

Eliminating the Undamaging Fatigue Cycles Using the Frequency Spectrum Filtering Techniques

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1. Introduction

1.1 Fatigue mechanism in structural failures

In 1982, the Battelle group has been found that between 80 – 90 % of all structural failures occur through a fatigue mechanism. Based on the finding, considerable effort has been applied in order to address this fact (Halfpenny, n.d.). The fatigue behaviour of mechanical components under service loading and its evaluation are usually affected by numerous uncertainties and characterized by several random variables such as material and structural properties, and load variation. The repeated fluctuating loads lead to microscopic physical damage of materials (Nizwan, et al., 2007).

Many vehicle components, like engine, steering, and suspension parts, are frequently subjected to a variety of driving conditions. When an automobile is driven on any road surface and hit a pothole, bump or curb, the lower suspension arm is effected by a significant shock amount compared to other components. The load is then transmitted through the control arm while it serves to maintain the contact between the wheel and the road. Furthermore, this component plays a vital role in the failure of automotive parts and it is submitted to multi axial fatigue loading under service conditions with generally nonproportional and variable amplitude loading (Nadot & Denier, 2004).

1.2 Signal processing of fatigue

With the advances in the digital signal processing research, there has been an increasingly strong interest in the application of the fatigue signal analysis for life prediction in automotive components. Several methods for analysis of signals have been proposed and performed for achieving this task. Among those is the Fast Fourier Transform (FFT) which has been widely applied to engineering problems. In the Fourier transform, the frequency components of an entire signal are analysed for producing the frequency information only. Since time information is lost, it is impossible to know when a particular event took place. For stationary signals, for which the frequency information is not changed by time, this

drawback is not very important. However, most interesting signals contain numerous nonstationary or transitory characteristics which often occur in the most important part of an experimental measured signal with variable amplitude pattern. This means that this Fourier transform method was found to be an unsuitable method to investigate the behaviour of nonstationary patterns in a signal (Misiti et al., 2008; Valens, 1999).

Therefore, the time-frequency localisation technique was identified to overcome this drawback of analysis of a nonstationary signal. During the last decade, a new mathematical technique, called the wavelet transform (WT), has been frequently used in the field of vibrational diagnostics and also in fault detection. In addition, the wavelet coefficient analysis has also have been applied to detect fatigue transverse cracks in rotors. Its peak absolute value is highly sensitive to the depth of a crack and even a very shallow crack can be detected. The rotor is not required to stop and the detection process can be applied to a rotating shaft making the methodology more versatile, convenient and unambiguous (Darpe, 2007).

1.3 Fatigue data editing

For many automotive components, the primary mode of failure can be attributed to fatigue damage resulted from the application of variable amplitude loading (VAL). It contains large percentage of small amplitude cycles and the fatigue damage for these cycles can be small. For this reason, in many cases, the signal was edited by removing these cycles in order to produce representative and meaningful yet economical testing (Stephens et al., 1997). Therefore, it seems appropriate to see a method to summarise a fatigue strain signal. Without editing the service load, the testing time and cost become prohibitive (Abdullah, 2007).

The effectiveness of the edited signals depends on the retention of the fatigue damage and signal statistical parameter values. Those values are measured in order to observe the signal behaviour. They are compared with the original signal to ensure the edited signal obtained can retain the original signal features. A 5 % difference of the fatigue damage and ± 10 % difference of the root-mean-square (r.m.s) and the kurtosis are required in order to produce an edited signal which has equivalent fatigue damage and signal statistics to the original signal.

In the previous study, Nizwan et al., (2007) developed a fatigue data editing using the FFT. This algorithm was performed by eliminating unwanted cycles in a fatigue strain signal. Using Power Spectral Density (PSD), energy distribution in the frequency domain displayed strain characteristic of the input signal. In order to trace higher amplitude cycles, low pass filter was applied to filter out higher frequency containing small amplitude which not causes the fatigue damage. Thus, a smoothen signal was obtained. Despite using the frequency spectrum filtering technique could not shorten the signal, but it still could simplify the signal by reducing the numbers of cycle counting for the signal. The optimum Cut Off Frequency (COF) for lower pass filter application was determined to observe the effect of fatigue data editing technique in frequency domain.

Since the technique could not shorten the original signal, it gave a motivation to the authors for developing a similar data extraction approach in the WT. Therefore, a new algorithm for fatigue feature extraction using the Morlet wavelet was developed. The WT is probably the

most recent solution to overcome the nonstationary signals. This time-frequency technique is applied by cutting time domain signal into various frequency components through the compromise between time and frequency-based views of the signal. It presents information in both time and frequency domain in a more useful form (Valens, 1999; Percival & Walden, 2000; Addison, 2002).

This paper discussed on the study of fatigue data editing by using the frequency spectrum filtering techniques. Both the techniques were used to eliminate undamaging fatigue cycles in order to simplify raw signal for the simulation testing purposes. The WT results were compared to the findings using the FFT extraction approach in order to see the suitability approach in fatigue history editing.

