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RESEARCH ARTICLE

Seismic Random Noise Suppression Using Optimal ANFIS as an Adaptive Self-Tuning Filter and Wavelet Thresholding

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ABSTRACT Random noise attenuation plays a vital step in seismic signal processing. Numerous attenuation algorithms have been developed to separate and remove the random noise; nevertheless, they have failed to attain high precision. In this work, a hybrid framework based on an optimal adaptive neuro-fuzzy inference system (OANFIS) and a recent wavelet thresholding (WT), specifically OANFIS WT, is proposed to attenuate the random noise present in the seismic signals. In the suggested OANFIS WT method, the OANFIS extract the relevant seismic signal information from the contaminated signal using the premise and consequence parameters of ANFIS. These parameters are determined optimally using the Honey badger algorithm with mean square error value as an objective function. Here, OANFIS acts as an adaptive self-tuning filter that extracts the appropriate seismic signal information without any knowledge of the amount of noise in the contaminated signal. Therefore, some noise may be present in the output of OANFIS. Thus, the WT is applied to the extracted signal, with different values of the adjusting parameters in the thresholding function, to attenuate the noise effectually. Lastly, the experimental results on the synthetic and real seismic signals reveal that the proposed OANFIS WT method is more effective in reducing random noise and preserving relevant signal information than other contrastive methods.

INDEX TERMS Adaptive noise cancellation (ANC), honey badger algorithm (HBA), optimal adaptive neuro-fuzzy inference system (OANFIS), random noise, seismic signal, wavelet thresholding (WT).

I. INTRODUCTION

In seismic exploration, recorded seismic signals are corrupted with random noise from diverse sources like wind, instruments, and geophones [1]. This background noise implies difficulty in the subsequent processing and analysis of seismic signals. Hence, it is imperative to develop a noise attenuation method in order to enhance the signal-to-noise ratio (SNR) of the seismic signal.

Over the past few decades, numerous techniques have been developed to minimize the random noise in seismic signals. The most commonly used method is the prediction-filter-based approach, assuming the seismic signal to be a local superposition of the linear events in the f-x domain [2]. Next, the sparse transform-based method transfers the corrupted seismic signal into the transform domain and then filters the noise in the transform domain. The sparse transform-based methods such as the curvelet transform [3], dreamlet transform [4], seislet transform [5], and wavelet transform [6] have been applied in seismic signals to effectively minimize the noise. The rank reduction method [7] is another type of sparse representation method that relies on the rank of the matrix. These methods are based on the assumption that a noise-free signal can be transformed into a low-rank matrix. Also, the denoising approaches based on decomposition methods like singular value decomposition (SVD), empirical mode decomposition (EMD), ensemble EMD (EEMD), complete EEMD (CEEMD), empirical wavelet transform (EWT), and variational mode decomposition (VMD) techniques have been employed to reduce the noise in the recorded signal.

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Several researchers have suggested hybrid techniques [8], [9], [10], [11], [12], [13], [14], [15] to eradicate the noise using decomposition-based methods. Also, some filtering approaches, including Weiner filtering [16], Kalman filtering [17], mathematical morphological filtering (MMF) [18], non-local means (NLM) filtering [19], and others, are continually investigated to attenuate random noise in the signal. The combination of such approaches leads to the magnificent interpretation of seismic signals.

Usually, researchers use some known filters to eradicate unwanted noise and retain the data information. However, the design of such filters should be optimal, and the filters used there can be fixed or adaptive [20]. The adaptive filters can automatically vary their parameters and can be designed with little or no prior knowledge of noise and signal attributes. Therefore, an adaptive filter is used as an adaptive noise canceller (ANC) to remove the unknown noise in the signal. Recently, adaptive filters have been used to remove artifacts in biomedical signal processing [21], [22]. Similarly, adaptive filters have been employed in seismic applications to reduce noise in the signal [23]. The author [24] has developed a hybrid combination of CEEMD with recursive least squares (RLS) to extract the time-varying wavelet magnitude spectrum of the seismic signal. The important aspects of adaptive filter estimation are convergence, steady-state tracking ability, and steady-state error. The step size holds a significant importance in adaptive filters. A larger step size value results in faster convergence and raises the steady-state mean square error (MSE). On the other hand, if the steady-state MSE is reduced by selecting a smaller step size, the convergence speed is relatively slow. Further, adaptive filter algorithms with the highest filter order outperform one another, potentially leading to complicated filter architectures. However, for the non-linear phenomenon, the linear filter performance seems to be poor, and it is necessary to develop non-linear filters to attenuate the noise in the signal [25]. Therefore, applying neural networks in adaptive signal processing has become popular because of their non-linear learning ability and the fact that they do not require prior knowledge of signal and noise attributes [26].

In the past decades, soft computing gained popularity in the study of geophysical [27]. The machine learning field has a variety of frameworks based on adaptability, learning rate, versatility, and complexity. Many researchers suggested techniques such as fuzzy logic, artificial neural networks (ANN), random forest, support vector regressors (SVR), regression and optimization algorithms to attain their goals. The hybrid of the above techniques has been developed in such a way as to overcome the deficiencies and also attain robustness [28]. A noise reduction method was developed using neural networks to remove the noise in real and synthetic seismic records [29]. Lin et al. [30] used a fuzzy clustering process with time-frequency peak filtering to suppress the unwanted noise. A semi-automatic procedure that consists of ANN and wavelet packets was developed to eradicate the undesirable noise in real, synthetic, and common offset sorted gathers [31]. A denoising method was suggested to enhance the SNR of the seismic reflection data by eradicating the noise using the Weiner and adaptive neuro-fuzzy inference system (ANFIS) filtering techniques [32]. This paper calculates and sorts the adaptive Weiner filter output values and standard deviation of the signal. The points with the highest standard deviation could be examined as noise attributes and given as input to train the ANFIS. A simple ANC structure was developed based on the normalized least mean square error [33] and RLS algorithm [34] to attenuate the narrow band noise (sinusoidal noise) and broadband noise present in the signal.

Generally, the seismic signal is affected by random noise (broadband interference) [35], and no external noise-free signal is available to execute the ANC process. It seems that the ANC cannot be used to remove the noise from the corrupted seismic signal. In such cases, ANC can act as an adaptive self-tuning filter [20], capable of retrieving the filtered signal from the contaminated signal. Therefore, based on error, non-linear characteristics, convergence speed, accuracy, and filter structure, many researchers have used the ANFIS as an ANC to remove the unknown noise in the signal.

ANFIS [36] is a five-layered neural network structure with a fuzzy inference system (FIS). ANFIS combines elements of neural networks and fuzzy systems, achieving low MSE, high speed, and high prediction. ANFIS determines the premise and consequent parameters, where fuzzy if-then rules can relate these parameters together. In general, the membership function parameters denote the system behavior of ANFIS, and these parameters could be updated using hybrid and backpropagation methods. However, these methods directly impact the FIS membership functions, output, and input. These methods use gradient descent (GD) to estimate the premise parameters and least square estimation (LSE) to calculate the consequence parameters. Since these algorithms are derivative-based, there is a chance of trapping at the local minimum [37]. Due to such reasons, some metaheuristic optimization algorithms may be used to optimize the membership function parameters (premise and consequence parameters) to enhance the performance of ANFIS. Therefore, in this article, we have proposed an optimal ANFIS (OANFIS) that regulates the premise and consequence parameters using the Honey Badger algorithm (HBA). In addition, since the amount of noise in the signal is uncertain, in this work, the OANFIS acts as a proficient adaptive self-tuning filter, extracting the seismic signal information from the contaminated signal. However, there might be some noise in the extracted signal. Hence, the noise in the extracted signal can be attenuated effectually by applying the wavelet thresholding (WT) technique [38]. Because in WT, the adjusting parameters are essential for fine-tuning the speed and growth rate of the thresholding function. Therefore, the use of OANFIS and WT motivates the proposal of a hybrid denoising approach (OANFIS WT) to reduce the noise in the signal.

