Running Damage Extraction Technique for Identifying Fatigue Damaging Events

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Abstract: - This paper presents the development of a new fatigue data editing technique, called Running Damage Extraction (RDE), for summarising long records of fatigue data. This technique is used to extract fatigue damaging events in the record that cause the majority of fatigue damage, whilst preserving the load cycle sequence. In this study, fatigue damaging events are identified from the characteristic of abrupt changes that exist in the fatigue data. Then, these events are combined to produce a mission signal which has equivalent statistics and fatigue damage to the original signal. The objective of this study is to observe the capability of RDE technique for summarising long records of fatigue data. For the purpose of this study, a collection of nonstationary data that exhibits random behavior was used. This random data was measured in the unit of microstrain on the lower suspension arm of a car. Experimentally, the data was collected for 60 seconds at a sampling rate of 500 Hz, which gave 30,000 discrete data points. Global signal statistical value indicated that the data were non Gaussian distribution in nature. The result of the study indicates that this technique is applicable in detecting and extracts fatigue damaging events that exist in fatigue data.

Key-Words: - Abrupt changes, fatigue data, global statistics, nonstationary data, RDE technique,

1 Introduction

In fatigue data analysis, data editing plays an important role in calculating the damage that are caused by the stress loading. The function of fatigue data editing is to remove the small amplitude cycles for reducing the test time and cost. By using this approach, large amplitude cycles that cause the majority of the damage are retained and thus only shortened loading consisting of large amplitude cycles are produced [1].

Previous studies have shown that several data editing technique has been developed for use in time domain. Some computational algorithms were developed to omit the small amplitude cycles as to retain the large amplitude cycles, such as: the application of local strain parameter and linear damage rule in selecting the edit levels of VA loading while retaining the original history in sequence, the use of a non linear damage rule incorporating overstrain and sequence effect, the use of a damage window joining function to produce an edited signal, the application of Smith-Watson-Topper (SWT) parameter to determine the range of low amplitude cycles that should be eliminated, bump extraction algorithm by using wavelet transform for summarising long record of fatigue data [2], and the application of Short-Time-Fourier-Transform (STFT) in removing low amplitude cycles to produce a shortened signal [3].

This paper discusses a new technique that has been developed for extracting fatigue damaging events. The characteristics of these event are identified from the abrupt changes that exist in mechanical fatigue signal data. An abrupt change is defined as a mean change in characteristics that occur very suddenly with respect to the sampling period of the measurements, if not instantaneously. Since significant information contained in the measurement lies in their nonstationarities, and because most adaptive estimation algorithms can basically only follow slow changes and are very complex to understand, a new method is needed to be developed in detecting the abrupt changes that exist in the fatigue data [4].

In solving this problem, a new technique called Running Damage Extraction (RDE) method was proposed. This technique is designed to identify and extract fatigue damaging event that exist in variable amplitude (VA) loading data. This method was developed by combining the overlapping window concept and fatigue damage calculation. Later, this technique were expanded to be used in summarising the fatigue data by moving small amplitude cycles for reducing the time and cost. The goal of this study is to investigate whether this technique can be used accurately to shorten the typical fatigue histories data.

2 Literature Review

2.1 Signal Analysis

A signal is a series of numbers that come from measurement, typically obtained using some recording method, as a function of time. In real applications, signals can be classified into two types which are stationary and non-stationary behavior. Stationary signals exhibit statistical properties which remain unchanged with t changes in time. On the other hand, statistics of non-stationary signal is dependent on the time of measurement. In the case of fatigue research, the signal consists of a measurement of cyclic loads, i.e. force, strain and stress against time. The observations of a variable were taken at equally spaced intervals of time [5].

In normal practice, the global signal statistical values are frequently used to classify random signals. In this study, mean, root mean square (r.m.s.) and kurtosis were used [6]. For a signal with *n* data points, the mean value of $\bar{x}$ is given by

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

On the other hand, root mean square (r.m.s) value, which is the 2nd statistical moment, is used to quantify the overall energy content of the signal and is defined by the following equation:

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

where x_j is the j^{th} data and *n* is the number of data in the signal.

