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Long-Term Health Monitoring Data Processing on Post-Tensioned Concrete Box-Girder Bridge by Wavelet-Based

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ABSTRACT

The concrete box-girder bridge is designed to have a long service life of around 100 years. To ensure safety and performance degradation during long service life, a Structural Health Monitoring System (SHMS) has been implemented in the box-girder bridge. SHMS can reliably assess structural response due to real-time applied loads, detect anomaly activities and locate the structural damage in the structure. Several sensors have been implemented in the bridge to continuously record the behavior of the bridge in all environmental conditions. Due to real-time natural conditions, false alarms occur frequently in SHM due to the disruption of noises and lead to misunderstanding of who is evaluating. Nevertheless, numerous SHM data that have been collected make it complicated to determine the anomaly of the structures. Therefore, it required signal processing to maximize the potentialities of the massive SHM data, as well as the efficiency of the time work. In this study, wavelet transformation, a rapid and unsupervised signal processing approach, was used to analyze the huge signal data by removing noise, and separating different signal sources as well. Further, with time-frequency analysis and multi-resolution capabilities, the transformation of wavelet is a promising tool for analyzing long-term SHM data. The suggested approach is shown by using long-term strain data from a 40 m concrete box-girder bridge in 24h. The results showed that after the denoising process, the highest discrepancy between the reconstructed and original strain signal is 2.73 $\mu\mathcal{E}$ and lost their energy less than 1%. Hence, the strain gauge sensor was successfully able to eliminate the noise through wavelet technology.

1. Introduction

Bridges are an example of infrastructure that serves to connect roads separated by rivers, valleys, and other traffic crossings. With the bridge, travel time will be more efficient and the cost of traveling will also be much reduced, so this will have a positive impact on the economy of a country.

Concrete box girder bridge has a service life of more than 100 years. Having a long-time service makes concrete box girders one of the most commonly used bridges in Indonesia. However, with long-term service age, the bridge will experience various external effects that have the potential to cause structural component damage such as cracking, shrinkage, or corrosion which will affect the durability of the structure [1].

As an essential component of the highway transportation system, bridges must have inspection systems that enable repairing, effective observation, and detection [2]. Due to the challenge of thorough visual assessment of structures, to detect the damage and manage bridges effectively, the Structural Health Monitoring (SHM) system is used. The system method uses instrumentation tools to detect the actions that occur in the structure in real time so that efficient and proactive steps can be taken [3].

It is critical to gather structure monitoring signals from the bridge in order to maintain the bridge's safe operation. The deflection monitoring signals are crucial indicators to illustrate the operating conditions of the bridge [4]. The sustainability of monitoring or measuring the effects of the surrounding environment and the critical response of a bridge structure is very important for the success of the installed SHM system in determining the health and

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performance of the structural system during its service life [5].

However, since the monitoring environment of the bridge is difficult, the monitoring signals always contain a lot of ambient noise. The presence of this noise significantly reduces the accuracy of bridge health analysis. As a result, denoising the structure measurement data has been identified as a critical approach in bridge structural health monitoring.

In the last two decades, there has been significant advancement in civil engineering SHM technology. Extensive research has demonstrated the usefulness of damage detection utilizing HMS, including related frequency response, statistical process, probabilistic view, temperature effect, displacement, and strain analysis.

However, due to the large SHM data which was continuously recorded in the real-time condition of the bridge make the assessment is still challenging, and need more time to conclude the information on structural condition. In addition, civil constructions have enormous physical dimensions, and the loadings and environmental conditions are diverse and complicated. Due to the effect of various factors in real-time natural conditions, mistakes may occur in the sensor. As a result, the signals are nonstationary and frequently polluted by noise, and spikes which lead to inaccurate interpretation [6].

According to Ren [7] who studied how noise affects the accuracy of damage detection using modal analysis, the influence of noise is strongly dependent on the degree of the damage. Hence limited damage conditions will be harder to identify at high noise levels rather than severe damage. Therefore, it required signal processing to maximize the potentialities of the massive SHM data, as well as the efficiency of the time work.