The contributions of the work are summarized as follows:

1) We proposed an OANFIS to determine the premise and consequence parameters of ANFIS. We used the HBA with mean square error (MSE) as an objective function to determine the appropriate membership function parameters. Besides, the noise level of the recorded seismic signal can be pretty unpredictable; the OANFIS performs as an effective adaptive self-tuning filter. Its purpose is to obtain the signal information from the contaminated signal without knowing the amount of noise in the signal.
2) Further, the WT is applied to the extracted signal, where threshold calculation is carried out at each wavelet decomposition level, effectively leading to random noise attenuation.
3) Then, we validate the effectiveness of the proposed technique (OANFIS WT) with EMD DWT [8] and VMD DWT [10] for both the synthetic and real seismic signals.

The sections of the article are organized in the following manner. In Section II, the proposed methodology is outlined. In Section III, the results of the proposed algorithm are discussed and compared with the existing algorithm. Section IV provides a detailed discussion, while Section V presents the conclusions derived from our work.

II. METHODOLOGY OF THE PROPOSED METHOD

In this article, we proposed a hybrid framework that employs an OANFIS and WT to attenuate the noise from the corrupted signal. Fig. 1 shows the block diagram of our proposed algorithm. Here, OANFIS acts as an adaptive self-tuning filter which extracts the seismic signal information without knowing the amount of noise present in the signal. Hence, in the rest of the section, we first use ANC as an adaptive self-tuning filter. Then, we present the ANFIS, optimization algorithm and WT, which are the prototypes of our proposed model. Later, we describe the structure and workflow of our proposed OANFIS WT model in detail.

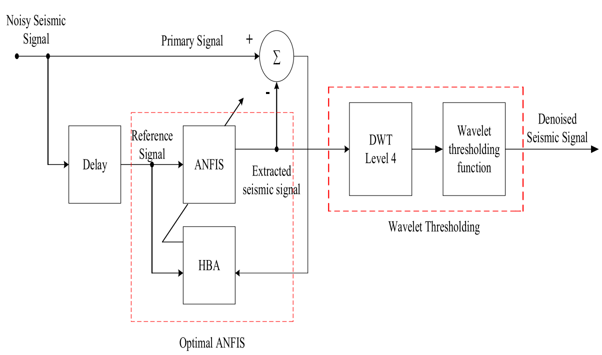

FIGURE 1. Block diagram of our proposed algorithm.

A. ADAPTIVE NOISE CANCELLER

An ANC usually requires two inputs: a primary signal corrupted with noise and a reference signal that contains the noise associated with the primary signal. In many circumstances, the seismic signal is contaminated by random noise (broadband interference) [35], and the noise level is unknown to perform the ANC process. If this is the scenario, a predetermined delay is introduced in the reference input, which is taken from the primary input [20], as shown in Fig. 2. Here, ANC acts as an adaptive self-tuning filter (the output is taken from the adaptive filter), which can extract the relevant signal from the corrupted data. In this work, we used ANFIS as an ANC to eradicate the noise in the signal.

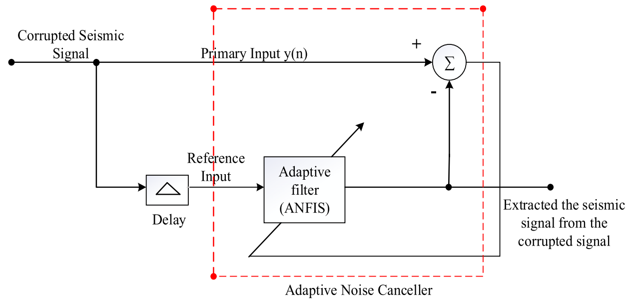

FIGURE 2. Schematic sketch of adaptive noise canceller as an adaptive self-tuning filter using ANFIS.

B. OPTIMAL ANFIS

1) ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

The ANFIS is a hybrid of fuzzy systems and AI networks that incorporates the advantages of both processes. The fuzzy if-then rules module establishes a link between inputs and outputs, and the neural network algorithms resolve the parameters connected to the membership part.

Therefore, ANFIS integrates the neural network learning capabilities with the potential of a FIS. This system generates and achieves a non-linear relationship between inputs and outputs based on linguistic perceptions. The ANFIS structure is determined based on the input data, membership degree, rules, and output membership function. Fig. 3 illustrates a five-layer fuzzy neural network built with two rules using the ANFIS algorithm. An ANFIS was designed using a first-order Sugeno framework fuzzy model with

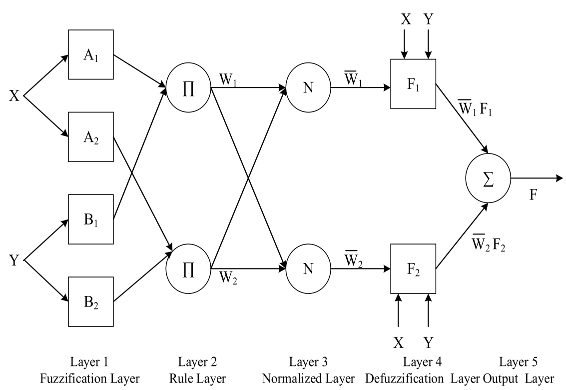

FIGURE 3. 2- input and type 3 ANFIS with two rules.

IF-THEN rules [36].

Rule 1: if m is P_1 and n is Q_1, then $F_1 = u_1\, m + v_1\, n + w_1$.
Rule 2: if m is P_2 and n is Q_2, then $F_2 = u_2\, m + v_2\, n + w_2$.

where m and n denote the inputs, P_i and Q_i denote the fuzzy sets, u_i, v_i, and w_i are the design parameters, and F_i denotes the outputs well defined by the fuzzy rule. We use circular and square nodes in the ANFIS framework to represent distinct adaptive capabilities. In ANFIS, a square node, also known as an adaptive node, requires parameter updates, while the circle node, or fixed node, does not need any parameter updates to enhance performance. The ANFIS structure has two parameter sets: consequent parameters (u_1, u_2, v_1, v_2, w_1, and w_2) and premise parameters denoting the output and input membership functions. These parameters are restructured based on the training information and learning process described below.

Layer 1 – Fuzzification Layer: The nodes i in layer 1 are adaptive and are controlled by a node function.

$$O_i^1 = \mu_{P_i}(m) \tag{1}$$

where m signifies the input node i, μ_{P_i} represents the membership function of P_i The Gaussian membership function is selected and represented as

$$\mu_{P_i}(m) = \exp\left(\frac{-(m-c)^2}{2\sigma^2}\right) \tag{2}$$

where c and σ denote the mean and standard deviation, called premise parameters.