The kurtosis, which is the signal 4th statistical moment, is a global signal statistic which is highly sensitive to the spikeness of the data. It is defined by the following equation:

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

Frequency analysis data is typically presented in graphical form as a Power Spectral Density Function (PSD). It is used to convert a signal from time domain to the frequency domain using the Fast Fourier Transform (FFT method). To convert a time domain signal into the frequency domain, the signal is separated into a number of discrete sinusoidal waves of varying amplitude, frequency and phase. In the relation of the PSD with the FFT, the PSD is normalized density plot that describe the mean square amplitude of each sinusoidal wave with respect to its frequency. The PSD is mathematically defined as the Fourier transform of its autocorrelation function. In the PSD plot, each frequency step value is characterized by amplitude, A_k as following equation;

$$A_k = \sqrt{2\Delta f . S(f_k)} \qquad (4)$$

where $S(f_k)$ is the underlying PSD of the signal and f_k is the harmonic frequency[2] .

2.2 Fatigue Data Editing

Fatigue durability testing of mechanical structure is performed extensively in all industries as one of the parts of a design process. In real applications, the fatigue loading services such as stresses on a car wheel, bending moment on the stub axle of a car, stresses on the rear axle of a passenger car etc. are variable amplitude histories [7]. The histories often contain a large percentage of small amplitude cycles and the fatigue damage for these cycles can be small. Therefore, in many cases the fatigue loading history were edited by removing those small amplitudes cycles in order to produce representative and meaningful yet economical testing [8].

In fatigue life assessment study, fatigue data editing is described as a method of summarising the fatigue data by removing small amplitude cycles for reducing the testing time and cost. There are two key factors that have been suggested in order to achieve efficient design and modification processes to ensure adequate fatigue performance, i.e., the fatigue damage should be as accurate as possible and the component durability tests should be as short as possible [9].

2.3 Fatigue Damage

It is common that the service loads acquired by components of machines, vehicles, and structures are analysed for fatigue life using crack growth approaches. For these components, it is important to predict crack initiation in order to avoid fatigue failure by replacing the part from service at the appropriate time [10]. Hence, a fatigue life estimation based on the related strain-based approach is usually used in these cases.The strain-life approach considers the plastic deformation that occurs in the localised region where fatigue cracks begin under the influence of a mean stress.

The total strain amplitude, ε_a is produced by the combination of elastic and plastic amplitude

$$\varepsilon_a = \varepsilon_{ea} + \varepsilon_{pa} \qquad (5)$$

where ε_{ea} is the elastic strain amplitude and ε_{pa} is the plastic strain amplitude. The elastic strain amplitude is defined by

$$\varepsilon_{ea} = \frac{\sigma_a}{E} = \frac{\sigma'_f}{E}(2N_f)^b \qquad (6)$$

while the plastic strain amplitude is given as

$$\varepsilon_{pa} = \varepsilon'_f (2N_f)^c \qquad (7)$$

where σ_a is the stress amplitude, N_f is the number of cycles to failure, σ'_f is the fatigue strength coefficient, b is the fatigue strength exponent, ε'_f is the fatigue ductility coefficient, c is the fatigue ductility component and E is the modulus of elasticity.
Combining Equations 8 and 9 gives the Coffin-Manson relationship, which is mathematically defined as

$$\varepsilon_a = \frac{\sigma'_f}{E}(2N_f)^b + \varepsilon'_f(2N_f)^c \qquad (8)$$

which is essentially Equation 8 above and is the foundation of the strain-life approach.

Some realistic service loads involve nonzero mean stresses. One common mean stress effect model is the Smith-Watson-Topper (SWT) strain-life model, which is defined by

$$\sigma_{\max}\varepsilon_a = \frac{\sigma'^2_f}{E}(2N_f)^{2b} + \sigma'_f\varepsilon'_f(2N_f)^{b+c} \qquad (9)$$

where the damage parameter is taken to be the product of the maximum stress and the strain amplitude of a cycle. In our study the strain-life approach and the Smith-Watson-Topper (SWT) strain-life model for mean stress effect were used in all fatigue damage calculations.

