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Fatigue Road Signal Denoising Process Using the 4th Order of Daubechies Wavelet Transforms

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Abstract: This study explores an application of the wavelet denoising technique in a fatigue road load variable amplitude data set. In this study, the wavelet denoising application has been implemented using the 4th order of Daubechies family, with the adaptation of fifteen levels decomposition process. From the view of current research trend, the wavelet-based denoising approach is widely used using vibration random signal, but it is rarely been used in the scope of fatigue road loadings, or also known as fatigue strain signals. The idea of this study came from the some previous vibration analysis research and it was found to be suited to the approach of fatigue signal denoising process. High amplitude events in a fatigue road signal are very important and they should be retained because of these features caused significant damage of the components, particularly in automotive applications. After the fatigue signal has been denoised, the global signal statistical calculation and fatigue damage/life analysis were performed in order to validate the applicability of this denoising technique. From the analysis, it was found that the wavelet denoising approach was not suitable to analyse fatigue data and the major concern is the omission of high amplitude events from the original road loading, hence to a significant fatigue damage difference when compared to the edited road loading.

Key words: Fatigue, daubechies wavelet, denoising, signal, statistical analysis

INTRODUCTION

With the advances in digital signal processing methods, there has been an increasingly strong interest in the application of fatigue data analysis for life prediction in automotive component. Since fatigue is one of the major causes in vehicle component failure, its life prediction has become a subject of discussion in many texts (Nadota and Denier, 2004). In order to obtain accurate data analysis, some of the techniques in noise removing, such as signal filtering technique, have been carried out (Guangming *et al*., 2002). In addition to the traditional frequency spectrum-based signal filtering analysis, the wavelet denoising approach has become an alternative step in fault detection of a vibration signal (Bozchalooi and Liang, 2007) due to intensive noise contaminations. Many researchers used this approach in order to separate noise from a raw signal before furthering with other processes in various field, particularly for the gear damage diagnosis (Jafarizadeh *et al*., 2008), the electrocardiogram signal disturbance (Poornachandra, 2007) and the fault detection (Bozchalooi and Liang, 2007).

The wavelet transform is a time-frequency signal localisation method, which has been particularly improved from earlier time-frequency localisation analysis in recent years. This transform has a local characteristic of the time-domain and the frequency domain and its time-frequency window is also varied. In the processing of non-stationary signals, wavelet presents better performance and outstanding results compared to the traditional Fourier analysis and short-time Fourier transform (Jafarizadeh *et al*., 2008; Staszewski, 1998b). Studies by Abdullah *et al*. (2004, 2006) with the application of two fatigue strain loadings that having a variable amplitude data pattern, for which both data was measured on the lower suspension arm of a vehicle travelling onto the pavé road surface, found that the loadings were typically non-stationary based on their global signal statistical parameter values.

Automotive industries are seeking the way how to reduce the development times while simultaneously achieve higher quality levels for their vehicles (Lin and Heyes, 1999). One of the essential elements to achieve these targets is durability analysis. By definition,

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durability is the capacity of an item to survive its intended use for a suitably long period of time. Therefore, good durability minimises the cost of maintaining and replacing the item, the prevention of failures and the optimisation of automobile or component design (Dowling, 1972; Palma and Martins, 2004). The main task performed during the durability analysis is the fatigue life assessment of components, such as engine parts, suspension parts and body structures (Bignonnet, 1999). In addition automotive manufacturers have made large investments in this area so as to achieve products which meet a specified fatigue life target (Smith, 1999). Components such as suspension arms are submitted to multiaxial fatigue under service conditions with generally non-proportional and variable amplitude loading (Nadota and Denier, 2004). In relation to this, the application of signal processing technique by means of the wavelet transform can be considered as a new field to the aspect of fatigue design and also durability analysis (Oh, 2001; Abdullah *et al.*, 2006), which a part of the subject of this research.

In this study, a fatigue strain loading was measured on an automobile lower suspension arm and the purpose to analyse this component is because of this part has been identified as a critical component in an automobile. As example, when an automobile is driven on any road surface and hit a pothole, bump or curb, this lower suspension arm is then affected by a significant shock compared to other components. The significant amounts of load are then transmitted through the control arm while it serves to maintain the contact between the wheel and the road. Furthermore, this component plays a vital role in the failure of automotive part and it is submitted to multiaxial fatigue loading under service conditions with generally non-proportional and variable amplitude loading (Nadota and Denier, 2004). Thus, it can be a hypothesis mentioning an idea to perform a study related to the denoising approach of the collected fatigue road load variable amplitude loading which was measured on a lower suspension arm of an automobile. This is the generally a new approach in the scope of fatigue life assessment, which is not only to remove the background noise of the raw collected data, but also the intention is to retain the original global statistical signal value and fatigue damage potential. The gathered results is the noise-free signal which can be used to predict the lower arm fatigue life with more precise information compared to the original signal.

Literature Background: The global signal statistics are frequently used to classify random signals and the most commonly used statistical parameters are the mean value, the standard deviation value, the root-mean-square (rms) value, the skewness and the kurtosis (Hinton, 1995). In actual applications, mechanical signals can be classified to have a stationary or non-stationary behaviour. Stationary signal behaviour showed that the statistical property values remained unchanged with the changes in time. For non-stationary, however, the statistical parameter values of a signal are dependent to the time of measurement (Bendat and Piersol, 1986).

For both stationary and non-stationary signal, the engineering-based signal analysis is important to explore the characteristics and behaviour of the signal and the outcomes of these can also related to the fault detection and analysis. Among the earliest and established engineering signal analysis methods used in the most signal processing simulation is the fast Fourier transform (FFT). However, the FFT methods have been found to be not a suitable method to process a non-stationary signal, as the method has a drawback in revealing the inherent information of this type of signal (Peng and Chu, 2004; Abdullah *et al.*, 2006). Another engineering signal analysis technique is the time-frequency localisation, which it is the most popular method for analyzing the non-stationary signals. Among the approach included in this category are the Wigner-Ville distribution, the short time Fourier transform (STFT) and the wavelet transform (Staszewski *et al.*, 1997; Peng and Chu, 2004; Kahaei *et al.*, 2006). However, the STFT seems to be not suitable for a non-stationary signal as the time-frequency tiling in the STFT is prefixed and its precision in time-frequency domain is therefore limited (Kahaei *et al.*, 2006; Bosnyakova *et al.*, 2006). In addition, the STFT technique provides resolution accuracy in analysing this signal type.