Layer 2 – Rule layer: Each node in Layer 2 functions as a fixed node whose output is obtained by multiplying all the signals and determining the rule's firing strength.

$$O_i^2 = \omega_i = \mu_{P_i}(m) \times \mu_{Q_i}(m), \quad i = 1, 2 \tag{3}$$

Layer 3 – Normalized layer: Every node in this layer estimates the ratio of the i^{th} firing rule to the sum of all the firing rules.

$$O_i^3 = \bar{\omega}_i = \frac{\omega_i}{\omega_1 + \omega_2}, \quad i = 1, 2 \tag{4}$$

Layer 4 – Defuzzification layer: The output of Layer 4 is determined by the product of a first-order polynomial and firing strength, which has been normalized. Each node in the layer functions adaptively. The parameters in this layer are referred to as consequence parameters $\{u_i, v_i, \text{and } w_i\}$.

$$O_i^4 = \bar{\omega}_i F_i = \bar{\omega}_i\,(u_i m + v_i n + w_i), \quad i = 1, 2 \tag{5}$$

Layer 5 – Output layer: The single node in this layer estimates the output by adding all incoming signals.

$$O_i^5 = \text{output} = \sum\nolimits_i (\bar{\omega}_i F_i) = \frac{\sum_i \omega_i F_i}{\sum_i \omega_i} \tag{6}$$

Fig. 3 illustrates a 2-input, type 3 ANFIS with two rules. The input space is separated into two fuzzy subspaces, each controlled by fuzzy if-then rules and two membership functions are connected to each input. The premise of a rule states a fuzzy subspace, and the consequent component defines the output within that fuzzy subspace.

2) TRAINING ANFIS USING OPTIMIZATION ALGORITHM

The ANFIS is trained to determine its premise and consequence parameters using a hybrid optimization technique. Premise parameters $\{c, \sigma\}$ are the members of the functions on the first layer, and consequent parameters $\{u_i, v_i,$ and $w_i\}$ are the parameters on the fourth layer of the first-order polynomial. A hybrid learning approach was used to train the classical ANFIS. The GD algorithm was used in this learning approach to identify premise parameters, while the LSE method was used to determine consequence parameters. However, these methods rely on derivatives, which introduces the possibility of getting struck at the local minimum [37]. As a result, employing metaheuristic approaches rather than derivative-based algorithms yields more efficient results. Therefore, an optimal model is developed by fine-tuning the ANFIS parameters using a metaheuristic algorithm to achieve the minimum differences between the actual and the expected outcomes derived by ANFIS. In this work, we have used the HBA optimization process to determine the ANFIS parameters optimally in order to achieve adequate performance.

3) HONEY BADGER ALGORITHM (HBA)

The HBA was developed on the long lifespan of honey badgers [39]. The honey badger follows the honeyguide bird or uses its sense of smell to locate and excavate food. The initial stage is the digging phase, followed by the honey phase. It uses its smelling skills to locate the prey during the early phase. When it arrives, it examines the surroundings above the prey to determine the optimal solution. Finally, a honeyguide bird assists in locating the beehive. In addition, the HBA incorporates three control factors: density, flag, and intensity factors. The HBA demonstrates exceptional expertise in local search capabilities through its effective honey attraction mechanism, enabling candidates to optimize their values within the search space. The density factor assists the algorithm in exploring a wide range of possibilities, avoiding getting stuck in a local solution. The complete HBA method has been thoroughly explained in [39]. The initializing parameters required to run the HBA algorithm are the search agents (set as 50), the maximum iteration (set as 300), the lower bound and upper bound (should be specified), the dimension (set as 14) and the objective function as MSE.

4) EVALUATE THE ANFIS USING FITNESS FUNCTION

In this work, we used the fuzzy c-means clustering (FCM) method to process the FIS in ANFIS. The FCM has the benefit of not restricting cluster boundaries, which permits elements to be involved in multiple groups rather than just one group. In addition, it has good speed-boosting intelligence [40]. Here, we have employed the HBA optimization process to enhance the performance of ANFIS. The OANFIS groups all of the membership function parameters into a vector; then, using an HBA method, the optimal values of premise and consequence parameters are determined with minimum fitness value. The fitness function is represented as,

$$\min_{\theta} \text{Error} = \frac{1}{M} \sum\nolimits_{i=1}^{n} e_i^2 \tag{7}$$

$$e_i = t_i - y_i \tag{8}$$

where M represents the number of ANFIS inputs, e_i denotes the error, θ represents the ANFIS parameters, t_i represents the target value and y_i denotes the ANFIS output.

C. WAVELET THRESHOLDING FUNCTION

Researcher often utilize soft thresholding (ST) and hard thresholding (HT) functions for filtering the wavelet coefficients. Nevertheless, issues with discontinuity in HT can lead to oscillation during reconstruction, and the constant deviation problems in soft thresholding can negatively impact the quality of the signal. Many researchers have developed different wavelet thresholding functions to address the limitations of traditional thresholding. Li et al. [38] proposed a continuous and differentiable WT function that can defeat the problems of discontinuity and deviation. In this work, we have used the WT function proposed by Li et al. [38], which is represented as,

$$\tilde{\omega}_{k,j} = \begin{cases} \omega_{k,j} - \dfrac{\lambda_j}{\alpha\left(\omega_{k,j} - \lambda_j\right)^{\beta} + 1}, & \omega_{k,j} > \lambda_j \\ 0, & \left|\omega_{k,j}\right| \leq \lambda_j \\ \omega_{k,j} + \dfrac{\lambda_j}{\alpha\left(-\omega_{k,j} - \lambda_j\right)^{\beta} + 1}, & \omega_{k,j} < -\lambda_j \end{cases} \tag{9}$$

where β and α represent the shape adjustment factors, $\omega_{k,j}$ denotes the wavelet coefficient, $\tilde{\omega}_{k,j}$ denotes the wavelet coefficient processed by the threshold value and λ_j represents the threshold value. The threshold calculation is represented as,

$$\lambda_j = \frac{\delta_j\sqrt{2lnN_j}}{\sqrt[j+1]{j}} = \frac{\text{median}\left(\left|\omega_{k,j}\right|\right)\sqrt{2lnN_j}}{0.6745\sqrt[j+1]{j}} \tag{10}$$

where j denotes the decomposition level and N_j represents the dimension of the wavelet coefficient. Here, the level of the wavelet coefficient can adaptively evaluate the noise amplitude and effectually eradicate the noise.

D. STEPS TO PERFORM THE PROPOSED METHODOLOGY

Our suggested method exhibits the use of the HBA-based ANFIS technique with the WT algorithm to denoise the corrupted seismic signal. Fig. 4 demonstrates the flowchart, and Table 1 presents the pseudocode of our proposed algorithm. It has three phases:

Phase 1- Determine the premise and consequence parameters of ANFIS using the HBA algorithm.