Fatigue damage is derived from the number of cycles to failure where the relationship is

$$Damage = \frac{1}{N_f} \qquad (10)$$

therefore fatigue damage values have the range [0, 1] where zero denotes no damage (extremely high or infinite number of cycles to failure) and 1 means total failure (one cycle to failure).

The RDE plot in this study has many non-parallel lines that contain a significant number of local optima, which can be classified as either peaks or valleys. A peak is defined to be associated with change in the slope from positive to negative, while a valley is associated with a change in the slope from negative to positive [11]. Peaks in a RDE are essentially the local maxima and valleys are the local minima. Depending on the resulting RDE, some points can be classified as neither peaks nor valleys.

Peak-Valley (PV) identification can be used to segment signals so that each segment may contain certain numbers of peaks and/or valleys, according to the needs of the study. This is particularly useful for fatigue time series data, since peaks and valleys feature predominantly in rainflow counting algorithms for fatigue damage calculations [12]. PV-based techniques are also used in mechanical modeling [13], quantifying roughness of materials [13, 14, 15], and image segmentation [16].

2.3 Fatigue Signal Segmentation

In signal processing, a segmentation algorithm was used to split the signal into homogenous segments, the lengths of which are adapted to the local characteristics of the analyzed signal. The homogeneity of a segment can be in terms of the mean level or in terms of the spectral characteristics [17]. Segmentation can be explained as follows:

An m-segmentation $S_T^m\,(m \leq n)$ of time series T is a partition of T to m non-overlapping segments;

$$S_T^m = \{\{(S_T(a_i, b_i)|1 \leq i \leq m)\}\} \qquad (11)$$

Such that a_i=1, $b_m = n$, and $a_i = b_{i-1} + 1$ for $1 \leq i \leq m$. In other words, an m-segmentation splits T into m disjoint time intervals. For simplicity, the segments are denoted by $S_1, \ldots, S_m$ [18].

In fatigue life assessment study, fatigue signal extraction is described as a method to summarise a fatigue signal. The first step of summarizing the fatigue signal is to isolate the low and high amplitude events into different segments. All the extracted segments (the complete section between the start and the end of the segments) are selected based on peak and valley time location of the running damage values.

3 Methodology

The data that was used in this study is variable fatigue strain loading data. It was collected from an automobile component during vehicle road testing. It was obtained from a fatigue data acquisition experiment using strain gauges and data logging instrumentation.

The collected fatigue data was measured on the car's front lower arm suspension as it was subjected to the road load service. All the data that was measured from this experiment was recorded as strain time histories.
The strain value from this test was measured using a strain gauge that was connected to a device, a data logger, for data acquisition. Experimental parameters that need to be controlled in this test such as sampling frequency and type of output data being measured were specified in the data acquisition software.

In order to collect a variety of data, the car was driven on three different road:- pave route, highway and campus roads. Experimentally, the data was collected for 60 seconds at a sampling rate of 500 Hz, which gave 30,000 discrete data points. This frequency was selected for the road test because this value does not cause the essential components of the signal to be lost during measurement. The road load conditions were from a stretch of highway road to represent mostly consistent load features, a stretch of brick-paved road to represent noisy but mostly consistent load features, and an in-campus road to represent load features that might include turning and braking, rough road surfaces and speed bumps.

To fullfill the main purpose of this study, the RDE algorithm is used to identify and extract the abrupt changes for fatigue damaging events. The generic problem of detecting abrupt changes in process parameters has been widely studied. These changes may be due to shifts that exist in the mean value (edge detection) or a variation in signal dynamics [17].

This technique is based on the running concept which the original data are separated by using overlapping window. For a signal with n data points, the numbers of overlapping window is given by $x_i \in X$, where X is the signal data, h is the size of overlap and m is the size of the window

$$\{ x_j , x_{j+1} , x_{j+2} ,..., x_{j+k-1} \}, \tag{12}$$

where

$$i = 1,2,3,...$$
$$j = 1,1+h,1+2h,...$$
$$k = m,m+h,m+2h,...$$

A flowchart describing the RDE technique is presented in Fig. 1 and it involves several stages: the input signal and global statistics parameter; transform input signal into overlapping window; calculation of running damage based on the overlapping window; identification of optimized running damage; the identification and extraction of abrupt changes for fatigue damaging events; and decision making process.

