The Morlet Wavelet Analysis for Fatigue Feature Clustering

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Abstract: - This paper presents clustering of fatigue features resulted from the segmentation of SAESUS time series data. The segmentation process was based on the Morlet wavelet coefficient amplitude level which produced 49 segments that each has overall fatigue damage. Observation of the fatigue damage and the wavelet coefficients was made on each segment. At the end of the process, the segments were clustered into three in order to identify any improvements in the data scattering for fatigue data clustering prospects. This algorithm produced a more reliable and suitable method of segment by segment analysis for fatigue strain signal segmentation. According to the findings, the higher Morlet wavelet coefficient presented damaging segment, otherwise, it was non-damaging segment. This indicated that the relationship between the Morlet wavelet coefficient and the fatigue damage was strong and parallel.

Key-Words: - Fatigue strain signal, segmentation, fatigue damage, Morlet wavelet coefficient, clustering

1 Introduction

Occasionally, fatigue signals measured from critical automotive parts have variable amplitude patterns with mean value of the data that change with time (each pattern has different statistical value). They contain a 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 [1-2].

Several fatigue data editing approaches have been introduced in various domains: time, peak and valley, frequency, cycles, damage, and histogram. The most commonly applied procedures in the research literature have been based on time and frequency domains [3]. One of the new approaches that was developed for the fatigue signal extraction is the one in time-frequency domain. Previously, the time-frequency approach had been applied to the problem of fatigue signal extraction, but only for the purpose of spike removal and de-noising [4]. Among the time-frequency domain analyses that have been used widely in engineering problems are Short-time Fourier Transform (STFT), S-transform and wavelet transform (WT).

The STFT or windowed Fourier transform is one of the methods for transforming the time domain signal into the time-frequency domain [5]. In addition, the STFT adapted the Fourier transform to analyse only a small section of the signal at one specific time [6]. The STFT is performed by dividing the signal into small sequential or overlapping data frames. Then, Fast Fourier Transform (FFT) has been applied to each data frame. The output of successive STFT can provide a time–frequency representation of the signal. In order to accomplish this, the signal is truncated into short data frames by multiplying it by a window so that the modified signal is zero outside the data frame. In order to analyse the whole signal, the window is then translated into time and reapplied to the signal.

For the resolution, the length of the window used in this method is fixed on every time and frequency axis. Window size used will determine the obtained resolution, where small windows present good time resolution, and longer windows represent good frequency representations [7]. Finally, the STFT provides information on when and at what frequency a signal occurs. However, this information is only obtained with limited precision determined by the size of the window. Many signals require a more flexible approach, to determine more accurately either time or frequency [6].

The S-transform is an invertible time-frequency spectral localization technique which combines elements of the wavelet transforms and the STFT [8]. It is an extension of the STFT which uses frequency-dependent scaling windows in analogy to the wavelet transform. This permits a frequency-dependent resolution with narrower windows at higher frequencies and wider windows at lower frequencies [9].

The S-transform has an advantage in that it provides multi-resolution analysis while retaining the absolute phase of each frequency. This has led to its application for detection and interpretation of events in time series in a variety of disciplines. Some examples are analysis of the time variation in the amplitudes and phases of sea-level data in oceanography [10], representation of the spectral content of seismic traces using a spectral color technique [11], and decomposition of gear vibration signals [12].

With the advances in digital signal processing research, there has been an increasingly strong interest in the related application for fatigue life assessment of automotive components. During the last decade, an improved signal processing technique, called the 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 crack and even a very shallow crack can be detected. The rotor is not required to stop and the detection process is applied for a rotating shaft makes the methodology more versatile, convenient and unambiguous [13].

This paper discusses the clustering of fatigue data (represented as time series) by evaluating the fatigue damage and the Morlet wavelet coefficient of each segment, resulting data scattering, and clustering the data. It is hypothesized that the fatigue damage and the Morlet wavelet coefficient have a strong correlation. The fatigue features were identified and extracted by segmenting SAE-owned fatigue strain data set.

