WAVELET BUMP EXTRACTION (WBE) ALGORITHM FOR THE ANALYSIS OF FATIGUE DAMAGE

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ABSTRACT

This paper presents a new algorithm known as Wavelet Bump Extraction (WBE) for summarising long records of fatigue data by extracting the important features that cause the majority of the damage. One of the main elements in WBE is the orthogonal wavelet transform. In WBE the input signal is decomposed using Daubechies wavelets and the wavelet levels are grouped into characteristic frequency bands. Features, called bumps, are extracted from each wavelet group and they are later synchronised together to produce a bump signal. The accuracy of the WBE algorithm has been evaluated by application to two experimentally measured data sets. One data set had a predominantly tensile mean load and the length of the extracted bumps was 41% of the signal. The fatigue damage ratio between the original and reduced time histories was 96% and 99% as calculated using the nSoft® package with the Smith-Watson-Topper and Morrow strain-life models, respectively. The other data set had predominantly compressive mean load and the bump signal length was 55% of the original signal. The fatigue damage ratio between the original and reduced time histories was 97% and 90% as calculated using the Smith-Watson-Topper and Morrow strain-life models, respectively. The results suggest that the WBE algorithm is an efficient approach for summarising long records of fatigue data.

KEYWORDS

Fatigue damage; bumps; vehicles; wavelet; algorithm

INTRODUCTION

Fatigue analysis is a major stage in the design of vehicle structural components since these components are often subjected to lengthy and random stochastic loadings. In addition, many experimental road load data sets contain transient features such as potholes and curb strikes. Since specific events in the signal can cause the majority of the damage, methods for summarising and reconstructing the loadings are useful. Methods for removing non-damage producing sections of data have been developed for particular domains: time, peak and valley, frequency, cycles, damage and histogram. Time domain editing has proven to be a popular technique as it maintains the phase and frequency characteristics of the original signal. Different approaches have been used in time domain editing, i.e. damage window joining function [1], strain range and Smith-Watson-Topper (SWT) parameter criteria [2] and spike removal and denoising process using the wavelet transform method [3].

Current signal editing procedures for fatigue testing or life prediction tend to disregard the sequence of cycles associated with physical events in load spectrum. The aim of this work is to seek a method of identifying the important fatigue damaging event and extract it from the history whilst preserving its sequence of load cycles. The shortened signal would retain

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almost all of the fatigue damage in the correct order of high and low cycles. A recent example of a signal editing method is the Mildly Nonstationary Mission Synthesis (MNMS) algorithm which was originally developed for the analysis of comfort missions [4-5]. The MNMS algorithm was later modified for fatigue mission analysis in automotive applications [6]. A further analysis of the fatigue damage potential of each individual bump event found in several road data signals has lead to the development of an algorithm that is designed specifically to retain the time history during the principal damaging events. This algorithm is called Wavelet Bump Extraction (WBE) and is the subject of this paper. It is a data editing technique which is capable of extracting the bump events so as to produce a shorter bump signal that is close to the original signal in terms of damage potential.