In order to solve the problem in the above said time-frequency resolution, the wavelet transform is then introduced. The wavelet transform is a method for time-frequency analysis and it has been recognized a tool to summarise data or functions to work on various frequency components. This type of transform also can also be used in a study of each signal component with a resolution that is relative to its scale, so that the information in both time and frequency domain can then be produced (Abbasion *et al.*, 2007). By definition, a wavelet is said to be a small wave with a signal energy concentrated in time on the condition of admissibility condition (Burrus *et al.*, 1998). The wavelet transform is defined in the time-scale domain and it is a significant tool to analyse the signal time-localised features. The wavelet transforms can be divided into two categories, i.e., the Continuous Wavelet Transform (CWT) and the Discrete Wavelet Transform (DWT). The CWT is a time-scale method that can be mathematically expressed as:

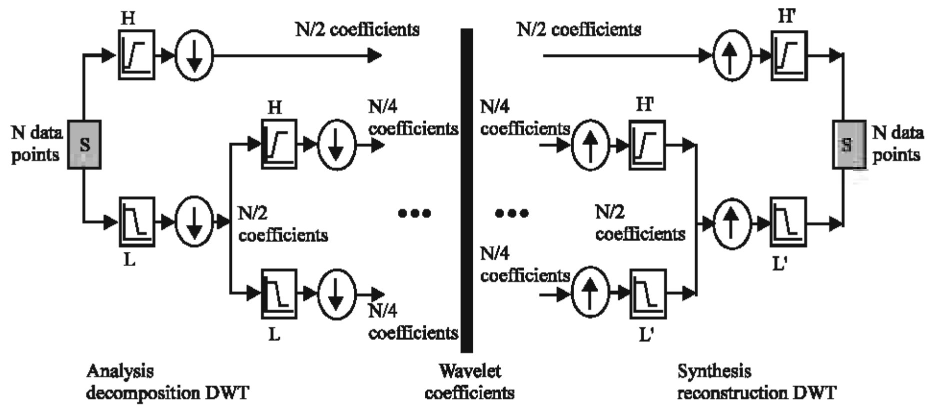

Fig. 1: Schematic representation of the multi step wavelet transform decomposition-reconstruction process. S = Raw signal, H = High pass filter, L = Low pass filter, DWT = Discrete wavelet transform, IDWT = Inverse discrete wavelet transfer

$$W_\psi(a,b') = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{a}}\psi^*\left(\frac{t-b'}{a}\right)dt \quad (1)$$

where, $\psi_{a,b}(t)$ are the scaled wavelets and ψ^* is the complex conjugate of ψ. The basis wavelet $\psi(t)$ can be chosen from a number of functions that satisfy asset of admissibility conditions. A natural extension of continuous analysis is the discretisation of time b' and scale a according to $a = a_0^m$, $b = na_0^n b_0$, where m and n are integers and $b \neq 0$ is the translation step. This implies the construction of a time scale grid and thus a discrete wavelet transform can then mathematically be defined by:

$$W_\psi(m,n) = \int_{-\infty}^{\infty} x(t)a_0^{-m/2}\psi^*(a_0^{-m}, t-nb_0)dt \quad (2)$$

When the wavelets $\psi_{m,n}(t)$ form a set of orthonormal functions there is no redundancy in the analysis; i.e., the procedure can be precisely inverted. The DWT based on such functions is called the Orthogonal Wavelet Transform (OWT) and this OWT is normally applied for the compression, denoising and feature selection of the random signals (Oh, 2001; Staszewski, 1998b).

The measured signals are often contaminated by noise intensive in its acquisition, for which a term of denoising is often defined as a process to remove background noise effects so as to keep important signal features. A previous work proved that the wavelet denoising becomes a major step for the purpose of the fault detection of mechanical components (Bozchalooi and Liang, 2007) and this technique took advantages of the properties that differentiate the signal from noise (Tirtom *et al*., 2008). The main advantages of applying the wavelet-based denoising approach when compared to the signal filtering is that the wavelet based technique retains the signal time information, while the filtering technique only operates algebraically on the data sequence. Thus, the implementation of signal filtering, particularly in the FFT scope, loses the signal time information.

The wavelet-based denoising approach can be performed using the signal decomposition method, by means of the implementation of a certain level in wavelet family order. In order to reduce the effect of the noise on the gathered data, the denoising procedure which is based on the orthogonal wavelet transform has been chosen. Thus, the Daubechies wavelet function was selected for this purpose since it has been proven useful in many engineering applications, especially in the signal reconstruction research that is related the mechanical damage detection (Staszewski, 1998a; Li *et al*., 1999; Lin and Zuo, 2003) and fatigue life assessment (Oh, 2001; Abdullah *et al*., 2004). For the use of Daubechies wavelet with the time series analysis, it has been suggested that the lower order of the Daubechies family (such as the 4th order) is suitable for the non-stationary signals. On the other hand, the higher order (such as the 20th order) is seemly suitable for the stationary signals. For some of the non-stationary signals that contain transient events, however, both the 4th and the 20th orders wavelet has been found to show similar results (Staszewski, 1998b).

The DWT decomposes a signal into two parts, i.e., approximations and details (Smith *et al*., 2007). It also allows the decomposition of an input signal into frequency bands. The decomposed parts of the signal can be reconstructed to form the original signal. The basic procedure of the signal decomposition-reconstruction is shown in Fig. 1. In the wavelet analysis, the approximations are the output of the low-pass filters and the details are the output of the high pass filters

(Smith *et al.*, 2007). The decomposition process can be repeated using the approximated version, so that a signal can be decomposed into different resolutions (Wu, 2001). The numbers of discrete points (N) in the signal sequence determine how many wavelet levels can be produced from the decomposition process. If the sample sequences and discrete data points have a relationship of $N = 2^n$, thus n + 1 wavelet levels can be generated.