Certain researchers have used the Fast Fourier Transform (FFT) in signal processing, Nevertheless, A significant issue with applying the FFT is the result of an accumulation throughout the whole signal period. This indicates that the time of occurrence of a transitory signal cannot be determined by signal decomposition. Through FFT-based, the system can identify damage incidence if used to monitor frequency spikes. In contrast, the information is purely on the frequency domain where time information has a possibility to lost. As a result, while the FFT can give strong frequency resolution, it cannot provide time resolution.

These days, where the technology of SHM is continuously growing, different resolutions in the time and frequency domains are required for a viable digital signal processing approach that can assess both continuous and transient signals. Signal denoising is a significant challenge in engineering, especially in bridge monitoring and structural health evaluation. The presence of noise in bridge signals can obscure critical information and affect the accuracy of structural analysis. Wavelet transformation is a powerful method for breaking down signals into multiple frequency components. Wavelet transformation has developed as an effective method for denoising bridge signals, allowing noise to be separated from the underlying structural response. Wavelets can be utilized to perform multi-resolution analysis, obtaining data in both the time and frequency domains. The scale or resolution of the data that is normally seen has an essential influence. The Wavelet algorithm analyzes data at various sizes or resolutions.

Reda [8] presented the summary of wavelet transformation features functions for damage identification by using Wavelet multi-resolution (WMRA) and Wavelet Packet Transform (WPT) analysis. He found that analysis of WT, WMRA, or WPT when combined with some sort of artificial intelligence such as Fuzzy Logic, and Artificial Neural Network (ANN), attained better results in damage detection.

Wavelet is also used in medicine, Bernadinus. [9], applied WT for anomalies recognizing such as noise on the signal of ECG (Electro Cardio Graph), an instrument used to obtain information about the functioning of the human heart. Through that approach, he successfully eliminated 36.20 dB of noise by 8 levels of Daubechies Mother Wavelet.

Xia and Ni [10] illustrated a great wavelet performance in large displacement data signals from Tsing Ma Bridge. They applied 7 level of decomposition of wavelet Symlet 8 (sym8) through four estimations of threshold such as Universal, TI, SURE and MINIMAX, as well as their rate of computation. Hence, she obtained UNI threshold is the greatest than other thresholds.

Meanwhile, [11] and [12] evaluated the influence of temperature and displacement response as well as time lag on the box girder concrete bridge. By using WT, they effectively extracted the form of temperature in the signal. They stated that the concrete box girder has a 5 – 6 hours structural temperature lagging behind the ambient temperature.

Therefore, the Discrete Wavelet Transform (DWT) approach is suggested in this paper to analyze numerous SHM data such as strain data sensors of the bridge, especially in denoising and separating the source of the signal which are still challenging nowadays by mother wavelet Daubechies.

2. Methods

This research concerns SHM data at the 40-meter span length Tol AP Pettarani Bridge, a PC-box girder bridge in Makassar, South Sulawesi, Indonesia. After its construction was completed in 2020, A fixed SHM system was installed on this bridge. As a result, there is currently a plethora of filed data available for procesing and analysis. Moreover, the author selected 3rd May 2022 as a sample of data for this paper, since it was an extreme environmental temperature. The strain gauge (STR) sensor was studied over a lengthy period of time, specifically for 24 hours. STR 2 was chosen for analysis since this sensor was positioned at the top of piers closest to the traffic loading surface, which was highly contaminated by noise. Following that, the majority of this project used Matlab software to analyze the data.

2.1 Denoising

Signal de-noising is the process of recovering valuable information from raw data since noise is a signal that contained unuseful information due to disturbance of the sensor. Noise can come from a variety of sources, including ambient conditions, technological interference, transmission problems, sensor limits, or intrinsic flaws in signal collection devices. It frequently manifests as random oscillations or undesired disruptions that distort or hide the underlying information of interest. Xia and Ni [13], described a noisy signal f(t) by:

$$f(t) = s(t) + \delta \mathcal{E}(t) \tag{1}$$

where s(t) is the raw signal, $\mathcal{E}(t)$ is white noise standard N(0,1) and δ is volume of the noise.

