150 kHz. The sensors were amplified by preamplifiers with 40 dB gain. Data was recorded using AE system by Mistras.

Threshold of the system was also set as 40 dB level. The specimen was damaged in flexure and 21703 signals were recorded from all sensors. Table 1 shows mean values and standard deviations of AE features of the signals collected from the test. As seen from the signal characteristics, higher standard deviations of average frequency and rise time parameters indicate while some signals represent more tensile-type cracking, some of them are more flexural-shear-type.

Table 1. AE features of the data collected

	Mean value	Standard deviation
Energy (aJ)	22.16	231.69
Average frequency (kHz)	156.44	303.70
Rise time (μsec)	135.43	622.84
Amplitude (dB)	46.75	7.69
Peak frequency (kHz)	82.62	52.70
Frequency centroid (kHz)	131.96	32.82

3.2.Characteristics of the selected acoustic signal

In order not only to study on a specific crack type, but also to investigate a signal containig high-level noise, signal S1, one of these AE signals recorded during this loading test, was chosen in this study. This signal was selected because it represents a typical concrete cracking signal (Figure 3). Sampling frequency, length and SNR of the signal is 1 μsec, 2048 and 3.07 dB, respectively. As can be seen, pre-trigger length is 512. While the system was recording, when the sensor caught the pulse exceeding the threshold value (40 dB), it added 512 pulses before the trigger and created the whole signal for this reason, arrival time of the signal to the sensor was also included in pre-trigger window with the ambient noise. Thus, using threshold crossing approach causes erroneous results since the arrival time is missed.

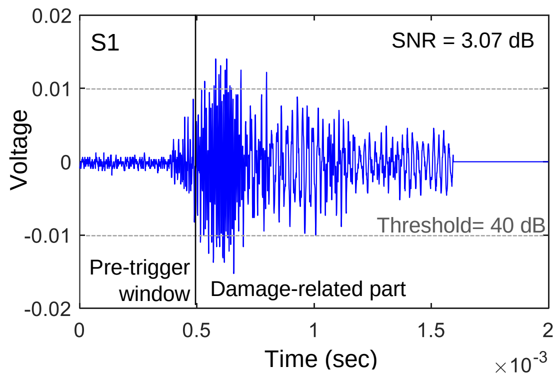

Figure 3. A typical acoustic signal caused by concrete cracking used in the study

To determine the effect of the noise on energy-traced picking of the arrival time, first the signal was filtered with different-approach filters. These filters were Band Pass, Wavelet, Wiener and Savitzky-Golay, which are frequently used for acoustic and ultrasonic waves in the literature. A Band Pass filter eliminates frequencies outside a certain band. In this study, the Band Pass filter was designed with 1 kHz of stopband, 2 kHz and 60 kHz of passband frequencies, and 100 kHz of sampling frequency. In Wavelet filtering, the signal was filtered by both scaling and shifting the main function, which acts as a window in the wavelet transform [26-28]. Unlike most other filters with Wiener, the noisy signal was filtered by comparing it with an estimation of the filtered signal [29-31].

Finally, a polynomial was fitted with the Savitzky-Golay filter, which is a low-pass filter, and the value of the polynomial at the midpoint of the window was taken as the filtered pulse [32-34]. To determine the effect of sampling frequency and signal length, the arrival time was calculated by varying the lengths of the signal S1 with different ratios. Thus, the sampling frequency of the signal also changed at these rates. For the effect of the focal window lengths for AIC function, the arrival time was picked according to the ratio of the 1st and 2nd window lengths to the signal length (n).

4. Results and Discussion

4.1. Effects of the noise

Since the power of the noise decreased after filtering S1 signal, the SNR value increased compared to its raw state (3.07 dB), as expected. Thus, the arrival times according to the five different SNR values of the signal were picked by AIC and the results were given in Figure 4. The arrival times for each signal were captured in the pre-trigger window when the energy-traced AIC function reached its minimum value and the signal energy suddenly increased. However, the point to be considered here is which of the filtered forms of the signal is the most accurate and the appropriate arrival time should be referenced to compare it with others.

