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Extraction of Fatigue Damaging Events from Road Spectrum Loadings Using the Wavelet-Based Fatigue Data Editing Algorithm

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Abstract: This paper describes a technique to identify the important features in fatigue road spectrum loading, for which these features cause the majority of the total damage. Fatigue damaging events, called bump segments, are extracted from the spectrum loading using a wavelet-based algorithm, called Wavelet Bump Extraction (WBE). This algorithm is also used to produce a shortened mission signal that retains most of the fatigue damage whilst preserving the cycle sequences. The bump identification process has been evaluated by analysing two road spectrum loadings having a variable amplitude pattern. These data sets were obtained from the strain measurement on the lower suspension of different vehicles travelling over different road surfaces. In this study the total fatigue life caused by the combination of all bump events was close to the original data sets. For this case, the fatigue life of the original spectrum loading and the WBE extracted loadings are predicted using three strain-life fatigue damage models, i.e. the Coffin-Manson relationship, the Morrow and the Smith-Watson-Topper (SWT) mean stress correction effects. In addition, the correlation analysis showed that the coefficient of variation (R^2) between the fatigue lives of the original and the total of bump segments was found to be 99.9% or 0.999. These findings suggested that WBE is a suitable approach for mission synthesis applications by producing a shortened mission signal for accelerated fatigue test.

Keywords: extraction, WBE, fatigue damaging events, fatigue life, spectrum loading

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1 Introduction

The presence of large amplitude cycles is common in time histories of ground vehicle vibration and fatigue. The effect had been noticed at first for heavy wheeled and tracked vehicles, and then for automobiles (Giacomin *et al.* 1999; 2000; 2001; Steinwolf *et al.* 2002; Abdullah *et al.* 2004), which all these road vehicles were driven over different road surfaces. In fatigue study irregular road surfaces contribute high amplitude events in the time histories, contributing to the damage effects on to the vehicle components or structures. For example, a road spectrum loading with high amplitude events with higher peaks can be obtained in a situation where a vehicle is driven on a pavé road surface (Steinwolf *et al.* 2002), and this loading produces higher fatigue damage Abdullah, Giacomin, and Yates (2004), Since this specific events cause the majority of fatigue damage, there is a need to reduce development time while simultaneously improving confidence in the fatigue road spectrum load analysis. It means that it is a significant interest to investigate the issue of fatigue loading compression, or specifically known as fatigue data editing. Using this approach, high amplitude events are retained and small amplitude events are removed. A shortened loading consists only high amplitude events can be produced.

The fatigue data editing technique using a variable amplitude (VA) fatigue loading (or also called road spectrum loading) is used to produce a shortened signal for the laboratory accelerated fatigue tests. The test is related to the application of a component or the complete automobile to a test loading which is much shorter than the target loading, but which has approximately equivalent damage potential. Without editing the service load before performing the durability fatigue tests, the testing time and costs become prohibitive.

Several approaches for retaining high amplitudes events have been introduced in different data domains, i.e. time, peak and valley, frequency, cycles, damage and histogram. Most of the commonly procedures explained in the research literature have been based in the time and the frequency domains (Austen and Gregory 1995, El-Ratal *et al.* 2002) In the time domain, the local strain (Conle and Topper 1980), damage window joining function (El-Ratal *et al.* 2002) and Smith-Watson-Topper (SWT) parameter range (Stephens *et al.* 1997; Nizwan *et al.* 2007a; 2007b) approaches have been defined to identify high amplitude cycles that produce higher fatigue damage. In the frequency domain, a VA loading is low pass filtered based on the fact that high frequency cycles have small amplitudes which produce little damage (Morrow and Vold 1997). In spite of this, the filtering method does not shorten a fatigue loading series as the number of points are similar to the original loading (Austen and Gregory 1995). The time-frequency approach has also been applied to the problem of fatigue data editing through its use in spike removal and denoising (Oh 2001). Yet, none of these methods showed the importance of extracting individual fatigue damaging events from VA loadings.

Practically, a method for summarising the road load fatigue data based on the identification of fatigue damaging events and extract them from the original road load data is important. This has led to the development of a wavelet-based fatigue data editing algorithm (Abdullah *et al* 2003; 2006) and it is the first fatigue data editing approach implemented for automotive applications using the orthogonal wavelet transforms. Using this algorithm, known as Wavelet Bump Extraction (WBE), the fatigue damage potential of the shortened or mission signal is intended to be as close as possible to that of the original signal, as well as the vibrational signal energy and amplitude ranges.

2 Theoretical Background

2.1 Fatigue Life Prediction Using Strain-Life Approach

It is common that the service loads acquired on components of machines, vehicles, and structures are analysed for fatigue life using crack growth approaches. This approach is suitable for high capital valued structures. On the other hand, the ability to inspect for cracks and monitor their growth until a maximum allowable defect size is reached, enables a component or structure useful life to be extended beyond the original design life. However, it is not generally feasible for applying the crack inspection process for the inexpensive components that are made in large numbers because of the costs restriction. Examples of components which fall in this category are automobile engine, steering and suspension parts (Conle and Landgraf 1983), showing that the prediction of crack initiation is important for these components in order to avoid fatigue failure. For that reason, a fatigue life estimation based on the related strain-based approach is usually used in these cases (Dowling 2006).

Current industrial practice for fatigue life prediction is to use the Palmgren-Miner linear damage rule (Palmgren 1924; Miner 1945). For strain-based approach, this rule is normally applied with strain-life fatigue damage models. The first strain-life model introduced in the life prediction method is the Coffin-Manson relationship (Coffin 1954; Manson 1965). This relationship is mathematically defined by

$$\varepsilon_a = \frac{\sigma'_f}{E}(2N_f)^b + \varepsilon'_f(2N_f)^c \tag{1}$$

where E is the material modulus of elasticity, ε_a is the true strain amplitude, $2N_f$ is the number of reversals to failure, σ'_f is the fatigue strength coefficient, ε'_f is the fatigue ductility coefficient, b is the fatigue strength exponent and c is the fatigue ductility exponent.

In some realistic cases, the situation of fatigue spectrum loading involves non-zero mean stresses or strain. Thus, two mean stress effect models are applicable to be used, i.e. Morrow and

SWT strain-life models. Mathematically, the Morrow model is mathematically defined by Morrow (1968)

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

where σ_m is the mean stress. The SWT strain-life model is mathematically defined by Smith *et al.* (1970)

$$\sigma_{\max}\varepsilon_a = \frac{\left(\sigma'_f\right)^2}{E}(2N_f)^{2b} + \sigma'_f\varepsilon'_f\,(2N_f)^{b+c} \qquad (3)$$

where $\sigma_{\max}$ is the maximum stress for the particular cycle.

Despite of the fact that these models are widely used for fatigue life prediction, several limitations were also found in the analysis using VA or spectrum loadings which may lead to the erroneous prediction. Using the Palmgren-Miner rule with these three models, the fatigue damage is accurately calculated for constant amplitude (CA) loadings. However, the life prediction based on the CA-based fatigue damage models is still acceptable for the research and industrial applications (Fatemi and Yang 1998).

2.2 Fatigue Data Editing Techniques

Fatigue data editing is a technique to remove small amplitude cycles that lead to minimal fatigue damage. Large amplitude cycles of a spectrum loading are retained, so as to produce a shortened loading for accelerated fatigue tests. Many approaches of the fatigue data editing can be performed in various domain of the signal analysis.