Another analysis to be performed for the purpose of this paper is the fatigue life assessment. Generally, fatigue failure is a process involves a crack initiation and propagation that occurred on a component under repeated loadings, such as in a thousands to millions repeats. The fatigue behaviour of components under service loading and its evaluation are usually affected by numerous uncertainties. This behaviour were also characterised by several random variables, such as the materials properties, structural properties and load variation (Svensson, 1997). Three major approaches have widely been used to analyse fatigue damage or fatigue life, namely the stress-life approach, the strain-life approach and the linear elastic fracture mechanics. However, the strain-life is used for the analysis as the case study is related to the low cycle fatigue, which is a suitable approach to analyse random data collected from automotive components.

The foundation of the strain-life approach is the Coffin-Manson relationship (Coffin, 1954; Manson, 1965) and it is defined as the following equation:

$$\varepsilon_a = \frac{\sigma'_f}{E}(2N_f)^b + \varepsilon' f(2N_f)^c \quad (3)$$

In the real data application of the fatigue service loading, mean stress can have a substantial effect on the metallic fatigue behaviour. In this strain-life approach, two mean-stress effect models are commonly being used, i.e., the Morrow and the Smith-Watson-Topper (SWT) strain-life models. The Morrow's strain-life model (Morrow, 1968) is mathematically defined by:

$$\varepsilon_a = \frac{\sigma'_f}{E}\left(1 - \frac{\sigma_m}{\sigma'_f}\right)(2N_f)^b + \varepsilon'_f(2N_f)^c \quad (4)$$

and the SWT strain-life model (Smith *et al.*, 1970) is mathematically expressed by:

$$\sigma_{max}\varepsilon_a = \frac{(\sigma'_f)}{E}(2N_f)^{2b} + \sigma'_f\,\varepsilon'_f(2N_f)^{b+c} \quad (5)$$

For all those three strain-life expressions, E is the material modulus elasticity, σ_{max} is the true maximum stress, σ_m is the mean stress, ε_a is the true strain amplitude, $2N_f$ is the number of reversals to failure, σ'_f is the fatigue strength coefficient, b is the fatigue strength exponent, ε'_f is the fatigue ductility coefficient and c is the fatigue ductility exponent. The Morrow's strain-life model is significant at lower values of plastic strain and has little effect at higher plastic strains. For loading sequences that are predominantly in tensile, the SWT approach is recommended to be used for fatigue life estimation. In the case where the loading is predominantly compressive the Morrow approach can be used to provide more accurate life estimates (Dowling, 1972; Jafarizadeh *et al.*, 2008).

The fatigue damage caused by each cycle is calculated by reference to material life curves, i.e., stress life (S-N) or strain life (ε-N) curves. The N_f value for each cycle can be obtained from Eq. 3 to 5 for all three models and the fatigue damage value, D, for one cycle is calculated as:

$$D = \left(\frac{1}{N_f}\right) \quad (6)$$

The total damage caused by N cycles is referred to the Palmgren-Miner rule, for which the accumulated damage, ΣD, is expressed as:

$$\sum D = \sum \frac{N_i}{N_f} \quad (7)$$

where, N_i is the number of cycles within a particular stress range and mean and N_f is the number of cycles to failure for a particular stress range and mean. A fatigue cycle is defined as a closed loop on a cyclic stress-strain curve. The fatigue damage is mainly related to cyclic amplitude, or ranges and not to peak values. For a uniaxial random loading, the rainflow cycle counting is the most established counting method used for determining a complete fatigue cycle.

MATERIALS AND METHODS

The input signal that was used in this study was a variable amplitude (VA) strain loading and it was sampled at 500 Hz for the 46 sec record length. Thus, the time series of 23,000 data points was then produced. The arrangement of the data acquisition apparatus that was used in this data collection is shown Fig. 2. The signal was measured on the front left lower suspension arm of a car travelling over a pavé surface at 34 km h^{-1}. This signal was applied in several studies related to the development of the wavelet-based fatigue data editing (Abdullah *et al.*, 2004, 2006). It can be regarded as an important data since

Fig. 2: Arrangement of fatigue data acquisition system for data measuring experiment

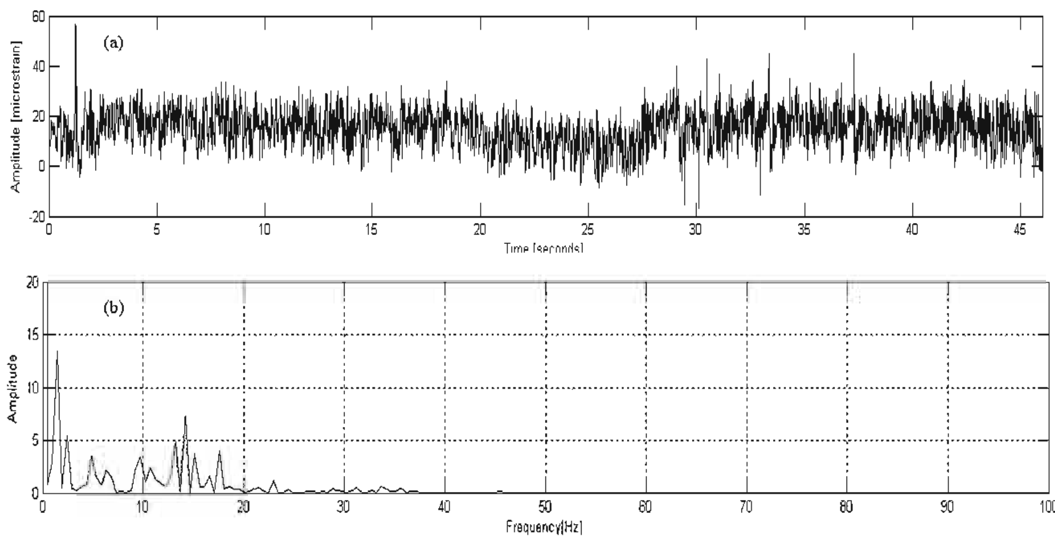

Fig. 3: The original test signal; (a) time histories plot and (b) power spectral density plot

because it represents an extreme road surface condition. The time series plot for this data is presented in Fig. 3a and the Power Spectral Density (PSD) is displayed in Fig. 3b. For this case, the PSD plot shows the distribution of vibrational energy content in the frequency domain. The global statistical parameter values of this fatigue signal are shown in Table 1.