2. Literature background

2.1 Fatigue signal

Signals are a form of information, as a function of time, coming from many sources obtained by measuring and using some recording method. Most data samples are normally measured using an analogue-to-digital converter, so as to produce an experimental signal at a series of regularly spaced times, known as a discrete time. The analysis of time series aims to determine the statistical characteristics of the original function by manipulating the series of discrete numbers.

Signals can be divided into two main categories, i.e. deterministic and nondeterministic. A deterministic signal can be described by a mathematical relationship between the value of the function and the value of time. Many signals in nature exhibit nondeterministic or random characteristics, which provide a challenge to analysis using signal processing techniques (Tacer & Loughlin, 1998). A signal representing a random physical phenomenon can not be described in a point by point manner by means of a deterministic mathematical equation.

A signal representing a random phenomenon can be characterised as either stationary or nonstationary. A stationary signal is characterised by values of the global signal statistical parameters, such as the mean, variance and root-mean-square (r.m.s.), which are unchanged across the signal length. In the case of nonstationary signals, the values are dependent on the time of measurement. Nonstationary signals can be divided into two categories: mildly nonstationary and heavily nonstationary. A mildly nonstationary signal is defined as a random process with a stable mean, variance and r.m.s. values for most of the recorded data, but with short periods of differing signal statistics due to the presence of transient behaviour. A heavily nonstationary signal is defined as being similar to a mildly nonstationary signal, but with the presence of transient events over a large interval of the time history. Since nonstationary loadings are common in the case of fatigue and vibrational analysis (Giancomin et al., 1999), signal modelling has often been used in the time domain due to its simplicity and efficiency for the purpose of loading simulations.

2.2 Global signal statistical parameters

In the case of fatigue researches, the signals consist of a measurement of cyclic loads, i.e. force, strain, and stress against time. A time series typically consists of a set of observations

of a variable were taken at equally spaced intervals of time. Global signal statistical parameters are frequently used to classify random signals and monitor the pattern of analyzed signals. For a signal with a numbers of data point n in a sampled sequence, the mean \bar{x} is given by:

$$\bar{x} = \frac{1}{n} \sum_{j=1}^n x_j \quad (1)$$

In the fatigue signals, the calculation of the r.m.s. and the kurtosis are very important in order to retain a certain amount of the signal amplitude range characteristics (Nuawi et al., 2009). The r.m.s. is the signal 2nd statistical moment used to quantify the overall energy content of the oscillatory signal. The r.m.s. relationship is defined as:

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

The kurtosis is the signal 4th statistical moment. In an engineering field, it is used as a measure of nongaussianity for detection of fault symptoms since it is highly sensitive to spikiness or outlier signal among the instantaneous values. Mathematically, the kurtosis expression is defined as:

$$K = \frac{1}{n(r.m.s.)^4} \sum_{j=1}^n (x_j - \bar{x})^4 \quad (3)$$

where x_j is the amplitude of signal. In some definitions of the kurtosis, a deduction of 3.0 is added to the definition in order to maintain the kurtosis of a Gaussian distribution to be equal to zero. For clarity and convenience, in this study the original definition of the kurtosis, where the Gaussian distribution has a kurtosis value of approximately 3.0 was used for the analysis. Therefore, a kurtosis value of higher than 3.0 indicates the presence of more extreme values than one that should be found in a Gaussian distribution (Abdullah et al., 2006). This situation indicates that the fatigue damage is higher than Gaussian stresses due to higher amplitude fatigue cycles (Braccesi et al., 2009).

2.3 Fatigue life assessment

In material science, fatigue is defined as a process of progressive and localised structural damage duo to cyclic loads, which depend on the stresses and the strains at critical regions of a component (Prawoto, 2002). The repeated or otherwise varying loads never reach a level sufficient for causing failure in a single application. The loads cause plastic deformation (slip) locally which results in a crack beginning, crack propagation, and then a breakage. This plastic deformation might arise through the presence of a small crack or pre-existing defect on the surface of a component. In the case of the fatigue research, the signals consist of a measurement of cyclic loads, i.e. force, strain, and stress against time (Nuawi et al., 2009).

Three major approaches to predicting fatigue life namely stress-life, strain-life, and fracture mechanics. The strain-life fatigue approach relates the plastic deformation that occurs in the

localized region where fatigue cracks begin to the durability of a structure under the influence of a mean stress. It is often used for ductile materials at relatively short fatigue life. It also can be used where there is little plasticity at long fatigue life. Therefore, this is a comprehensive approach that can be used in place of the related stress - based approach (Halfpenny, n.d.).