Segmentation was always used to classify data in order to analyse discrete data in time domain in vibrational and fatigue data analyses. Segmentation aimes to remove lower or minimal damaging features of an original signal. It is performed by segment identification and extraction of those that contribute to the more fatigue damaging events of 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 edited signal and this signal can be used to reduce the testing time and cost [14].

This method is also known as the fatigue feature extraction. Two key factors are suggested for achieving an efficient design and modification processes to ensure adequate fatigue life assessment, i.e.: the signal statistical parameters and the fatigue damage should be as accurate as possible and the component durability tests should be as short as possible.

2 Literature Background

2.1 Fatigue Life Assessment

These are three major approaches to predicting fatigue life namely stress-life, strain-life, and fracture mechanics. At below the transition point (approximately 1000 cycles), the ε-*N*-based approach is appropriate method and is commonly used to predict fatigue life for ductile materials at relatively short fatigue life. The crack initiation method relates the plastic deformation that occurs at a localized region where fatigue cracks begin to the durability of the structure under influence of mean stress [15].

The total strain amplitude ε_a is produced by the combination of elastic and plastic amplitudes, i.e.:

$$\varepsilon_a = \varepsilon_{ea} + \varepsilon_{pa} \tag{1}$$

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

$$\varepsilon_{ea} = \frac{\sigma'_f}{E}\left(2N_f\right)^b \tag{2}$$

while the plastic strain amplitude is given as:

$$\varepsilon_{pa} = \varepsilon'_f \left(2N_f\right)^c \tag{3}$$

where N_f is the numbers of cycle to failure for a particular stress range and mean, 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 exponent and E is the material modulus of elasticity.

Combining Equations (2) and (3) gives the Coffin-Manson relationship, which is mathematically defined as:

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

which is essentially Equation (1) above and is the foundation of the strain-life approach.

Current industrial practice uses the Palmgren-Miner [16-17] linear cumulative damaging rule normally associated with the established strain-life fatigue damaging models, i.e. the Coffin-Manson [18-19], the Morrow [20], and the Smith-Watson-Topper (SWT) [21]. The cumulative fatigue damaging approach presented in this research was based on the Morrow strain-life relationship. In a case of the loading being predominantly compressive, particularly for wholly compressive cycles, this model provides more realistic life estimates. The mean stress correction effect seems to work reasonably well for steels. The model is mathematically defined as the following expression [20]:

$$\varepsilon_a = \frac{\sigma'_f}{E}\left(1 - \frac{\sigma_m}{\sigma'_f}\right)\left(2N_f\right)^b + \varepsilon'_f\left(2N_f\right)^c \tag{5}$$

where σ_m is the mean stress.

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 and the total fatigue damage *ΣD* caused by cycles are expressed respectively as [16-17]:

$$D = \frac{1}{N_f} \tag{6}$$

$$\Sigma D = \Sigma\left(\frac{N_i}{N_f}\right) \tag{7}$$

where N_i is the numbers of cycle within a particular stress range and mean.

Fatigue damage has value in 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).

2.2 Signal Statistical Parameters

In the case of the fatigue research, a signal consists 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 being taken at equally spaced intervals of time. Global signal statistical parameters are frequently used to classify random signals and monitor the pattern of analysed signals. For a signal with a numbers of data points *n* in a sampled sequence, the mean $\bar{x}$ is given by:

$$\bar{x} = \frac{1}{n}\sum_{j=1}^{n} x_j \tag{8}$$

For a fatigue signal, the calculation of the root-mean-square (r.m.s.) and the kurtosis are important in order to retain a certain amount of the signal amplitude range characteristics. The r.m.s. value 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:

$$r.m.s. = \left\{\frac{1}{n}\sum_{j=1}^{n} {x_j}^2\right\}^{1/2} \tag{9}$$

The kurtosis is the signal 4th statistical moment. In 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 [22]:

$$K = \frac{1}{n(r.m.s.)^4}\sum_{j=1}^{n}\left(x_j - \bar{x}\right)^4 \tag{10}$$

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 is 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 the one that should be found in a Gaussian distribution [14]. This situation indicated that the fatigue damage is higher than Gaussian stresses due to higher amplitude fatigue cycles [23].