For the fatigue damage calculation, the material chosen for the simulation purposes was the SAE1045 steel. This material was selected because it was commonly used to fabricate an automobile lower arm suspension. The material properties and their definitions are given in Table 2 and Fig. 4 shows the strain-life curve of this material type.

Table 1: The global statistical value for original test signal

Statistical parameter	Value
Mean	15.12
rms	16.72
Skewness	-0.13
Kurtosis	3.32

Table 2: Mechanical properties of the SAE1045 steel

Properties	SAE1045 steel
Ultimate tensile strength, S_u (MPa)	621
Modulus of elasticity, E (GPa)	204
Fatigue strength coefficient, σ'_f (MPa)	948
Fatigue strength exponent, b	-0.092
Fatigue ductility exponent, c	-0.445
Fatigue ductility coefficient, ε'_f	0.26

For the denoising analysis using wavelet, the signal was decomposed using the 4th order of Daubechies

Table 3: Frequency range for L1-L15 for signal decomposition

Level	Frequency range (Hz)
L1	125-250
L2	62.5-125
L3	31.25-62.5
L4	15.625-31.25
L5	7.813-15.625
L6	3.906-7.813
L7	1.953-3.906
L8	0.977-1.953
L9	0.488-0.977
L10	0.244-0.488
L11	0.122-0.244
L12	0.061-0.122
L13	0.031-0.061
L14	0.015-0.031
L15	0.008-0.015

Fig. 4: The theoretical strain-life curve for the SAE 1045 steel

wavelet with 15 decomposition levels. Since the number of data point were 23,000, which n = 14 at the 2^n, the decomposition level is up to 15 level (Abdullah *et al*., 2006). This signal has the kurtosis value of 3.32 (Table 1), indicating a non-stationary pattern behaviour has been observed in it. Thus, it proved that this signal is suitable to decompose using the 4th order Daubechies wavelet. After the decomposition, the signal was then denoised with a specific cut off threshold value. The decomposed signal, which is formed from the wavelet coefficients in each level, in Level one (L1), Level two (L2), Level three (L3) and the denoised signal in Level four (L4) were then used to calculate the fatigue life. The statistical properties for all these signals were also calculated in order to observe the statistical pattern. The L1 to L3 signals were eliminated because of these signals have higher frequency ranges with low amplitude cycles. From the previous study by Oh (2001), the low amplitudes strain data can be eliminated because of these data types did not contribute to the fatigue life. Table 3 shows the frequency ranges for all the decomposition levels. The denoised signal that has been produce in Level 4 (after the omission of Level 1-3) and above should be retained because these parts contain low frequency ranges, which contained high amplitude cycles and these features are the main criterion in predicting fatigue lives.

RESULTS AND DISCUSSION

Wavelet denoising analysis: Figure 5 and 6 show the time history plots that was re-developed from the OWT coefficients for all decomposition levels 1 to 15. At the right side of these figures are the distributions of vibrational energy in the frequency spectrum, which is in the form of the PSD plots. Since the L1 to L3 signals coefficients were eliminated from the original signal, L4 became the new signal which contains all signal elements or the respective OWT coefficients for L4 to L15. The plot of this L4 signal is presented in Figure 7 and the PSD representations for the original signal and the denoised signal are shown in Fig. 8. From Fig. 8, the original and denoised signals are illustrated as the dotted and solid lines, respectively. The difference in this PSD distribution for both signals can be seen between 10 and 20 Hz, as it may be caused by the fatigue cycles omission from the original loading, particularly within that frequency range, which is the significant finding obtained from the denoising process.

Statistical analysis: The global signal statistical values for the original signal, L1-L3 and the denoised signal were calculated for further analysis. Another shortened signal from this type of loading, named as the WBE signal, was also introduced for the purpose of data comparison. The WBE signal has the equivalent signal behaviour and pattern as the original signal, but it has been edited using the Wavelet Bump Extracted (WBE) algorithm. This WBE algorithm, which is the recently developed wavelet-based fatigue data editing computational method, has been developed by the first author of this paper and the detail of this development and validation can be found in this related literature (Abdullah *et al*., 2006). This shortened signal contains the extracted fatigue damaging events from the original signal. These events were identified and extracted from the characteristic frequency bands in the load spectrum using the 12th orders of Daubechies wavelet. In the final analysis using this pavé fatigue strain loading, the WBE shortened signal has the overall length of 18.8 sec. The WBE shortened signal plot is shown in Fig. 9.

The purpose of implementing the WBE shortened signal is to compare the ability of this wavelet denoising technique with another similar technique that has the wavelet approach. The global statistical parameters, i.e., the mean, the rms, the skewness and the kurtosis values

