Acceleration Data Extraction Associating to the Peak-Valley Segmentation Approach Using the Morlet Wavelet Transform

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Abstract: This paper presents a peak-valley segmentation procedure for the wavelet-based extraction of acceleration data. A 60-second acceleration signal was measured on a McPherson frontal coil spring of a 2000 cc Proton sedan car, and the data was used for the simulation. The Morlet wavelet-based analysis was used to extract higher amplitude segments in order to produce a shortened signal that has an equivalent behaviour. Using this process, it has been found that the Morlet wavelet was able to summarise the original data up to 49.45% with less than 10% difference with respect to statistical parameters. This clearly indicates that the Morlet wavelet can be successfully applied to compress the original signal without changing the main history as well. Finally, it has been proven that the Morlet wavelet successfully identified the higher amplitudes in the acceleration data.
Keywords: Acceleration data, Peak-valley extraction, Morlet wavelet, Modified data.

1. Introduction

Control and stability of a car entirely depend on the contact between the road surface and the tires [1]. The dynamic interaction between vehicle and road surface causes problems with respect to the vehicle structure and the ride quality. Collision between uneven road surfaces and tires gives a certain amount of vibration which contributes to mechanical failure of car components due to fatigue as the car structure was subjected to cyclic loading. This vibration also interfaces the function of the car suspension system and gives a great impact on the performance of the car [2-5].

According to Jinhee [6], car suspension systems experience vibration when is subjected to variable driving conditions leading to strain at this component. If this condition continues it will increase the probability of fatigue failure for the car suspension system. The problems arising have been solved by simulating the dynamic behaviour of a structural component on which the dynamic forces are

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acting. Measured road surface profiles are generally considered as external disturbances acting through the automotive suspension system onto the vehicle body. Road surface profiles are usually used to describe the bumpiness of the road. Because of weakness of measuring equipment used, there is noise in the road surface profile data. Thus, the accuracy and reliability of the road surface profile is reduced. If the signal trends are not extracted from the input signal used, it will directly affect the test results, leading to inappropriate judgments and conclusions. Therefore, it is an important task that the signal trend is extracted and separated from the noise during road surface data processing [7].
Based on this background, methods for the signal trend extraction of road surface profile are introduced. At present, the popular methods for the signal trend extraction are: least-squares fitting, low-pass filtering, wavelet decomposition, empirical mode decomposition, etc., as reported in [7]. The objective of this work is to extract acceleration data in order to remove white noise in the data. In order to address the objective of the research, acceleration data is edited to produce shorter data while retaining its original characteristics. Therefore, a data editing technique is necessary for producing new modified signals as required. Continuous wavelet transform (CWT) has been applied to the digital signal processing algorithm. An algorithm for signal trend extraction of road surface profile has been developed by adopting a fatigue feature algorithm developed by Putra et al [8]. It is hypothesized that the pattern of an acceleration data is similar to the pattern of a fatigue signal.

2. Literature Overview

2.1. Global signal statistics

Statistical parameters are used for random signal classification and pattern monitoring. Common statistical parameters that are directly related to the observation of the data behaviour are the mean value, standard deviation (SD), the root-mean square (r.m.s.), skewness, kurtosis and the crest factor (CF). From these parameters, the r.m.s. and kurtosis give significant effects to evaluate the randomness of the data [9]. The r.m.s. calculates the energy distribution, wherein higher r.m.s. indicates a higher energy content, which in turn indicates higher fatigue damage in the signal. On the other hand, kurtosis represents the continuity of peaks in a time series loading. The peaks also reveal higher fatigue damage, suggesting that a higher kurtosis indicates higher fatigue damage.
The r.m.s. is the second statistical moment used for determining the total energy contained in a signal. The r.m.s. of signals with zero mean value is equal to the SD. The r.m.s. of discrete data can be calculated as follows:

$$r.m.s. = \left\{ \frac{1}{n} \sum_{j=1}^{n} x_j^{\,2} \right\}^{1/2}$$

In addition, kurtosis is the fourth statistical moment that is very sensitive to spikes and it represents the continuation of peaks in a time series loading. The kurtosis value of a Gaussian normal distribution is close to 3.0. Higher kurtosis shows that the value is higher compared to the appropriate value in the Gaussian normal distribution, indicating that only a small proportion of data is closer to the mean value [10]. The kurtosis for a set of discrete data is formulated as:

$$K = \frac{1}{n(SD)^4} \sum_{j=1}^{n} \left(x_j - \bar{x}\right)^4$$

2.2. Continuous Morlet Wavelet Transform

The continuous wavelet transform (CWT) is conducted on each reasonable scale, producing a lot of data and is used to determine the value of a continuous decomposition to reconstruct the signal accurately [11]. The Morlet wavelet is one of the mother wavelets that are involved in the CWT, and it can be described by the following equation:

$$\psi(t) = \exp\left(-\beta^2 t^2/2\right)\cos(\pi t)$$

By dilation with *a* (scale factor) and translation with *b* (position), a son wavelet can be acquired [12]:

$$\psi_{a,b}(t) = \exp\left[-\frac{-\beta^2(t-b)^2}{a^2}\right]\cos\left[\frac{\pi(t-b)}{a}\right]$$

Wavelet decomposition calculates the resemblance index, also called the coefficient, between the signal being analyzed and the wavelet. Generally, the wavelet coefficient is expressed with the following integral [11]:

$$C_{a,b} = \int_{-\infty}^{+\infty} f(t)\psi_{(a,b)}(t)dt$$

The Morlet wavelet coefficient indicates the distribution of the internal energy of the signal in the time-frequency domain [13]. The signal internal energy *e* can be expressed as:

$$e_{(a,b)} = \left|C_{(a,b)}\right|^2$$

2.3. Peak-valley segmentation-based signal extraction

Fatigue damage is very sensitive to peak and valley in a time series loading. Thus, in the extraction, time series data needs to be converted in the form of peak-valley. For the development of the extraction algorithm, the input required was the distribution of the magnitude in the time domain obtained by the time-frequency method. The distribution was decomposed into the time domain spectrum by taking the magnitude cumulative value for an interval of time.

A gate value was used for the extraction of the damage feature. The gate value was the energy spectrum variable that maintains the minimum magnitude level. Segments with magnitudes exceeding the minimum magnitude value were maintained, whereas the segments with magnitudes less than the minimum magnitude value were removed from the signal. The concept refers to the concept of the cut-off level used in the extraction in the time domain [14].
To obtain the optimum of the gate value, the maintained segments then were merged with each other to form a shorter modified signal, compared to the original signal. In the case of global signal statistical parameters, a difference of 10% is used considering that at least 10% of the original signal contains a lower amplitude cycle leading to the minimum structural damage to obtain a final signal corresponding to the original signal [15].

3. Methodology

Acceleration data measured at a McPherson frontal coil spring of a 2.000 cc Proton Wira sedan car was used for the current study. At the same time, strain data on the component was measured as well. The behaviour of both the acceleration and strain data was to be observed. According to Gillespie [16], the coil spring of a car at the similar brand of this research was made from SAE5160 alloy steel. Its properties are tabulated in Table 1 [17].

Table 1. The mechanical properties of the SAE5160 alloy steel.

Properties	Values
Modulus of elasticity, E (GPa)	207
Density, ρ (kg/m^3)	7.85
Poisson's ratio, ρ	0.27

An accelerometer was placed at the location of the coil spring showing the highest stress concentration which was obtained through finite element analysis. The car was driven on a highway road surface at a velocity of 70 km/h. The original signal produced by the accelerator was a variable amplitude load sampled at 500 Hz and recorded using a data acquisition setup, as shown in Figure 1.

(a) (b)

Fig. 1. The data acquisition setup: (a) accelerometer, (b) PXI system.

4. Results and Discussion

4.1. Acceleration data

The collected data contained many small amplitudes and higher frequency patterns in the signal background. The data is a time domain signal measured at the coil spring sampled at 500 Hz for 30,000 data points. Therefore the total record length was 60 seconds. Based on the acceleration obtained, the data obtained revealed parts with higher amplitudes because the vehicle was driven on a bumpy surface. The original acceleration data, the Morlet wavelet coefficient and the signal internal energy are shown in Figure 2.