2.3 The Morlet Wavelet Coefficient

The WT approach 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 [24-26].

The WT analysis is started with a basic function (called the mother wavelet) scaled and translated to represent the signal being analysed [27]. 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. 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 [24].

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 localized area of larger signal, also known as local analysis [6].

The wavelet decomposition calculates a resemblance index between the signal being analysed and the wavelet, called the coefficient. It is the result of regression of an original signal produced at different scales and different sections on the wavelet. It represents the correlation between the wavelet and a section of the signal. If the index is large, the resemblance is strong, otherwise it is slight. Generally, the wavelet coefficient C is expressed with the following integral [6]:

$$C_{(scale,position)} = \int_{-\infty}^{\infty} f(t)\psi(scale, position, t)dt \tag{11}$$

The Morlet wavelet is one of functions that are generally used in the Continuous Wavelet Transform (CWT) analyses [28]. The WT of any time-varying signal $f(t)$ is defined as the sum of all of the signal time multiplied by a scaled and shifted version of the wavelet function $\psi(t)$ [7]. The CWT is expressed by the following integral:

$$CWT_{(a,b)} = \int_{-\infty}^{+\infty} f(t)\psi_{a,b}(t)dt \tag{12}$$

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 time.

$\Psi_{a,b}(t)$ denotes the mother wavelet, i.e. [29]:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right) a,b \in R; a \neq 0 \tag{13}$$

$$CWT_{(a,b)} = \int_{-\infty}^{+\infty} f(t)\frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right)dt \tag{14}$$

In addition, the wavelet coefficient indicates how the energy in the signal is distributed in the time-frequency plane [13]. 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.

2.4 Data Clustering

Running fatigue damaging window, running global signal statistical window, analysis of the wavelet transform, the integrated kurtosis-based algorithm for Z-filter (I-kaz), and data correlation are required parameters for fatigue data classification. Fatigue data analysis technique based on signal classifying has to develop more detail to ensure higher amplitude signals can be determined and be extracted from the original signal, and also at the same time retain ability of fatigue damage. Outcomes from this analysis will be used to develop an algorithm which can cluster and classify fatigue signal that gives the fatigue damage to automotive components. For this purpose, artificial intelligence concept can be used from the Morlet wavelet coefficient analysis for optimizing fatigue data analyses. With that, a mapping classification of fatigue history in the signal can be generated.

Clustering is the classification of objects into different groups, or more precisely, the partitioning of a data set into subsets (clusters), so that the data in each subset (ideally) share some common trait - often proximity according to some defined distance measure. The purpose of clustering is to identify natural / intrinsic groupings of data from a large unlabeled data set to produce a concise representation of a system behaviour.

Fuzzy C-Means (FCM) is a data clustering technique wherein each data point belongs to a cluster to some degree that is specified by a membership grade. This technique was originally introduced by Jim Bezdek in 1981 as an improvement on earlier clustering methods. It provides a method that shows how to group data points that populate some multidimensional space into a specific number of different clusters. This technique starts with an initial guess for the centers, which are intended to mark the mean location of each cluster. The initial guess for these cluster centers is most likely incorrect. Additionally, it assigns every data point a membership grade for each cluster. By iteratively updating the cluster centers and the membership grades for each data point, FCM iteratively moves the cluster centers to the right location within a data set. This iteration is based on minimizing an objective function that represents the distance from any given data point to a cluster center weighted by that data point membership grade [30].