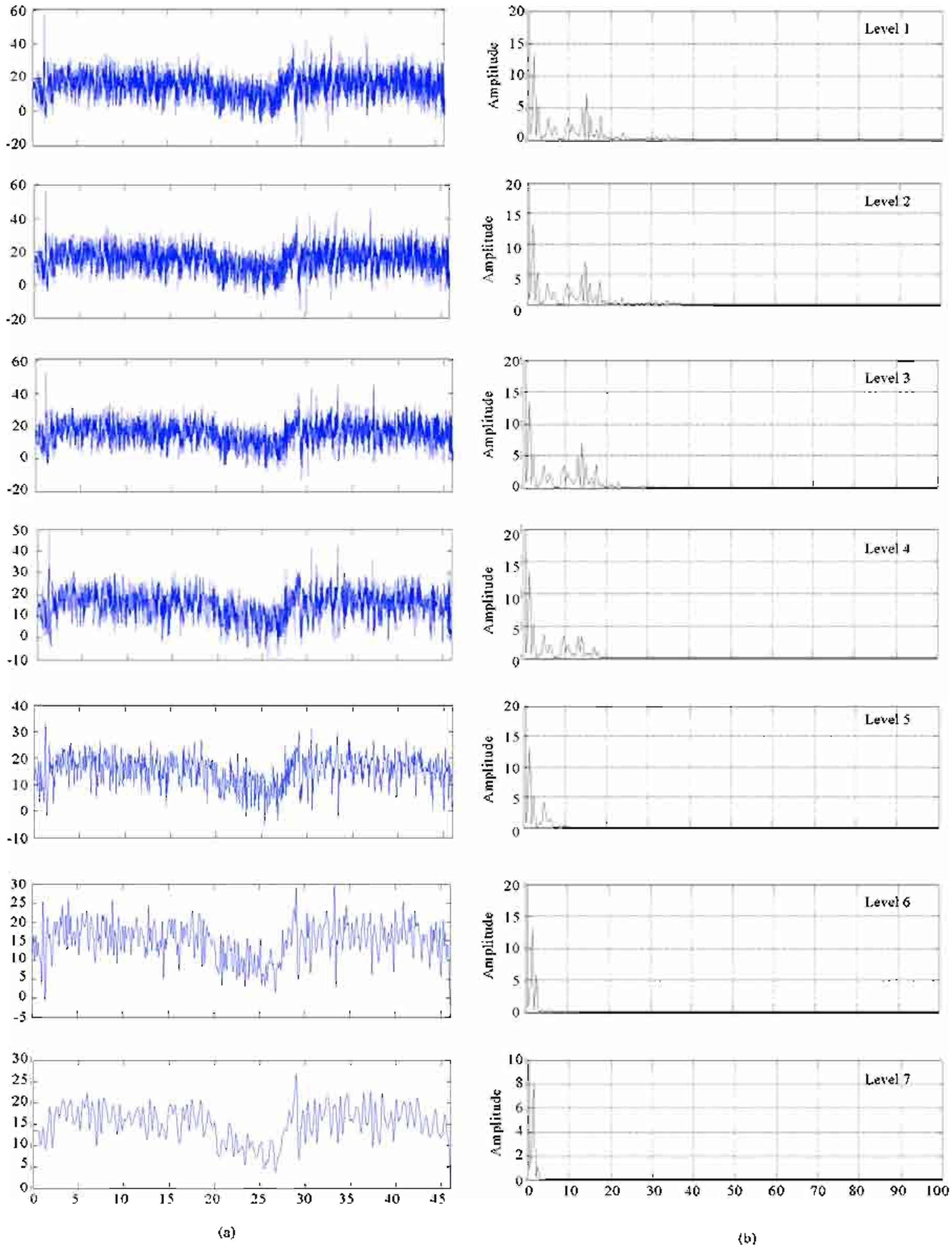

Fig. 5: Wavelet decomposition of the signal from Level 1 to Level 7: (a) Series of wavelet coefficient plots, (b) The respective power spectral density plots

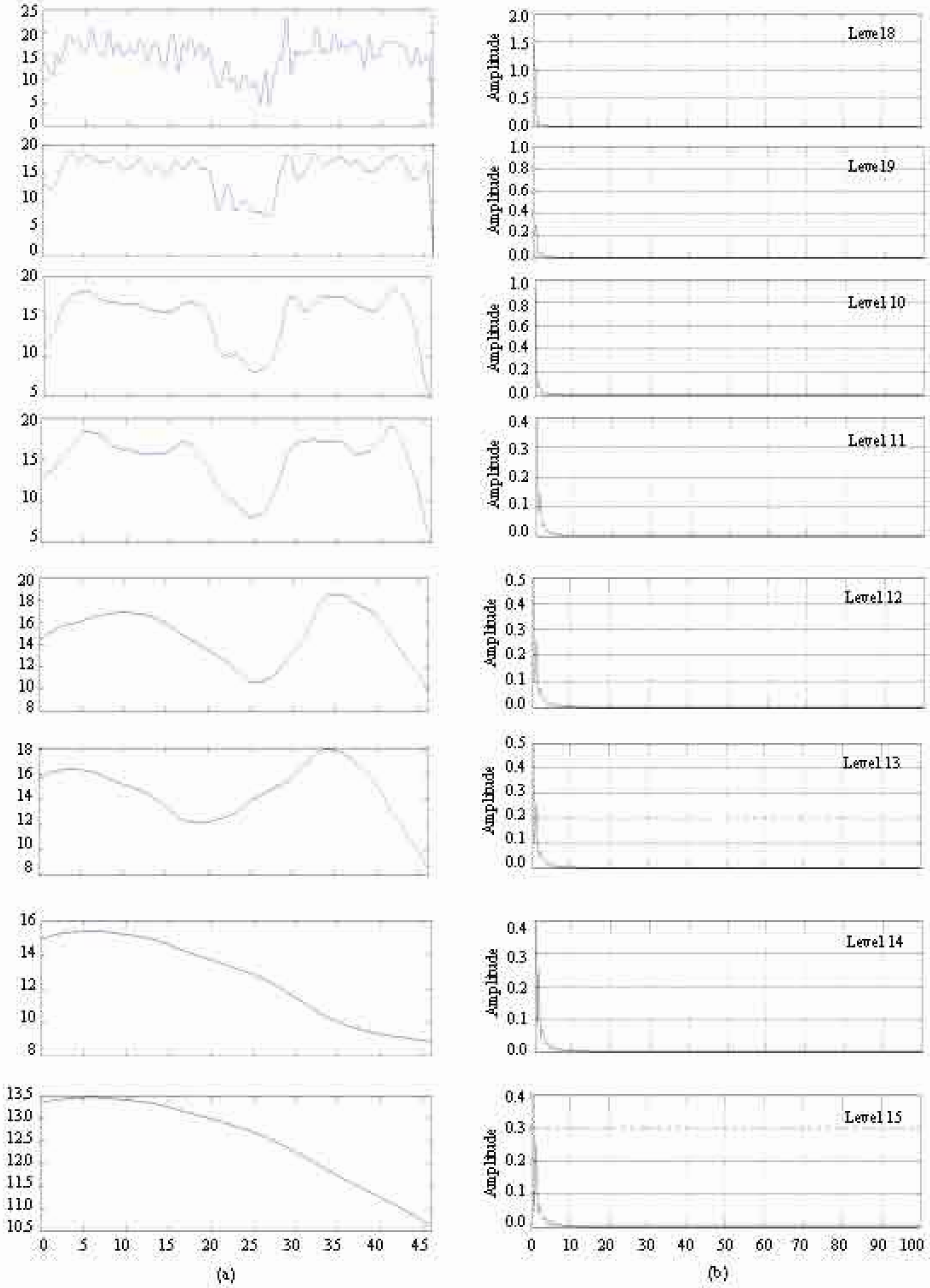

Fig. 6: Wavelet decomposition of the signal from Level 8 to Level 15: (a) Series of wavelet coefficient plots, (b) The respective power spectral density plots