In removing the noise, thresholds must be determined to establish the "high" and "low" detail coefficients based on the DWT approach. The low-frequency component is more useful because it contains the fundamental characteristics of the structure, whereas the high-frequency component exposes the signal's features and contains plenty of noise. At various decomposition levels, wavelet threshold denoising decomposes the signal into multiple frequency scales and eliminates noise from the high-frequency component [14]. The threshold value approximates the noise level calculated by taking the standard deviation of the detail coefficient [15].

Donoho [16] presented a universal threshold by:

$$\lambda_u = \hat{\delta}\sqrt{2x\, ln(n)} \tag{2}$$

$$\hat{\delta} = \frac{me\, dian|\hat{a}j-k|}{0.6745} \tag{3}$$

where $\hat{\delta}$ is estimation of the noise level regarding on detail coefficient of median absolute deviation at greatest resolution degree and n is length of signal.

Following the determination of the thresholding value, the type of thresholding, both hard and fine thresholding, is carried out. According Donoho [16], In hard thresholding, a threshold value is applied to the wavelet coefficients. If the absolute value of a coefficient is lower than the threshold, it is adjusted to zero. If the absolute value exceeds the threshold, the coefficient remains unchanged. This method successfully removes coefficients related with noise or low-energy components while retaining coefficients relating to the intended signal.

Meanwhile, in soft thresholding, instead of setting the coefficients to zero as in hard thresholding, they are shrunk towards zero. If the absolute value of a coefficient falls below a given threshold, it is decreased by a specific amount. If the absolute value exceeds the threshold, it is decreased by the threshold value. In comparison to strong thresholding, this approach softens the effect of the thresholding process, resulting in a smoother denoised signal. Soft thresholding preserves signal features while reducing noise amplification during reconstruction. It generates a denoised signal with a more continuous structure, which is particularly advantageous when the noise level is high.

Ningsih [15] denoted both of the threshold by;

$$\text{Hard Thresholding} = \begin{cases} y = 0, x, if\ |x| \le \lambda \\ y = x, if\ |x| > \lambda \end{cases} \tag{4}$$

$$\text{Soft Thresholding} = \begin{cases} y = x + \lambda, if\ |x| < -\lambda \\ y = 0, if\ |x| \le \lambda \\ y = x - \lambda, if\ |x| > \lambda \end{cases} \tag{5}$$

The threshold value must be chosen carefully in both hard and soft thresholding procedures. It should be chosen depending on the input signal's noise characteristics and signal-to-noise ratio (SNR). To estimate or optimize the threshold value, several approaches such as universal thresholding, Stein's unbiased risk estimate (SURE), or cross-validation can be used. Wavelet-based denoising employs both hard and soft thresholding approaches to effectively remove noise in signals. The decision between them is determined by the intended trade-off between signal preservation and noise reduction. In this study, fine thresholding is applied in the denoising process since mean square error (MSE) is lower.

In summary, the wavelet thresholding method is composed of three steps: (1) using the DWT for forwarding-transforming the signal to domain of wavelet (2) coefficients which is lower than threshold must be eliminating or shrinking; and (3) using the remaining detail coefficients and approximation coefficients to reconstruct the signal. Along this approach, the following elements will have an impact on the results of denoising: in step 1, the selection and decomposition of wavelet; and in step 2, the thresholding approach and estimation.

2.2 Decomposing

Discrete Wavelet Transform (DWT) was used as an approach in this research. DWT is determined by taking a discrete subset of the scale and changing parameters by the power of two. The discrete wavelet transform's primary premise is to obtain the time and scale representation of a signal utilizing digital filter techniques and sub-sampling processes. A wavelet transform divides the original signal into several levels or scales.

After passing the signal through a sequence of high-pass and low-pass filters, half of each output is sampled using a sub-sampling procedure. This method is known as a one-stage decomposition procedure. The low-pass filter output is utilized as input in the next-level decomposition process. This step is sepeated until the breakdown process reaches the desired degree . The signal can be divided into approximation coefficients (low-frequency components) and detail coefficients (high-frequency components) through this decomposition. The number of levels is determined by the required resolution and the signal's characteristics.