3 Materials and Methods

The strain signal selected for the simulation purpose was from the database of Society of Automotive Engineers (SAE) profiles, i.e. the SAESUS. The signal (in the unit of microstrain) was collected from a suspension component of a car and it was assumed to be sampled at 204.8 Hz for 25,061 data points. It gave the total record length of the signal of 122.4 seconds, as illustrated in Fig. 1.

For the calculation of the fatigue damage, the selected material for the simulation purpose was the SAE1045 carbon steel shaft. It was chosen as a common material used in automotive industries for fabricating a vehicle lower suspension arm structure [31]. The material properties and their definitions are given in Table 1 [32].

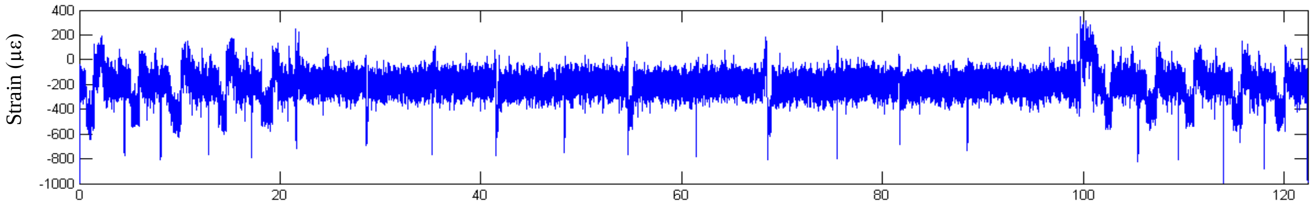

Fig. 1 Time history of the SAESUS strain signal

Table 1 The mechanical properties of the SAE1045 carbon steel shaft

Properties	Values
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

For the purpose of this study, segmentation on the signal was done by implementing a fatigue feature extraction algorithm defined as an algorithm that inputs the signal and produces retained segments. As the algorithm was run, a lower wavelet coefficient would gradually be removed until a stopping criterion was met. The criteria were set to 10 % difference of the fatigue damage. The segments were scattered and then clustered in order to develop a correlation between the fatigue damage and the Morlet wavelet coefficient. The flowchart is schematically illustrated in Fig. 2.