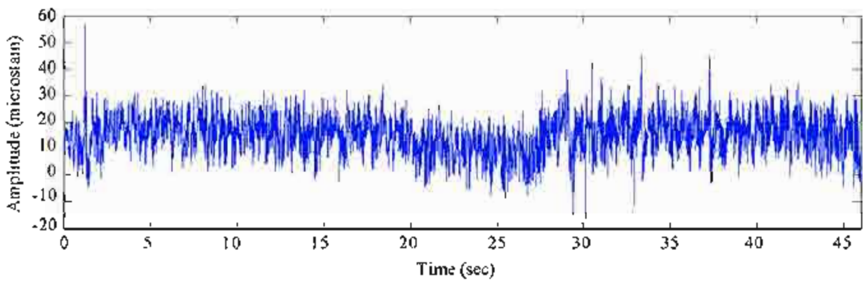

Fig. 7: The denoised signal

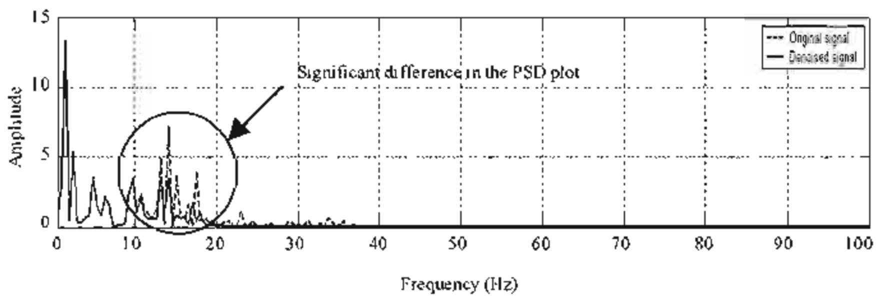

Fig. 8: Power Spectral Density (PSD) of the original and the denoised signal

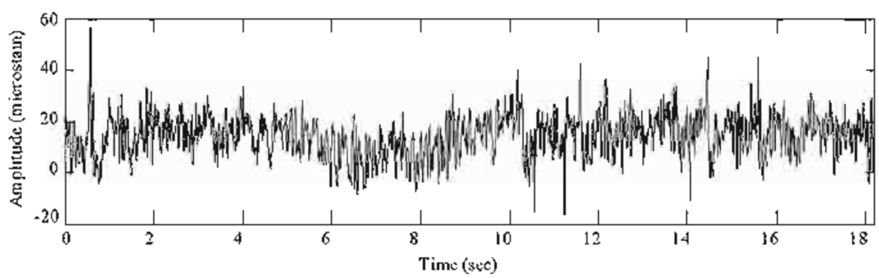

Fig. 9: The time history plots for the WBE Signal

were calculated and they are tabulated in Table 4 for all listed signals. From this table, it can be seen that the mean values for all signals were similar to the original signal. However, the value for the WBE signal is different compared to others, i.e., at the 3.37% difference and it might be caused by the changes of the signal strain range. The rms value for L2, L3, the denoised and the WBE shortened signals were lower than the value of the original signal. The lower value in rms meant that the overall energy content for all shortened signal were also lowered. The difference of 1.83% in rms between the original and the denoised signal has also been obtained, as shown in Table 4. The original signal has the negative value in skewness and the shortened signals produced from the denoising process also has a similar skewness distribution. The negative value in skewness indicated that the data in these signal were mainly distributed to the left side. In addition, the kurtosis values for each signal were calculated in order to observe the data peakedness and outlier behaviour. From the tabulated data of Table 4, the WBE shortened signal has the highest kurtosis value and it was caused by this method was effectively

Table 4: Statistical value of the original, L1, L2, L3, denoised and WBE shortened signals

Parameter	Mean	rms	Skewness	Kurtosis
Original signal	15.12	16.72	-0.130	3.32
L1 signal	15.12	16.72	-0.125	3.32
L2 signal	15.12	16.71	-0.124	3.22
L3 signal	15.12	16.64	-0.1313	3.28
Denoised signal	15.12	16.57	-0.2140	3.34
WBE shortened signal	14.61	16.57	-0.0142	3.65

Table 5: Comparison of fatigue cycles and fatigue life for the analysed signal

Parameter	Original	L1	L2	L3	Denoised	WBE
No. of fatigue cycles	1412	1440	1656	1216	784	571
Fatigue life [No. of block to failure]	6092	6085	6100	8061	15094	7831
Difference in cycles counting [%]	-	2	17	14	44	59
Difference in fatigue life [%]	-	1.17	1.28	32.3	143	22.2

eliminated low amplitude events and in the same time retained the correct high amplitude cycles in the edited signal.

Fatigue life assessment: In order to verify the effectiveness of the edited signal in term of damage prediction, the fatigue damage potential for the original and the denoised signals were estimated using the specific commercial software. The calculated fatigue damage of the denoised signal was also compared to the WBE shortened signal, as this WBE signal was taken as a benchmark of this study as it was proven to be a successful wavelet-based fatigue data editing method. The fatigue damage calculation presented in this research was based on the SWT strain-life relationship because the mean value of the original signal is greater than zero. For this model, as mathematically defined in Eq. 5, the damage parameter is taken to be the product of the maximum stress and the strain amplitude of a cycle. Using this equation, the number of reversals N_f, were determined for calculating the fatigue damage value. The values of σ'_f, E, ε'_f, b and c were given in Table 2, while the values of ε'_a were obtained from the rainflow cycle counting method of the time history.