WAVELET BUMP EXTRACTION (WBE) ALGORITHM

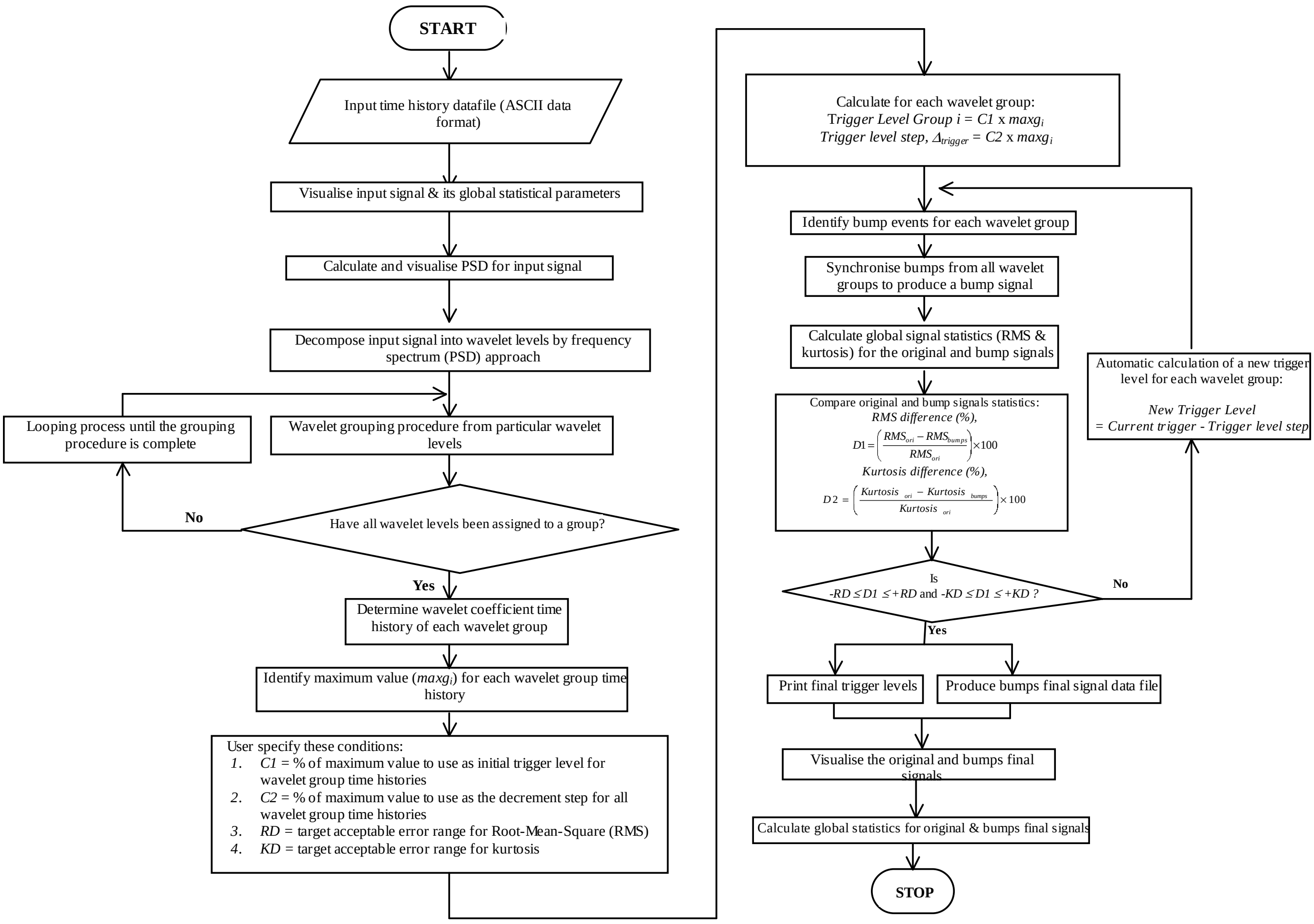


Figure 1: A flowchart of the WBE algorithm

A flowchart describing the WBE algorithm is shown in Figure 1. The first stage of WBE is to calculate the power spectral density (PSD) of the input signal to determine its frequency domain characteristics. Each frequency step value of the PSD is characterised by an amplitude value of $A_k = \sqrt{2\Delta f \cdot S(f_k)}$, where $S(f_k)$ is the underlying PSD of the Gaussian signal and f_k is the frequency of the harmonic.

The second stage of the WBE processing is a wavelet decomposition and wavelet level grouping procedure. Wavelets are analytical functions $\psi(t)$ which are used to decompose a signal $x(t)$ into scaled wavelet coefficients, $W_{\psi}(a,b')$. The wavelet function chosen in WBE is the 12th order of Daubechies wavelet, which is the orthogonal wavelet transform, due to its proven usefulness in automotive applications [4-6,7]. A wavelet grouping stage in WBE then permits the user to group wavelet levels into single regions of significant energy [4-6]. Each wavelet group is defined by the user to cover frequency regions of specific interest such as high energy peaks caused by a subsystem resonance. This subdividing of the original signal permits 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.

The final stage of the WBE algorithm consists of bump extraction procedures as shown in Figure 2. In WBE bump events have been defined as oscillatory transients which have a monotonic decay envelope either side of the peak value. Bump events are identified from a given wavelet group time history by means of an automatic trigger. The user specifies the maximum percentage difference between the root-mean-square (RMS) and kurtosis of the original and the bump signals, and the initial trigger level is automatically determined to achieve the requested statistics for each wavelet group. The RMS is used to quantify the overall energy content of the oscillatory signal, and the kurtosis is used as a measure of nongaussianity since it is highly sensitive to outlying data among the instantaneous values.

