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The Wavelet Transform for Fatigue History Editing: Is it Applicable for Automotive Applications?

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Abstract: The actual road load time histories which were experimentally measured on a automotive component contains variable amplitude patterns, having a mixture of low and high amplitudes cycles. In terms of fatigue damage characterization, these low amplitude cycles have little or no effects to the failure of metallic components. Due to the importance of high amplitude events in the fatigue time histories, it shows an interest to explore a fatigue data compression technique (or also known as fatigue history editing) using a signal processing approach. Several computational algorithm of the fatigue data editing have been previously developed. Instead of these, the author used the time-frequency (or wavelet) approach in developing an alternative solution and it is called Wavelet Bump Extraction (WBE). For the scope of this study, the discussion will focus on the applicability of WBE using variable loadings.

Key words: Bump, data editing, fatigue, variable amplitude loading, wavelet

INTRODUCTION

In fatigue research, accelerated fatigue testing is often accomplished by correlating the fatigue damage produced by specific test tracks with the damage produced by public roads. Severe and short duration of time histories are seldom used instead of longer public roads. In a durability laboratory, testing is often further accelerated by use of a fatigue history editing technique which retains high amplitude cycles that produce the majority of damage. The need to reduce development time with the improvement in the durability analysis leads to an interest of investigating the issue of fatigue data compression.

A fatigue history editing method using a Variable Amplitude (VA) strain time history is used to produce a shortened loading for the accelerated fatigue tests. For this situation both original and shortened loadings have equivalent fatigue damage potential. This 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. Without editing the service load, the testing time and cost become prohibitive.

Considering to the importance of the fatigue history editing for VA loadings, hence, the objective of this paper is to discuss the suitability of the wavelet-based fatigue data editing algorithm for automotive applications. In addition, the information contained in this study is also important in order to give the general insight of the verification of this algorithm effectiveness for shortening variable amplitude fatigue loadings.

Data editing approaches for accelerated fatigue tests: Durability analysis requires knowledge of service loads since these loads are used for the laboratory testing of the component (Goswani, 1997). The purpose of laboratory accelerated fatigue 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.

Three techniques were previously used to accelerate laboratory fatigue testing (Frost *et al.*, 1974): to increase the frequency of the cyclic loading; to increase the load level; and to remove small amplitude cycles from the time history.

For the first approach, increasing the frequency of the cyclic loading is an alternative solution to perform accelerated fatigue tests. In the second approach, automobile manufacturers tend to increase load levels by scaling up the service load by a constant value. The final approach is to remove small amplitude cycles from the original measured time histories. Such a technique is known as fatigue history editing (or also called fatigue data editing). This method is described as a method for omitting the small amplitude cycles that caused a minimal contribution to the fatigue damage (high amplitude cycles which are the most damaging sections are retained).

Earlier fatigue history editing research was performed (Conel and Topper, 1979) with the small cycle omission procedure using strain loading. A similar technique was also performed Conel and Topper, 1980) to edit VA loading but using lower overall strain levels in order to omit smaller cycles. A related study (Healer and Jeeger, 1986) using the aircraft service loading showed the small cycles were omitted from the original loading according to the fatigue limit criteria.

The fatigue data editing analysis involving the concept of PV reversals conducted by Stephens *et al.* (1997). In these studies, the Society of Automotive Engineers Fatigue Design and Evaluation (SAEFDE) committee Log Skidder Bending (LSB) loading was selected due to a large number of small cycles in the total record length. The combination of strain amplitude and mean obtained from the formulation of the Smith-Watson-Topper (SWT) strain-life model was used in order to produce an omission level to remove the small cycles. Research by El-Ratal *et al.* (2002) discussed the application of time correlated damage analysis for time domain fatigue data editing by using the nSoft® software package. Using this approach, the analysed VA loading that was measured from automobile suspension was divided into many small windows and the fatigue damage for each window was calculated.