The objective is to optimally determine the two parameter sets (premise and consequence) to enhance the performance

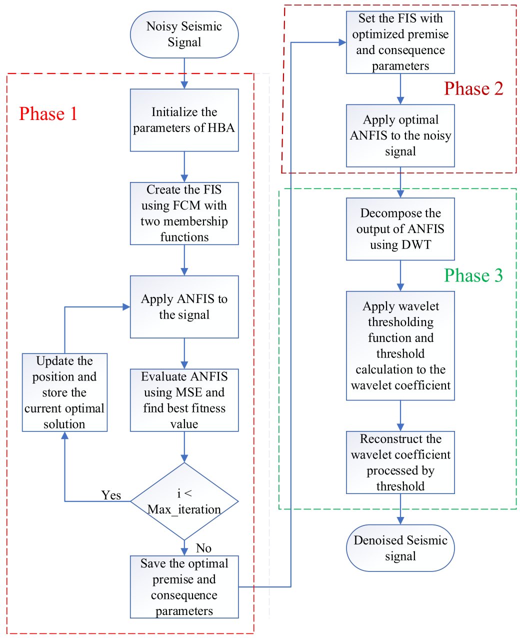

FIGURE 4. Flow chart of our proposed method (OANFIS WT).

TABLE 1. Pseudocode of OANFIS WT (proposed method).

1: Load the noisy seismic signal.
2: Set the initial parameters of HBA: lb, ub, maximum iterations, search agents, d_{min} and fitness functions.
3: Create the FIS with the fuzzy c-means clustering method.
4: Extract the range of premise and consequence parameters of ANFIS from the created FIS and set them as the lower and upper bound of HBA.
5: Perform HBA for the specified number of iterations.
6: Train the signal using ANFIS during each iteration.
7: Determine the fitness values and store the finest one.
8: Save the global fitness value and set the FIS with optimal premise and consequence parameters.
9: Re-run ANFIS with updated FIS to extract the relevant information from the noisy signal.
10: Apply DWT with a specified wavelet thresholding function on the extracted signal to attenuate the noise effectively.
11: Reconstruct the signal to obtain the filtered seismic signal.

of ANFIS. Thus, these parameters are obtained using the HBA optimization process. In this work, we used the FCM method and two membership parameters to create the FIS and then extracted the range of two parameter sets as upper and lower bounds to perform the HBA optimization process.

The optimization algorithm evaluates the output using MSE as an objective function.

Phase 2 – Denoising using optimized two parameter sets of ANFIS.

The optimized two parameter sets (premise and consequence) are used to set the new FIS. Then, the corrupted seismic signal is applied to OANFIS to extract the filtered seismic signal. However, some noise may persist in the OANFIS output.

Phase 3 – Filtering using the WT technique.

The output from the optimal ANFIS is filtered using four-level wavelet decomposition with *sym11* as a mother wavelet. In this work, we have used the wavelet thresholding function and threshold value calculation proposed by Li et al. [38], represented in Eq. (9) and Eq. (10). This wavelet thresholding function can overcome the discontinuity and deviation problems. Also, each level of wavelet coefficient may effectively remove the noise in the signal.

III. NUMERICAL EXPERIMENTS

In this section, we test the denoising performance of the suggested OANFIS WT method based on real and synthetic signals. Meanwhile, to validate the effectiveness of our proposed method, we compare our OANFIS WT method with two contrastive denoising methods, i.e. EMD DWT [8] and VMD DWT [10]. In addition, to compare the denoising capability of each method quantitatively, we choose the signal-to-noise ratio out ($\mathrm{SNR_{OUT}}$), the mean square error (MSE), the root mean square error (RMSE), the percentage root mean square differences (PRD), and correlation coefficient (CC) as a quantitative measure, defined as

$$\mathrm{SNR_{OUT}} = 10\log\left(\frac{\sum_n s^2(n)}{\sum_n [s(n) - s(n)]^2}\right) \tag{11}$$

$$\mathrm{MSE} = \frac{1}{N}\sum_n \left[s(n) - \hat{s}(n)\right]^2 \tag{12}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_n \left[s(n) - \hat{s}(n)\right]^2}{N}} \tag{13}$$

$$\mathrm{PRD} = 100 * \sqrt{\frac{\sum_n \left[s(n) - \hat{s}(n)\right]^2}{\sum_n s^2(n)}} \tag{14}$$

$$\mathrm{CC} = \frac{N\left(\sum s(n)\,\hat{s}(n)\right) - \left(\sum s(n)\right)\left(\sum \hat{s}(n)\right)}{\sqrt{\left[N\sum s(n)^2 - \left(\sum s(n)\right)^2\right]\left[N\sum \hat{s}(n)^2\right] - \left(\sum \hat{s}(n)\right)^2}} * 100 \tag{15}$$

where $s(n)$ is the noise-free signal, N is the length of the sample, and $\hat{s}(n)$ represents the filtered signal.

A. SYNTHETIC SIGNAL

We first examine the performance of our proposed approach and the contrastive methods using synthetic signals. Fig. 5(a) illustrates the synthetic signal, which comprises two zero-phase Ricker wavelets with different dominant frequencies, 15 and 20 Hz at 0.4 and 0.8 s. Fig. 5(b) shows a noisy seismic signal with an SNR of 4 dB obtained by adding additive white Gaussian noise (AWGN) to the synthetic seismic signal. Evidently, the relevant information in seismic signals is immersed with background noise, which makes it challenging to remove noise in seismic signals.

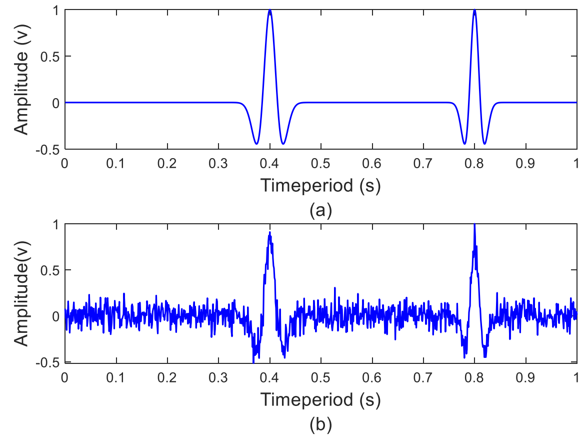

FIGURE 5. (a) Synthetic signal (b) Noisy synthetic signal.

The proposed OANFIS WT method does not require a reference signal (consisting of only noise attributes) to process the ANFIS. Since ANFIS acts as an adaptive self-tuning filter, the corrupted seismic signal with an inevitable delay can be given as a reference signal. As stated, we employ the FCM method with two membership functions to evaluate the FIS in ANFIS. The standard ANFIS was trained using a hybrid learning approach, and this approach may be trapped at a local minimum [37], which may reduce the performance of ANFIS. Thus, the HBA is utilized in this work to determine the two-parameter sets optimally. Here, we limit the HBA to 300 iterations and 50 search agents for our analysis. Fig. 6 illustrates the convergence curve for the synthetic signal,

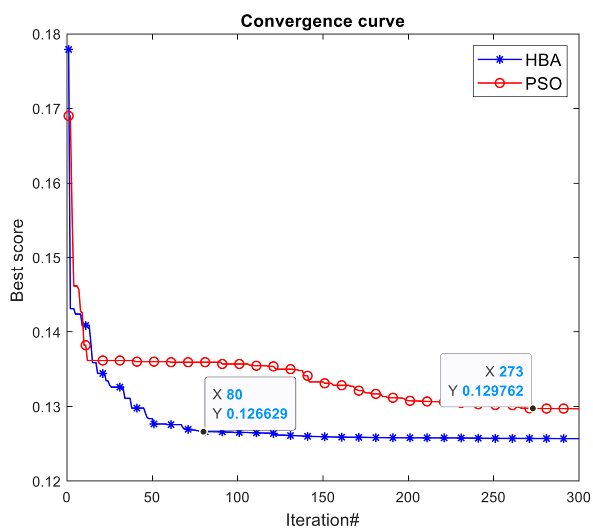

FIGURE 6. Convergence curve of HBA and PSO algorithms for synthetic signal.

comparing the HBA and particle swarm optimization (PSO) methods. After analyzing the outcomes, it is evident that HBA outperforms PSO regarding fitness value. HBA achieves its best fitness value at the 80^{th} iteration, while PSO takes longer and attains its best fitness value at the 273^{rd} iteration. Thus, HBA aids the ANFIS in obtaining the best values of two parameter sets of ANFIS with a fast convergence curve.