In general, decomposing processed by choosing the suitable wavelet basis function and n decomposition layers. Decompose the wavelet space n times to produce the detail coefficients cDk and suitable coefficients cAk can be seen in Figure 1. The coefficients of approximation cAk illustrate the low-frequency band, which typically include useful characteristic about original signal. As a result, it should be preserved unaltered during the de-noising process. However, there are just a few major detail coefficients cDk include crucial data, whereas the small coefficients dj,k are assigned as the noise [10]. Following that, an author can separate the source of the signal, especially temperature and live load which generated by highway traffic.

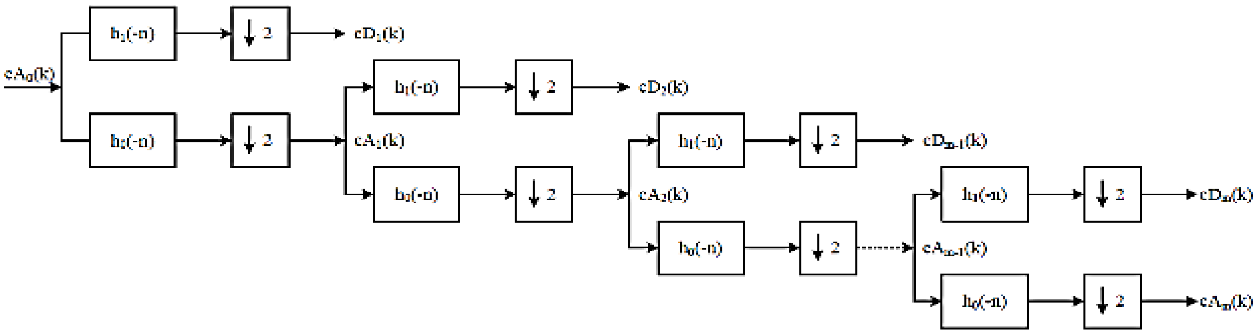

Figure 1 Decomposing of discrete wavelet transform

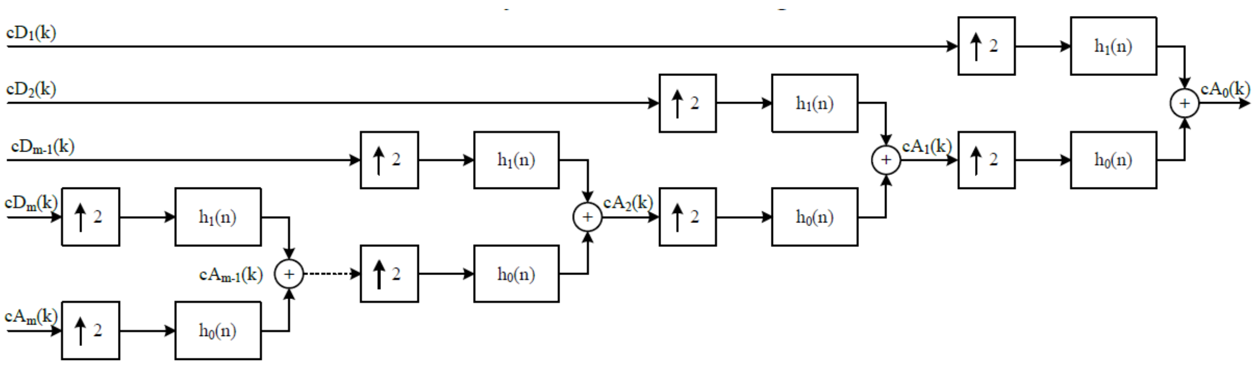

Figure 2. Recontruction of discrete wavelet transform

2.3 Recontruction

Signal may alter or degrade when it is converted or modified, such as by filtering, compression methods, or denoising procedures. The purpose of signal reconstruction is to reverse these modifications and recreate an approximation or estimate of the original signal. Signal that has been decomposed back into the original signal without information loss can be seen in Figure 2. The term for the inverse of the discrete wavelet transform is known as wavelet reconstruction. An inverse wavelet operation is used to recreate the denoising sequence, which uses the detail coefficients of each layer as well as the appropriate coefficients of the *n* th layer [14].