When the noise function is filtered from the signal, decreases in the voltage of damage-related part of the signal is expected. But in order not to change the signal behavior and the damage information it represents, it is desirable that the form does not change after triggering. As can be seen, although the highest SNR value (8 dB) was obtained with the Band Pass filter, the voltage level in the damage-related part of the signal was also very low and it did not exhibit the expected behavior from the signal caused by concrete damage. For this reason, the arrival time obtained from S2 was not taken as the reference. When other filters were evaluated from the abovementioned point of view, among the remaining signals the best filtering was obtained from Wiener (S4), which eliminates the pre-triggering noise and did not lose much of the voltage value by not distorting the form in the damage-related part of the signal. In particular, the presence of very low-voltage pulses in the pre-triggering noise window of S4 caused this signal to be chosen as the reference for comparing arrival times.

On the other hand, although the voltage values decreased after filtering, the earliest time of arrival was obtained as 0.000362 sec with using S4. As can be seen from S4, arrival time could be determined earlier than 0.000390 sec obtained from the noisy state of the signal. This shows that filtering without distorting the signal form and voltage values is more effective for accurate arrival time picking rather than increasing the SNR.

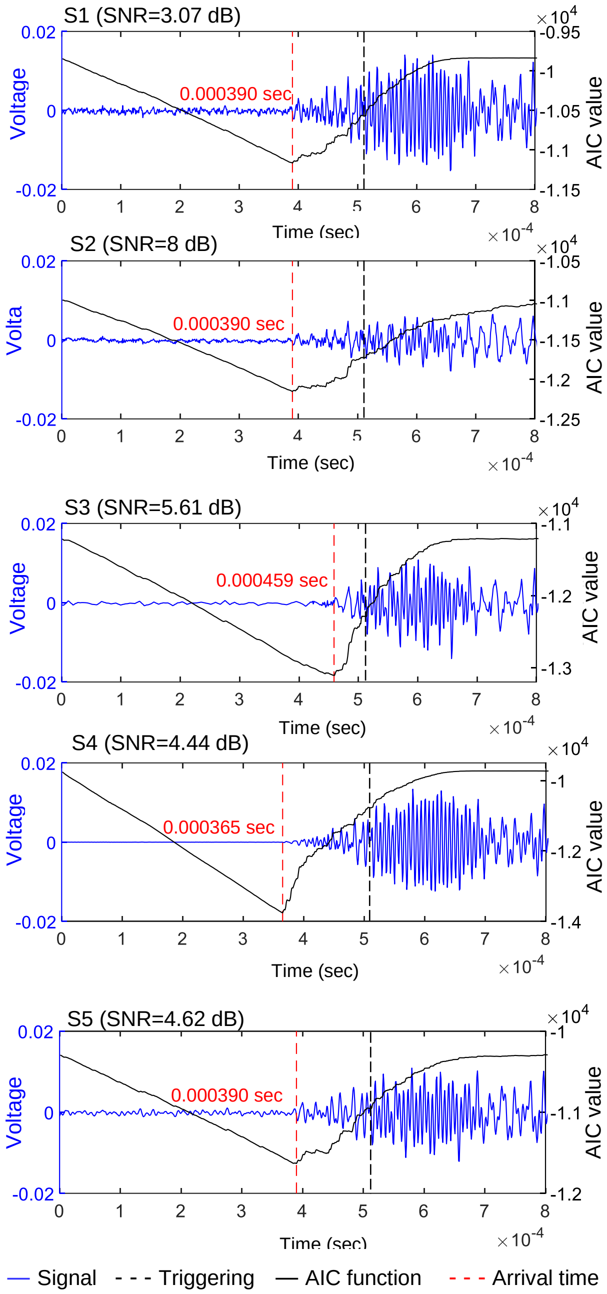

Figure 4. Picking the arrival time of the signal according to different SNR values after noise filtering

Since the arrival time of the signal is the most important factor in determining the location of the damage, Table 2 was composed to reveal how the arrival time affects the distance to be calculated between the sensor and the source. Here, the distances were calculated using the propagation velocity of P wave in concrete as 3500 m/sec. As can be seen, although the differences between the arrival times are in the order of microseconds, they are of great importance in terms of determining the location of the damage, and distance deviations were measured up to 32.9 cm with S3 and 8.75 cm with other filters. These values cause to inaccurate localization results.