The application of the time-frequency domain by means of the wavelet transform was rarely used for the fatigue studies. This approach was initially performed by Oh (2001) using a VA loading measured on a light railway train component and by Abdullah *et al.* (2004) using the signals measured on a lower suspension arm. A recent wavelet-based fatigue history editing algorithm was developed by (Abdullah *et al.* 2003, 2006), called Wavelet Bump Extraction (WBE). This new algorithm exhibits interesting outcomes in shortening variable amplitude fatigue strain loadings. Extensive studies will then be needed in order to prove the suitability of this algorithm for automotive applications.

In general, different VA loadings have been used for all those techniques discussed. There seem to be no generally agreed rules that clarify which method is the best, or what amplitude should be chosen for load omission (Wang and Chen, 1999; Yan *et al.*, 2001) Practically, any fatigue data editing technique must reduce the testing period and be technically valid.

Approaches in the wavelet-based fatigue data editing: The Wavelet Bump Extraction (WBE) algorithm is a computational method and it was developed using the FORTRAN programming language. Since the application of the wavelet transforms was found to be a potential approach in the fatigue history editing research, the use of a uniaxial VA fatigue loading is essential at earlier stage of this research. This is an important aspect to investigate the effectiveness of WBE to edit different VA loading patterns.

Many experimental signals exhibit time-varying, or nonstationary characteristics, which provide a challenge in signal analysis. Traditional approach for the frequency domain analysis of the time series was performed using the Fourier transform. However, this kind of analysis is not suitable for nonstationary signal, as it cannot provide any information of the spectrum changes with respect to time (Newland, 1993). Realising the limitation of the Fourier transform for nonstationary signals, therefore the wavelet transform is more suitable. The wavelet transforms is a function in the time-scale domain and it is a suitable tool for presenting local features of a signal. The wavelet transform gives a separation of components of a signal that overlap in both time and frequency. Using wavelet, the time and frequency of an oscillating signal can be detected.

The WBE algorithm uses the 12th order (Daubechies, 1992) wavelets as the basis functions. 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. A wavelet grouping stage, which is based on the Power Spectral Density (PSD) plot, permits the user to cluster wavelet levels into a single region of signal vibrational energy. Figure 1 shows an artificial signal containing a mixed of sinusoidal and random pattern and the PSD plot

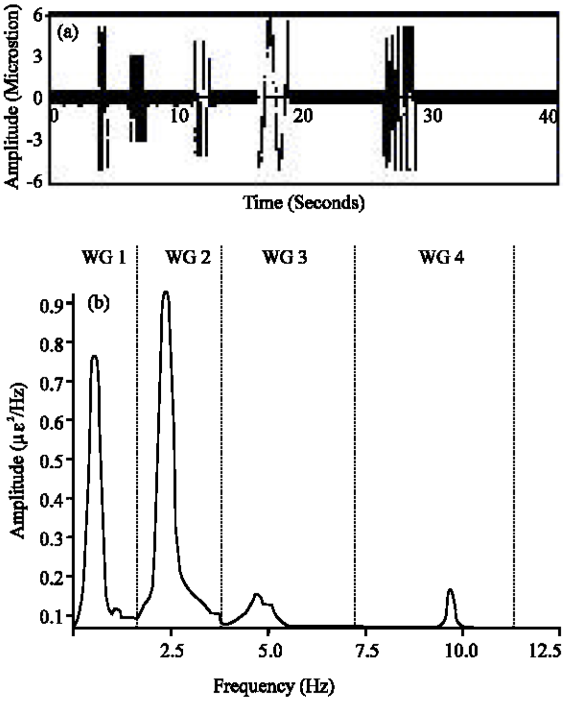


Fig. 1: An artificial signal: (a) The time history, (b) The PSD plot showing four wavelet groups

which indicates four significance energy groups with clear resonance peak. This group is called a wavelet group. In (Fig. 1b), the notation of WG1 to WG4 is Wavelet Group 1 to Wavelet Group 4, respectively. It is showed that a lower number of wavelet group containing lower frequency content of a signal.