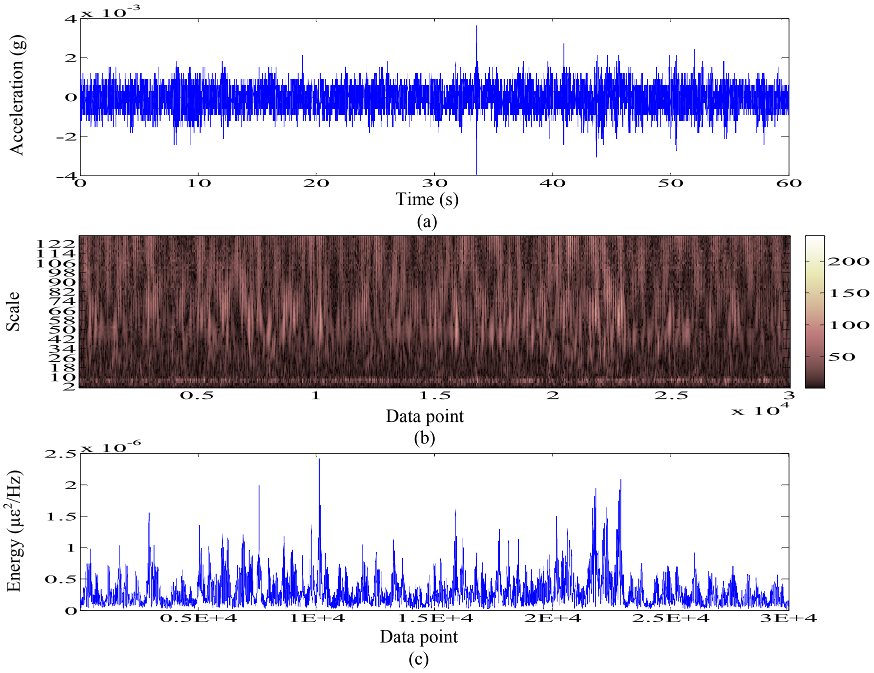

Fig. 2. (a) acceleration data, (b) wavelet coefficient, (c) internal energy.

4.2. Acceleration data extraction

Various gate values were used in this extraction. The values were chosen because most of the magnitudes were below the gate value, whereas if the lower magnitude section was removed, it did not affect the damage relevance and the original properties of the signal. The gate values used were $4\text{x}10^{-7}$ $\mu\varepsilon^2$/Hz, $5\text{x}10^{-7}$ $\mu\varepsilon^2$/Hz and $6\text{x}10^{-7}$ $\mu\varepsilon^2$/Hz. After the data was extracted, the retained energy containing higher signal internal energy was obtained. Furthermore, based on the time positions of the retained energy and referring to the original signal before the extraction, maintained segments were obtained. The extractions produced segments that were not uniform in length because the

Morlet wavelet algorithm extracted the time series based on the energy content of the signals.

For this purpose, the retained segments were reattached into a single load to validate if the process satisfied the requirements in data editing, i.e., maintaining 90% of the original statistical values. A verification process was done by comparing the statistical parameter values between the original and the modified signal. From the analysis of the modified signal, an optimal gate value was determined based on the gate value ability (refer to the modified signal) to produce the shortest signal with the minimum signal statistical parameter deviation. Figure 3 shows the differences in the length of modified signals from the extraction at various gate values.

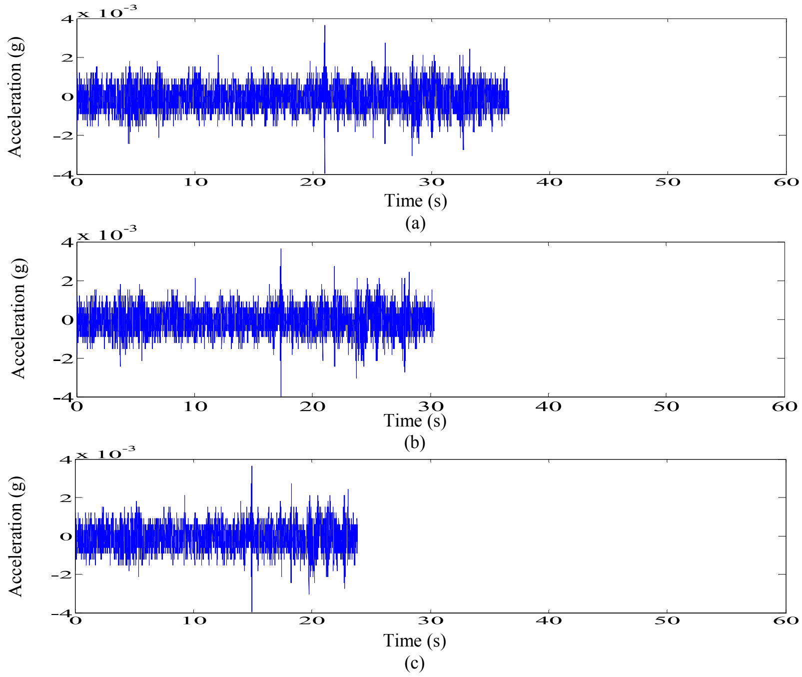

Fig. 3. Edited signals at: (a) 4x10^{-7} $\mu\varepsilon^2$/Hz, (b) 5x10^{-7} $\mu\varepsilon^2$/Hz, (c) 6x10^{-7} $\mu\varepsilon^2$/Hz.