In the time domain, time history data is the most general format data, containing all the information of relevance to the random data analysis. The time domain fatigue data editing techniques have been developed to remove time segments, such as the Time Correlated Fatigue Damage (TCFD) method which can be found in the nSoft® software package (nSoft® User Manual 2001). This TCFD method is used to remove non-damaging sections of the time history on the basis of time correlated fatigue damage segments. Using TCFD, the input time history is divided into a number of time segments and the fatigue damage potential is then calculated for each segment. Segments having minimal damage are removed and the segments with the majority of the fatigue damage are retained. The retained segments are then assembled to produce a shortened signal. In TCFD, both the percentages of damage retention and the required acceleration factors, or one of them, could be set as editing targets. Practically, this technique is recommended as it maintains the phase and amplitude of the original time history (El-Ratal *et al.* 2002).

In the frequency domain, fatigue loading time histories are often low-pass filtered, as small amplitudes located in the high frequency region of the power spectral density (PSD) distribution (Morrow and Vold 1997). The low pass filter does not reduce the length of the signal, but almost certainly reduces the fatigue damage. For practical applications, the frequency domain editing technique is rarely used, even this method is not recommended to be used as an appropriate fatigue data editing. It is because of the time series regenerated from a frequency spectrum does not produce the same fatigue life

The peak-valley (PV) editing technique reduces the number of points of the original loading, and it is used when the signal frequency content is not important for the fatigue damage analysis. However, the time information of the original time history is lost when using this fatigue data editing technique (Mercer *et al.* 2003).

The rainflow cycle counting method (Matsuishi and Endo 1968) is used to identify fatigue cycles in a variable amplitude loading. This counting method is also useful as the basis for the cycle domain fatigue data editing. A time history is rainflow cycle counted in order to extract the fatigue cycles and to produce a range-mean histogram. For the application, a range-mean histogram is produced from a spectrum fatigue loading. Then, the identified small cycles having minimal damage are removed and the damaging cycles are retained in the edited loading.

The application of time-frequency in fatigue data editing is recently introduced in the fatigue research. Using this transform, the data is processed in order to provide the localised features of the original signal. For wavelet-based fatigue data editing, only two previous studies have been found in literature, i.e. studies using a VA loading measured on light railway train component (Oh 2001) and automobile component (Abdullah *et al.* 2004). In a research by Oh (2001), the Daubechies wavelet transforms was used to remove the unwanted time history data points using the denoising and spike removal techniques. A loading measured on a light railway train component travelling at 80 km/h was used for the analysis, giving the original signal was compressed at 71% of the time length. At this length, approximately 80% of the original fatigue damage was retained.

For the automotive application, the use of wavelet transform was performed by Abdullah *et al.* (2004) using the Mildly Nonstationary Mission Synthesis (MNMS) algorithm. The MNMS algorithm was previously developed for comfort and vibration studies (Giacomin *et al.* 1999; 2000; 2001). Using MNMS, statistically accurate fatigue mission loadings were produced when the original signal was substantially shortened by up to 10 times compression ratio. However, the shortened VA loadings did not have similar fatigue damage as the original loading. Realising the limitation of MNMS in the fatigue data editing and the bright future of the wavelet transform, it has been highly considered for the development of a new wavelet-based fatigue data editing by Abdullah *et al.* (2003; 2006).

For all fatigue data editing techniques discussed in this section, different VA fatigue loadings were used for different techniques. There seem to be no generally agreed rules that clarify which method is the best, or what amplitude should be chosen for load omission (Yan *et al.* 2001). Ideally, a fatigue data editing technique must be able to summarise VA fatigue loadings with the retention of the majority of the fatigue damage.

3 The Wavelet Bump Extraction (WBE) Algorithm

Many experimental signals exhibit time-varying, or nonstationary characteristics, which provide a challenge in signal analysis. Traditional approach to determine the frequency distribution of the time series was performed using the Fourier transform. This kind of analysis is not suitable for nonstationary signal, as it cannot provide any information of the spectrum changes with respect to time. Knowing this restriction, the wavelet transform is seemed to be a suitable method for the analysis of nonstationary signals. The wavelet transform is a function in the time-scale domain and it is a useful tool for presenting local features of a signal. This transform gives a separation of signal features overlap in both time and frequency, giving an accurate local description of the signal characterisation (Newland 1993).

Several wavelet families are available for the use in engineering field. One of them is the Daubechies wavelet which has the orthogonal basis functions (Daubechies 1992). This wavelet family allows the decomposition of the input signal into separate frequency bands, and reconstructs the decomposed signal to produce the original signal. This procedure is known as analysis-synthesis, for which it is a unique characteristic of the orthogonal wavelet transforms. A range of applications of the orthogonal wavelet transform can be found in previous studies, i.e. the application of nonstationary signals for the mechanical damage detection (Staszewski 1998), the signal compression and de-noising process (Barclay and Bonner 1997), the application of MNMS using vibration data sets (Giacomin *et al.* 1999; 2000; 2001; Steinwolf *et al.* 2002). This transform was also performed in a fatigue study, i.e. the compression of nonstationary fatigue signals measured from a light railway train component (Oh 2001) and the automobile data sets by Abdullah *et al.* (2004).

For this paper, the Wavelet Bump Extraction (WBE) algorithm was developed for the purpose to identify and extract fatigue damaging events (or later called bump segments) from uniaxial fatigue spectrum loadings or the VA fatigue loadings. It is a computational algorithm which was developed using the FORTRAN programming language. Since the application of the wavelet transform was found to be a new approach in the fatigue data editing research, the use of a uniaxial VA fatigue loading is essential, especially at the earlier stage of this WBE research. This is a vital aspect for checking the effectiveness of WBE in editing different patterns of VA loadings. In the future, the WBE algorithm will be also redeveloped for solving related data editing problems using multiaxial VA fatigue loadings.

The WBE algorithm uses the 12^{th} order Daubechies wavelets as the basis functions. This function was chosen due to the efficiency in providing a large number of vanishing statistical moments. In addition, the 12^{th} order representation was adopted due to its successful use in the studies using the previous MNMS algorithm. The wavelet levels produced in the wavelet decomposition consist of the reconstructed signals for a given value of a wavelet scale and each level describes the time behaviour of the signal within a specific frequency band. High amplitude events are then identified in the respective wavelet groups. A wavelet grouping stage permits the user to cluster wavelet levels into a single region of signal vibrational energy. Each wavelet group is defined by the user to cover frequency regions of specific interest, such as high energy peaks caused by a subsystem resonances. This subdividing of the original signal permits an analysis to be performed for each frequency region independently, avoiding situations where small bumps in one region are concealed by the greater energy of other regions of the frequency spectrum. A bump, which is define as an oscillatory transient with a monotonic decay envelope either side of a peak value (Figure 1), is identified in each wavelet group by means of an automa tic trigger level (Figure 2).