Furthermore, when comparing PSO and HBA, it is worth noting that HBA achieves a significantly lower *MSE* value of 0.126629. The most suitable premise and consequence parameters of ANFIS are identified through a comprehensive analysis of the data. Then, these parameters are used to establish an optimal FIS, which effectively extracts the seismic signal from the corrupted data.

Using the optimized parameters, we execute the OANFIS algorithm to extract the seismic signal at the output of ANFIS, as depicted in Fig. 1 and Fig. 2. Since the relevant information is extracted without knowing the level of noise present in the contaminated signal, it is possible that some noise may exist in the extracted signal. Therefore, the WT technique is utilized to filter out the remaining noise in the extracted signal. By executing the thresholding process at each DWT level and identifying the appropriate threshold values, the WT can attenuate the unwanted noise and reconstruct a filtered version of the signal. The seismic noise attenuation results of the three methods are shown in Fig. 7. The EMD DWT and VMD DWT denoising methods have the ability to minimize the noise, but they are inadequately efficient. After comparing the denoising method as illustrated in Fig. 7, the subsequent points are mainly observed: 1) compared with the EMD DWT method, the VMD DWT method enhances the denoising capability but falls short of choosing the parameters of VMD adaptively and also struggles to balance noise suppression and signal reconstruction. As a consequence, valid seismic signals may be lost in the process. 2) Despite the improvement in the denoising performance with OANFIS, some noise may exist in the signal, and 3) The suggested method has diverse benefits in the extraction of signal amplitude due to the selection of ANFIS parameters optimally and the magnificent flexibility of WT. Therefore, the proposed OANFIS WT has achieved outstanding performance compared with the other existing approaches, as shown in Fig. 7.

TABLE 2. Denoising evaluation parameters of the synthetic signal.

METHOD	SNR OUT	MSE	RMSE	PRD	CC
EMD DWT	18.172	0.03817	0.1953	7.36e-04	93.039
VMD DWT	20.805	1.04e-02	0.1018	3.92e-04	94.213
OANFIS WT	27.202	6.79e-03	0.0824	4.19e-04	96.772

Table 2 compares the noise attenuation impact and signal preservation capability among different denoising algorithms based on the evaluation parameters. It is clear that the proposed denoising approach outperforms other contractive denoising methods to achieve maximum SNR_{OUT} and minimum *MSE* value. As part of our analysis, we have compared the SNR_{OUT} of three denoising approaches at various *SNR* levels to determine the effectiveness of the proposed technique. Fig. 8 demonstrates the comparison of SNR_{OUT} across different SNR levels. A lower *SNR* makes the synthetic signal susceptible to more random noise. As shown in Fig. 8, the SNR_{OUT} value demonstrates a positive correlation with the *SNR* levels across all three denoising methods. We have observed that the proposed method attains better denoising capability and extracted the signal information efficiently.

B. REAL SIGNAL

For the real seismic signal, we chose the real data from the Pacific Earthquake Engineering Research Center (PEER) ground motion database [41], as shown in Fig. 9(a). Seismic data can have varying levels of SNR due to factors like acquisition methods, geological conditions, and processing

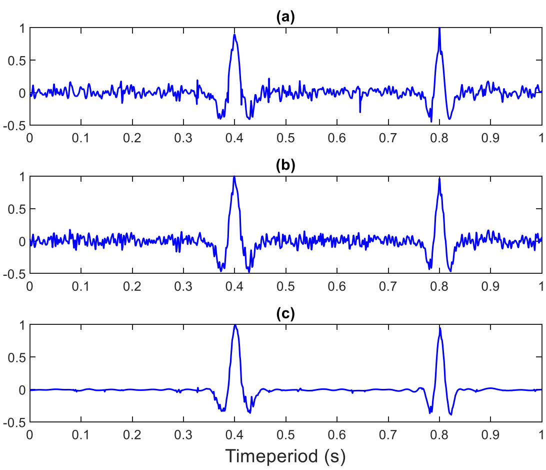

FIGURE 7. Denoised outputs of various methods in the synthetic signal. (a) EMD DWT. (b) VMD DWT. (c) Proposed method (OANFIS WT).

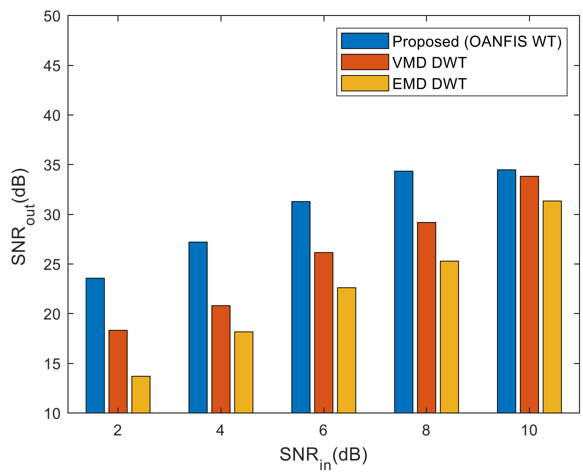

FIGURE 8. Comparison of SNROUT with different SNR levels for the synthetic signal.

techniques. Thus, incorporating the AWGN into the real signal yields a noisy seismic signal with an SNR of 4 dB, illustrated in Fig. 9 (b). Reducing noise in seismic signals can be challenging due to background noise obscuring the valuable signal information.

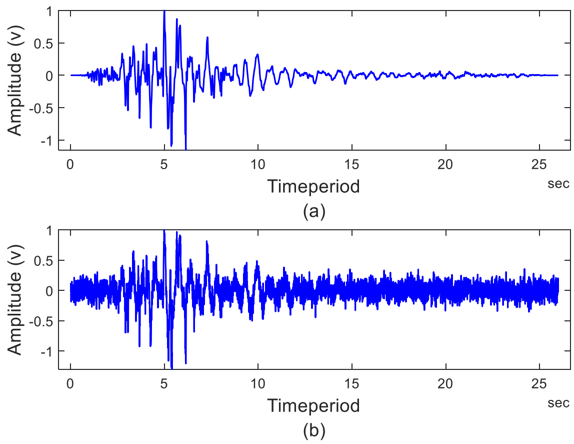

FIGURE 9. **(a) Real signal (b) contaminated with AWGN noise.**

Fig. 10 demonstrates the convergence curve for the real signal, presenting a comparison between the HBA and PSO methods. After thoroughly analyzing the results, it becomes clear that HBA surpasses PSO regarding fitness value. It is evident that HBA reaches its optimal fitness value at the 10^{th} iteration, whereas PSO achieves its best fitness value at the 40^{th} iteration.