Based on Figure 3 above, at gate value of 4x10^{-7} $\mu\varepsilon^2$/Hz, data of 36.57 seconds shortened only by 39.05% and its r.m.s. and kurtosis became 2.68% and 5.45%, respectively. For a gate value of 5x10^{-7} $\mu\varepsilon^2$/Hz, the Morlet wavelet-based extraction resulted in a 30.33-second edited signal, which was 49.45% shorter than the original. The modified signal changed the r.m.s. and the kurtosis to 3.41% and 8.21%, respectively. For a gate value of 6x10^{-7} $\mu\varepsilon^2$/Hz, the data was modified by 60.22% and changed the r.m.s. and kurtosis values became 5.14% and 10.98, respectively.

Based on the results, 5x10^{-7} $\mu\varepsilon^2$/Hz was selected as the optimum gate value because at higher values, i.e. 6x10^{-7} $\mu\varepsilon^2$/Hz, the change in kurtosis reached

10.98%. It was detrimental the original properties of the signal. The 30.33-second edited signal resulted at the optimum gate value experience increasing of the r.m.s. and kurtosis values. Increased r.m.s. indicated that the internal energy content of the signal also increased. Different kurtosis values showed the extraction method was capable of effectively removing lower amplitude while maintaining higher amplitude in the modified signal. In addition, at gate value of 5×10^{-7} $\mu\varepsilon^2$/Hz, it gives similar distribution of frequency spectrum and power spectral density, as shown in Figure 4. It shows the noise in the road surface profile had been removed. The data were successfully edited based on the relationship between the higher amplitude and the Morlet wavelet coefficients of the time-frequency domain obtained. This Morlet wavelet algorithm removed segments with magnitudes less than the gate value based on their positions on the time axis.

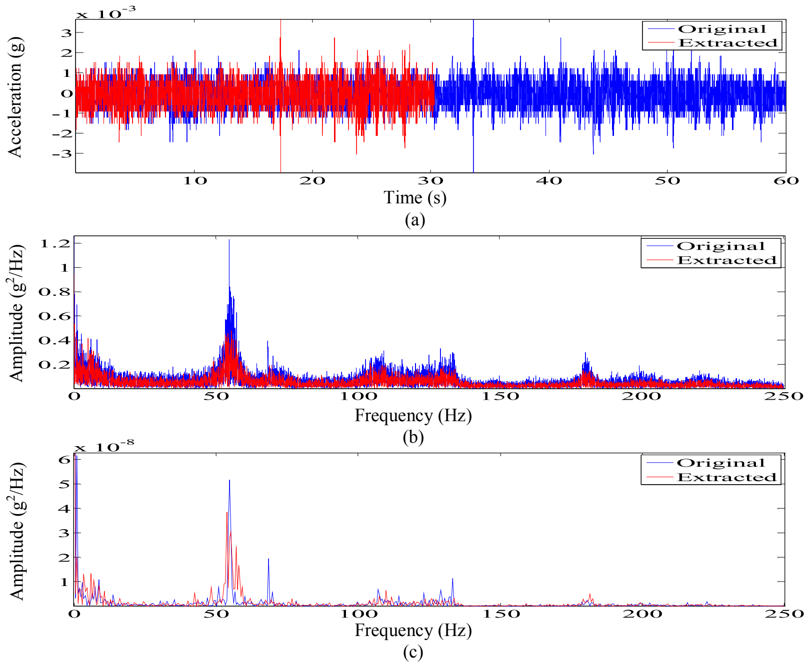

Fig. 4. Original and edited signals: (a) length, (b) frequency spectrum, (c) power spectral density.

5. Conclusion

In this study, an experiment was conducted to collect data for the purpose of obtaining acceleration data to simulate the extraction algorithm. The acceleration data causes vibration that will increase the probability to the fatigue failure at car components. The extraction process yielded data on the damaging segments by identifying and extracting segments based on the coefficient distribution of the Morlet wavelet transform. The damaging segments were combined to form shorter signals while maintaining original behaviours. Overall, the Morlet wavelet algorithm was able to shorten the signal up to 49.45% but maintained more than 90% of the statistical parameters and gave similar distribution of power spectral density as original data. The extraction method was able to identify the structural damage values of each segment. Finally, this study proved that the Morlet wavelet is an appropriate technique to extract acceleration data, especially for the automotive applications.

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