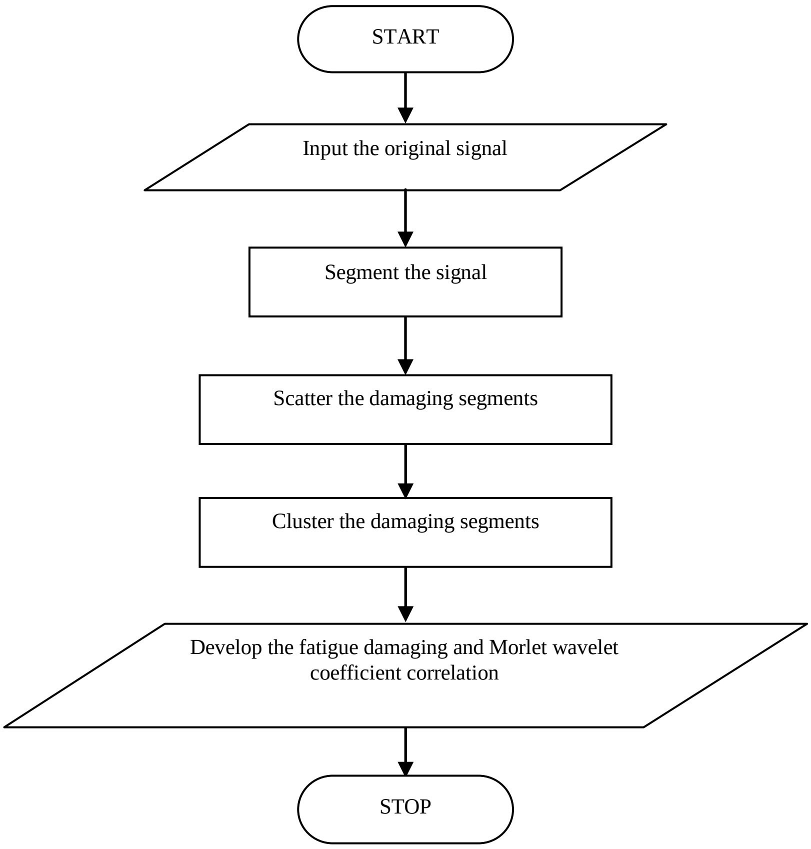

Fig. 2 Simplified flowchart of the study

4 Results and Discussions

4.1 Segmentation process

It was found that solely using the usual method to segment the fatigue time series data, in the end, produced scatter plots that contain certain data that was anomalous to what was projected. This uncharacteristic data was mostly outliers that made it difficult for any observable pattern of data scattering to be identified. Therefore this scatter plot was deemed unsuitable and unreliable for further use in data classification and clustering [33-34].

By introducing the wavelet coefficient segmentation, the segmental wavelet coefficient analysis can be made more accurately since every segment contained only an overall peak. Therefore, it is more reasonable and practical to perform the wavelet coefficient analysis on data segments so that the wavelet coefficient measurement is a better representative of the segmental peakedness of the time series.

This fatigue signal summarising algorithm uses peak to peak amplitude range as a parameter to determine gate value for the eliminating process. The value obtained from the wavelet coefficient amplitude at a cut off point or fatigue limit of the particular material is used to slice the original signal. The extracted segment identification is performed by searching the events start and finish points 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. 3. In the figure, the selected segment is at gate value of 400 $\mu\varepsilon^2$/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 [14] 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.

After all the segments are identified, the fatigue time history is then sliced in order to remove lower wavelet coefficient amplitudes (less than the gate value) contained in the original time history range. 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.

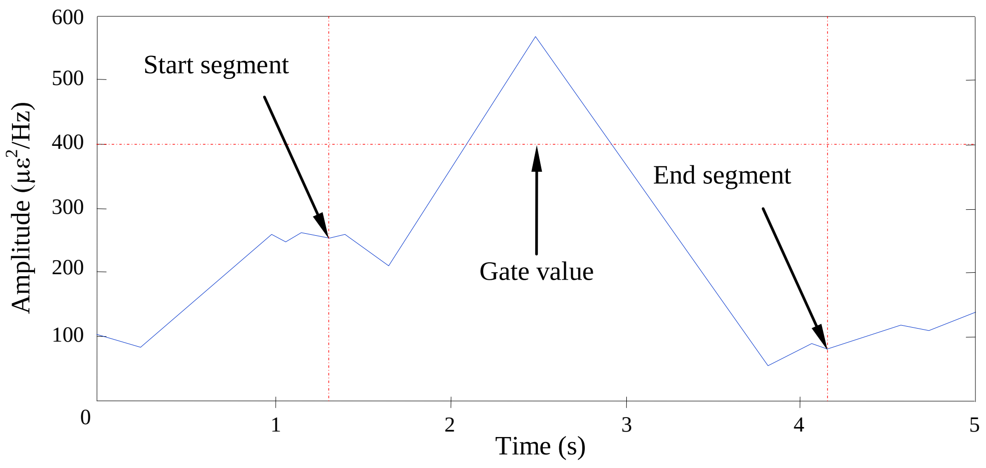

Fig. 3 The extracted segment identification

The Morlet wavelet coefficient and segmental data can be seen in Fig. 4. In the presented scalogram, the *x*-axis denotes the time parameter and the *y*-axis represents the scale that is inversely related to the frequency value. 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 energy distribution display with respect to the particular time and frequency information. Accordingly, a lower scale indicated higher frequency and had small amplitude which means these cycles had lower energy, indicating minimal or no fatigue damaging potential. A large scale was indicative of lower frequency and higher amplitude which 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.