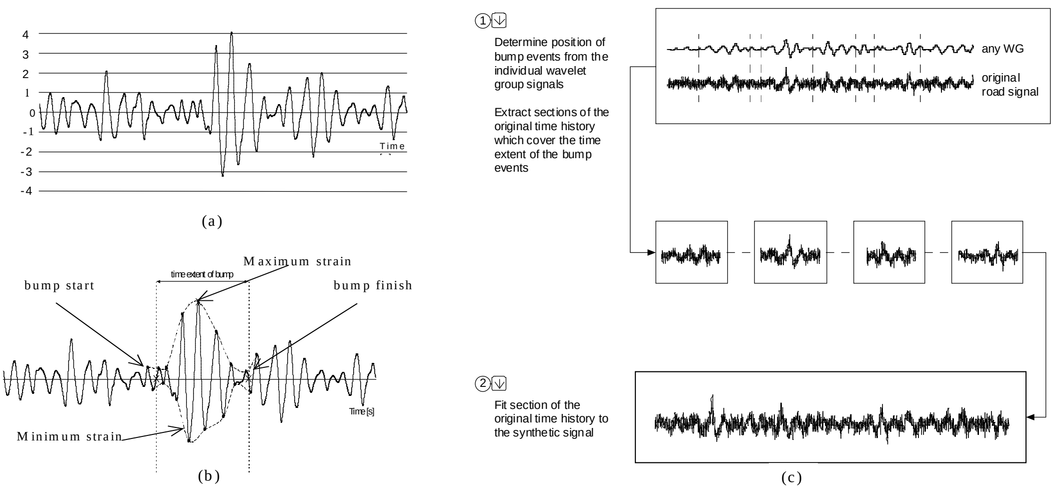
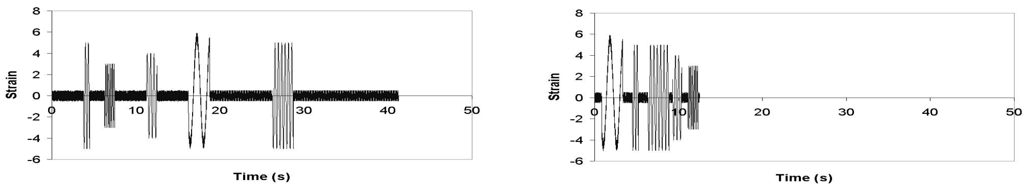


Figure 2: (a) Bump identification using trigger levels, (b) Decay enveloping of a bump event, (c) Schematic diagram of bump synchronisation

Figure 2(a) presents a set of possible trigger levels for an individual wavelet group for determining a bump. Bump identification is performed by means of a search which identifies the points at which the signal envelope inverts from a decay behaviour. The two inversion points, one on either side of the peak value, define the temporal extent of the bump event as shown in Figure 2(b). A method to synchronise the bumps from all wavelet groups has been defined as shown in Figure 2(c). If a bump event is found in any of the wavelet groups a block of data covering the time extent of the bump feature is taken from the original data set. This synchronisation strategy retains the amplitude and phase relationships of the original signal. The RMS and kurtosis values of the bump signal are then compared to those of the original signal. If the statistics do not meet the required difference, the trigger levels are reduced incrementally by a step size that is specified by the user until both statistical values of the bump signal achieve the user-specified closeness to the original signal.

ARTIFICIAL VALIDATION SIGNAL CASE STUDY

An artificial test signal (Figure 3(a)) was defined for validating the WBE algorithm. The zero-mean signal contains 16000 data points sampled at 400 Hz and consists of a combination of sinusoidal and random signals at various amplitudes. This validation signal was intentionally defined to be a mixture of high amplitude bump events and low amplitude harmonic background. The signal was used to test the effectiveness of the algorithm when selecting bump events. Using the WBE algorithm the bumps were extracted from each wavelet group at ±75% statistical difference between the original and the bump signals. With a signal length at 12.5s (Figure 3(b)) the bump signal was 31% of the 40s length of the original test signal.

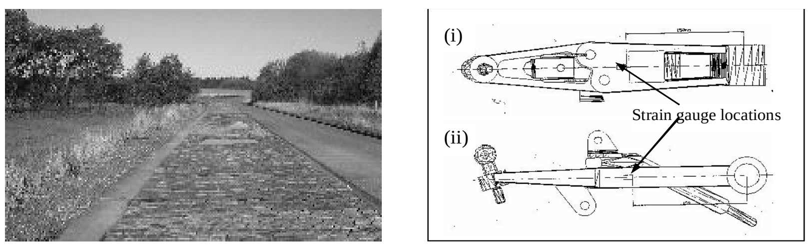


(a) (b)

Figure 3: Plots of the test signal: (a) original signal *(no. of data points, n = 16000, RMS = 1.51, kurtosis, K = 7.37)*; (b) bump signal *(n = 4997, RMS = 2.62, K = 2.53)*