Table 2. Source-sensor distance errors according to different SNR values after noise filtering

Signal	Arrival time (μsec)	Source-sensor distance (m)	Source-sensor distance error (cm)
S1	390	1.365	8.75
S2	390	1.365	8.75
S3	459	1.606	32.9
S4	365	1.278	-
S5	390	1.365	8.75

4.2. Effect of the sampling frequency and signal length

The arrival time was calculated by varying the lengths of the signal S1 (S1N1) with the ratios of 0.5 (S1N05), 2 (S1N2), 3 (S1N3) and 4 (S1N4). Thus, the sampling frequency of the signal also changed at these rates.

Figure 5 shows the arrival time results obtained when the signal length and sampling frequency were changed by these coefficients. As can be seen from the figure, when the signal length and sampling frequency were halved (S1N05), the same arrival time with the noisy state of the signal (S1N1) was picked. However, in the other three cases, the arrival times were delayed by 0.3 μsec and 0.5 μsec. This shows that as the sampling frequency increases, the sensitivity in picking the arrival time also increases.

However, as can be seen, these changes are not as higher as the changes obtained after noise filtering. In other words, eliminating the noise is a much more effective factor in accurately picking the arrival time, rather than the sampling frequency and length of the signal. For these reasons, Table 3 shows how these small changes affect the distance between the source and the sensor in localization, to determine how necessary it is to upload such data to the recording system by increasing the data frequency in terms of time and energy consumption. As can be seen, the distance difference calculated according to the earliest and the latest arrival times (0.000390 sec and 0.0003905 sec) is 0.175 cm where the propagation velocity of the P wave in concrete was taken as 3500 m/sec.

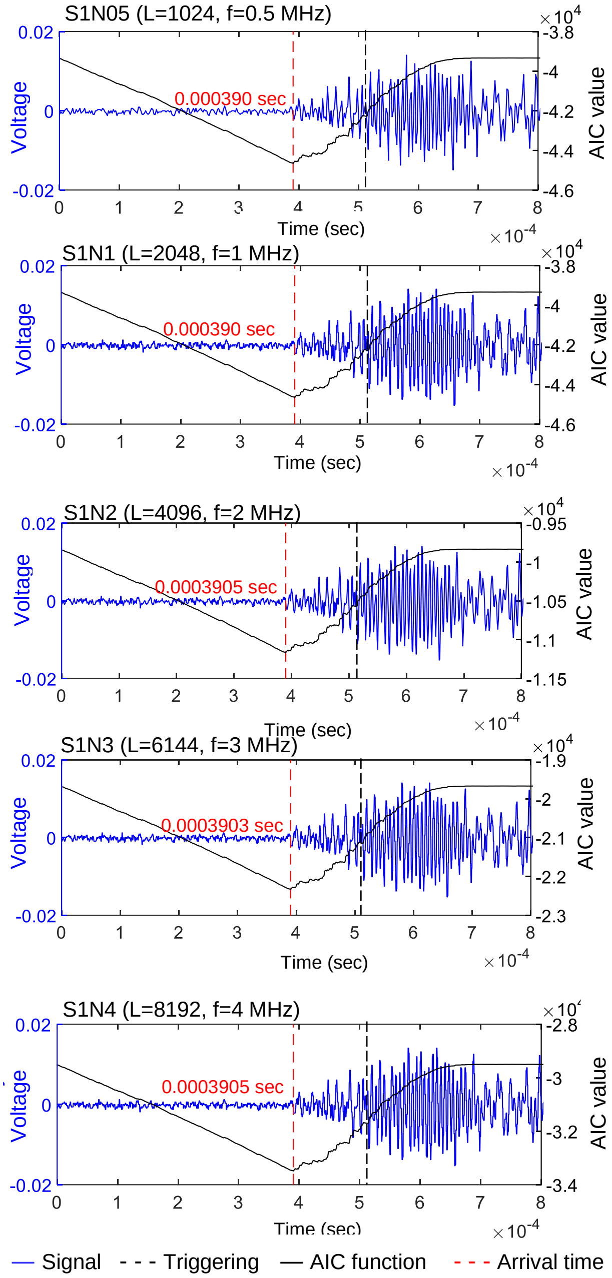

Figure 5. Picking the arrival time of the signal according to different sampling frequencies and signal lengths