For the purpose of simplicity and criteria acceptability, the algorithm was used for segmenting the signal into 49 segments. These segments were not uniform in size; their lengths varied from one segment to another. This was because the algorithm segmented the wavelet coefficient time series so that each segment and its corresponding linear representation would have the least amount of error. The segmentation was used to ensure that like features in the time series data would be isolated and be grouped into the same segments. Further analyses of each segment would help to determine which parts of the data gave significant contributions to the overall fatigue damage.

The segmentation process resulted in a 101 second edited signal. With respect to the fatigue damage, the shortened signal contained at least 90.8 % of the original fatigue damage (removing less than 10 %). Furthermore, the signal contained 98.9 % of original mean value, 97.6 of original r.m.s. value and 95.3 % of original kurtosis value. It means that the algorithm preserved the originality of the fatigue damage and the signal behaviour.

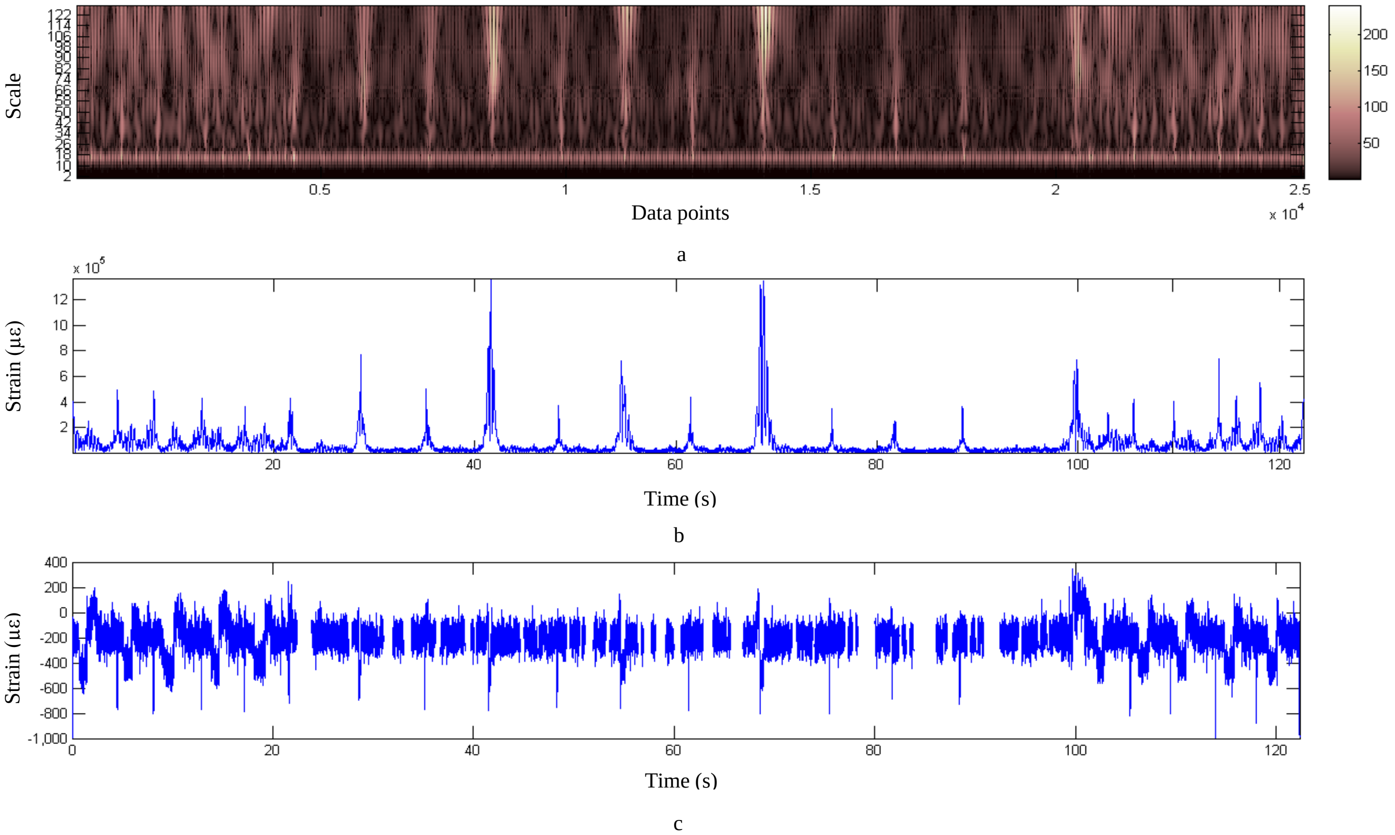

Fig. 4 The segmentation process: (a) the Morlet wavelet coefficient in time-frequency representation, (b) the Morlet wavelet coefficient in time representation, (c) 49 damaging segments

4.2 Clustering of the fatigue damage and the Morlet wavelet coefficient

The fatigue damage of these segments was then calculated using a specific commercial software package. The segments were also run through other software that calculated the Morlet wavelet coefficient of each segment. Another algorithm generated scatter plot of the fatigue damage against the wavelet coefficient values. Based on this scatter plot, patterns of data scattering, if any, were identified and noted.