The first stage of RDE algorithm is to display the three different types of fatigue data in times series plots and global statistic parameters. In normal practice, the global signal statistical values are frequently used to classify random signals. In this study, mean, root mean square (r.m.s.) and kurtosis were used [2].

The next stage is the most crucial part in the development of the RDE technique. At first, the data was divided in different window by using the overlapping algorithm. In each window, there were 500 data points. The original data points in each window that were then overlapped between each other from 10% to 90%. Then, the data that was produced in each window was transferred into Glyphwork software for calculating the value of fatigue damage. The purposed of overlapping in this study was based on the assumption to reduce the possibility of damaged calculation for each window that crosses over the peak values in the original signal and to mitigate the "loss" at the edges of the window.

Then, the identification of the optimised running window was needed. Each overlapping window for running damage was plot over time. Regression analaysis is proposed to be used in analyzing the variation component in the running damage data. The trend values for the running damage were then compared to the trend values of original signal. In this study, it is proposed that the optimum value for overlapping running damage be based on the minimum values of trend analysis as it represents the removal of the trend component from the actual data.

The third stage of the RDE algorithm is to identify and extract the abrupt changes for fatigue damaging events. The Running Damage (RD) data point can be classified as either peak or valleys. A peak is defined to be associated with change in the slope from positive to negative, while a valley is associated with a change in the slope from negative to positive.

Data points and time points on the RD values are grouped into sets and set of ordered pair is obtained using the Cartesian product of sets. The modified condition for peak and valleys that were used in this study can be explained as follows:

$$D = \{d_j : j = 1, 2, \dots, n; d_j \neq d_j + 1\} \tag{13}$$

$$T = \{t_j : j = 1, 2, \dots, n\} \tag{14}$$

$$A = D \times T \tag{15}$$

The ordered set D contains elements that denote the data points of the RDE, while the ordered set T contains the corresponding time points, n is the number of points and A is the ordered pair obtained by pairing each data point in the D with a time point in T.

$$P = \{d_j : d_{j-1} < d_j > d_{j+1}\} \cup \{d_1 : d_1 > d_2\} \cap \{d_n : d_n > d_{n-1}\} \tag{16}$$

$$V = \{d_j : d_{j-1} > d_j < d_{j+1}\} \cup \{d_1 : d_1 < d_2\} \cap \{d_n : d_n < d_{n-1}\} \tag{17}$$

$$P \cap V = \emptyset \tag{18}$$

$$(P \cup V) \subset D \tag{19}$$

The ordered set of P will contain elements of D that are classified as peaks in the damage window data points, V is an ordered set of data points that are classified as valleys, and P and V are non-intersecting and their union is a proper subset of D. After the RDE data points were simplified by using peak and valley algorithm, the decision function for the extraction is based on energy enveloping in the original signal, the time points that correspond to valley data points are then identified. In this stage, the RDE was combined with peak and valley calculation so that the decision function for the time series segmentation can be performed.

As in equation (17), a data point d_j is classified as a peak if it is strictly greater than d_{j-1} (the data point before it) and d_{j+1} (the data point after it), while equation (18), states that a data point is classified as a valley if it is strictly smaller that the points before and after it. The identification for abrupt changes in the original signal was based on the method of searching in bump extraction [2]. The low and high amplitude events in the original signal were isolated in different segmentation. A new parameter which includes the zero damage value in the segmented data and represents the uncritical part in fatigue signal behavior that was needed to be removed from the original signal was set. This means that, the segmented data that has high impact of damage will be retained and the segmented data that has zero impact of damage will be eliminated. Thus, a new shortened edited signal which neglected low amplitude cycles is produced. The last stage involves the identification on whether the RDE algorithm can detect transient events in fatigue data. It is assumed that the RDE algorithm can be used in predicting the abrupt changes that exist in fatigue data. For validation purposes, the fatigue damage potential for both original and edited signals were calculated in order to study the efficiency of the edited signal based on the fatigue damage retention. In order to retain the originality of the signal, the statistical parameter of the edited signal need to be equivalent to the original signal. For this case, a 10% difference in the root-mean-square and kurtosis values between the edited and the original signals was used for analyzing experimental road load data sets. This is important in order to retain the signal energy and amplitude ranges [3, 18].