In this present paper, type of Daubechies was selected as a mother of wavelet and by trial error approach of MSE (Mean Square Eror) and SNR (Signal Noise Ratio) value, the level of decomposition and the scale were determined. Bernadinus [9] defined MSN and SNR by;

$$SNR_{dB} = 10\log\frac{\sum_{n=0}^{N-1} s(n)^2}{\sum_{n=0}^{N-1} v(n)^2}$$

$$\approx 10\log\frac{\sum_{n=0}^{N-1} \bar{s}(n)^2}{\sum_{n=0}^{N-1}((s(n)+v(n))-\bar{s}(n))^2} \quad (4)$$

$$MSE = E\{(s(n) - \bar{s}(n))^2 \approx \frac{1}{N}\sum_{n=0}^{N-1}\left(s(n) - \bar{s}(n)\right)^2 \quad (5)$$

where, s(n) is raw signal, Sˆis denoised signal and v(n) is noise.

SNR (Signal to Noise Ratio) is the ratio of desirable signal power to unwanted signal power (noise) at a given measurement location. SNR denotes the signal-to-noise ratio of the information signal received on the transmission system. SNR is also the acceptable analog signal threshold. The better the signal quality, the higher the SNR value. While MSE is a way of determining the accuracy of a predicting model. The MSN number is comparable to a model's variance plus squared bias, and it is particularly excellent at indicating how consistent the model is.

Finally, the residual energy value, SNR, and MSE of the reconstruction signal must be calculated in order to quantify the success rate of the denoising and separating process. In summary, method of this article illustrated on Figure 3.

3. Results

Noise reduction tests were carried out in this study utilizing the wavelet technique, by monitoring the levels of decomposition and reconstruction to obtain noise values that are nearly constant when the various levels of the wavelet decomposition.

Table 1. Deciding wavelet decomposition level

Decomposition	MSN x 10^2	Deviation
Level 1	12.59	0.000
Level 2	25.05	12.454
Level 3	34.83	9.784
Level 4	41.39	6.560
Level 5	46.42	5.027
Level 6	52.04	5.617
Level 7	57.87	5.833
Level 8	62.83	4.959
Level 9	66.16	3.331
Level 10	67.84	1.681

The Mean Square Noise (MSN) number is used to determine how much noise has been properly eliminated. The experimental findings for the ten levels of wavelet decomposition-reconstruction are shown in Table 1 and visually can be seen in Figure 5.