At program launch the user specifies the maximum acceptable percentage difference between the root-mean-square (r.m.s.) and kurtosis of the original and the mission signals. The r.m.s. value

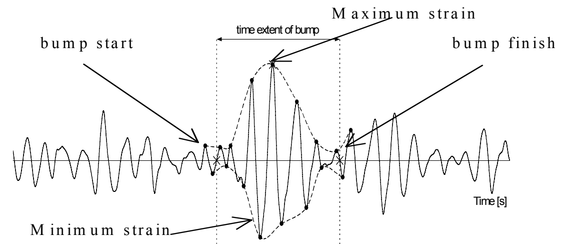


Figure 1: Schematic diagrams of a decay enveloping process to determine a bump in a wavelet group

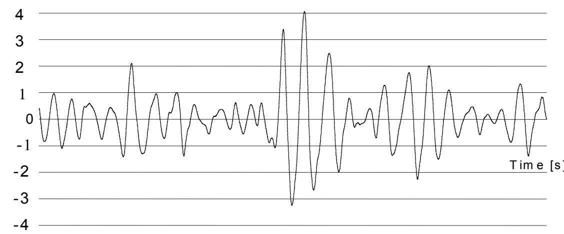


Figure 2: Schematic diagrams to determine possible trigger level values across a VA loading

is used to quantify the overall energy content of the oscillatory signal, and the kurtosis is used as a measure of non-gaussianity since it is highly sensitive to outlying data among the instantaneous values. Mathematically, r.m.s. and kurtosis are defined by following equations

$$\text{root-mean-square, } r.m.s. = \left\{ \frac{1}{N} \sum_{j=1}^{N} x_j^2 \right\}^{1/2} \tag{4}$$

$$\text{kurtosis, } K = \frac{1}{N(r.m.s.)^4} \sum_{j=1}^{N} (x_j - \bar{x})^4 \tag{5}$$

where x_j is the instantaneous value, N is the number of points and $\bar{x}$ is the mean of the time history. At a later stage of WBE, the r.m.s. and kurtosis values of the mission signal are compared to those of the original signal. If the statistics exceed the required difference, the trigger levels are reduced by a user specified step until the statistical values achieve the user-specified tolerance.

After all bumps are identified in the wavelet groups, a method of searching the bump start and finish points from the original time history has been introduced. If a bump event is found in any of the wavelet groups, a block of data covering the time frame of the bump feature is extracted from the original data set. This data selection strategy, which is shown in Figure 3, retains the amplitude and phase relationships of the original signal. The final process in the WBE processing is to produce a mission signal, for which the extracted bump segments are joined together to be a single loading.

The complete WBE algorithm is shown in Figure 4, showing three main stages in this algorithm, i.e. the wavelet decomposition process, the identification and extraction of the fatigue damaging events, and the production of a shortened loading, or also known a mission signal. The decision stage of this flowchart or WBE processing is to determine and optimise the trigger level (*are the trigger values optimal for bump identification?)* for bump identification and extraction. This is the key point or the central focus of this WBE processing, which is the main subject of this paper. In this stage, the parameter of r.m.s. (Equation (4)) and kurtosis (Equation (5)) are needed for the bump extraction checking process. If all the extracted bumps fulfilled the requirement set in the WBE processing, therefore, the optimum shortened loading can then be produced.

In summary of this section, the WBE algorithm is able to identify and extract fatigue damaging events from variable amplitude fatigue loadings, so as to produce a shortened mission signal which preserves the original load sequences. The WBE algorithm is the first fatigue data editing technique that has been developed using the orthogonal wavelet transform. In this research, the 12^{th} order Daubechies wavelet was chosen due to its successful application in previous studies involving automotive road data (Giacomin *et al.* 1999; 2000; 2001; Steinwolf *et al.* 2002; Abdullah *et al.* 2004).

In relation to the study of fatigue life assessment of a metallic component, the WBE produces a shortened loading which have an equivalent fatigue damage t the original variable amplitude fatigue loading. This shortened loading is suitable for the simulation or experimental testing of any

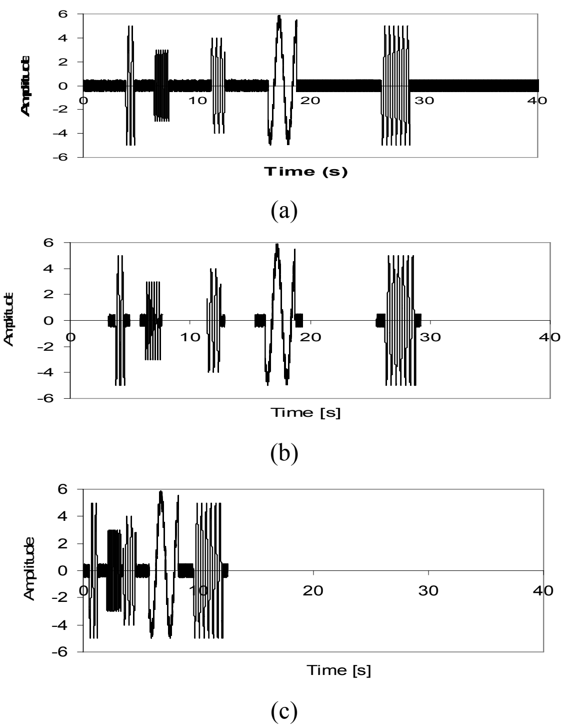


Figure 3: Data processes in WBE: (a) The original signal, (b) The extracted bump segments, (c) The mission signal.

structures or materials where cycle sequence effects may play a prominent role in the overall fatigue life. WBE is thus an appropriate algorithm for use when accelerated (time shortened) laboratory fatigue tests are desired. The objective of this accelerated testing is to expose the component or the complete automobile to a test loading which is much shorter than the target loading, but which has approximately the same damage potential.

4 Case Study: Using Road Spectrum Loadings for the WBE Application

The accuracy of the fatigue damaging event identification process was evaluated by the application of two VA fatigue loadings that were measured on vehicle suspension arms. These are strain data which were measured by means of the microstrain unit. Figure 5 shows the schematic geometry of a lower suspension arm, indicating the strain gauge location for the data measurement.

The first signal, named T1, is a strain signal which

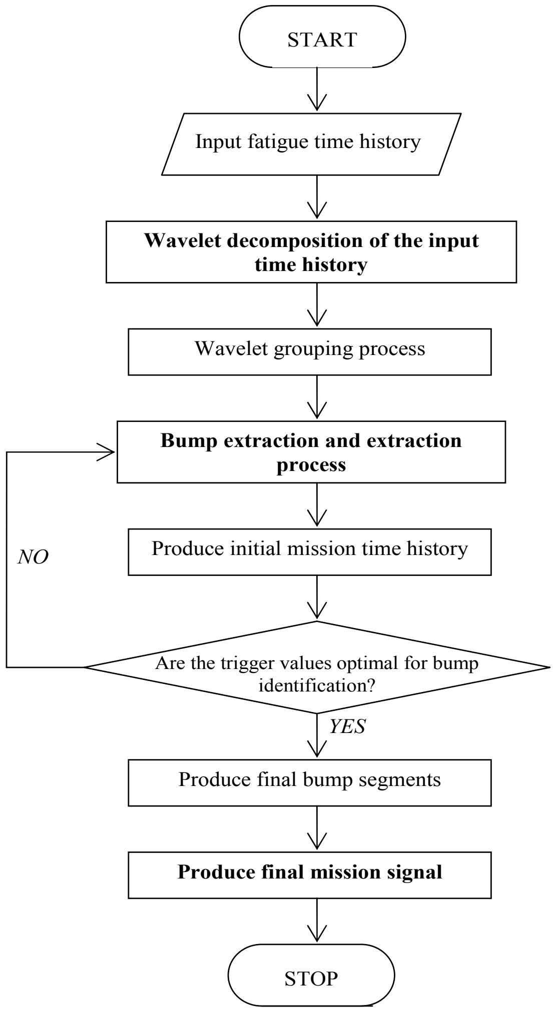


Figure 4: Flowchart of the WBE algorithm

was measured on a lower suspension arm of a van travelling at 34 km/h over a pavé test track. T1 was sampled at 500 Hz for a total of 23,000 data points, producing a record length of 46 seconds. This signal exhibits a slight change in mean of the whole signal with a little low frequency content. This data set was chosen because it contained many small amplitude and high frequency bumps in the signal background. The time history and the PSD distribution of this signal are presented in Figure 6a.