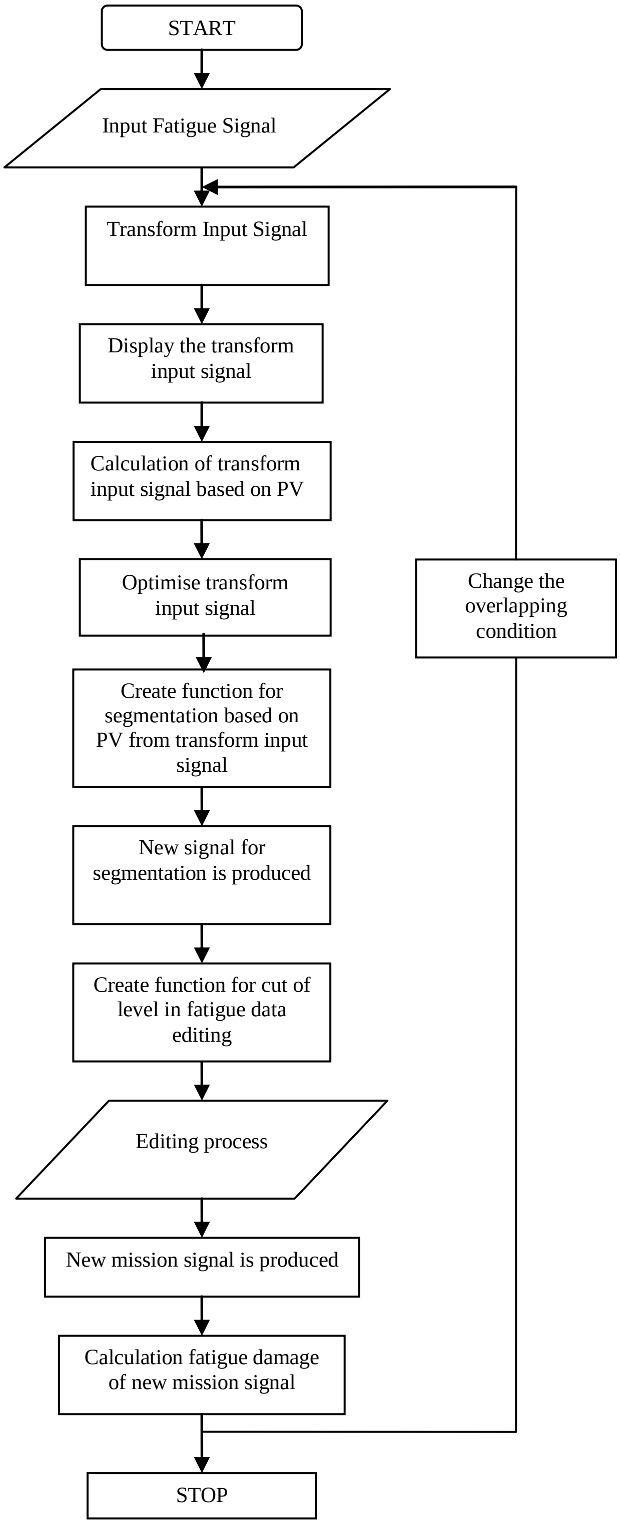

Fig. 1: The RDE method flowchart

4 Results and Discussion

Fig. 4, 5 and 6 represent PSD plots for the original signal which is Pave route, highway and campus signal respectively. Based on the frequency analysis, PSD plot for all signal shows a significant result by concluding all the collected data has the similar characteristics. It was found that all the collected signal has the same process which is 'broad band process'. It is one that covers a wide range of frequencies. This might consist of a single, wide spike or a number of distinct spikes as shown in the figures below.