Although this value is not as much as the noise effect, it will cause incorrect localization of the cracks that occur in the sections of the reinforced concrete beams or columns whose dimensions are much smaller than their lengths. While noise elimination is recommended in this respect; if the filtering has been done sufficiently, the decision whether to change the sampling frequency is left to the engineer according to the capacity of the recording system used.

Table 3. Source-sensor distance errors according to different sampling frequencies and signal lengths

Signal	Arrival time (μsec)	Source-sensor distance (m)	Max. distance error regarding the earliest and the latest two arrival times (cm)
S1N05	3900	1.365	0.175
S1N1	3900	1.365	
S1N2	3905	1.36675	
S1N3	3903	1.36605	
S1N4	3905	1.36675	

4.2.Effect of the focal window length

Arrival times calculated according to the ratio (n) of the 1st and 2nd focal window lengths to the signal length are given in Table 4. As can be seen, by changing the focal window lengths of the unfiltered signal S1, 5 μsec differences occurred in the arrival times. On the other hand, focal window length did not change the arrival time of signal S5, which was references and in which the noise was best filtered as mentioned in title 4.1.

Table 4. Arrival times of the filtered signals according to different focal window lengths

Window length			Arrival time (μsec)				
L_{P1}	L_{P2}	L_{P2}/L_{P1}	S1	S2	S3	S4	S5
50	50	1	385	389	459	365	384
100	100	1	390	390	459	365	385
100	50	0.5	385	389	459	365	384
500	500	1	390	390	459	365	390
500	250	0.5	390	390	459	365	390

For this reason, in the absence of noise filtering, especially as the length of the 2nd focal window increases, the amount of noise increases the signal energy, and it causes greater differences in picking the arrival time. Especially in these cases, it is recommended to use the 1st and 2nd focal window lengths with a ratio of 2/1, as it is more successful in picking earlier arrival times.

5. Conclusions

In this study, the effects of SNR, sampling frequency, signal length, and focal window length on the determination of the arrival time of the acoustic signals to the sensors were investigated. For this purpose, a frequently used energy-traced arrival time picking approach AIC was applied to a typical concrete crack-related acoustic signal that can be recorded while monitoring concrete structures. The results of the study suggest the necessity of noise elimination, the optimum level of data logging and the ratios of focal window lengths for accurate time of arrival picking in the field monitoring of the structures. Accordingly,

1. Among the filters used in the study, Wiener filter was the best to predict the arrival time at earliest by eliminating the noise best and not distorting the damage-related part of the signal.

2. It has been seen that filtering without distorting the signal form and voltage values is more effective for accurate arrival time picking rather than increasing the SNR.

3. It has been revealed that the differences in the order of microseconds between the arrival times cause relatively large distance deviations in the order of centimeters which cannot be ignored.

4. Eliminating the noise is a much more effective factor in accurately picking the arrival time, rather than the sampling frequency and signal length. For this reason, while noise elimination is recommended, it is suggested that the signal sampling frequency can be selected according to the performance of the data recording system if the filtering is done sufficiently.

5. In the absence of noise filtering, especially as the length of the 2nd focal window increases, the amount of noise increases the signal energy and larger differences in arrival times occur. Especially in these cases, it is recommended to choose the 1st and 2nd window lengths with a ratio of 2/1.

6. For future works, development of a statistical analysis can be recommended to prove the results of more and different-type signals.

Article Information Form

The Declaration of Conflict of Interest/ Common Interest

No conflict of interest or common interest has been declared by the authors.

The Declaration of Ethics Committee Approval

This study does not require ethics committee permission or any special permission.