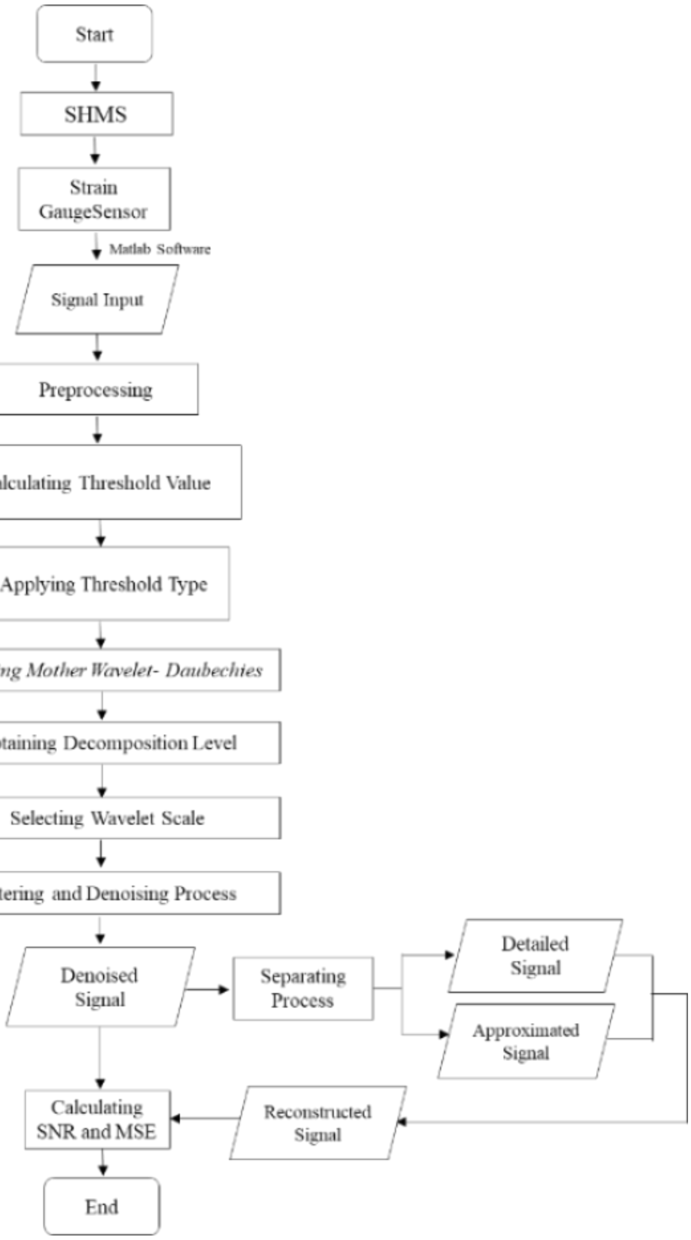

Figure 3. Method

From Table 1, it showed that level 5 of decomposition starts to be constant in deviation. It means the effect of decomposition is no longer quite significant on MSN.

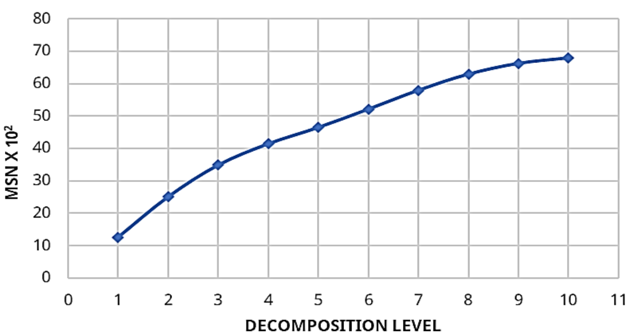

Figure 3. Decomposition level

The scale of Wavelet Daubechies was picked by trial examination on SNR value which has the most optimal effect from scale 1 to scale 7.

Table 2 selecting wavelet scale level

Scale	SNR	Deviation
dB1	23.07	0.00
dB2	23.35	0.28
dB3	23.22	-0.12
dB4	23.15	-0.08
dB5	23.17	0.03
dB6	23.13	-0.05
dB7	22.80	-0.33

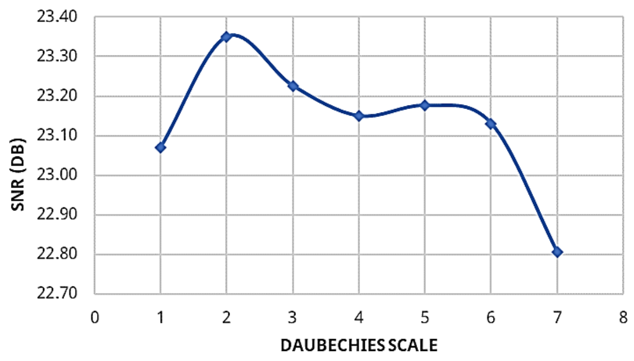

Figure 4. Daubechies scale

Moreover, the scale of dB2 was selected as the scale of wavelet in signal processing because it has a more significant effect than other level scales as shown in Figure 6.

3.1 Denoising

As demonstrated in Figure 7, there is a clear trend in the time history of daily strain of AP Pettarani Elevated Bridge. Large of noises has contaminated the strain signals during the day. These noises can be caused by a variety of factors, including environmental factors, technical interference, transmission issues, sensor restrictions, or inherent defects in signal gathering systems.

Through wavelet decomposition and limited by soft threshold at 1.174. The signal was successfully denoised as shown in Figure 8.