A key part of the WBE algorithm is the desire to maintain the fatigue damage of the bump signal to that of the original history. In this work, the original history and the bump signal were used as input into nSoft® analysis package and the endurance were predicted. Two commonly used mean strain models were used: the Smith-Watson-Topper (SWT) and Morrow methods. The predicted lifetime of the original and bump histories were compared for both strain-life models. This was not intended to be absolute measure of the fatigue life, but a check to ensure that the fatigue damage of the two histories was almost unchanged. For this validation signal, the damage ratios between the bump signal and the original signal were 98% as calculated using both strain-life models. In the case of this artificial signal a large (±75%) difference in RMS and kurtosis values between the bump and original signals occurred because approximately 70% of the original signal contained low amplitudes. The large differences in the global signal statistics between the original and the bump signals, obtained when nearly matching the actual fatigue damage, illustrates the difficulties of performing fatigue mission analysis based only on global signal processing statistics.

VEHICLE SUSPENSION ARM CASE STUDY



(a) (b)

Figure 4: (a) Pavé test track used for the road tests, (b) Schematic view of strain gauge locations on the component for: i) tensile mean loading, ii) compressive mean loading [8]

In the case study, two strain signals were measured on the lower suspension arm of a vehicle travelling at 34 km/h over a pavé test track [8] shown in Figure 4(a) and the strain gauge locations are shown in Figure 4(b). The signals were measured at the top of the component for the predominantly tensile mean load (mean = 15.0με) called S1 in this paper and the side of the component for the predominantly compressive tensile mean load (mean = -48.1με), called S2. The signals were sampled at 500 Hz for a total of 23000 data points that produced at total record length of 46 seconds. The time histories and PSDs for both signals are presented in Figure 5. The strain signals were decomposed into 12 wavelet levels and assembled into 4 wavelet groups using WBE. The fatigue damage values were calculated for both the original and the bump signals using the SWT and Morrow models as implemented in the nSoft® software.

Figure 5 presents the original strain signals, the bump signals, and the PSD of both. The WBE bump signal length was only 41% (Figure 5(b)) of the original S1 (bump signal length = 18.8 seconds), and 55% (Figure 5(e)) of the original S2 (bump signal length = 25.3 seconds). These findings were obtained at ±10% RMS and kurtosis difference between the original and bump signals. The energy distribution in the frequency domain for both the original and the WBE bump signal can be seen to be similar and overlapped as shown in Figure 5(c) and Figure 5(f). In the post-processing analysis to determine the fatigue damage potential of the original and bump signals, the ratio of fatigue damage between the bump and original signals of S1 was 96% and 99% as calculated using the SWT and Morrow strain-life model, respectively. In addition, S2 had the fatigue damage ratio between the bump and original signals at 97% and 90% for the SWT and Morrow strain-life models, respectively.

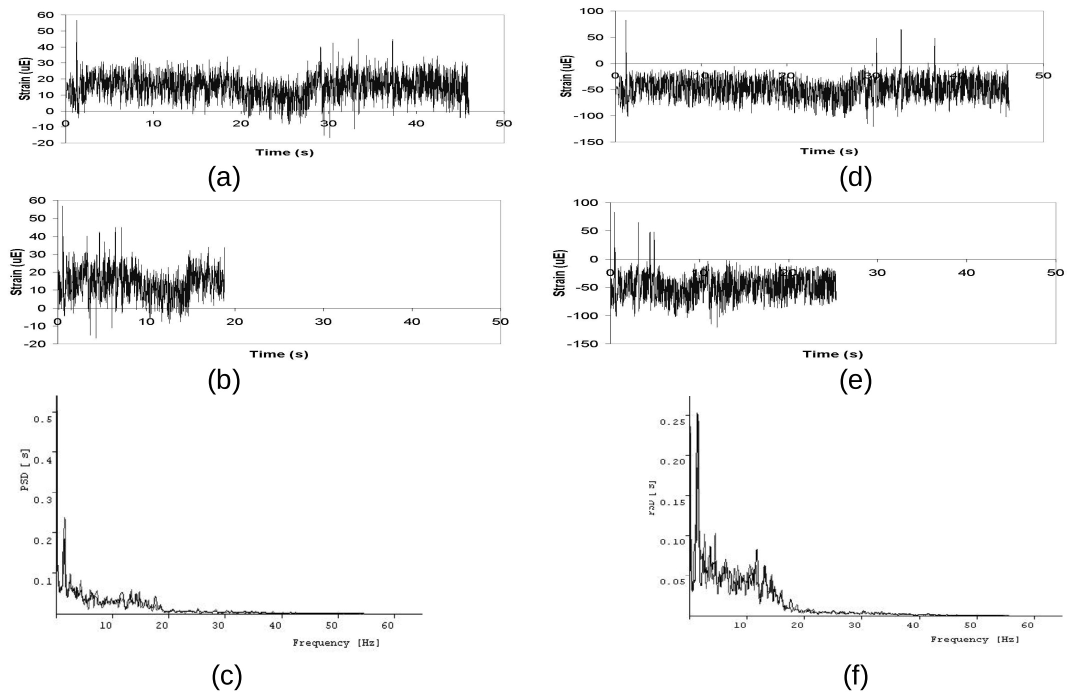
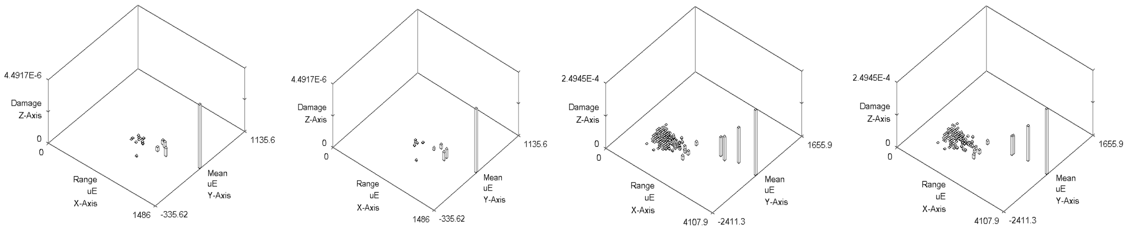