The second signal, T2 (Figure 6b), contains 12,500 data points and was sampled at 204.8 Hz, producing a record length of 61 seconds. This signal was measured on a front suspension compo-

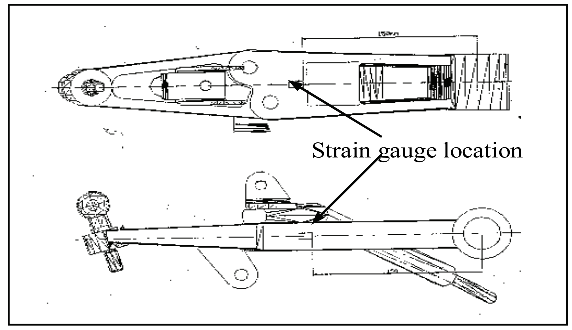


Figure 5: A schematic diagram of a lower suspension arm for signal measurements

nent of an automobile while travelling over proving ground manoeuvres, containing rough road surface. This signal, which was taken from the database of Society of Automotive Engineers Fatigue Design Evaluation (SAEFDE) committee and has previously been used in fatigue signal reconstruction (Leser *et al.* 1998), exhibits a low frequency background containing occasional shocks. Table 1 shows the statistical signal properties for the T1 and T2 signals.

Table 1: Global statistical parameters of two variable amplitude loadings used in this study.

Signal Name	T1	T2
No. of data points	23,000	12,500
Signal length [s]	46.0	61.0
Mean [$\mu\varepsilon$]	15.0	205.5
r.m.s. [$\mu\varepsilon$]	16.7	235.5
Skewness	-0.1	0.5
Kurtosis	3.4	2.6

5 Results and Discussions

5.1 Fatigue Data Editing Application

Using the WBE algorithm T1 was decomposed into 15 wavelet levels and the levels were then assembled into four wavelet groups. The wavelet coefficients from the wavelet levels were used to construct a time history of the respective wavelet group, as illustrated in Figure 7. Referring to the PSD plots in Figure 7, the resonance peaks of this signal were found at four different frequencies, i.e. 1.4 Hz, 2.7 Hz, 11.7 Hz and 35.9 Hz, suggesting the T1 signal can be divided into four wavelet groups. The location of fatigue damaging events or bumps present in each wavelet group is shown in Figure 8, for which the individual bumps in each wavelet group are identified within the $\pm 10\%$ r.m.s. and kurtosis difference between the original and mission signals. The difference value of $\pm 10\%$ was used with a consideration of at least 10% of the original road data contained low amplitudes which gave minimal fatigue damage.

For T2, the original data set was decomposed into 14 wavelet levels and the levels were clustered into two wavelet groups for which their time histories are shown in Figure 9. Referring to the respective PSD plot of T2, resonance peaks were found at two frequencies, i.e. 0.1 Hz and 1.4 Hz, giving two wavelet groups can be formed. The individual bumps which were identified in each wavelet group at the $\pm 10\%$ in the global statistical difference are shown in Figure 10.

For both data sets, the extracted bumps from all wavelet groups were used for identifying the start and finish points of the respective bump segments. Figure 11a for T1 and Figure 12a for T2 show all bump segments at their original time position in the original signals time scale. Nine segments of fatigue damaging events were extracted from T1 and two segments from T2. The mission signals of T1 and T2 are shown in Figure 11b and Figure 12b. By comparing the bump segments for both signals, it can be seen that the low frequency content of the spectrum loading has an important role to determine the overall length of the bump segments and the mission signal.

Referring to Figure 11 and Figure 12, the bump segments of T2 had longer time extent compared to the bump segments of T1. From these findings, it is not easy to heavily compress VA fatigue loadings with a substantial low frequency content (such as signal T2) because most of the mission time length was caused by a single bump from the low frequency wavelet group. Since the T1 signal was measured on a pavé test track surface, a higher compression factor (more than 50% of the time length) is obtainable to produce the mission signal.

5.2 Validating the WBE Algorithm Using the Fatigue Life Prediction

In order to have efficiency in the extraction of the bump segments, the WBE algorithm need to be validated in terms of bump segments fatigue life prediction approach. The three strain-life models, Equation (1) to (3), are used for this kind of analysis. However, some parameters related to these models need to be determined using the experimental data set for a specific material. Data from experiments performed by Abdullah *et al.* (2006) were used for this purpose, for which BS 080A42 steels were the test samples. This material was chosen because of its use in the fabrication of the suspension components of passenger cars. For the purpose of the laboratory fatigue tests, specimens were manufactured as an hourglass profile round bar for tension-compression loading (ASTM E606-92-1998). The tensile test data was used to determine monotonic mechanical properties as listed in Table 2. On the other hand, uniaxial constant amplitude (CA) loading fatigue tests were used to determine cyclic mechanical properties of BS 080A42 steel, as also tabulated in Table 2.

The material properties of the BS 080A42 steel (listed in Table 2) were used to define the expression of strain-life fatigue damage models of the BS 080A42 steel. Thus, the complete Coffin-Manson relationship for this material, which is based on the parameter in Table 2, is defined by

$$\varepsilon_a = \frac{1505}{210000}(2N_f)^{-0.144} + 0.176(2N_f)^{-0.400} \quad (6)$$

The Morrow and SWT model for the BS 080A42 steel are then defined as in Equation (7) and (8), respectively:

$$\varepsilon_a = \frac{1505}{210000}\left(1 - \frac{\sigma_m}{\sigma'_f}\right)(2N_f)^{-0.144} + 0.176(2N_f)^{-0.400} \quad (7)$$

$$\sigma_{\max}\varepsilon_a = \frac{(1505)^2}{210000}(2N_f)^{2(-0.144)} + (1505)(0.176)(2N_f)^{-(0.144+0.400)} \quad (8)$$