Fig. 5 shows scatter plot of the fatigue damage over the Morlet wavelet coefficient. In the figure, after including the wavelet coefficient segmentation, it is evident that no significant outliers were present to affect the overall look of the scatter. Thus, it can be seen certain patterns of scattering concentrated at the same areas of the scatter plot, although the points are widely distributed. The variations are mainly due to the randomness of the data and the variety in size of each segment.

In this case, it can be seen clearly that as a result of scatter pattern, where small fatigue damaging corresponds to small wavelet coefficient values and vice versa. The higher wavelet coefficient points were only presented in the higher fatigue damaging range. Shorter segments with higher amplitude usually result in higher wavelet coefficient values, whereas longer segments with lower amplitude would result in lower wavelet coefficient values. Therefore, for the higher fatigue damage, the wavelet coefficient values are theoretically higher.

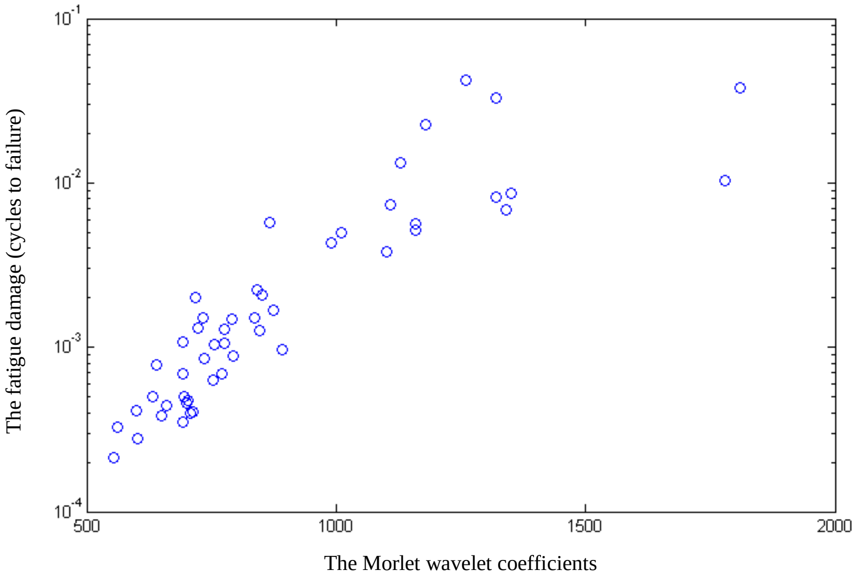

Fig. 5 Scatter plot of the fatigue damage and the Morlet wavelet coefficient

For further research work, scatter plot of the segmental fatigue damage versus the segmental wavelet coefficient as shown in Fig. 5 could be utilized for fatigue data classification and clustering. The utilization of the wavelet coefficient segmentation has resulted in the production of reliable data scatter for the purpose described. The clustering plot is shown in Fig. 6.