Figure 5**:** Plots for S1: (a) original signal *(n = 23000, RMS = 7.0, K = 3.4)*; (b) bump signal (*n = 9413, RMS = 7.8, K = 3.6)*; (c) PSD of the original signal (black colour) and bump signals. Plots for S2: (d) original signal *(n = 23000, RMS = 19.0, K = 3.8)*; (e) bump signal *(n = 12674, RMS = 21.0, K = 4.0)*; (f) PSD of the original signal (black colour) and bump signals

In the case study of the lower suspension arm, an accuracy of ±10% for the global signal statistics and ±11% for the fatigue damage between the bump and the original signals was obtained with bump summary signals of less than half of the original length. Almost all of the original damage was retained in the WBE extracted signals as shown by the fatigue histogram distributions of Figure 6.



(a) (b) (c) (d)

Figure 6: Fatigue damage distribution histogram for S1: (a) original signal, (b) bump signal; and for S2: (c) original signal, (d) bump signal

CONCLUSIONS

The Wavelet Bump Extraction (WBE) algorithm has been developed for use in fatigue mission synthesis. It is a signal processing algorithm which extracts fatigue damaging events in specifically defined wavelet groups. This validation study has focused on the fatigue damage analysis of two different preloading data sets for a lower suspension arm of a vehicle travelling over a pavé test surface. With this procedure, the original experimentally measured fatigue signal was compressed by up to 41% of the signal length with, at most, 10% lost in the fatigue damage. Based on the current results, it is suggested that the WBE algorithm is an efficient approach for summarising long records of fatigue data.

REFERENCES

[1] I. Austen and R. Gregory: Component test during duration prediction and acceleration by fatigue analysis and fatigue editing. VTT Symposium, 3 (1995) 169-187.

[2] R.I. Stephens, P.M. Dindinger and J.E. Gunger: Fatigue damage editing for accelerated durability testing using strain range and SWT parameter criteria. International Journal of Fatigue, 19 (1997) 599-606.

[3] C-S. Oh: Application of wavelet transform in fatigue history editing. *International Journal of Fatigue*, 2001, 23, 241-250.

[4] J. Giacomin, A. Steinwolf and W.J. Staszewski: A vibration mission synthesis algorithm for mildly nonstationary road data. ATA 6th Int. Conf. on the New Role of Experimentation in the Modern Automotive Product Development Process, 1999, 17-19 Nov., Florence, Italy.

[5] J. Giacomin, A. Steinwolf and W.J. Staszewski: An algorithm for Mildly Nonstationary Mission Synthesis (MNMS). Engineering Integrity 7 (2000) 44-56.

[6] S. Abdullah, J.A. Giacomin and J.R. Yates: A mission synthesis algorithm for fatigue damage analysis. paper submitted to Proc. of the Instn. of Mech. Engrs, Part D, Journal of Automobile Engineering 2003.

[7] A. Steinwolf, J. Giacomin and W.J. Staszewski: On the need for bump event correction in vibration test profiles representing road excitations in automobiles. Proc. of the Instn. of Mech. Engrs, Part D, Journal of Automobile Engineering 216 (2002) 279-295.

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