The total strain amplitude ε_a produced by the combination of elastic and plastic amplitude is defined as:

$$\varepsilon_a = \varepsilon_{ea} + \varepsilon_{pa} \quad (4)$$

where the elastic strain amplitude ε_{ea} and the plastic strain amplitude ε_{pa} are defined by:

$$\varepsilon_{ea} = \frac{\sigma_a}{E} = \frac{\sigma'_f}{E} (2N_f)^b \quad (5)$$

$$\varepsilon_{pa} = \varepsilon'_f (2N_f)^c \quad (6)$$

where σ_a is the stress amplitude, σ'_f is the fatigue strength coefficient, E is the material modulus of elasticity, N_f is the numbers of cycle to failure for a particular stress range and mean, b is the fatigue strength exponent, ε'_f is the fatigue ductility coefficient, and c is the fatigue ductility exponent.

Combining Eq. (5) and (6) gives the Coffin-Manson relationship, which is mathematically defined as (nCode, n.d.):

$$\varepsilon_a = \frac{\sigma'_f}{E} (2N_f)^b + \varepsilon'_f (2N_f)^c \quad (7)$$

where ε_a is the true strain amplitude, σ'_f is the fatigue strength coefficient, E is the material modulus of elasticity, N_f is the numbers of cycle to failure for a particular stress range and mean, b is the fatigue strength exponent, ε'_f is the fatigue ductility coefficient, and c is the fatigue ductility exponent.

Fatigue damage is derived from the number of cycles to failure. The fatigue damage caused by each cycle of repeated loading is calculated by reference to material life curves, such as S - N or ε - N curves. The fatigue damage D for one cycle is calculated as:

$$D = \frac{1}{N_f} \quad (8)$$

and the total fatigue damage ΣD caused by cycles is expressed as (Abdullah, 2005):

$$\Sigma D = \Sigma \left(\frac{N_i}{N_f} \right) \quad (9)$$

where N_i is the numbers of cycle within a particular stress range and mean. Therefore, fatigue damaging values have the range (0 - 1) where zero denotes no damage (extremely

high or infinite numbers of cycle to failure) and 1 means total failure (one cycle to failure). For strain - based fatigue life prediction, current industrial practice uses the Palmgren-Miner linear cumulative damaging rule normally associated with the established strain-life fatigue damaging models, such as the Coffin-Manson.

2.4 The FFT

Frequency domain is a term used to describe the analysis of mathematical functions or signals with respect to frequency. A frequency domain graph shows how much of the signal lies within each given frequency band over a range of frequency. A frequency domain representation can also include information on the phase shift that must be applied to each sinusoid in order to be able to recombine the frequency components to recover the original time signal. The frequency domain relates to the Fourier transform or Fourier series by decomposing a function into an infinite or finite number of frequency. This is based on the concept of Fourier series that any waveform can be expressed as a sum of sinusoids (Nizwan et al., 2007).

The Fourier transform has been most commonly used to denoise signals for a frequency - based editing method, which cannot provide any information regarding the time localization of the spectral components. This Fourier representation has been found inadequate in analyzing nonstationary signals (Oh, 2001). Frequency analysis data is typically presented in graphical form as PSD. Essentially, a PSD displays the amplitude of each sinusoidal wave of a particular frequency which is given on the x -axis. The mean squared amplitude of a sinusoidal wave at any frequency can be determined by finding the area under the PSD over that frequency range (nCode, 2005).

A filter is used to remove undesirable frequency information from a dynamic signal. Filter can be broadly classified as being low pass, high pas, bandpass, and notch. Low pass filter permits frequency below a prescribed COF to pass while blocking the passage of frequency information above the COF. Similarly, a high-pass filter permits only frequency above the COF to pass. A bandpass filter combines features of both the low pass and high pass filter. It describes a lower and higher COF to define a band of frequency that is permitted to pass through the filter. A notch filter permits the passage of all frequency except those within narrow frequency band (Nizwan et al., 2007).

2.5 The Morlet wavelet

The WT analysis is started with a basic function (called the mother wavelet) scaled and translated to represent the signal being analyzed (Berry, 1999). The transform shifts a window along the signal and calculates the spectrum for every position. The process is repeated many times with a slightly shorter (or longer) window for every new cycle. In the end, the result will be a collection of time-frequency representations of the signal with different resolutions. The WT provides information on when and at what frequency the change in signal behaviour occurs (Valens, 1999). The major advantage is the ability to analyze a localized area of larger signal (local analysis) (Misiti et al., 2008).

Obviously, the WT represents a windowing technique with variable-sized regions. This technique allows the use of long time intervals (more precise low frequency information) and shorter regions (high frequency information). It means the wavelet method solves the

resolution problem because the window length is long for low frequency and short for high frequency. Therefore, the frequency resolution is good for low frequency (at high scales) and the time resolution is good at high frequency (at low scales). The major advantage is the ability to analyse a localised area of a larger signal, also known as the local analysis (Misiti et al., 2008).

