Wavelet Threshold Denoising Algorithm

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The denoising performance is affected by several factors, including wavelet basis function, decomposition level, thresholding method, and the threshold selection criteria. Traditional threshold selection rules rely on statistical and empirical variables, which influence their performance in noise reduction under various conditions.

Keywords: discrete wavelet transform ; acoustic emission ; particle swarm optimization

1. Introduction

A great deal of attention has been paid to the acoustic emission (AE) method for fault diagnosis in various fields such as civil engineering, big data analytics, and aerospace engineering, because of its convenience in data acquisition. The operation of the sensor, the difference in travelling path and the process of data acquisition adds noise to the signal. The complex noises in the AE signals make it difficult to extract the signal characteristics. The reduction in noise is indispensable for successful and reliable processing of AE signals [1].

Several strategies have been developed in recent years to reduce noise and improve the signal-to-noise ratio (SNR) [2][3][4][5][6][7]. For denoising a noisy signal with a fixed noise frequency, the Fourier transform filter (FFT) approach is often applied. It is determined by withdrawing Fourier components with frequencies beyond a cutoff frequency. Nevertheless, it is difficult to determine the noise frequency [8]. Therefore, it makes the conventional technique inappropriate when dealing with AE signals [9]. Singular value decomposition (SVD) is a numerical approach for noise reduction using matrix decomposing [10]. SVD offers a good noise reduction performance for fault signals with low background noise. However, when there is a lot of background noise, the SVD decomposition is imperfect, and the components still have a lot of noise. Singular spectrum analysis (SSA) requires manually setting the embedded dimension, and good results can only be obtained by selecting the proper embedded dimension [11]. Mallat suggested the wavelet transform (WT) for the first time in 1989 [12]. Because of its two main advantages, WT is preferred in signal processing. Firstly, it can obtain both the time and frequency information of a signal effectively, and it can also show the coarser low-frequency features. Secondly, the short time Fourier transform (STFT) is improved by WT, which distinguishes and prevents noise elements effectively. The WT technique has gained popularity due to its ease of use and impressive noise reduction potential. The determination of optimal wavelet type with a suitable decomposition level, and the selection of threshold rule are typically the three steps involved in wavelet thresholding to obtain a clean signal [13].

Furthermore, rigrsure, sqtwolog, heursure and minimaxi are the conventional methods for threshold selection. Their performance is optimal in case of less dispersed noise in the high-frequency band. The denoising performance of sqtwolog rule is superior [14]. These methods, on the other hand, are based on statistical and empirical indicators, which could change the efficiency and effectiveness of noise reduction in different situations. With a broad use of artificial intelligence in recent years, adaptive threshold selection techniques based on intelligent optimization algorithms, such as Cuckoo Search (CS) algorithm, artificial bee colony (ABC) [15], genetic algorithm (GA) [16], Fruit Fly Optimization (FOA) [14], and Improved Fruit Fly Optimization (IFOA) [17] have been adopted gradually.

Kennedy developed particle swarm optimization method (PSO) in 1995, to mimic the behavior of natural swarms such as birds and fish [18]. PSO algorithm is simple and efficient. It can accommodate new concepts in multi-agent collaboration. It has shown to be a strong opponent for other metaheuristic algorithms. In many applications, a faster near-optimum convergence of PSO has been observed as compared to GA [19]. Besides its advantages, PSO has certain shortcomings including the possibility of falling into local optimum and the lack of high search accuracy [20]. PSO exploitation capacity is less competitive in comparison to local search algorithms. PSO algorithm is prone to being stuck at the boundary conditions of computing the objective function, resulting in significant reduction in the convergence in PSO implementation.

2. Wavelet Threshold Denoising

Band-pass, Kalman, and median filters are traditional approaches for the denoising of signals and images. These techniques target either the time or frequency domain. Single scale representation of the noisy signals is not sufficient to extract meaningful information. Wavelet threshold denoising is obviously superior to other noise reduction algorithms since it combines both the scales. According to Donoho's theory of wavelet threshold denoising, the ideal threshold should reduce the noise while maintaining the maximum amount of signal [21]. The conventional hard thresholding may be unstable and more susceptible to tiny changes in the data. It causes some discontinuities, while soft thresholding create a divergence when reconstructed because the wavelet coefficients are reduced by a value equal to the threshold [22]. Furthermore, the threshold is set just once only throughout the denoising process and cannot be changed. Several researchers developed adaptive denoising techniques to address the shortcomings of Donoho′s original threshold approaches. The improved solutions fall into two categories. The first one focuses on improving threshold function, while the second focuses on using intelligent algorithms to search the optimal threshold. The approaches that utilize a threshold function attempt to create an acceptable function with continuous derivative and choose thresholds using gradient descent algorithm. Zhang and Desai [23] presented a SURE model-based adaptive denoising function with continuous derivative of first and second order. To determine the best threshold for each decomposition level, Meng et al. [24] introduced a logarithmic threshold denoising function. When compared with hard and soft thresholding, the suggested method significantly improved SNR by 44.2% and 27.9%, and the lowered the processing time by 37.6% and 38.5%, respectively. The solution presented by Li et al. [16] used threshold function based on genetic algorithm (GA) for partial discharge signals. The findings show considerably less waveform distortion and magnitude errors as compared to Donoho′s soft threshold estimation. Soni et al. [15] utilized stochastic global optimization techniques such as the Cuckoo Search (CS) algorithm, artificial bee colony (ABC), and PSO, as well as their many variations, to learn the parameters of the adaptive threshold function in order to eliminate noise components from satellite pictures. Qiu et al. [14] utilized Fruit Fly Optimization Algorithm (FOA) for the selection of wavelet threshold for denoising AE signals. This method could successfully produce higher SNR and lower RMSE as compared to other comparative methods. To denoise the magnetic resonance (MR) and ultrasound (US) images of the brain, Vaiyapuri et al. [25] proposed a multi-objective-technique-based genetic algorithm (GA) to obtain the threshold optimized within the denoising framework of wavelets.