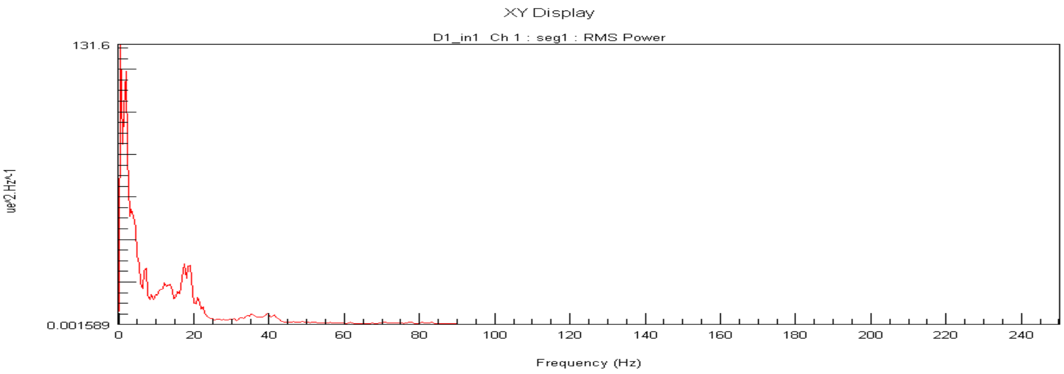

Fig.3: PSD plot for Pavé Route data

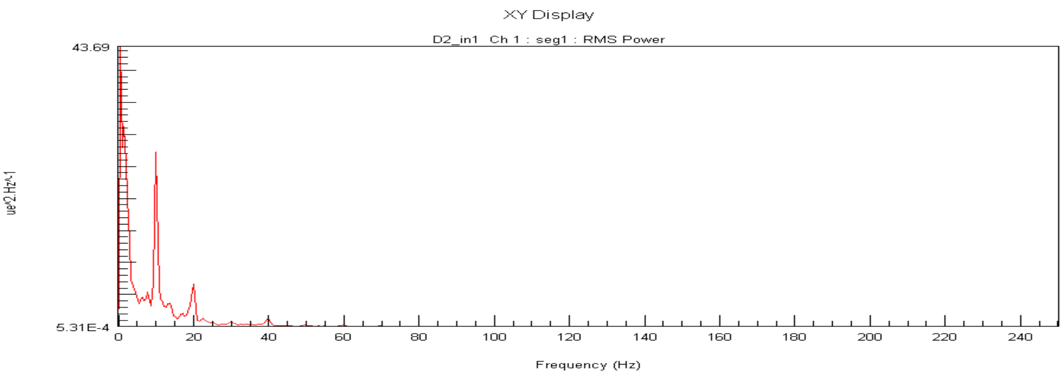

Fig.4: PSD plot for Highway data

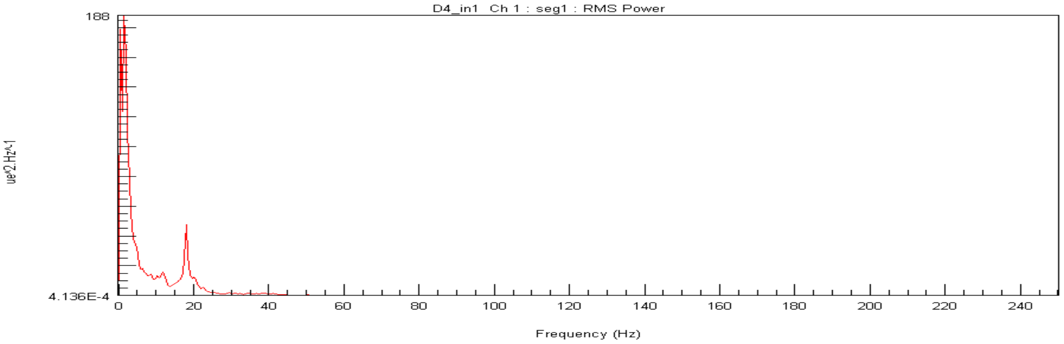

Fig.5: PSD plot for Campus data

From the result, the optimum condition for overlapping window for case study data which is 80% shows a significant result in extracting fatigue damaging events. All of the edited signals gained from the zero value of damage were retained in the majority of the fatigue damage and were approximately the same as the original signal and they also retained the statistical parameters within 10% deviation. Figure 6, 7 and 8 represent the original and edited signal for Pave route, highway and campus signals respectively.