The cycle histograms obtained from the all analysed signals were presented in Fig. 10. When looking at each histogram in Fig. 10, most of the cycles were in the scale of 1 to 8.1 cycles and their cycle range was from 0.1 to 30 microstrain. The highest amplitude range obtained from all the analysed signal was at the 74.299 microstrain value. From this figure, it can be seen that the cycles range of the denoised signal was decreased from 79.299 to 59.385 microstrain. The decrement in the cycle range is because of the high amplitude cycles was diminished in the wavelet denoising process. Although the signal has been shortened in the WBE process, the range and the mean value in the WBE signal remain unchanged when compared to the original signal. However, the numbers of cycles in the WBE shortened loading were decreased because of some low amplitudes cycles was eliminated during the WBE data editing process.

The cumulative fatigue damage calculation was then applied using the established Palmgren Miner (PM) linear damage rule. The signal damage histogram was plotted as in Fig. 11, showing the damage potential for each cycle which was calculated using the SWT strain-life model. For the original signal as showed in Fig. 11a, the maximum damage has been contributed by cycles that having the highest range or the tallest column in the histogram plot. The value of the cumulative fatigue damage is decreased from L1 to denoised signal. The findings showed that the wavelet-based denoising approach may not suitable to be used because of this procedure were coincidently removed high amplitude cycles, by smoothing the random effects in higher cycle ranges. In the related analysis as presented in Table 5, the fatigue cycles in the denoised signal was only 784 cycles compared to 1412 cycles for the original signal. The objective of the signal denoising approach is to eliminate the background noise from the original signal, so as to retain the majority of fatigue damage (in the range of 10%) compared to the original fatigue damage. From the inverse calculation of the total damage, the number of life gathered for the denoised signal was 143% difference compared to the original signal.

Fatigue life calculation of a fatigue load history was ideally based on the number of the meaningful cycles in a variable amplitude fatigue strain loading. The damage potential for each cycle was calculated and the damage for each cycle was accumulated in order to get the total damage for a loading. In this study, the denoised approach has been found to be able in removing the fatigue cycles from the original signal. Due to the decrement in the fatigue cycles, the total damage for the denoised signal was also decreased, as being shown in Table 5 for the detail information. From the analysis of this research, it has been shown that the wavelet denoising approach lead the loosing of some information needed to predict the fatigue lives of a metallic material or component.

According to the wavelet-based denoising process, this technique eliminates the background noise by the removal of high amplitude events which are very important in the fatigue life assessment. With all the findings presented in this research, the 4th order of the Daubechies wavelet-based denoising process of a fatigue strain time history has been found not to be a suitable method for the fatigue data editing. It is because of this approach did not give the correct information as needed in predicting the fatigue life of a variable amplitude loading that is associated with random behaviour.

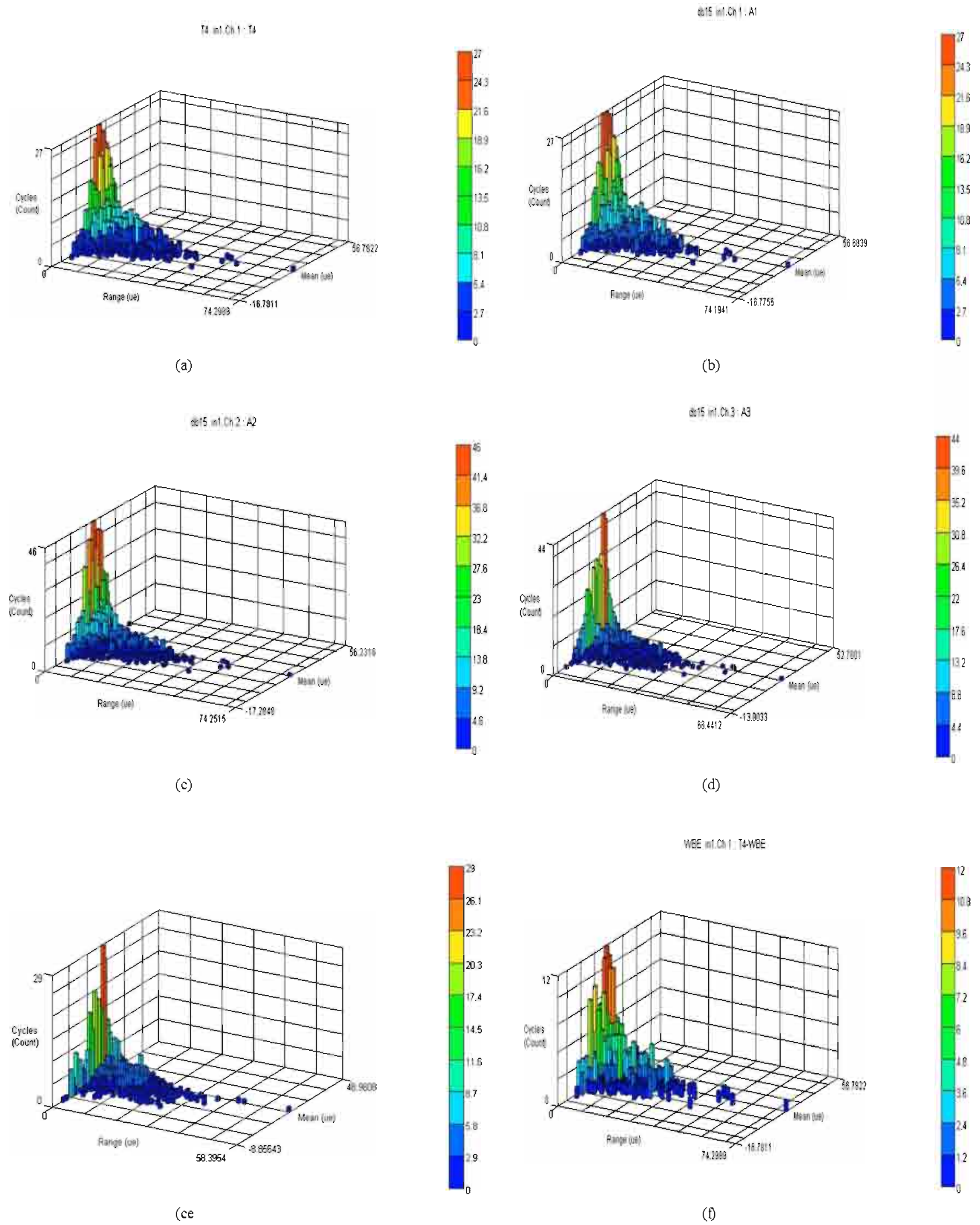

Fig. 10: The cycle counting histogram of the following signals: (a) The original signal, (b) L1, (c) L2, (d) L3, (e) the denoised signal, (f) the WBE signal