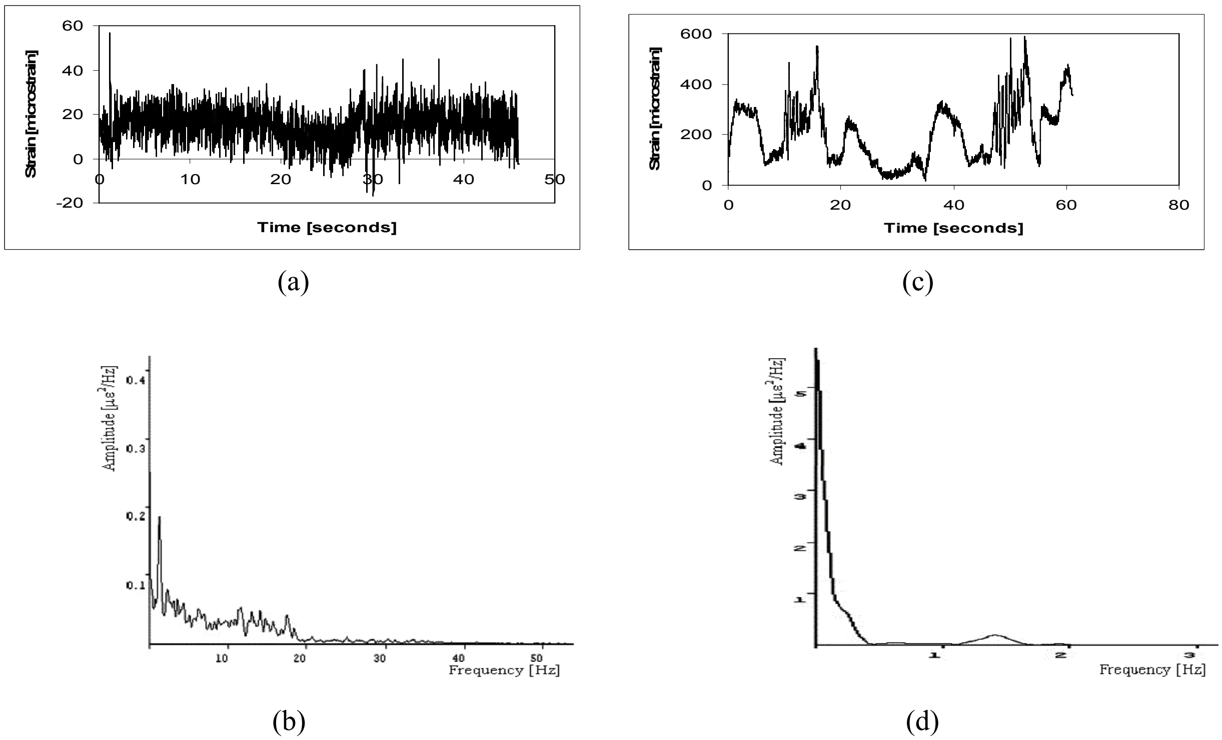


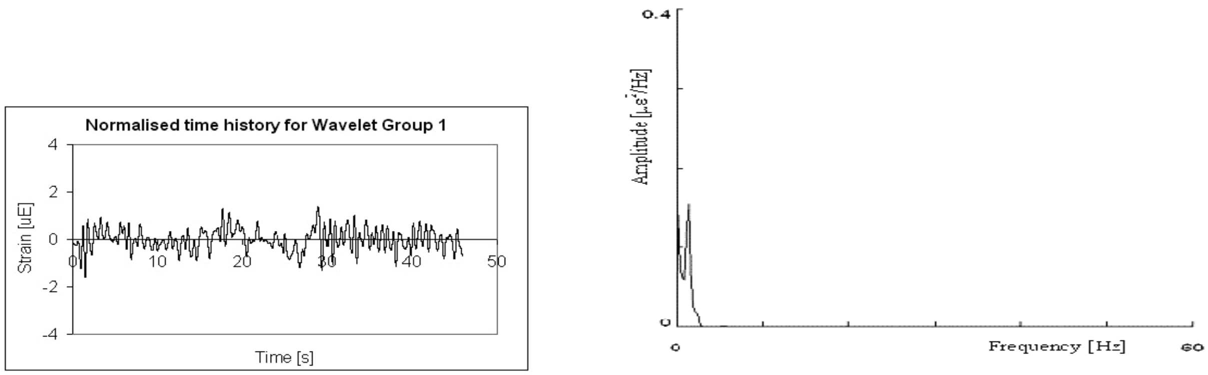
Figure 6: Plot of the signals used for this study: (a) Time history for T1, (b) PSD for T1, (c) Time history for T2, (d) PSD for T2

Table 2: Monotonic and cyclic mechanical properties of the BS 080A42 steel (Abdullah *et al.*-2006).

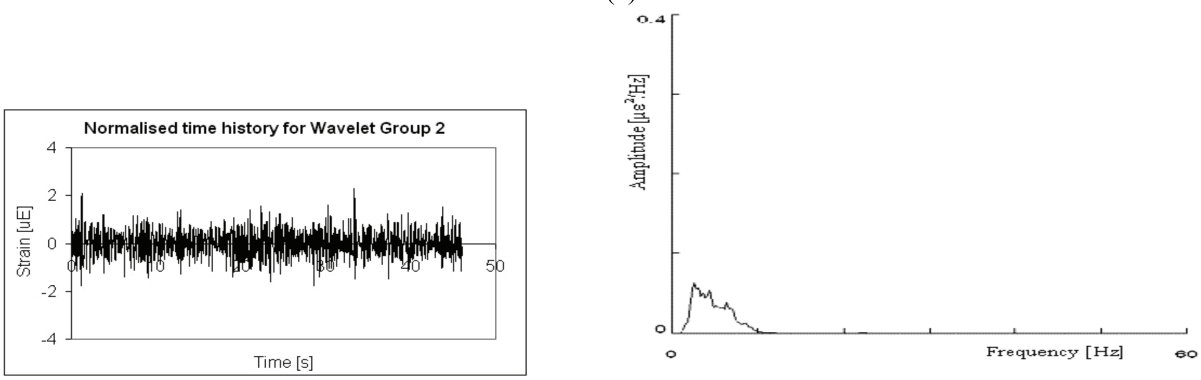
Monotonic Mechanical Properties	
Ultimate tensile strength, S_u [MPa]	624
Modulus of elasticity, E [GPa]	210
Static yield stress 0.2%, S_y [MPa]	342
Reduction in area, (%)	51.9
Elongation (%)	28.4
Cyclic Mechanical Properties	
Strain hardening exponent, n'	0.36
Material constant, H'[MPa]	2818
Fatigue strength coefficient, σ'_f [MPa]	1505
Fatigue strength exponent, b	-0.144
Fatigue ductility coefficient, ε'_f	0.176
Fatigue ductility exponent, c	-0.400

The fatigue lives of the T1 and T2 signals together with their bump segments are calculated using three strain-life models, i.e. Equation (6) to (8), and the results are listed in Table 3. The fatigue damage values can also be obtained from the values in Table 3 by inverting the value of the fatigue life. The fatigue damage value of all bump segments (for a particular signal) were then summed in order to obtain the total fatigue damage for all bump segments, notated as BT1 for T1 and BT2 for T2, respectively. Figure 13 shows the level of fatigue life in the logarithm scale for all the loadings used in this analysis. In this figure, B1 to B9 denoted as the number of extracted bump segments (refer to Figure 11a and 12a).

Using a statistical scatter of fatigue life based on



(a)



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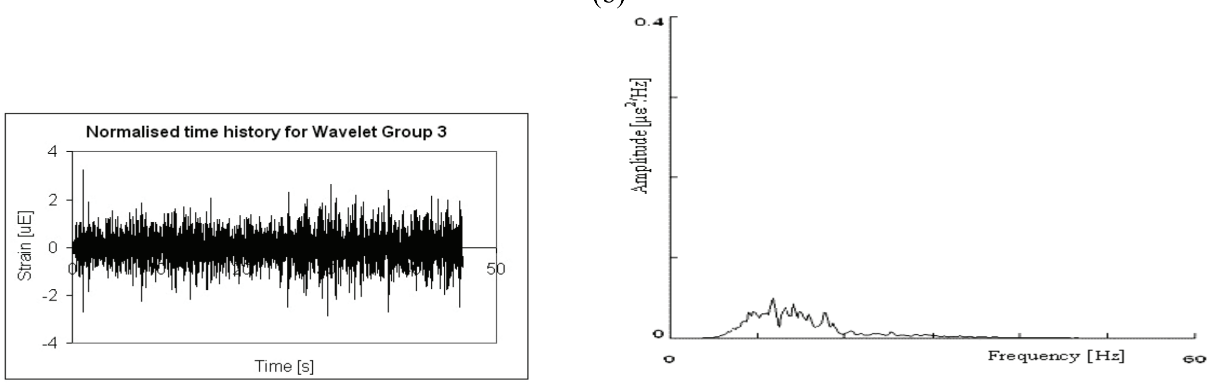
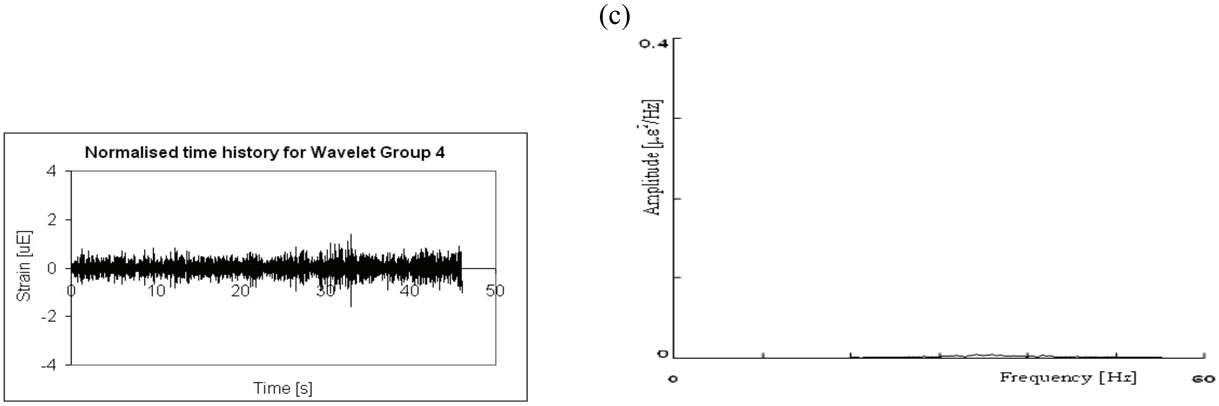