Additionally, it is important to highlight that HBA outperforms PSO with a significantly lower MSE value of 0.0421854. The most appropriate premise and consequence parameters of ANFIS are determined through a comprehensive analysis of the data. Thus, an optimal FIS is established through a thorough analysis, allowing for the extraction of the seismic signal from the corrupted data with great effectiveness.

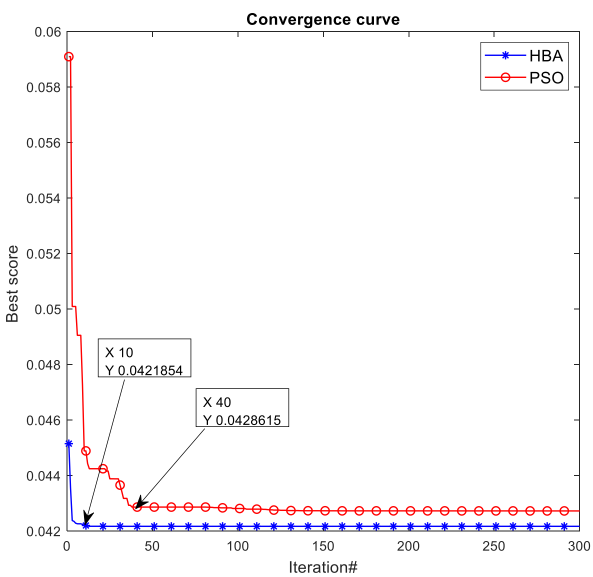

FIGURE 10. **Convergence curve of HBA and PSO algorithms for the real signal.**

In the proposed method, we varied the mother wavelets and quantitatively compared their denoising capabilities in real signals. The quantitative measures tabulated in Table 3 show that the *sym* wavelet attains a higher SNR_{OUT} and minimum *MSE* than the other mother wavelet. Also, the *sym* wavelet has been chosen for its superior symmetrical properties compared to the *db* wavelet [42].

TABLE 3. **Evaluation parameters for various mother wavelets for the real signal.**

WAVELET	SNR OUT	MSE	RMSE	PRD	CC
sym11	22.413	1.58e-04	0.0125	6.59e-05	95.391
haar	17.971	0.00021	0.0145	7.84e-05	92.710
db2	20.212	0.00053	0.0231	0.00012	94.238
coif5	21.378	0.00018	0.0135	7.15e-05	95.171
bior2.4	21.416	0.00028	0.0167	8.81e-05	95.154

Therefore, the *sym* wavelet is chosen as the mother wavelet for the decomposition process. Similarly, the level of decomposition is varied and the quantitative measures are presented in Table 4, indicating that the fourth level decomposition level achieves the lowest *MSE* and higher *CC* compared to other decomposition levels.

TABLE 4. **Evaluation parameters for various levels of decomposition for the real signal.**

LEVEL	SNR OUT	MSE	RMSE	PRD	CC
Level 3	22.332	2.59e-04	0.01608	8.25e-05	95.317
Level 4	22.413	1.58e-04	0.01258	6.59e-05	95.391
Level 5	18.622	2.54e-04	0.01594	8.73e-05	93.971

Similarly, HT and ST are applied and the results are compared with the Li et al. [38] thresholding function. The denoised results are presented in Table 5, demonstrating that the OANFIS WT achieves higher SNR_{OUT} and low *MSE* compared to the HT and ST methods.

TABLE 5. **Denoising evaluation parameters of the real signal with hard and soft thresholding.**

METHOD	SNR OUT	MSE	RMSE	PRD	CC
OANFIS WT	22.413	1.58e-04	0.0125	6.59e-05	95.391
OANFIS HT	20.332	0.00022	0.01486	7.80e-05	94.084
OANFIS ST	19.008	0.00020	0.01421	7.48e-05	93.412

Since, we found that the *sym11* mother wavelet and fourth level of decomposition achieve superior denoising capabilities than the other counterparts. Therefore, we used the same in the proposed OANFIS WT approach.

Further, to validate the efficacy of our proposed method, we compare our method with two contrastive denoising methods [8], [10]. The results of different approaches are displayed in Fig. 11. It is evident that the contrastive methods eliminate the random noise. However, this process also disrupts some relevant signals and causes the inadequate indications to appear inaccurate. A thorough analysis of the results indicates that the proposed OANFIS WT method surpasses the existing methods in processing real seismic signals. It is particularly notable in its ability to effectively attenuate the random noise and preserve the relevant signal information, as illustrated in Fig. 11.

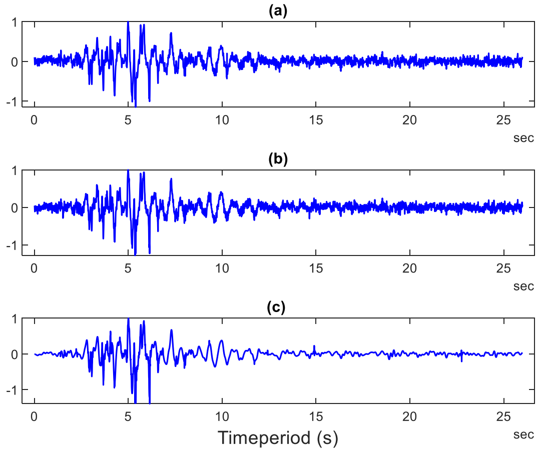

FIGURE 11. Denoised outputs of various methods in the real signal. (a) EMD DWT. (b) VMD DWT. (C) Proposed method (OANFIS WT).

Furthermore, Table 6 shows the comparative analysis of various denoising methods for the real signal using evaluation parameters. It is noted that the proposed technique attains a minimum *MSE* value and higher SNR_{OUT} than the existing methods. Also, it is evident that the SNR_{OUT} value is positively correlated with the SNR levels for all three denoising methods, as depicted in Fig. 12. We found that our proposed method is robust and effective in mitigating the random noise in the seismic signal.

TABLE 6. Denoising evaluation parameters of the real signal.