The Morlet wavelet is one of functions that are generally used in the Continuous Wavelet Transform (CWT) analyses (Gao et al., 2001). The wavelet decomposition calculates a resemblance index between signal being analyzed and the wavelet, called coefficient. It is a result of a regression of an original signal produced at different scales and different sections on the wavelet. It represents correlation between the wavelet and a section of the signal. If the index is large, the resemblance is strong, otherwise it is slight (Misiti et al., 2008).

The WT of any time-varying signal $f(t)$ is defined as the sum of all of the signals time multiplied by a scaled and shifted version of the wavelet function $\psi(t)$ (Kim et al., 2007). The CWT is expressed by the following integral:

$$CWT_{(a,b)} = \int_{-\infty}^{+\infty} f(t)\psi_{a,b}(t)dt \quad (10)$$

The parameter a represents the scale factor which is a reciprocal of frequency, the parameter b indicates the time shifting or translation factor, and t is the time. $\Psi_{a,b}(t)$ denotes the mother wavelet, i.e (Purushotham et al., 2005):

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{(t-b)}{a}\right), a, b \in R; a \neq 0 \quad (11)$$

$$CWT_{(a,b)} = \int_{-\infty}^{+\infty} f(t)\frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right)dt \quad (12)$$

In addition, the wavelet coefficient indicates how energy in the signal is distributed in the time-frequency plane (Darpe, 2007). The energy spectrum (the energy density over frequency) is plotted in order to observe the signal behaviour and its content gives significant information about the random signal pattern.

2.6 Fatigue data editing

In a fatigue life assessment, fatigue signal extraction is described as a method for fatigue data editing which lead to summarise a fatigue signal. The method is performed by segment identification and extraction that contribute to the more fatigue damaging events to a metallic material. On the other hand, segments containing lower amplitude cycles are omitted, since these data type theoretically gave minimal or no fatigue damage. The goal of the removal of those parts from the original signal is to generate a new shortened mission signal, for which this signal type can be used to reduce the testing time and costs for fatigue testing (Abdullah, 2005).

The magnitude of time domain spectrum level is used as a parameter to set gate value for the eliminating process. The value is used to slice the original signal. The extracted segment identification is performed by searching two inversion points (one on either side of the peak

value) which define the temporal extent of the extracted segment. The identification is based on energy loss concept, i.e. selected segments are at the start and finish points.

The example of the segment identification is described in Fig. 1. In the figure, the selected segment is at gate value of $400 \mu\epsilon^2/\text{Hz}$. Start point is a valley point if the peak before is higher than the peak after the point. While the finish point is selected if peak after is higher than peak before the point. This concept is performed by Abdullah (2005) based on transient vibration where start and finish points are selected based on transient form. The points are determined based on the signal where the shortening in signal background occurs.

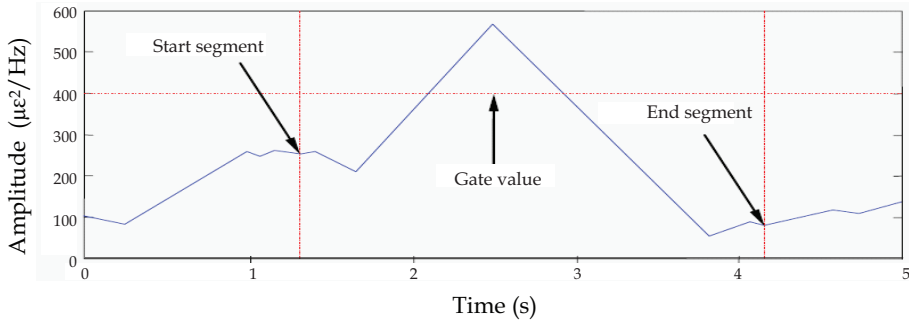


Fig. 1. The extracted segment identification

After all the segments are identified, the time history fatigue signal is then sliced to remove the lower amplitude (less than the gate value) contained in the original time history range with 100 % fatigue damaging retains. For this reason, the majority of the original fatigue damage is retained in the edited signal. All extracted segments (the complete section between the start and the end of the segments) selected based on time location of the wavelet coefficient amplitude are then combined together to produce a new mission time history. The mission signal replicates the signal statistical parameter and total fatigue damaging characteristics of the original time history. The optimum gate value is accordingly determined and it is based on the effectiveness of retaining the characteristics of the original signal in the mission signal. Ideally, the signal has shorter time length but is equivalent in the characteristic values.

3. Materials and methods

3.1 Finite element analysis

Every structure will experiences a transformation if it accepts a load, and an internal force, called stress, will stops the transformation. The load causes the structure to experience direct stress, not only tensile stress but also compressive stress. Structure accepting the tensile stress will become smaller, while structure accepting the compressive stress will cause buckling or permanent damage (Balía & Putra, 2006). If A is the cross-sectional area and F is the applied load, the true stress σ at fracture can be defined mathematically as the following expression (Draper, 2007):

$$\sigma = \frac{P}{A} \quad (13)$$

3.2 Data acquisition

For the data acquisition purpose, strain gauge was placed at the highest stress location of the front lower suspension arm of a passenger car. The car was travelled on pavé (cobblestone) road surface with velocity was 20 - 30 km/h. Fig. 2 shows the strain gauge position, the test track and the data acquisition set-up.