A bump is defined as an oscillatory transient with a monotonic decay envelope either side of a peak value (illustrated in Fig. 2). A bump can also be defined as a fatigue feature that contribute to the fatigue damaging effects to components.

Statistically, a bump section in a fatigue time history should have higher vibrational energy or root-mean-square (r.m.s.) value, as well as higher range of the time history or the kurtosis value. The r.m.s. 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, the r.m.s. and kurtosis values are defined by the following equations

$$\text{r.m.s.} = \left\{ \frac{1}{N} \sum_{j=1}^{N} x_j^2 \right\}^{1/2} \tag{1}$$

$$\text{Kurtosis} = \frac{1}{N(\text{r.m.s.})^4} \sum_{j=1}^{N} \left(x_j - \bar{x} \right)^4 \tag{2}$$

where x_j is the instantaneous value, N is the number of points and $\bar{x}$ is the mean of the time history.

In this algorithm, these fatigue features are identified in each wavelet group by means of an automatic trigger level of the strain amplitude. For this case, these trigger levels were determined by comparing the global signal statistics (r.m.s. and kurtosis) values between the original and the WBE shortened loadings. The difference of ±10% in the r.m.s. and kurtosis values was used with a consideration of about 10% of the original road data contained low amplitudes.

After all bumps are identified, a method of searching the bump start and finish points from the original time history has been introduced. This data selection strategy, which is shown in the schematic diagram of (Fig. 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, as schematically illustrated in (Fig. 3 and 4).

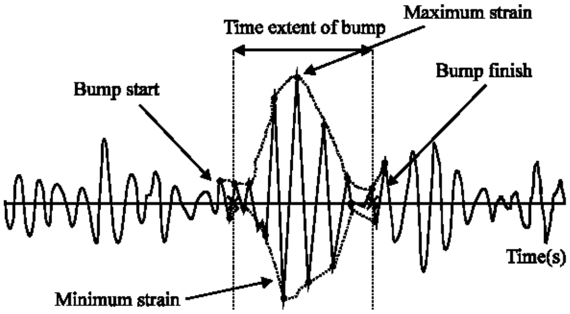


Fig. 2: Schematic diagrams of a decay enveloping process to determine a bump in a wavelet group

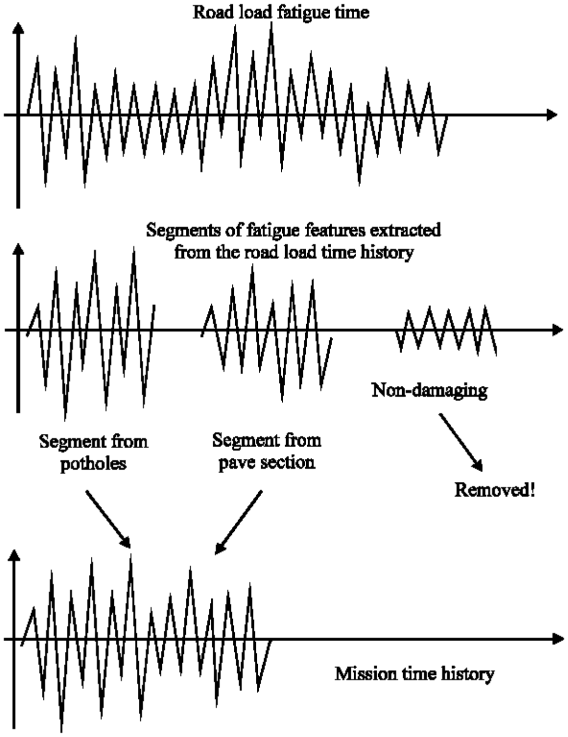


Fig. 3: Schematic diagram of data selection strategy

The processing of wavelet-based fatigue data editing: The accuracy of the fatigue damaging event identification process was evaluated by the application to two VA strain histories that were measured on different vehicle lower suspension arms. Both vehicle types were were driven on different road surfaces. The first signal, named *pavé signal*, was measured on a van while driven over a pavé test track. T1 was sampled at 500 Hz with a record length of 46 seconds. The second signal, *manoeuvres signal*, was measured on a suspension arm of an automobile driven through proving ground manoeuvres. This loading contains a low frequency background with