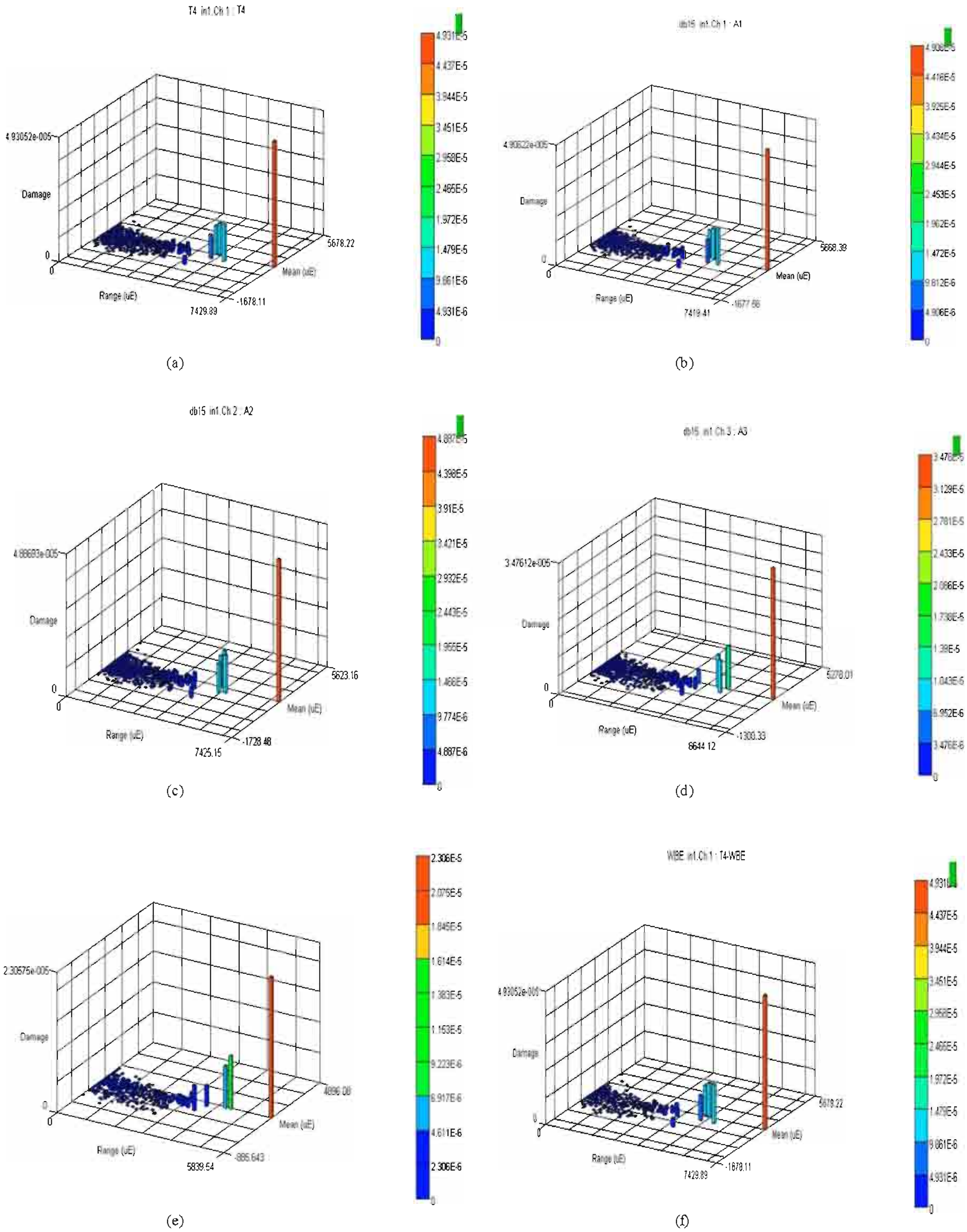

Fig. 11: The damage histogram of the following signals: (a) The original signal, (b) L1, (c) L2, (d) L3, (e) the denoised signal, (f) the WBE signal

CONCLUSION

This research discussed on the study of a fatigue signal denoising in time-frequency domain by using the 4th order Daubechies wavelet with fifteen level decomposition methods. The data collected from the lower suspension arm of an automobile which was driven over a pavé road surface was used as the subject of this study. A comparative study was also performed between the wavelet-based denoising approach and also the WBE fatigue data editing technique. From the analysis, the wavelet-based denoising technique using the 4th order of the Daubechies wavelet was not suitable to be applied as the fatigue data editing technique using a variable amplitude loading. The reason behind this statement is this denoising approach lead to the smoothing of the random pattern laying in the high amplitude cycles of the signal, or also the removal high amplitude cycle itself. In this case, higher amplitude events are important to be retained as it contributed to the fatigue damage in metallic materials.

The denoised analysis has been found as a common procedure for the vibration analyses, but it is a new application in the fatigue damage research. It is generally a recent trend for the fatigue life assessment research associated to the signal processing approach. In the related subject, the damage calculated was depended on the cycle counting and it is contrary to the vibration analysis, for which the overall signal was used to monitor the pattern of mechanical system behaviour. The denoising method which has been used in the vibration studies omitted high frequency signal component. The same procedure was applied for the fatigue data analysis and this approach removed the signal high frequency component. In the same time, the wavelet-based denoising technique also removed some of the high amplitude cycles. The omission of some features from this denoising process will cause the significant effect to the fatigue damage potential compared to the original fatigue loading. Thus, it is finally suggested that the wavelet-based denoising approach, by means of the 4th order of Daubechies wavelet transform, is not suitable to be used for the purpose of fatigue data editing application in the durability research.

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