The Declaration of Research and Publication Ethics

The authors of the paper declare that they comply with the scientific, ethical and quotation rules of SAUJS in all processes of the paper and that they do not make any falsification on the data collected. In addition, they declare that Sakarya University Journal of Science and its editorial board have no responsibility for any ethical violations that may be encountered, and that this study has not been evaluated in any academic publication environment other than Sakarya University Journal of Science.

References

[1] ASTM E 1316, “Standard Terminology for NDT”, 2002.

[2] C. U. Grosse, M. Ohtsu, “Acoustic Emission Testing, Basics for Research-Applications in Civil Engineering, Springer-Verlag, Berlin, Heidelberg, 2008.

[3] S. Tayfur, N. Alver, “Attenuation and Frequency Characteristics of Acoustic Waves in Steel and Synthetic Fiber-Reinforced Concrete: 3D-PCT and Unsupervised Pattern Recognition”, Applied Sciences, Vol. 12, 24, pp. 12976, 2022.

[4] S. Tayfur, N. Alver, S. Abdi, S. Saatcı, A. Ghiami, “Characterization of concrete matrix/steel fiber de-bonding in an SFRC beam: Principal component analysis and k-mean algorithm for clustering AE data”, Engineering Fracture Mechanics, Vol. 194, pp. 73-85, 2018.

[5] C. Van Steen, EVerstryng, “Signal-Based Acoustic Emission Clustering for Differentiation of Damage Sources in Corroding Reinforced Concrete Beams”, Applied Sciences, Vol. 12, 4, pp. 2154, 2022.

[6] Z. Li, F. Li, X. S. Li, W. Yang, “Determination and AE Characterization of Concrete”, Journal of Engineering Mechanics, Vol. 126, 2, pp. 194-200, 2000.

[7] S. Gollob, G. K. Kocur, T. Schumacher, L. Mhamdi, T. Vogel, “A novel multi-segment path analysis based on a heterogeneous velocity model for the localization of acoustic emission sources in complex propagation media”, Ultrasonics, Vol. 74, pp. 48-61, 2017.

[8] F. Zhang, L. Pahlavan, Y. Yang, “Evaluation of acoustic emission source localization accuracy in concrete structures”, Structural Health Monitoring, Volume 19, 6, pp. 2063-2074, 2020.

[9] Y. H. Lee, T. Oh, “The Measurement of P-, S-, and R-Wave Velocities to Evaluate the Condition of Reinforced and Prestressed Concrete Slabs”, Advances in Materials Science and Engineering, Vol. 2016, pp. 1-15, 2016.

[10] X. Shang, Y. Wang, R. Miao, “Acoustic emission source location from P-wave arrival time corrected data and virtual field optimization method”, Mechanical Systems and Signal Processing, Vol. 163, pp. 108129, 2022.

[11] J. H. Kurz, C. U. Grosse, H. W. Reinhardt, “Strategies for reliable automatic onset time picking of acoustic emissions and of ultrasound signals in concrete”, Ultrasonics, Vol. 43, 7, pp. 538-546, 2005.

[12] A. Carpinteri, J. Xu, G. Lacidogna, A. Manuello, “Reliable onset time determination and source location of acoustic emissions in concrete structures”, Cement & Concrete Composites, Vol. 34, pp. 529-537, 2012.

[13] F. Bai, D. Gagar, P. Foote, Y. Zhao, “Comparison of alternatives to amplitude thresholding for onset detection of acoustic emission signals” Mechanical Systems and Signal Processing, Vol. 84, pp. 717-730, 2017.

[14] M. Zhang, M. Li, H. Li, “Onset detection of ultrasonic signals for the testing of concrete foundation piles by coupled continuous wavelet transform and machine learning algorithms”, Advanced Engineering Informatics, Vol. 43, pp. 101034, 2020.

[15] H. Akaike, “Markovian representation of stochastic processes and its application to the analysis of autoregressive moving average”, Annuals of the Institute of Statistical Mathematics, Vol. 26, 1, pp. 363–387, 1974.

[16] G. Kitagawa, H. Akaike, “A procedure for the modeling of non-stationary time series”, Annuals of the Institute of Statistical Mathematics, Vol. 30, 1, pp. 351-363, 1978.