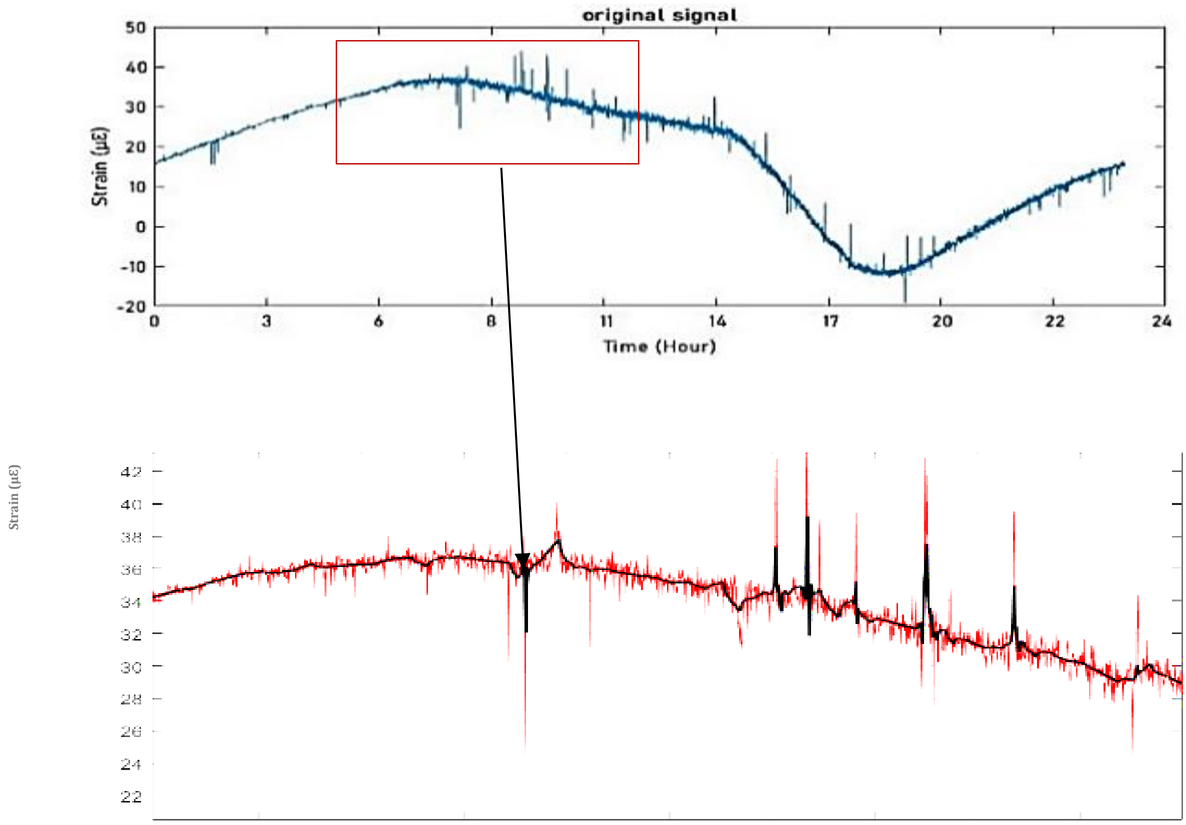

Figure 5. Noisy signal

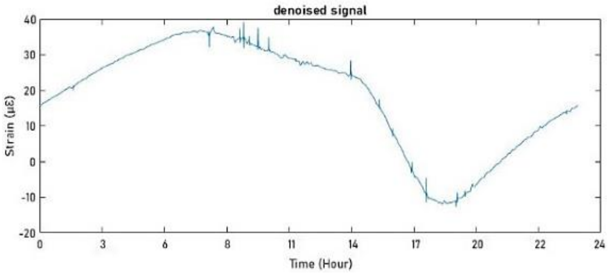

Figure 6. Denoised signal

3.2 Separating Signal Source

Strain data which was taken in a full day had been denoised. The approximation signal at 5-level decomposition based on the DWT showed that temperature fluctuation during the day influenced the natural signal's trend.

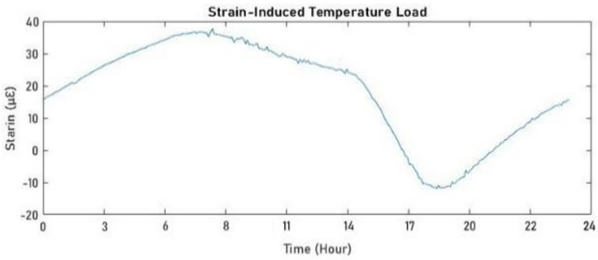

Figure 7. Strain-induced temperature load

Furthermore, after denoising, the detail coefficients signal represented the live load of the bridge such as the highway loads as described in Figure 9.