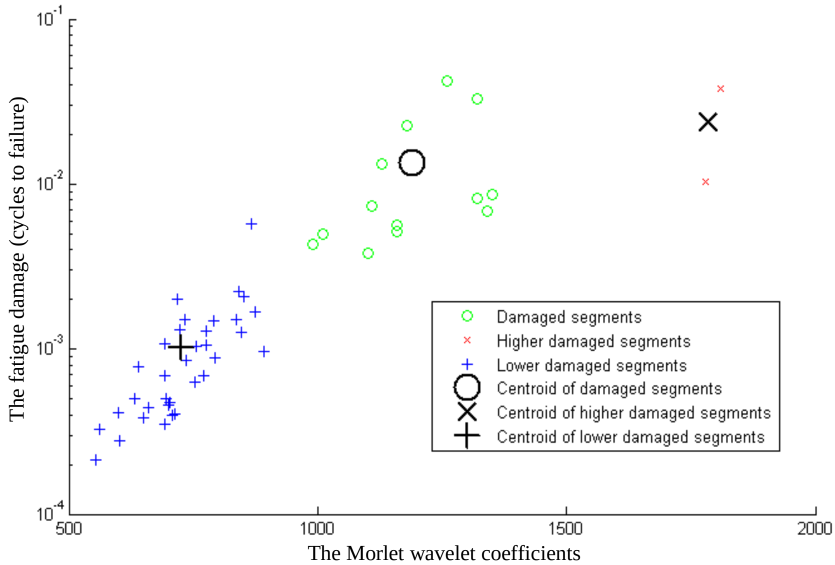

Fig. 6 Clustering of the fatigue damage and the Morlet wavelet coefficient

The clustering process divided the data in three clusters, they were lower damaging, damaging, and higher damaging segments. In the first cluster (lower damaging segments), it can be seen that all the data points concentrated at 0.0003 - 0.008 cycles to failure. At the points, the wavelet coefficients were between 550 - 900. For the second cluster, most of the data points seemed to be concentrated at 0.005 - 0.06. The wavelet coefficient values for this cluster were at the range 1000 - 1400. The last cluster was higher damaging segments. This cluster only had two data points at the wavelet coefficient of 1800. The fatigue damaging values for these data points were 0.01 and 0.04 cycles to failures.

Furthermore, each cluster has a centroid point. If these points in the plot were linked, it showed clearly correlation between the fatigue damage and the wavelet coefficient. At lower Morlet wavelet coefficient values, the fatigue damage was decreased (not damaging). Whereas at higher Morlet wavelet coefficient values, the fatigue damage was increased (more fatigue damaging). It indicated that the higher Morlet wavelet coefficient presented damaging segment, otherwise, it was non-damaging segment. It means that the relationship between the Morlet wavelet coefficient and the fatigue damage was strong and parallel. Therefore it was expected that clustering plot of the fatigue damage versus the wavelet coefficient should reflect this trend in some manner.

As for the figure, since the segmentation algorithm had been incorporated with the wavelet coefficient, it can observe a certain trend of proportional relation between the fatigue damage and the Morlet wavelet coefficient. The pattern shows that the higher fatigue damage generally translates to the higher wavelet coefficient, as expected prior to the analysis. This means that this scatter plot truthfully reflects the hypothesized relationship between the fatigue damage and the wavelet coefficient.

5 Conclusion

The study has demonstrated the use of the Morlet wavelet coefficient segmentation for fatigue data clustering. As our main focus in this study, we suggested that the implementation of the Morlet wavelet coefficient segmentation algorithm would produce significantly reliable and accurate scatter plot for fatigue data clustering prospects. Finally, as possible future work, after identifying and clustering the data in the signal, fatigue data editing through the elimination of certain noncontributory or insignificant segments of the signal may help in reducing the length and complexity of the data and may thus speed up the process of fatigue testing of metal components of mechanical systems or any similar applications.

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