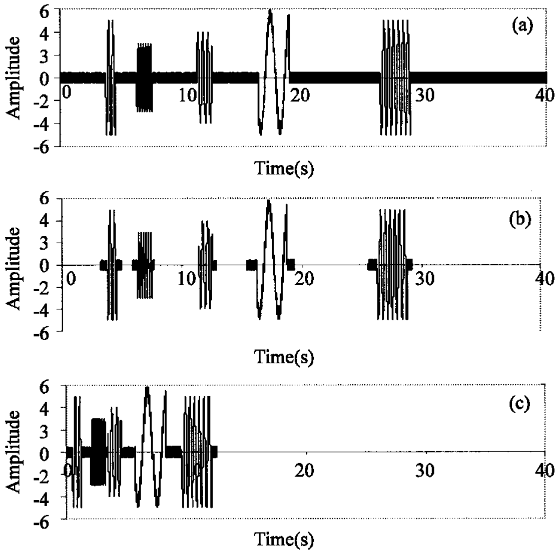


Fig. 4: Data processes in WBE using an artificial variable amplitude loading: (a) The original loading, (b) The extracted bump segments, (c) The WBE shortened loading

the sampling frequency at 204.8 Hz and its time length is 61 seconds. Figure 5 presents the time history and the PSD plots of the *pavé signal*. The plots for the *manoeuvres signal* is shown in (Fig. 6). Both data sets have been selected due to their characteristics that gave more fatigue damage to automotive components.

Using the WBE algorithm the *pavé signal* was decomposed into 15 wavelet levels and these levels were assembled into four wavelet groups. The wavelet coefficients from these levels were used to construct time history of wavelet groups, as illustrated in (Fig. 7a). In addition, the locations of fatigue damaging events or bumps present in each wavelet group is shown in (Fig. 7b). For the *manoeuvres signal*, the loading was decomposed into 12 wavelet levels and the levels were clustered into two wavelet groups (refer to Fig. 8a). The locations of fatigue damaging events in each wavelet group are shown in (Fig. 8b). For both cases, the individual bumps in each wavelet group were identified within ±10% r.m.s. and kurtosis difference between the original and the WBE shortened loadings.

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 7c for the *pavé signal* and (Fig. 8c) for the *manoeuvres signal* show all bump segments at their original time position with respect to the original loadings. Nine segments of fatigue damaging events were extracted from the *pavé signal* and two segments from the *manoeuvres signal*. The WBE shortened loadings were produced by adding the bump segments and they are shown in (Fig. 7d and 8d).