(c)



(d)

Figure 7: The wavelet group time histories and the PSD plots for T1: (a) Wavelet Group 1, (b) Wavelet Group 2, (c) Wavelet Group 3, (d) Wavelet Group 4.

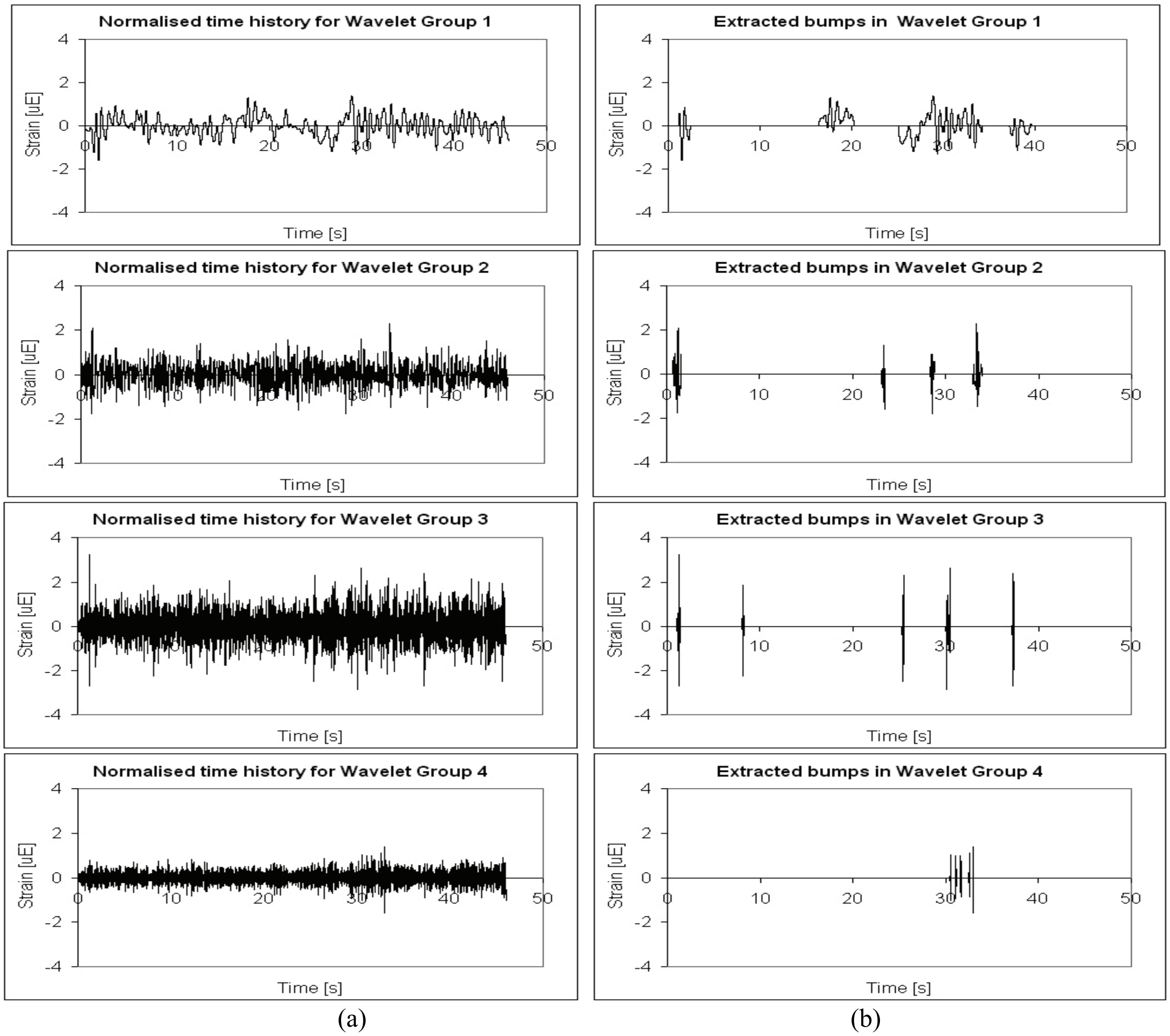
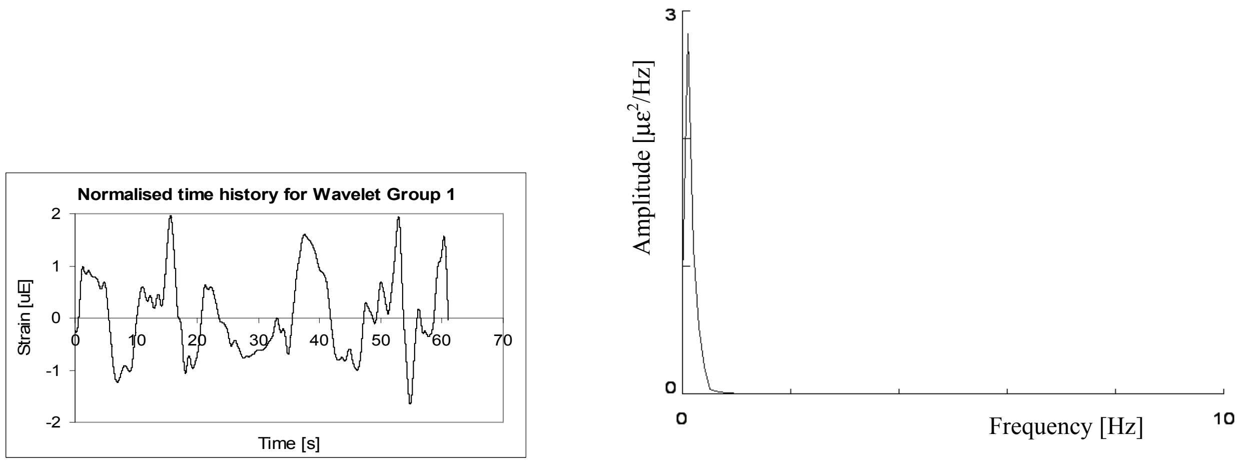