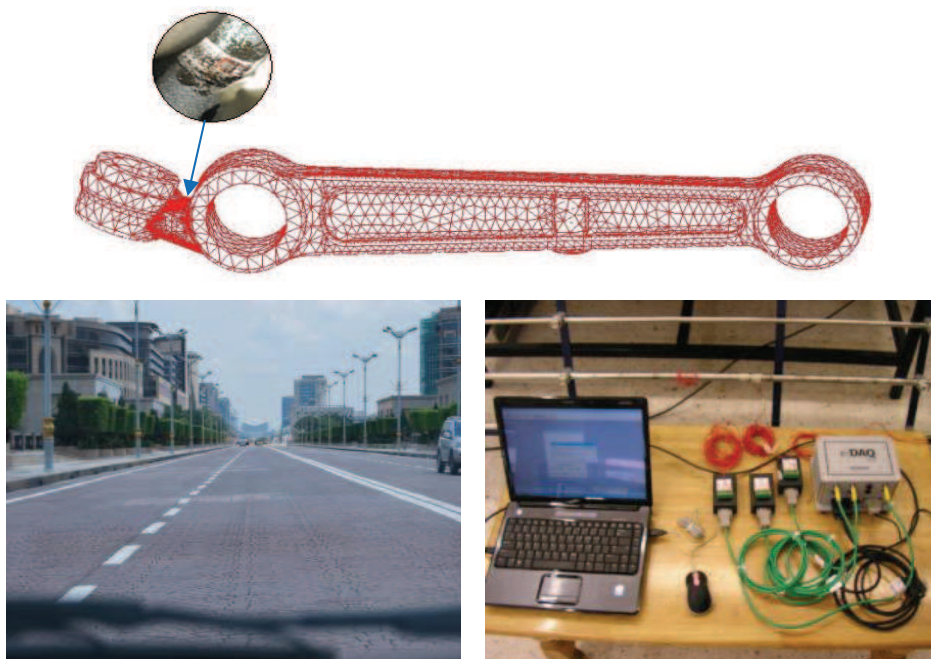


Fig. 2. The strain gauge position, a section of the pavé test track and the data acquisition set-up

The input signal was the variable amplitude loading sampled at 200 Hz since the fatigue damage occurs at lower frequency. From the data collection, it gave the total signal record length of 160 seconds. The collected signal recorded using a fatigue data acquisition system contained many small amplitude and high frequency in occurrence signal background. By

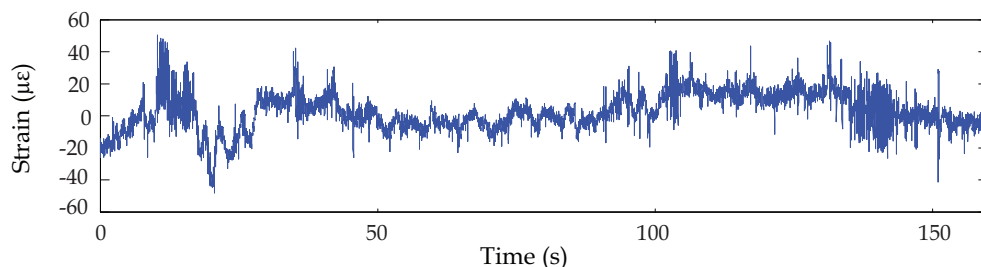


Fig. 3. The time history plot of the original test signal

multiplying the frequency and the signal length, it gave 32,000 data points. Fig. 3 shows the 160 second time history plotted for the original signal. The flowchart of the study is shown in Fig. 4.