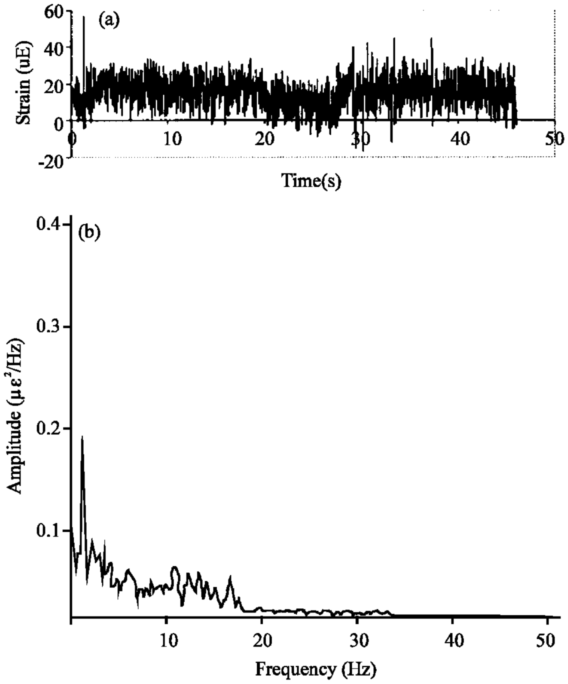


Fig. 5: Plots of the 46-seconds *pavé signal*: (a) Time history, (b) PSD

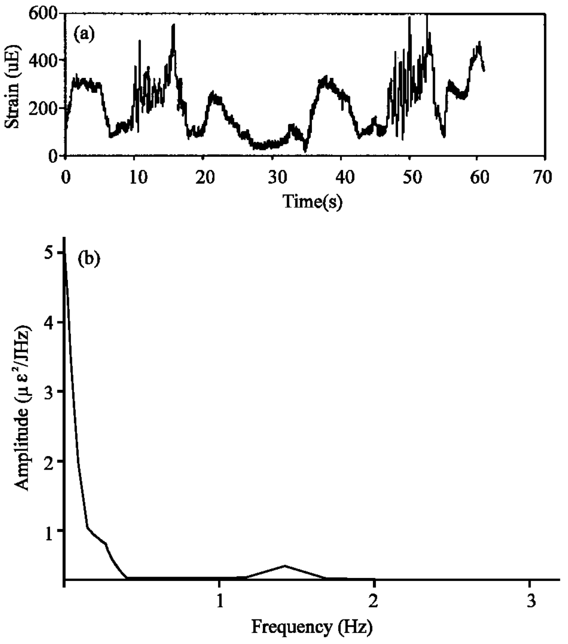


Fig. 6: Plots of the 61-seconds *manoeuvres signal*: (a) Time history, (b) PSD

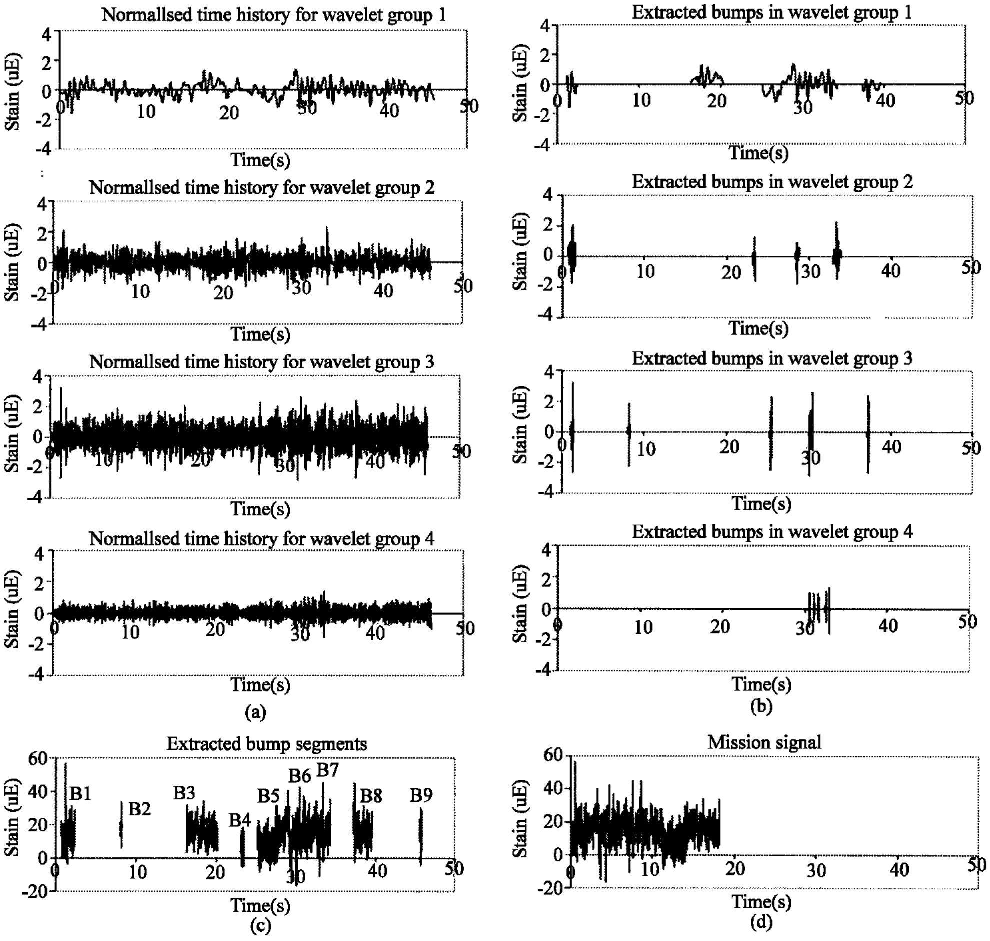


Fig. 7: Results for the *pavé signal* : (a) Normalised time history for all wavelet groups (b) Location of bumps in all wavelet groups, (c) The extracted bump segments (in original scale) at their original location of the input fatigue signal, (d) The 19-seconds mission signal

Is wbe applicable for automotive applications?: When applying WBE to both experimental loadings WBE was found to highly compress the pavé test track signal (refer to Fig. 7) but not for a low frequency content signal (refer to Fig. 8). In (Fig. 8), it can be seen that the low frequency content signal has an important role in determining the overall length of the bump segments. In (Fig. 8c), the time length of the first bump is 34.9 seconds and for the second bump is 11.5 seconds. The length of individual bump in Wavelet Group 1 produced the similar length of the bump segments, as illustrated in (Fig. 8b). The bump segments of the *manoeuvres signal* had longer time extent (46.4 seconds) compared to the *pavé signal.* Longer time length of the WBE shortened loading was caused by the difference value (in %) of the r.m.s. and kurtosis which were used to determine the trigger levels.