METHOD	SNR OUT	MSE	RMSE	PRD	CC
EMD DWT	19.789	0.09196	0.3032	1.33e-03	93.897
VMD DWT	21.548	6.96e-04	0.0263	1.18e-04	94.419
OANFIS WT	22.413	1.58e-04	0.0125	6.59e-05	95.391

IV. DISCUSSION

One important aspect to consider when evaluating adaptive filter methods is their ability to track changes, the level of steady-state error, and the speed at which they converge. However, the step size is a crucial parameter in an adaptive filter. The adaptive algorithms with the highest filter order outperform each other, resulting in intricate filter structures. Additionally, the computational complexity of updating the step size with respect to time is quite high, as it requires several parameters. Thus, many researchers have employed ANC

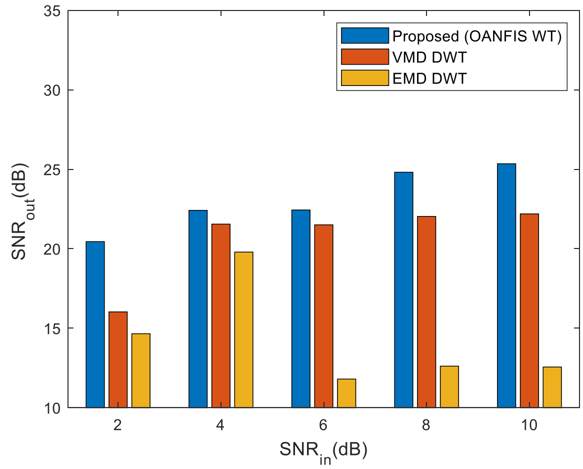

FIGURE 12. Comparison of SNROUT with different SNR levels for the real signal.

based on ANFIS to suppress the noise in the signal. In this work, we have proposed OANFIS to address the challenge of unwanted noise in seismic signals. The premise and consequence parameters of ANFIS are determined optimally to improve the denoising performance using the HBA optimization process. Since the extracted signal from OANFIS might have some noise due to an unknown level of noise attributes in the contaminated seismic signal, it may be beneficial to employ wavelet thresholding techniques to remove the noise. Thus, we have put forward a hybrid framework (OANFIS WT) to address the issue of random noise in seismic signals.

We will discuss the key points of the proposed method from four different perspectives. First, in this work, ANFIS acts as an adaptive self-tuning filter which does not require the noise attributes signal as a reference signal to extract the relevant information from the corrupted seismic signal. Here, the corrupted seismic signal with a necessary delay is provided as a reference signal to the ANFIS in order to acquire the relevant signal. Second, it is important to note that the ANFIS algorithm requires premise and consequence parameters. However, it is worth mentioning that these parameters are of a derivative type, which can potentially lead to getting stuck at a local minimum. Thus, we have optimized the two parameter sets using HBA optimization. Third, the WT eliminates the remaining noise in the signal extracted by OANFIS. In WT, two adjusting parameters, α and β, play a crucial role in fine-tuning the overall speed and growth rate of the thresholding function. This improved thresholding function allows for easily adjusting the adjustable parameters between the traditional thresholding functions. Finally, through a meticulous examination of various methods, the OANFIS WT method has proved to be highly effective in preserving signal information and reducing random noise. Thus, the proposed method successfully achieves adequate denoising outcomes by effectively reducing random noise while preserving the important details of seismic signals.

V. CONCLUSION

In this article, we proposed a hybrid workflow that effectively attenuates the random noise using OANFIS and WT. We initially enacted the ANFIS as an ANC to acquire pertinent information from the contaminated signal. Here, ANFIS operates as an adaptive self-tuning filter because it determines the appropriate signal information without prior knowledge of the noise in the contaminated signal. Next, the premise and consequence parameters of ANFIS were determined based on the noise attributes using HBA optimization because the standard hybrid process in ANFIS may be trapped at a local minimum, which may fail to approximate the signal information. Then, we applied OANFIS to determine the appropriate signal information. However, some residual noise might still be present in the extracted signal. Thus, we employed WT to process the extracted signal using different values for the thresholding functions'' adjusting parameters to reduce random noise effectively. It should be mentioned that the proposed hybrid workflow adopted two parameter sets optimally and applied WT to remove the random noise and preserve valid seismic information. This approach prevents ineffective denoising by not relying entirely on one adjustable parameter. Based on the experimental outcomes on both the synthetic and real seismic signals, it can be concluded that the proposed workflow is highly effective in reducing random noise and preserving relevant signal information, surpassing other contrastive methods.

REFERENCES

[1] O. Yilmaz, ''*Seismic Data Analysis: Processing, Inversion, and Interpretation of Seismic Data*, 2nd ed. Tulsa, OK, USA: SEG, Jan. 2001, p. 169.

[2] C. Fu, Z. Gong, L. Chen, S. Yang, L. Zhang, and Y. Chen, ''3-D structural complexity-guided predictive filtering: A comparison between different non-stationary strategies,'' *IEEE Trans. Geosci. Remote Sens.*, vol. 60, 2022, Art. no. 5915415.

[3] J. Song, Z. Li, G. Wang, G. Lei, and J. Yang, ''Weak seismic signal enhancement using curvelet transform and compressive sampling,'' *IEEE Trans. Geosci. Remote Sens.*, vol. 61, 2023, Art. no. 5907011.

[4] W. Huang, R.-S. Wu, and R. Wang, ''Damped dreamlet representation for exploration seismic data interpolation and denoising,'' *IEEE Trans. Geosci. Remote Sens.*, vol. 56, no. 6, pp. 3159–3172, Jun. 2018.

[5] Y. Chen, ''Dip-separated structural filtering using seislet transform and adaptive empirical mode decomposition based dip filter,'' *Geophys. J. Int.*, vol. 206, no. 1, pp. 457–469, Mar. 2016.

[6] K. Geetha, M. K. Hota, and D. A. Karras, ''A novel approach for seismic signal denoising using optimized discrete wavelet transform via honey badger optimization algorithm,'' *J. Appl. Geophys.*, vol. 219, Dec. 2023, Art. no. 105236.

[7] R. Anvari, A. R. Kahoo, M. S. Monfared, M. Mohammadi, R. M. D. Omer, and A. H. Mohammed, ''Random noise attenuation in seismic data using Hankel sparse low-rank approximation,'' *Comput. Geosci.*, vol. 153, Apr. 2021, Art. no. 104802.

[8] L. Long, X. Wen, and Y. Lin, ''Denoising of seismic signals based on empirical mode decomposition-wavelet thresholding,'' *J. Vibrat. Control*, vol. 27, nos. 3–4, pp. 311–322, Feb. 2021.

[9] B. Li, L. Zhang, Q. Zhang, and S. Yang, ''An EEMD-based denoising method for seismic signal of high arch dam combining wavelet with singular spectrum analysis,'' *Shock Vib.*, vol. 2019, Mar. 2019, Art. no. 4937595.

[10] X. Yao, Q. Zhou, C. Wang, J. Hu, and P. Liu, ''An adaptive seismic signal denoising method based on variational mode decomposition,'' *Measurement*, vol. 177, Jun. 2021, Art. no. 109277.

[11] K. Geetha and M. K. Hota, ''An improved variational mode decomposition for seismic random noise attenuation using grasshopper optimization via shape dynamic time warping,'' *J. Appl. Geophys.*, vol. 205, Oct. 2022, Art. no. 104759.

[12] W.-L. Hou, R.-S. Jia, H.-M. Sun, X.-L. Zhang, M.-D. Deng, and Y. Tian, ''Random noise reduction in seismic data by using bidimensional empirical mode decomposition and shearlet transform,'' *IEEE Access*, vol. 7, pp. 71374–71386, 2019.

[13] M. Sun, Z. Li, Z. Li, Q. Li, Y. Liu, and J. Wang, ''A noise attenuation method for weak seismic signals based on compressed sensing and CEEMD,'' *IEEE Access*, vol. 8, pp. 71951–71964, 2020.

[14] W. Ha and C. Shin, ''Seismic random noise attenuation in the Laplace domain using singular value decomposition,'' *IEEE Access*, vol. 9, pp. 62029–62037, 2021.