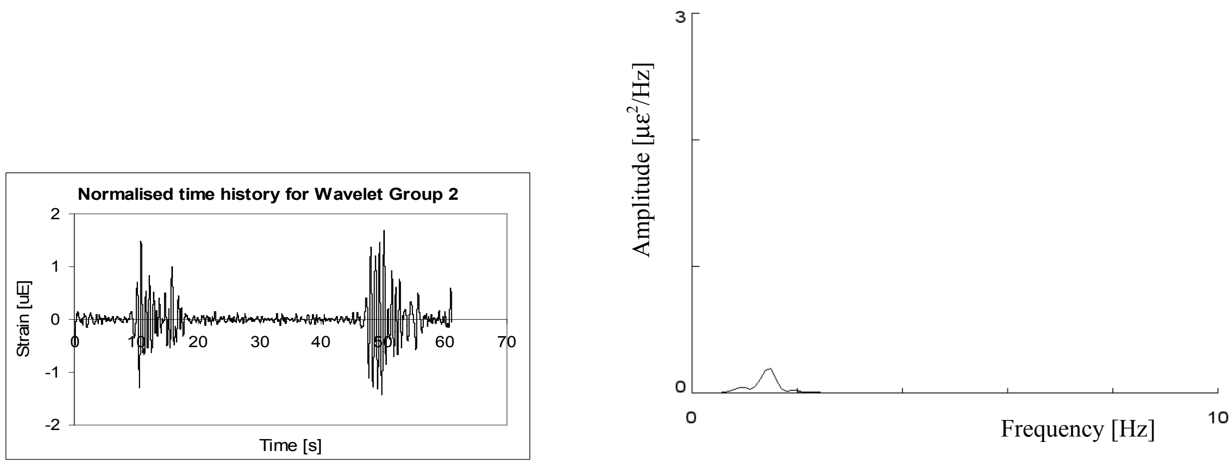
Figure 8: Identification of the individual bumps in the wavelet groups of T1: (a) Normalised time history for all wavelet groups, (b) Location of bumps in the wavelet groups.

Gaussian distribution, a skewed distribution usually occurs. Although the life distribution curve does not conform to Gaussian distribution, in many cases the logarithm of the fatigue life distribution or logarithm-normal distribution is a good estimation (Dowling 2006). Based on this argument, it is good to see the value of the fatigue life in the logarithm format. It is due to have accuracy in fatigue life comparison between the original signal and the total of bump segments. The results of this analysis were presented in Table 4. In this table, it is showed that the differences of 5.83 to 8.29% were found between the fatigue lives of the T1 original signal and the respective total bump segments or BT1. In addition, smaller difference values were found for similar comparison using the T2 signal, i.e. 1.82 to 2.42%. Small differences of fatigue lives between the original signal and total bump segments showed a close correspondence was obtained, suggesting the suitability of WBE to be used for extracting the fatigue damaging events from VA fatigue time histories.

Figure 14 presents the fatigue life correlation between the total of bump segments and the original signals, and the plot is meant for both signals. For this case, the fatigue lives was calcu-



(a)

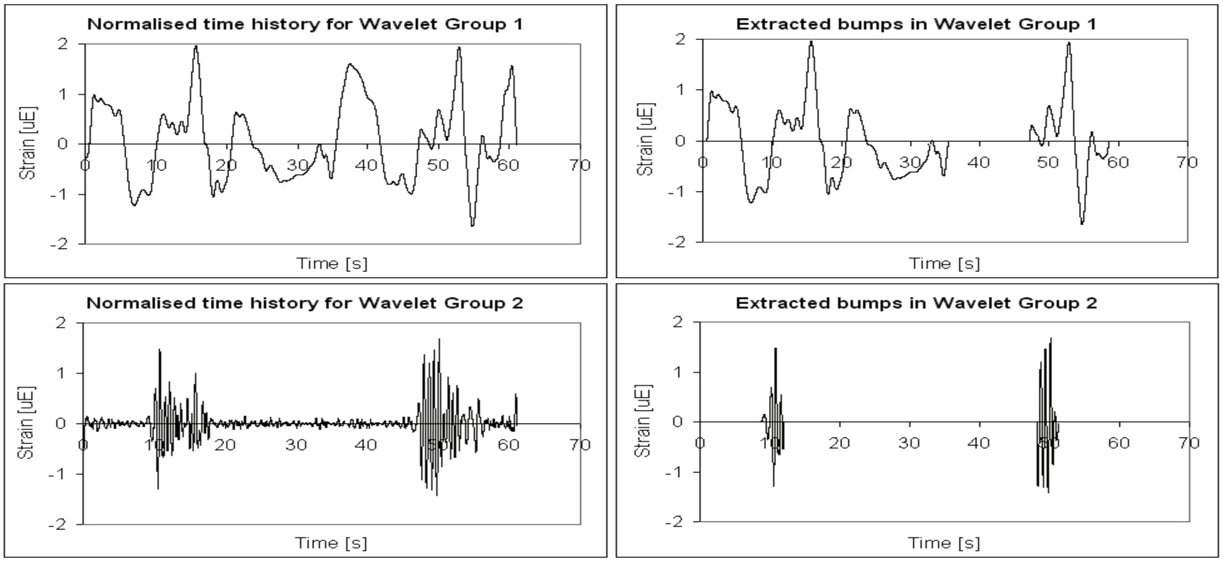


(b)

Figure 9: The wavelet group time histories and the PSD plots for T2: (a) Wavelet Group 1, (b) Wavelet Group 2.

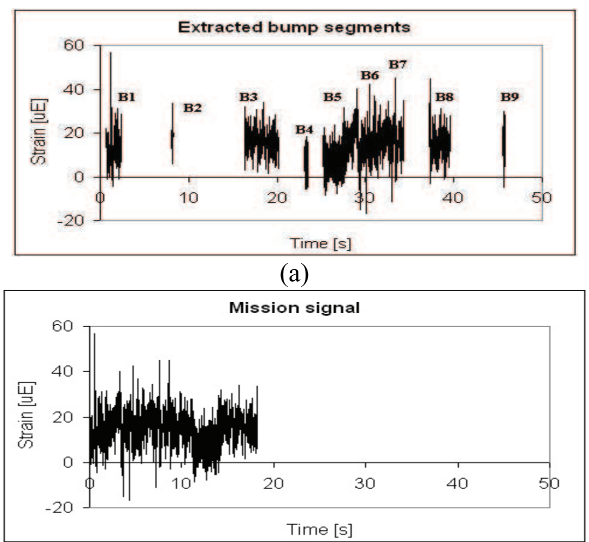
lated based on three identified strain-life models, i.e. Coffin-Manson, Morrow and SWT. In the figure each data point represents a loading condition from Table 4, represented as the logarithm scale of the fatigue life. In this figure, the relationship is distributed near the 1:1 correlation line and within $\pm$ a factor of 2, suggesting the closeness of the total of bump segments fatigue life to the original signal. In the field of fatigue life prediction, estimates within $\pm$ a factor of 2 with respect to the true fatigue life are commonly encountered and often considered acceptable. For both T1 and T2, the coefficient of variation (R^2) between the fatigue lives of the original and the total of bump segments was found to be 99.9% or 0.999 (see Figure 14). The results suggested that a very close correspondence was found between the original signal and all the WBE extracted fatigue damaging events.

From the results and related analysis of this section, it is noticed that most of the fatigue damaging events were identified and extracted using the WBE algorithm. These damaging features contribute the majority of fatigue damage in VA loadings, thus it is important to extract and retain them for further analysis in fatigue data editing purposes. Finally, it is suggested that WBE is a suitable algorithm for the fatigue data editing in automotive durability research by means of accelerated fatigue tests.