By comparing the bump segments for the two data sets, 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. Referring to (Fig. 7 and 8) the bump segments of the *manoeuvres signal* had longer time extent compared to the bump segments of the *pavé signal.* With WBE it is not easy to heavily compress VA fatigue loadings with a substantial low frequency content because most of the mission time length involves a single bump from a low frequency wavelet group. The result shows the difficulty of performing an automatic fatigue mission analysis based only on global signal statistics.

Figure 9 shows the PSD distribution of the original and WBE shortened loading. For both signal types, the PSD plots show the retention of frequency distribution of the original signals. The plots indicated that the pattern of the original vibrational signal energy was retained in the WBE shortened loading. All these conditions can also be seen from the overlapping pattern of the PSD curves for

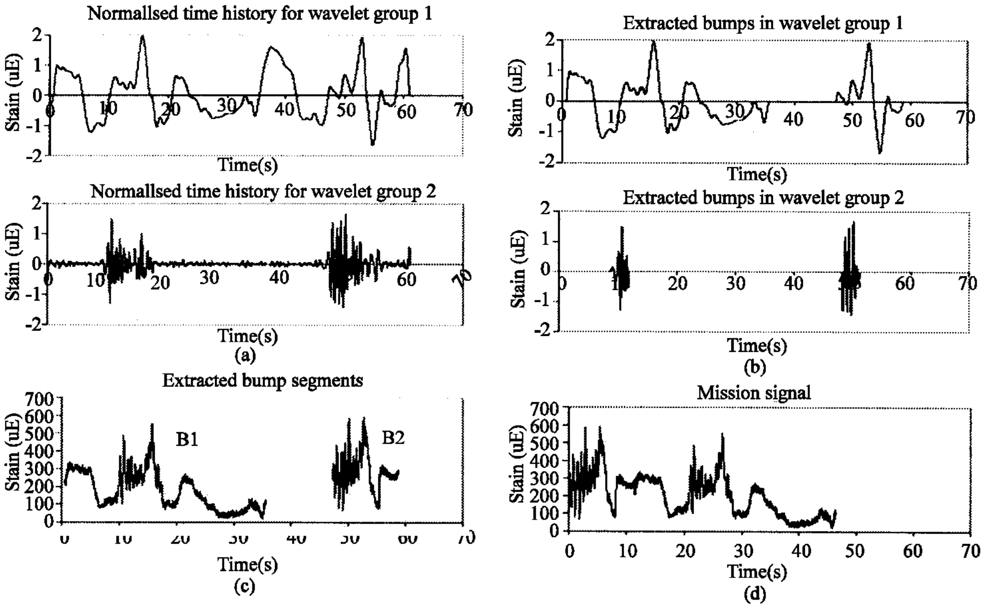


Fig. 8: Results for the *manoeuvres signal*: (a) Normalised time history for all wavelet groups (b) Location of bumps in all wavelet groups, (c) The extracted bump segments (in original scale) at their original location of the input fatigue signal, (d) The 46-seconds mission signal