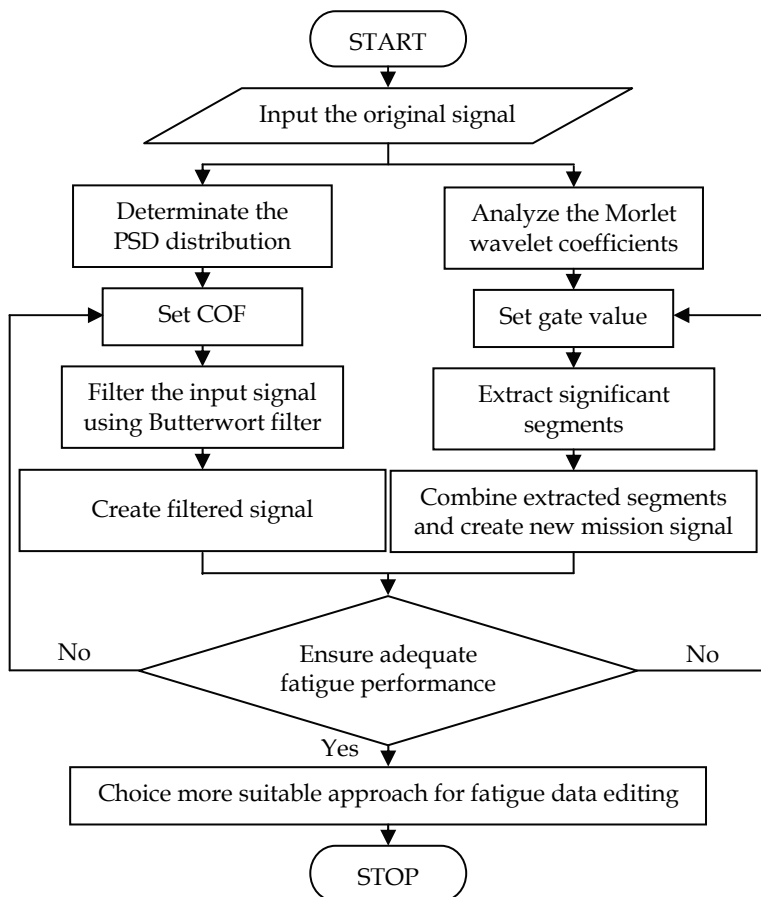


Fig. 4. Simplified flowchart of the undamaging cycle eliminating process

In this study, the selected material for the simulation purpose was the SAE1045 carbon steel shaft. This material was chosen because it was commonly used in automotive industries for fabricating a vehicle lower suspension arm structure (Khalil & Topper, 2003). The material properties and their definitions are given in Table 1 (nCode, 2005).

The fatigue damage and signal statistical parameter values for the each edited signal which was produced from the extraction process with differences COF and gate values would then be determined in order to observe the effectiveness of the methods for the fatigue data editing technique. The fatigue damage was estimated by utilizing the Coffin-Manson strain-life model. The cumulative fatigue damage was then determined from the Palmgren-Miner linear cumulative damaging rule. The edited signal required lower than 5 % difference of

fatigue damage to the original signal in order to produce a edited signal which retaining the original fatigue damage.

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

Table 1. The mechanical properties of the SAE1045 carbon steel shaft

4. Results and discussion

4.1 Stress distribution

The finite element modeling and analysis have been performed utilizing CATIA and MSC finite element analysis codes respectively. By using Eq. 13, this analysis determinates the maximum stress locations before doing the fatigue test. Based on the analysis performed by Al-Asady et al. (2008), it was obtained the stress distribution at the front lower suspension arm, as shown in Fig. 5.



Fig. 5. Stress distribution and strain gauge positions

In this simulation, the load was assumed of 300 kg. This value came from the car weight and the passengers. The stress level is presented by a colour contour, where the white colour shows the highest stress content and followed by black, blue, and so on.

4.2 The FFT analysis

In this frequency spectrum filtering analysis, data in time domain was then transformed into the frequency domain using the FFT algorithm in order to obtain its PSD distribution. The FFT formed a complex vector of values which each value represents the amplitude and phase of the particular sinusoidal wave at a particular frequency. The energy distribution showed on the PSD was applied to see the frequency region with lower energy in order to find the COF value for filtering purpose. The PSD display for original data is shown in Fig. 6.

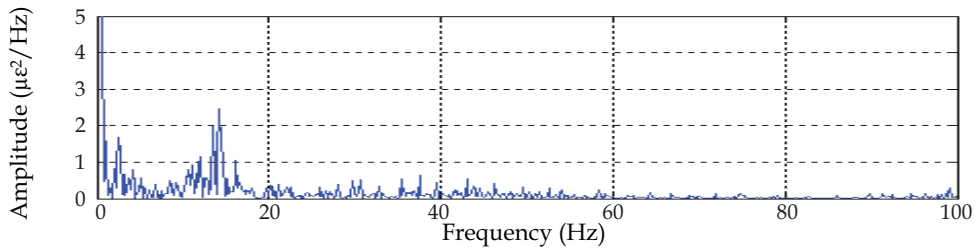


Fig. 6. The PSD distribution of the original signal

For fatigue data, lower amplitude region commonly located at higher frequency spectrum. Therefore, lower pass filter could be applied to remove higher frequency data which contain lower amplitude cycle in time history. Lower amplitude cycle could be removed because it gave minimal fatigue damage.

The filtering analysis with 4th order of Butterworth low-pass filter has been used for this data set. The 30 Hz COF was selected as the initial COF value, where getting from the PSD plotted. With 30 Hz COF, filtering process would filter out the frequency information higher than that value and obtain the new signal which contains only the allowed frequency. The same procedure was then repeated by using other COF values i.e. 35 Hz, 40 Hz, 45 Hz, 50 Hz, 55 Hz, 60 Hz, 65 Hz, 70 Hz, 75 Hz, 80 Hz, 85 Hz, 90 Hz, 92 Hz, 94 Hz, 96 Hz and 98 Hz. The difference in COF values were used in order to observe the effect of filtering behaviour related to fatigue life assessment for each filtered signal.