[15] K. Geetha and M. K. Hota, ''Seismic random noise attenuation using optimal empirical wavelet transform with a new wavelet thresholding technique,'' *IEEE Sensors J.*, vol. 24, no. 1, pp. 596–606, Jan. 2024.

[16] N. Iqbal, A. Zerguine, S. Kaka, and A. Al-Shuhail, ''Observation-driven method based on IIR Wiener filter for microseismic data denoising,'' *Pure Appl. Geophys.*, vol. 175, no. 6, pp. 2057–2075, Jun. 2018.

[17] E. Baziw and I. Weir-Jones, ''Application of Kalman filtering techniques for microseismic event detection,'' *Pure Appl. Geophys.*, vol. 159, no. 1, pp. 449–471, Jan. 2002.

[18] H. Li, S. Greenhalgh, B. Liu, X. Liu, Q. Hao, and Y. Chen, ''A generalized seismic attenuation compensation operator optimized by 2-D mathematical morphology filtering,'' *IEEE Trans. Geosci. Remote Sens.*, vol. 60, 2022, Art. no. 4510515.

[19] K. Geetha and M. K. Hota, ''Microseismic signal denoising based on variational mode decomposition with adaptive non-local means filtering,'' *Pure Appl. Geophys.*, vol. 180, no. 11, pp. 3709–3731, Nov. 2023.

[20] B. Widrow, J. R. Glover, J. M. McCool, J. Kaunitz, C. S. Williams, R. H. Hearn, J. R. Zeidler, J. Eugene Dong, and R. C. Goodlin, ''Adaptive noise cancelling: Principles and applications,'' *Proc. IEEE*, vol. 63, no. 12, pp. 1692–1716, Aug. 1975.

[21] C. Dai, J. Wang, J. Xie, W. Li, Y. Gong, and Y. Li, ''Removal of ECG artifacts from EEG using an effective recursive least square notch filter,'' *IEEE Access*, vol. 7, pp. 158872–158880, 2019.

[22] M. M. U. Faiz and I. Kale, ''Removal of multiple artifacts from ECG signal using cascaded multistage adaptive noise cancellers,'' *Array*, vol. 14, Jul. 2022, Art. no. 100133.

[23] G. Brahmi, M. C. Berguig, and L. Harrouchi, ''Attenuation of random noise using advanced adaptive filters in post-stack seismic imaging,'' *Bollettino Di Geofisica Teorica, Ed., Applicata*, vol. 62, no. 3, pp. 387–402, Sep. 2021.

[24] P. Zhang, Y. Dai, H. Zhang, C. Wang, and Y. Zhang, ''Combining CEEMD and recursive least square for the extraction of time-varying seismic wavelets,'' *J. Appl. Geophys.*, vol. 170, Nov. 2019, Art. no. 103854.

[25] I. Pitas and A. N. Venetsanopoulos, *Nonlinear Digital Filters*. Norwell, MA, USA: Kluwer, 1989.

[26] C.-T. Lin and C.-F. Juang, ''An adaptive neural fuzzy filter and its applications,'' *IEEE Trans. Syst., Man, Cybern., B*, vol. 27, no. 4, pp. 635–656, Aug. 1997.

[27] M. van der Baan and C. Jutten, ''Neural networks in geophysical applications,'' *Geophysics*, vol. 65, no. 4, pp. 1032–1047, Jul. 2000.

[28] S. Chopra, G. Dhiman, A. Sharma, M. Shabaz, P. Shukla, and M. Arora, ''Taxonomy of adaptive neuro-fuzzy inference system in modern engineering sciences,'' *Comput. Intell. Neurosci.*, vol. 2021, pp. 1–14, Sep. 2021.

[29] N. Djarfour, T. Aïfa, K. Baddari, A. Mihoubi, and J. Ferahtia, ''Application of feedback connection artificial neural network to seismic data filtering,'' *Comp. Rendus. Géosci.*, vol. 340, no. 6, pp. 335–344, Jun. 2008.

[30] H. Lin, Y. Li, B. Yang, H. Ma, and C. Zhang, ''Seismic random noise elimination by adaptive time-frequency peak filtering,'' *IEEE Geosci. Remote Sens. Lett.*, vol. 11, no. 1, pp. 337–341, Jan. 2014.

[31] R. Kimiaefar, H. R. Siahkoohi, A. R. Hajian, and A. Kalhor, ''Seismic random noise attenuation using artificial neural network and wavelet packet analysis,'' *Arabian J. Geosci.*, vol. 9, no. 3, pp. 1–11, Mar. 2016.

[32] R. Kimiaefar, H. R. Siahkoohi, A. Hajian, and A. Kalhor, ''Random noise attenuation by wiener-ANFIS filtering,'' *J. Appl. Geophys.*, vol. 159, pp. 453–459, Dec. 2018.

[33] J. R. Mohammed, "A new simple adaptive noise cancellation scheme based on ALE and NLMS filter," in *Proc. 5th Annu. Conf. Commun. Netw. Services Res.*, May 2007, pp. 245–254.
[34] J. R. Mohammed and G. Singh, "An efficient RLS algorithm for output-error adaptive IIR filtering and its application to acoustic echo cancellation," in *Proc. IEEE Symp. Comput. Intell. Image Signal Process.*, Apr. 2007, pp. 139–145.
[35] S. Linkwitz and A. Wilcox, "Techniques for measuring narrowband and broadband EMI signals using spectrum analyzers," in *Proc. RF Microw. Meas. Symp. Exhib.*, 1984, pp. 1–28.
[36] J.-S.-R. Jang, "ANFIS: Adaptive-network-based fuzzy inference system," *IEEE Trans. Syst., Man, Cybern.*, vol. 23, no. 3, pp. 665–685, Jun. 1993.
[37] A. Yonar and H. Yonar, "Modeling air pollution by integrating ANFIS and metaheuristic algorithms," *Model. Earth Syst. Environ.*, vol. 9, no. 2, pp. 1621–1631, Oct. 2022.
[38] H. Li, J. Shi, L. Li, X. Tuo, K. Qu, and W. Rong, "Novel wavelet threshold denoising method to highlight the first break of noisy microseismic recordings," *IEEE Trans. Geosci. Remote Sens.*, vol. 60, 2022, Art. no. 5910110.
[39] F. A. Hashim, E. H. Houssein, K. Hussain, M. S. Mabrouk, and W. Al-Atabany, "Honey badger algorithm: New metaheuristic algorithm for solving optimization problems," *Math. Comput. Simul.*, vol. 192, pp. 84–110, Feb. 2022.
[40] S. Oladipo, Y. Sun, and O. Adeleke, "An improved particle swarm optimization and adaptive neuro-fuzzy inference system for predicting the energy consumption of university residence," *Int. Trans. Electr. Energy Syst.*, vol. 2023, pp. 1–16, Mar. 2023.
[41] (2005). *Pacific Earthquake Engineering Research Center (2005) PEER Strong Motion Database on Line*. [Online]. Available: https://peer.berkeley.edu/peer-strong-ground-motion-databases
[42] G. Garg, "A signal invariant wavelet function selection algorithm," *Med. Biol. Eng. Comput.*, vol. 54, no. 4, pp. 629–642, Aug. 2015.

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