both *pave* and *manoeuvres signals*. This is one of the advantages of the WBE algorithm, for which the original frequency response and vibrational energy content can be retained in the WBE shortened loading.

For further analysis, the fatigue life was determined by applying the Palmgren-Miner's cumulative linear damage rule. Three established strain-life models were chosen with the Palmgren-Miner rule for comparison purposes, i.e., the (Coffin, 1954; Manson, 1965; Morrow, 1968; Smith *et al.*, 1970) models. The Coffin-Manson relationship is mathematically defined by

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

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

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

where σ_m is the mean stress. The SWT strain-life model is mathematically defined by

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

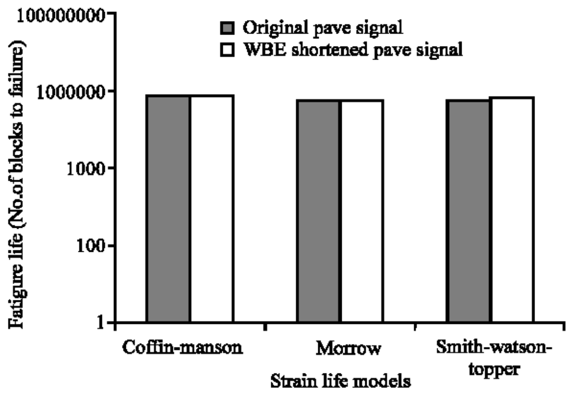
where σ_{max} is the maximum stress for the particular cycle. Using the properties of BS080A42 steel which can be found in (Abdullah *et al.*, 2006), the fatigue life for each original loading and the WBE shortened loadings were calculated. Table 1 shows the results obtained from the fatigue life calculations. The results were obtained using the available fatigue life prediction software. Figure 9 shows the level of fatigue life of those variable amplitude loadings. From these figures, it shows that majority of the original fatigue damage was retained in the respective WBE shortened loadings.

Quantitatively, almost all fatigue damage (i.e., at least 99%) for the *pavé signal* was retained when its original history was compressed to approximately 60% of the original time. However for the *manoeuvres signal*, at least 84% of the original fatigue damage was retained when the original signal was compressed up to 25% of the original time. For both loadings, the majority of the original damage was retained in the WBE shortened loadings, indicating the suitability of WBE to be used in fatigue data editing applications by means of fatigue damage retention.

Table 1: Calculated fatigue lives determined using the available fatigue life prediction software

	Coffin-manson	Morrow	Smith-watson-topper
Fatigue life (Number of blocks of failure			
Original pave signal	721450	589940	570100
WBE shortened pave signal	721450	594110	575100
Original manoeuvres signal	190	180	140
WBE shortened manoeuvres signal	220	200	160

(a) The pave signal



(b) The manoeuvres signal

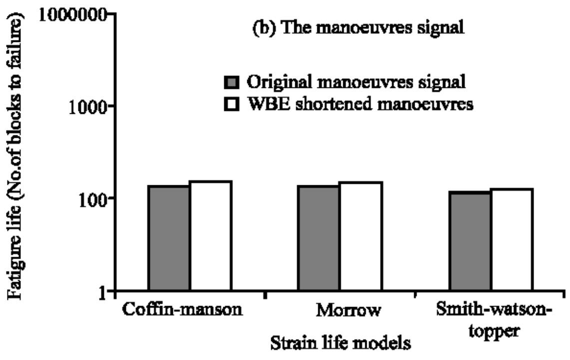


Fig. 9: Predicted fatigue lives distribution of the VA loadings using three strain-life models