[17] R. Madarshahian, P. Ziehl, J. M. Caicedo, “Acoustic emission Bayesian source location: Onset time challenge”, Mechanical Systems and Signal Processing, Vol. 23, pp. 483-495, 2019.

[18] H. Chen, Z. Yang, “Arrival Picking of Acoustic Emission Signals Using a Hybrid Algorithm Based on AIC and Histogram Distance”, IEEE Transactions on Instrumentation and Measurement, Vol. 70, pp. 3505808, 2020.

[19] H. Li, Z. Yang, W. Yan, “An improved AIC onset-time picking method based on regression convolutional neural network”, Mechanical Systems and Signal Processing, Vol. 171, pp. 108867, 2022.

[20] L. Geiger, “Probability method for the determination of earthquake epicentres from the arrival time only”, Bulletin of St. Louis University, Vol. 8, pp. 60-71.

[21] V. Matz, R. Smid, S. Starman, M. Kreidl, “Signal-to-noise ratio enhancement based on wavelet filtering in ultrasonic testing”, Ultrasonics, Vol. 49, 8, pp. 752-759, 2009.

[22] J. Xu, Z. Wang, C. Tan, L. Si, X. Liu, “A Novel Denoising Method for an Acoustic-Based System through Empirical Mode Decomposition and an Improved Fruit Fly Optimization Algorithm”, Applied Sciences, Vol. 7, 3, pp. 215, 2017.

[23] K. Prajna, C. K. Mukhopadhyay, “Fractional Fourier Transform Based Adaptive Filtering Techniques for Acoustic Emission Signal Enhancement”, Journal of Nondestructive Evaluation, Vol. 39, 14, pp. 1-15, 2020.

[24] C. Zhou, Y. Zhang Y, “Particle filter based noise removal method for acoustic mission signals”, Mechanical Systems and Signal Processing, Vol. 28, pp. 63-77, 2012.

[25] M. Sraitih, Y. Jabrane, “A denoising performance comparison based on ECG Signal Decomposition and local means filtering”, Biomedical Signal Processing and Control, Vol. 69, pp. 102903, 2021.

[26] N. Arı, S. Özen, Ö. H. Çolak, “Dalgacık Teorisi”, Palme Yayıncılık, Ankara, 2008.

[27] İ. V. Öner, M. K. Yeşilyurt, E. Ç. Yılmaz, “Wavelet Analiz Tekniği ve Uygulama Alanları”, Ordu University Journal of Science and Technology, Vol. 7, 1, pp. 42-56, 2017.

[28] R. Janeliukstis, “Continuous wavelet transform-based method for enhancing estimation of wind turbine blade natural frequencies and damping for machine

learning purposes", Measurement, Vol. 172, pp. 108897, 2021.

[29] N. Wiener, "The Interpolation, Extrapolation and Smoothing of Stationary Time Series", Report of the Services 19, Research Project DIC-6037 MIT, 1942.

[30] M. Jayawardhana, X. Zhu, R. Liyanapathirana, "Damage Detection of Reinforced Concrete Structures Based on the Wiener Filter", Australian Journal of Structural Engineering, Vol. 14, pp. 57-69, 2013.

[31] Y. W. Chen, "Noise Reduction by Wiener Filter (https://github .com/JarvusChen/ MATLAB-Noise-Reduction-by-wiener-filter)", GitHub. Retrieved April 22, 2022.

[32] A. Savitzky, M. J. E. Golay, "Smoothing and Differentiation of Data by Simplified Least Squares Procedures", Analytical Chemistry, Vol. 36, 8, pp. 1627-1639, 1964.

[33] H. Hassanpour, "A time–frequency approach for noise reduction", Digital Signal Processing, Vol. 18, 5, pp. 728-738, 2008.

[34] H. Azami, K. Mohammadiand B. Bozorgtabar, "An Improved Signal Segmentation Using Moving Average and Savitzky-Golay Filter", Journal of Signal and Information Processing, Vol. 3, 1, pp. 39-44, 2012.