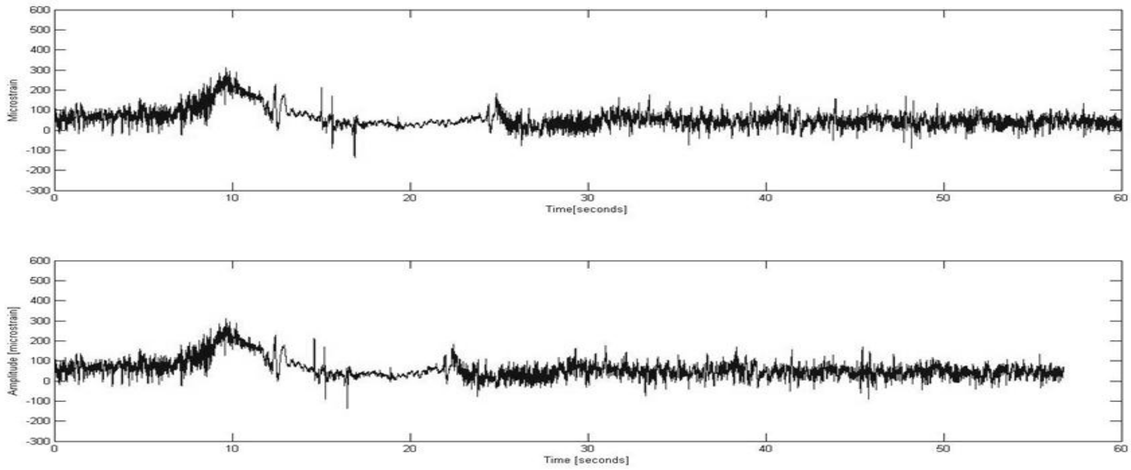

Fig.2: Comparison between the original and edited signal for Pavé Route data

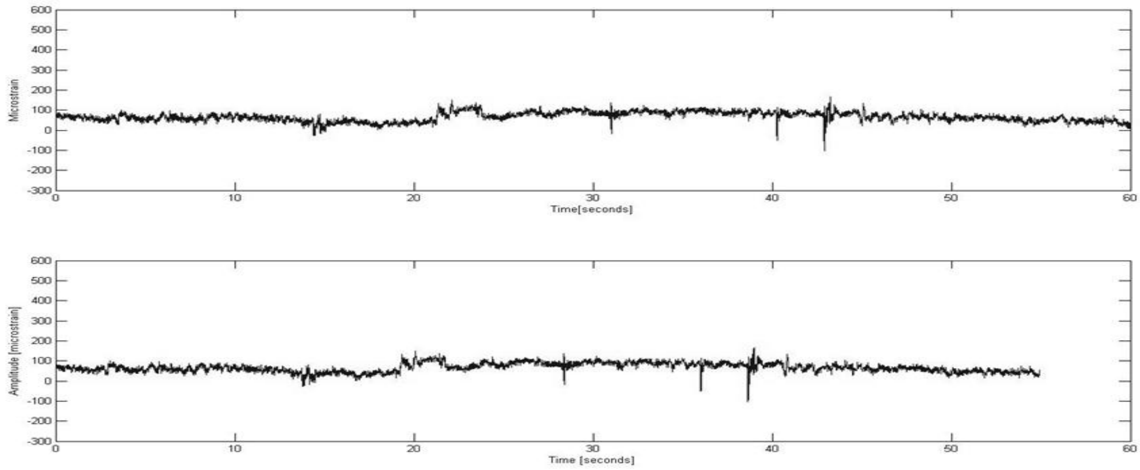

Fig.3: Comparison between the original and edited signal for Highway data

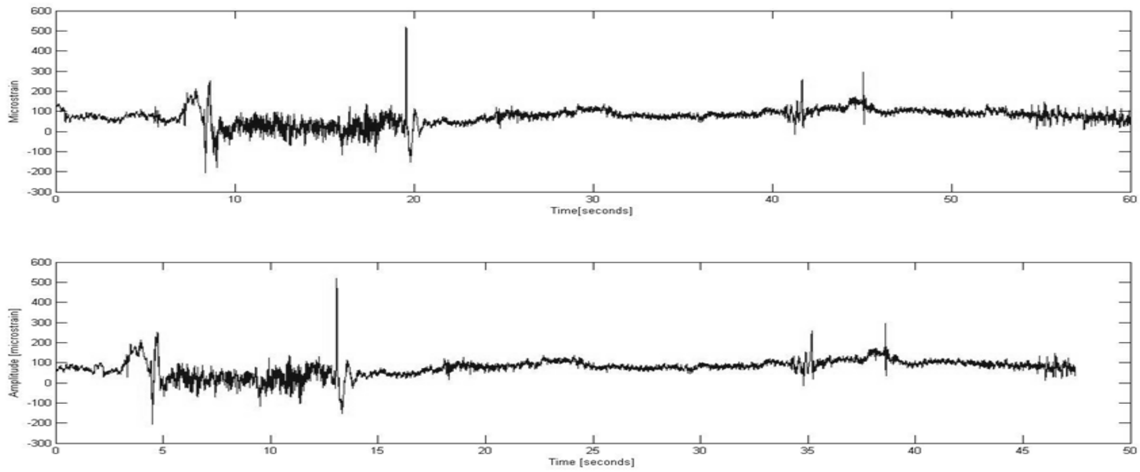

Fig.4: Comparison between the original and edited signal for Campus data

From all the figures above, it was shown that the high amplitude events were retained in the edited signals. The compression characteristics between the original and the edited signals are shown in Table 1. Overall, the analysis of this study suggested that the RDE fatigue data editing technique can successfully remove the low amplitude cycles while retaining the characteristics of original signal behaviour. With the basis of the statistical parameter retention between the original and the edited signals, this technique produced highly accurate signal which were similar to the original signal. The RDE plot shows relatively adequately the damage events in the fatigue signal and is a very useful tool for damage detection in the fatigue data analysis. The extraction of damaging events successfully created a new edited signal which retained the majority of fatigue damage.

Data	Signal Length (seconds)	Mean	RMS	Kurtosis	Damage
Original Pave	60	58.22	74.53	6.7	5.78E-03
Edited Pave	56.7	59.14	75.82	6.41	5.74E-03
Original Highway	60	66.32	70.3	3.58	5.13E-04
Edited Highway	54.9	66.46	70.27	3.89	4.94E-04
Original Campus	60	72.48	83.34	10.53	7.37E-03
Edited Campus	47.4	74.31	85.52	10.77	6.71E-03

Table 1: The Compression characteristics between the original and the edited signal

5 Conclusions

This study discussed the capability of a fatigue data editing technique in time domain using Running Damage Extraction (RDE) method. This technique was developed to remove the low amplitude cycles which were contained in the original signal. From the analysis, the editing process was performed based on the filtering parameter which eliminated the segment that contained zero values of damage.

In the presented case study data, i.e., the Pavé edited signal, the highway edited signal and campus edited signals have reductions of 5.5%, 8.5% and 21% respectively from the original signal. All signals also retained the major signal statistics with below 10% of the root-mean-square value (representing the vibration signal energy in a time series) and the kurtosis value (representing the amplitude range in a time series). Although this technique can shorten the original signal from the case study, a validation of the effectiveness of this method needs to be done. Validation steps need to be taken in order to make sure the robustness of this technique as an alternative in fatigue durability study, especially for the automotive engineering field would not be disputed.

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