From the analysis of each filtered signal, the optimum value of COF was accordingly determined and it was based on the effectiveness of retaining the value of the fatigue damage and the signal statistical parameters. Unfortunately, the filtered signal with lower COF gave an obvious deviation in retaining fatigue damage. Nevertheless, by increasing the COF value the fatigue damage was ascending and almost reaches the fatigue damage of the

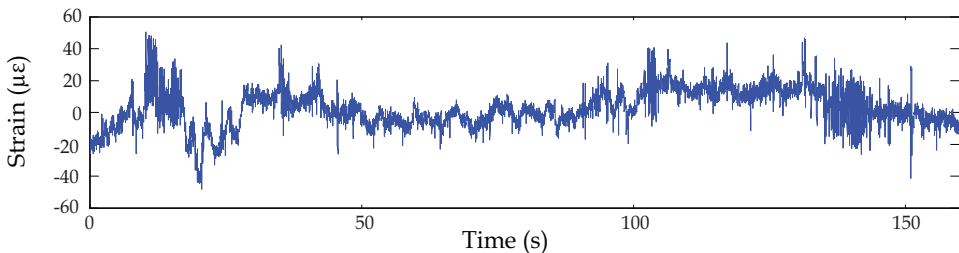


Fig. 7. Signal display after the filtering process

original signal. The filtered signal with COF 96 Hz was selected as the optimum values that giving lower than 5 % difference of fatigue damage. For the statistical parameter analysis, the values of the r.m.s. and the kurtosis for filtered signals were almost equivalent with the original signal, where those values were in the required range for any filtered signal with the differences were below than 10 %. Fig. 7 displays signal after the filtering process.

4.3 The Morlet wavelet analysis

For the Morlet wavelet based edited signal, it was started by analyzing the wavelet coefficients, as shown in Fig. 8. In the scalogram, the x -axis denoted the time parameter, the y -axis represented the scale that has an inversely related to the frequency value, and the colour intensity at each x - y point was proportional to the absolute value of the wavelet coefficients as a function of the dilation and translation parameters. It provided the signal energy distribution display with respect to the particular time and frequency information.

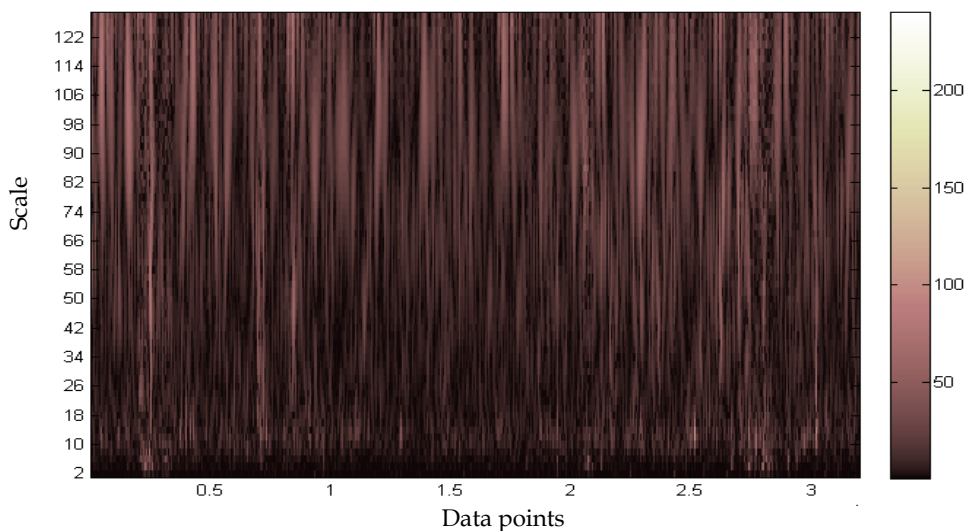


Fig. 8. The Morlet wavelet coefficients in time-frequency representation

Accordingly, a lower scale indicated higher frequency and had small amplitude that means these cycles had lower energy. They gave minimal or no fatigue damaging potential. A large scale was indicative of lower frequency and higher amplitude that indicates these cycles had higher energy causing the fatigue damage. Obviously, the lower frequency indicated higher magnitude distribution, and the lower magnitude distribution was presented at higher frequency event. Using the newly Morlet wavelet - based developed computational algorithm, the wavelet coefficient magnitude segments were transposed into time domain signal, as shown in Fig. 9. The representation showed a two dimensional view of the energy distribution, as observed in time-frequency plane.