3. Particle Swarm Optimization Algorithm

Since its inception, particle swarm optimization (PSO) has stimulated the interest of researchers and has been effectively utilized to address numerous real-world optimization issues in expert systems.

Wei et al. [26] proposed an enhanced particle swarm optimization (PSO) algorithm for detecting structural deterioration. They concentrated on the mutation of global or individual best-known positions to lead the swarm out of the local minima. The performance of the proposed method was better as compared to GA and original PSO. For optimal performance in image denoising, Bhutada et al. [27] proposed a PSO-based method for learning the parameters of the adaptive thresholding function. By using stochastic parameters, Minh et al. [28] proposed an enhanced particle swarm optimization algorithm (EHVPSO) for solving damage identification problems. Two equations have been introduced in EHVPSO method. One equation governs the convergence rate throughout the movement of ith particle, while another one controls the balance between local and global optimum values. Enhancing the convergence rate is the main advantage of EHVPSO. In WSN localization, an improved PSO algorithm (improved self-adaptive inertia weight particle swarm optimization (ISAPSO) was suggested by Yang et al. [29]. When compared with the original PSO and ISPSO, ISAPSO provided improved positioning accuracy, power consumption and real-time performance under various beacon node proportions, node densities and ranging errors. In order to transplant the learning ability and forgetting ability into PSO, Xia et al. [30] proposed XPSO by expanding the learning ability to multiple exemplars. Different forgetting abilities are assigned to different particles. The acceleration coefficients were updated through an adaptive scheme and the population topology is updated. In Ji et al. [31], an improved PSO was used to search for the optimal parameters of the LSTM. They evaluated the performance of the proposed IPSO-LSTM algorithm using RMSE, MAE, MAPE, and R2, and was compared with well-known algorithms as SVR and LSTM, PSO-LSTM, and IPSO-LSTM. At a look-back of 60 days, RMSE of the IPSO-LSTM is 72.527546, which is minimum.

References

1. Abbasion, S.; Rafsanjani, A.; Farshidianfar, A.; Irani, N. Rolling element bearings multi-fault classification based on the wavelet denoising and support vector machine. Mech. Syst. Signal Process. 2007, 21, 2933–2945.