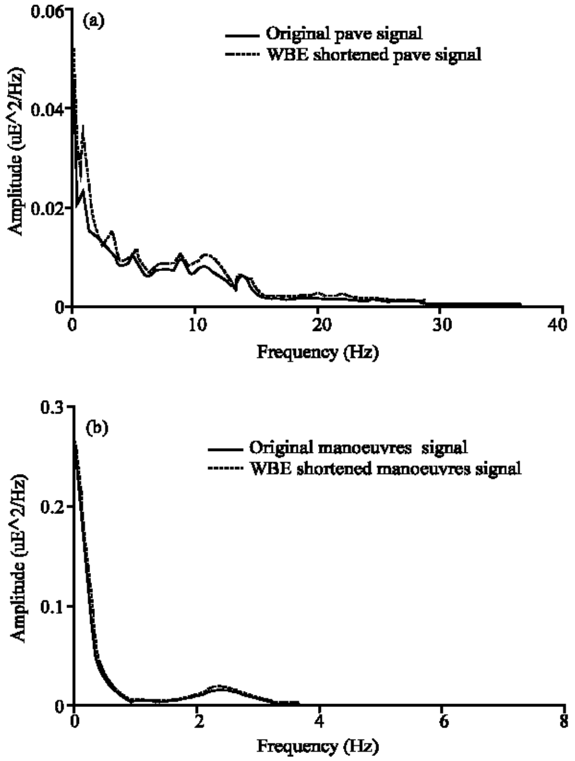


Fig. 10: Comparison of PSD plots btween the original and the WBE shortened signals

For automotive applications, this algorithm is able to produce the shortened loadings with equivalent fatigue damage to the original variable amplitude loadings. This can be seen from the results presented in (Fig. 7 and 8), as well as in Table 1. The WBE shortened loading is important in order to perform the accelerated fatigue tests, for which this kind of tests are seldom carried out in the durability laboratories. According to the results in (Fig. 10,) the shortened loadings were able to retain the frequency content and pattern as the original PSD. For automotive research, this finding is useful as the failure mode (in terms of the frequency response) caused by the measured road loadings can also be seen in the laboratory accelerated fatigue test.

Instead all these advantages of WBE, it can be seen that a low frequency content signal (The manoeuvres signal) can not be easily summarised compared to the *pavé signal*. Therefore, further investigation to overcome this issue should be performed. In this research the global signal statistics parameters were used to control the trigger level values determination. Since the original signal fatigue damage is the main element to be preserved in the WBE mission signal, further research is required to produce an optimum trigger level for each wavelet group based on fatigue damage parameters. Such a procedure may produce more accurate results when working with new and unfamiliar data.

CONCLUSIONS

This study discussed the applicability of the wavelet-based fatigue history editing, which have been previously developed for the purpose of accelerated durability fatigue test. A fatigue data editing using a variable amplitude (VA) strain time history is used to produce a shortened signal. Without editing the service load before performing the durability fatigue tests, the testing time and cost become prohibitive.

Considering the expansion in the application of the localised time-frequency analysis (or the wavelet transform) in the engineering data analysis, it seems to give a better route of exploring the applicability of the fatigue history editing research u sing the wavelet transforms. The key concept adopted in WBE is that a fatigue damaging event is extracted from its original signal. The bump segments are then assembled in order to produce a shortened loading with shorter time length.

WBE is thus also an appropriate algorithm for use when accelerated (time shortened) fatigue tests are desired. The unique of the WBE algorithm compared to other methods is the retention most of the original fatigue damage potential in the WBE shortened loading, as together with the retention of vibrational signal energy. In addition, the phase and amplitude of the original signal are also retained in the WBE shortened loading. However, WBE has a limitation in shortening a low frequency content signal as discussed in this study. Further investigation related to this issue should be performed in order to improve the efficiency of the WBE algorithm.

With the birth of the WBE algorithm in the automotive research, it offers an alternative solution to automotive engineers for the purpose of accelerated fatigue tests.

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