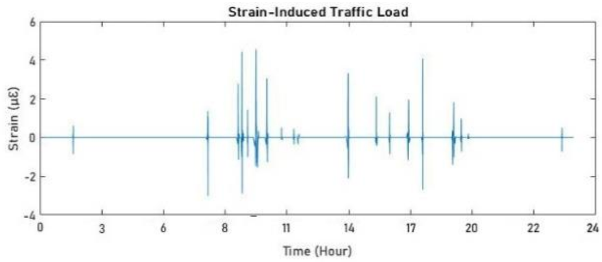

Figure 8. Strain-induced traffic load

As a result of the decomposition process, the energy detail and last approximation signal were determined in order to determine the signal's characteristic after denoising. Energy is used to describe how much potential a system has to change. The total energy in each component details and approximations in a signal provide helpful information about the location of the abnormality in the signal. Table 3 illustrates the decomposition signal energy result.

In addition, the results of the SNR and MSE parameter computations are shown in Table 4. This value is required to determine the effectiveness of the wavelet transform denoising.

Table 3. Decomposition of Signal Energy

Coefficient	Energy
D1	0.02
D2	0.03
D3	0.03
D4	0.02
D5	0.01
A5	99.89

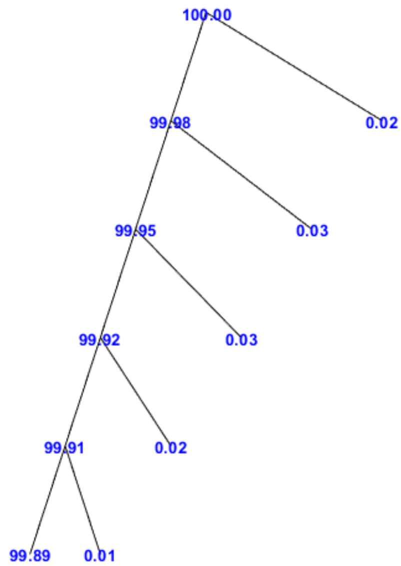

Figure 9. Wavelet Tree of Signal Energy

Table 4. SNR and MSE of Reconstructed Signal

SNR	MSE
33.76	0.23

4. Discussion

The results have shown that Wavelet Daubechies at level 5 with a scale of 2 (dB2) was the best decomposition level to remove the noisy signal where the signal deviation started to be constant at the 5 levels (Table 1). However, there is no significant event that happened after level 5.

Furthermore, strain data of extreme day showed that the signal of the data was full of noise. At original data, the maximum gained strain was 43,94 µƐ at 09.08 WITA and -19,31 µƐ at 19.00 WITA for minimum strain. After the denoising process, the author obtained maximum and minimum strains respectively 41.34 µƐ and -17.27 µƐ where the maximum deviation between the original and reconstructed was 2.73 µƐ. This process also gained 33.76

dB of SNR and 0.23 of MSE by comparing the original signal and the reconstructed signal.

Visually, trends of these events are due to variations in temperature load. When the temperature is low, the strain moves in a positive direction, while at a high temperature, the strain moves in a negative direction. Hence, the finest signal approximation A5, representing the global information, described the strain induced by thermal. Moreover, with strain-temperature which has been removed, the residual signal is predominantly produced by highway traffic.

In addition, stored signal energy after 5-level decomposition was 99.89%. Xia and Ni [10] stated that a decent graphic output must meet two criteria: After de-noising (1) the visual display is as smooth as possible, and (2) signal energy is attenuated by less than 1%. Following that, the wavelet transformation successfully denoised and separated the signals greatly.

5. Conclusion

The main concept of DWT is to acquire the temporal and scale representation of a signal using digital filter techniques and sub-sampling operations, both time and frequency domains. Following that advantage, noises in strain signals may be successfully eliminated, and various signal sources can be discriminated as predicted. The amount of noise SNR that can be reduced mathematically is 33.76 dB based on the mean of 8600 data samples. The results were unaffected by changes in the Daubechies-mother wavelet scale from 1 to 7, while the 5th level of decomposition and reconstruction offers the best results.

Acknowledgment

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