(a) (b)

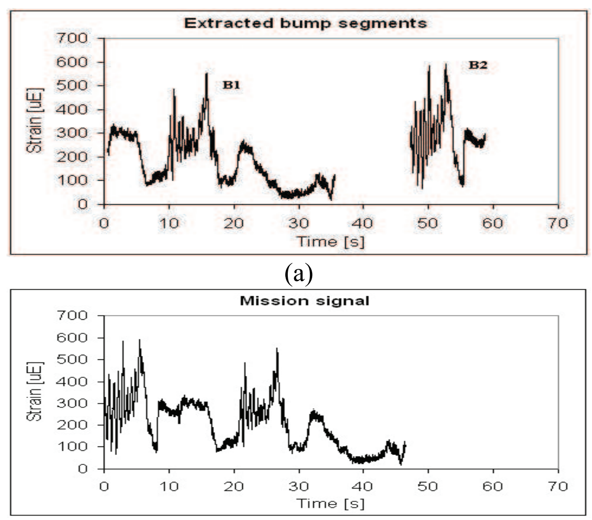
Figure 10: Identification of the individual bumps in the wavelet groups of T2: (a) Normalised time history for all wavelet groups, (b) Location of bumps in the wavelet groups.



(a)

(b)

Figure 11: Results for T1: (a) The extracted bump segments (in original scale) at their original location of the original signal, (b) The mission signal.



(a)

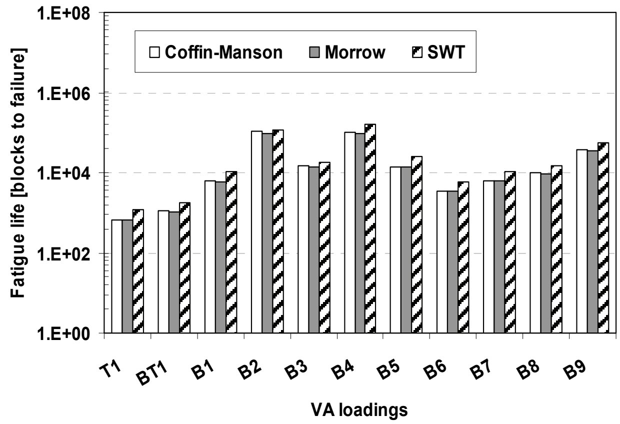
(b)

Figure 12: Results for T2: (a) The extracted bump segments (in original scale) at their original location of the original signal, (b) The mission signal.

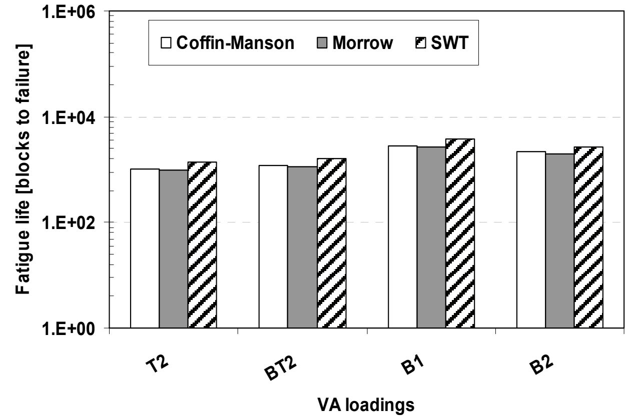
6 Conclusion

Wavelet Bump Extraction (WBE) is an algorithm which is able to identify the important fatigue damaging events or bumps, and to extract them from the original time history, whilst preserving their sequences of load cycles. Using the WBE procedure the total damage produced by the combination of the extracted fatigue damaging events was close to that of the original data set.

In the WBE application, the individual bumps in each wavelet group are identified within the $\pm 10\%$ r.m.s. and kurtosis difference between the original and mission signals. For the study pre-



(a) The T1 signal



(b) The T2 signal

Figure 13: Predicted fatigue lives distribution of the VA loadings using three strain-life models. BT* (BT1 for T1; BT2 for T2) and B1-B9 denoted as total of bump segments and number of bump segments, respectively.

Table 3: Calculated fatigue lives of the original and the WBE extracted loadings.

VA loadings	Fatigue Life, N_f [Number of blocks to failure]		
	Coffin-Manson	Morrow	SWT
T1			
B1	6214	5964	10462
B2	107000	97000	114000
B3	15199	14008	17720
B4	101000	96400	163000
B5	14287	13708	24566
B6	3569	3428	6070
B7	6512	6216	10409
B8	9890	9370	14783
B9	37811	35667	55200
BT1	1140	1087	1805
T1	665	642	1194
T2			
B1	2789	2629	3831
B2	2145	2005	2721
BT2	1212	1138	1591
T2	1025	965	1395

sented in this paper, nine bump segments were extracted from the T1 signal and two bump segments for T2. In the bump identification and extraction process, it can be seen that the low frequency content of the road load data has an important role in determining the overall length of the bump segments. Thus, it is not easy to heavily compress VA fatigue loadings with a substantial low frequency content (such as T2) because of the low frequency factor.

The differences in fatigue life between the original signal and the total bump segments results were found to be at 5.83-8.29% for T1 and 1.82-2.42% for T2. Small difference values showed that the closeness between the two. Based on

Table 4: Using logarithm-normal distribution approach to represent the analysis of fatigue life values

VA loadings	Coffin-Manson		Morrow		SWT	
	Fatigue life in normal distribution [blocks to failure]	Fatigue life in logarithm distribution	Fatigue life in normal distribution [blocks to failure]	Fatigue life in logarithm distribution	Fatigue life in normal distribution [blocks to failure]	Fatigue life in logarithm distribution
BT1	1140	3.06	1087	3.04	1805	3.26
T1	665	2.82	642	2.81	1194	3.08
*Diff-T1 [%] in log-scale	8.29		8.15		5.83	
BT2	1212	3.08	1138	3.06	1591	3.20
T2	1025	3.01	965	2.98	1395	3.14
#Diff-T2 [%] in log-scale	2.42		2.40		1.82	

* Diff-T1 [%] = | {(fatigue life of T1 - fatigue life of BT1)/(fatigue life of T1)} $\times$ 100 |
# Diff-T2 [%] = | {(fatigue life of T2 - fatigue life of BT2)/(fatigue life of T2)} $\times$ 100 |

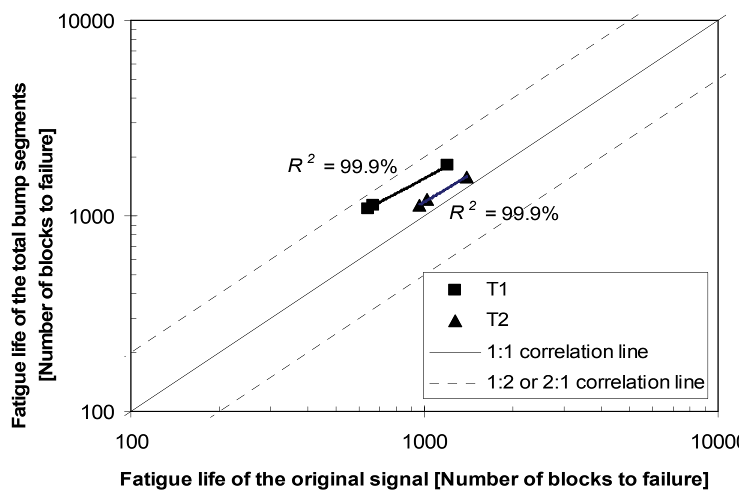


Figure 14: Correlation between the fatigue life of the total bump segments and the original signal of both T1 and T2.

these results, WBE appears to be a suitable wavelet-based approach for identifying fatigue damaging events and to produce a mission signal. Since the original fatigue damage is retained in the mission signal, therefore it is suitable for accelerated fatigue testing.

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