This extraction process involved 150 $\mu\epsilon$, 160 $\mu\epsilon$, 170 $\mu\epsilon$, 180 $\mu\epsilon$, 190 $\mu\epsilon$, and 200 $\mu\epsilon$ gate values. From the total fatigue damaging calculation results, it was found that 170 $\mu\epsilon$ was

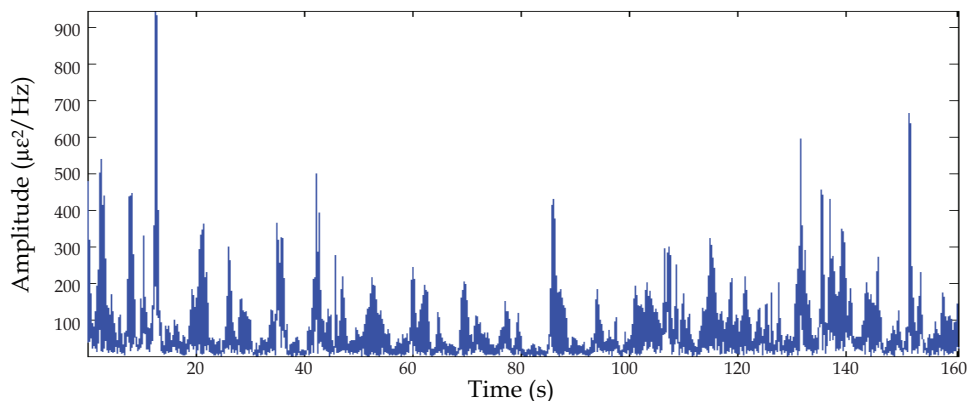


Fig. 9. The Morlet wavelet coefficients in time representation

selected to be the optimum gate value giving lower than 5 % difference of the fatigue damage. In this gate value, the numbers of cycle counting were only 4,561 cycles, which was 58 % less than the original signal. Furthermore, the new edited signal was produced of 68 seconds, which was 92 seconds shorter than the original signal length. The values of the r.m.s. and the kurtosis for the signal were in the required range with the differences were below than 10 %. Fig. 10 shows the plot of the edited signal.

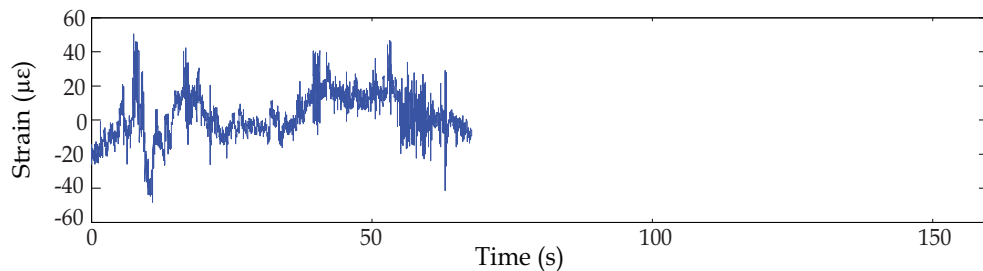


Fig. 10. The 68 second edited signal

Based on these two approaches, finally, the applicability of fatigue data editing with the adaptation of the Morlet wavelet method was proven for the situation to remove undamaging fatigue cycles with the retention of the majority of the original fatigue damage and shorten the signal length. The energy spectrum showed relatively adequate with damaging event in the fatigue signal and was a very useful tool for fatigue damaging detection in the fatigue signal.

5. Conclusions

This paper discussed on the study of fatigue data editing by using the frequency spectrum filtering techniques. Both the methods have been used to analyze random signal that can be applied to extract fatigue damaging events in the fatigue strain loading. The techniques were used to eliminate undamaging fatigue cycles in order to simplify raw signal for the

simulation testing purposes. Based on the simulation analysis, it was found that the Morlet wavelet was more suitable approach for eliminating undamaging cycles. The method removed 58 % of the original cycles in the 68 second edited signal with the retention of at least 95.5 % of the original fatigue damage. It removed 28 % more than the edited signal that was found using the FFT technique. The extraction of fatigue damaging events successfully removed the lower energy cycles in the time history. It created a new edited signal which retains higher fatigue damaging segments containing the majority of the fatigue damage. Hence, this fatigue data summarising computational algorithm can be used in laboratories in order to study the durability characteristics of automotive components. In overall, the analysis findings of this paper suggested that the Morlet wavelet was more suitable for the fatigue data editing.

6. Acknowledgement

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The field of material analysis has seen explosive growth during the past decades. Almost all the textbooks on materials analysis have a section devoted to the Fourier transform theory. For this reason, the book focuses on the material analysis based on Fourier transform theory. The book chapters are related to FTIR and the other methods used for analyzing different types of materials. It is hoped that this book will provide the background, reference and incentive to encourage further research and results in this area as well as provide tools for practical applications. It provides an applications-oriented approach to materials analysis written primarily for physicist, Chemists, Agriculturalists, Electrical Engineers, Mechanical Engineers, Signal Processing Engineers, and the Academic Researchers and for the Graduate Students who will also find it useful as a reference for their research activities.

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