2. Dong, L.; Hu, Q.; Tong, X.; Liu, Y. Velocity-Free MS/AE Source Location Method for Three-Dimensional Hole-Containing Structures. Engineering 2020, 6, 827–834.
3. Dong, L.; Tong, X.; Ma, J. Quantitative Investigation of Tomographic Effects in Abnormal Regions of Complex Structures. Engineering 2021, 7, 1011–1022.
4. Zhang, Y.B.; Yao, X.L.; Liang, P.; Wang, K.X.; Sun, L.; Tian, B.Z.; Liu, X.X.; Wang, S.Y. Fracture evolution and localization effect of damage in rock based on wave velocity imaging technology. J. Cent. South Univ. 2021, 28, 2752–2769.
5. Du, Y.; Feng, G.; Kang, H.; Zhang, Y.; Zhang, X. Effects of different pull-out loading rates on mechanical behaviors and acoustic emission responses of fully grouted bolts. J. Cent. South Univ. 2021, 28, 2052–2066.
6. Szafran, J.; Juszczyk, K.; Kamiński, M. Experiment-based reliability analysis of structural joints in a steel lattice tower. J. Constr. Steel Res. 2019, 154, 278–292.
7. Kamiński, M.; Solecka, M. Optimization of the truss-type structures using the generalized perturbation-based Stochastic Finite Element Method. Finite Elem. Anal. Des. 2013, 63, 69–79.
8. Yu, B.; Gabriel, D.; Noble, L.; An, K.-N. Estimate of the optimum cutoff frequency for the Butterworth low-pass digital filter. J. Appl. Biomech. 1999, 15, 318–329.
9. Sun, H.; He, Z.; Zi, Y.; Yuan, J.; Wang, X.; Chen, J.; He, S. Multiwavelet transform and its applications in mechanical fault diagnosis—A review. Mech. Syst. Signal Process. 2014, 43, 1–24.
10. Zhao, M.; Jia, X. A novel strategy for signal denoising using reweighted SVD and its applications to weak fault feature enhancement of rotating machinery. Mech. Syst. Signal Process. 2017, 94, 129–147.
11. Mi, X.; Zhao, S. Wind speed prediction based on singular spectrum analysis and neural network structural learning. Energy Convers. Manag. 2020, 216, 112956.
12. Mallat, S.G. A theory for multiresolution signal decomposition: The wavelet representation. Fundam. Pap. Wavelet Theory 2009, I, 494–513.
13. de Queiroz, R.L.; Rao, K.R. Time-Varying Lapped Transforms and Wavelet Packets. IEEE Trans. Signal Process. 1993, 41, 3293–3305.
14. Qiu, X.; Wang, Y.; Xu, J.; Xiao, S.; Li, C. Acoustic emission propagation characteristics and damage source localization of asphalt mixtures. Constr. Build. Mater. 2020, 252, 119086.
15. Soni, V.; Bhandari, A.K.; Kumar, A.; Singh, G.K. Improved sub-band adaptive thresholding function for denoising of satellite image based on evolutionary algorithms. IET Signal Process. 2013, 7, 720–730.
16. Li, J.; Cheng, C.; Jiang, T.; Grzybowski, S. Wavelet de-noising of partial discharge signals based on genetic adaptive threshold estimation. IEEE Trans. Dielectr. Electr. Insul. 2012, 19, 543–549.
17. Xu, J.; Wang, Z.; Tan, C.; Si, L.; Liu, X. A novel denoising method for an acoustic-based system through empirical mode decomposition and an improved fruit fly optimization algorithm. Appl. Sci. 2017, 7, 215.
18. Kennedy, J.; Eberhart, R. Particle Swarm Optimization. Part. Swarm Optim. 1995, 4, 1942–1948.
19. Banks, A.; Vincent, J.; Anyakoha, C. A review of particle swarm optimization. Part I: Background and development. Nat. Comput. 2007, 6, 467–484.
20. Mouna, H.; Azhagan, M.S.M.; Radhika, M.N.; Mekaladevi, V.; Devi, M.N. Velocity Restriction-Based Improvised Particle Swarm Optimization Algorithm. In Progress in Advanced Computing and Intelligent Engineering; Springer: Berlin/Heidelberg, Germany, 2018; pp. 351–360.
21. Donoho, D.L.; Johnstone, I.M. Adapting to unknown smoothness via wavelet shrinkage. J. Am. Stat. Assoc. 1995, 90, 1200–1224.
22. Yi, T.H.; Li, H.N.; Zhao, X.Y. Noise smoothing for structural vibration test signals using an improved wavelet thresholding technique. Sensors 2012, 12, 11205–11220.
23. Zhang, X.P.; Desai, M.D. Adaptive denoising based on SURE risk. IEEE Signal Process. Lett. 1998, 5, 265–267.
24. Meng, B.; Li, Z.; Wang, H.; Li, Q. An improved wavelet adaptive logarithmic threshold denoising method for analysing pressure signals in a transonic compressor. Proc. Inst. Mech. Eng. Part C J. Mech. Eng. Sci. 2015, 229, 2023–2030.
25. Vaiyapuri, T.; Alaskar, H.; Sbai, Z.; Devi, S. GA-based multi-objective optimization technique for medical image denoising in wavelet domain. J. Intell. Fuzzy Syst. 2021, 41, 1575–1588.
26. Wei, Z.; Liu, J.; Lu, Z. Structural damage detection using improved particle swarm optimization. Inverse Probl. Sci. Eng. 2017, 5977, 1–19.

27. Bhutada, G.G.; Anand, R.S.; Saxena, S.C. PSO-based learning of sub-band adaptive thresholding function for image denoising. Signal Image Video Process. 2012, 6, 1–7.
28. Minh, H.; Khatir, S.; Abdel, M.; Cuong-le, T. An Enhancing Particle Swarm Optimization Algorithm (EHVPSO) for damage identification in 3D transmission tower. Eng. Struct. 2021, 242, 112412.
29. Yang, Q. A new localization method based on improved particle swarm optimization for wireless sensor networks. IET Softw. 2021, 1–8.
30. Xia, X.; Gui, L.; He, G.; Wei, B.; Zhang, Y.; Yu, F.; Wu, H.; Zhan, Z.H. An expanded particle swarm optimization based on multi-exemplar and forgetting ability. Inf. Sci. 2020, 508, 105–120.
31. Ji, Y.I.; Liew, A.W. A Novel Improved Particle Swarm Optimization With Long-Short Term Memory Hybrid Model for Stock Indices Forecast. IEEE Access 2021, 9, 23660–23671.

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