Classification of Fatigue Damaging Segments Using Artificial Neural Network

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ABSTRACT

This paper focuses on the classification of the fatigue damaging segments datasets associated with the measurement of Variable Amplitude Loadings of strain signals from the coil springs of an automobile during road tests. The wavelet transform was used to extract high damaging segments of the fatigue strain signals. The parameters of the kurtosis, wavelet-based coefficients, and fatigue damage were then calculated for every segment. All the parameters were used as input for the classification analysis using artificial neural networks. Using the back-propagation trained artificial neural network, the corresponding fatigue damages were classified. It was observed that the classification method was able to give 100% accuracy on the classifications based on the damaging segments that were extracted from the training and the validation datasets. From this approach, it classified the level of fatigue damage for coils spring.

Keywords: *Artificial Neural Network, Classification, Fatigue damaging Segments, Variable amplitude loading, Wavelet Transform.*

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Introduction

Vehicle components such as the coil spring in suspension systems are subjected to Variable Amplitude Loading (VAL) due to the unevenness of road surface. These loading histories often contain a large of percentage of low and high amplitude cycles, which contribute to the fatigue failure. In the design phase, the assessment of component durability needs to be considered. The experimental assessment is time consuming and expensive to perform [1]. Therefore, in several cases, the fatigue time histories were edited by removing the low amplitudes cycles in order to reducing costs and product development time that require physical endurance test conduct in minimal time [2].

The classifier has been extensively tested on larger data sets acquired from fatigue experiments. The Artificial Neural Network (ANN) has been widely researched during the last decades, resulting in vast amounts of network structure types [3].Taylor et al. [4] classify the road surface in order to optimised the development of vehicle using ANN. Fejrmandi et al. [5] used ANN in classification of loading for plat structure. Most of the studies were in development of the safety index related to industrial structures such as marine structures, building structures and oil and the gas industry [6].

In fatigue research, especially for fatigue life assessment, many researchers developed techniques and tools, such as laboratory tests, data collection, and software, in order to identify and prevent fatigue damage [7]. Recently in fatigue research, not many works were done in classification of fatigue damage in automotive components especially for suspension systems.

In this paper, the features of damaging segments are classified in the ANN algorithm and it is divided into several different levels of the fatigue damage. The objective of this study is to detect the different levels of fatigue damage based on road conditions by using the ANN classification. In general, low fatigue damage is represented by a lower class and high fatigue damage is represented by a higher class in the classification results. This classification can be used as a database in order to classify the level of fatigue damage for coil springs.

Theoretical Background

Feature extraction of damaging segments is the process of creating a representation or transformation from the original strain signal data. Generally, there are several approaches used in signal processing to describe or determine the information of the signal. In this study, three type of analysis have been chosen in order to extract and select the features, i.e.

global signal statistical analysis, fatigue data extraction and fatigue life prediction.

A time series contains a set of information for the variable that was taken at equally spaced intervals of time. The global statistical parameter included mean, r.m.s, skewness and kurtosis is commonly used in order to determine the behaviour and pattern of the random signals. In fatigue data editing, the calculation of the parameters of kurtosis is vital. These parameters are used to retain the originality of the signal behaviour during editing. Kurtosis is the 4th order of statistical moment in the global statistical approach. Kurtosis is very sensitive to the spike of the data or signal. Kurtosis is commonly used to measure non-gaussianity for the detection of fault symptoms because of its sensitivity to the spike or outlier signals among the instantaneous values.

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

In some definitions of the kurtosis, a deduction of 3.0 is added to the definition in order to maintain the kurtosis of the Gaussian distribution to be equal to zero. Therefore, a kurtosis value of higher than 3.0 indicates the presence of more extreme values than that which should be found in a Gaussian distribution [8]. The increase of fatigue damage across all frequencies with the increased kurtosis levels causes faster component failure.

Signal analysis is a mathematical-based process that convert input signal to information into significant pattern in time domain, frequency domain and time-frequency domain. Analysis in time-frequency domain is based on Short-Time Frequency Transform (STFT) and Wavelet Transform (WT). A wavelet transform can be classified as either a Continuous Wavelet Transform (CWT) or a Discrete Wavelet Transform (DWT) depending on the discretisation of the scale parameter of the analysing wavelet. DWT based on such wavelet functions is called the Orthogonal Wavelet Transform (OWT). Orthogonal wavelet transforms are normally applied for the compression and feature selection of signals. DWT is derived from discrete CWT, and it is shown as the following expression [9]:

$$W_\psi(m,n) = \int_{-\infty}^{\infty} x(t) a_0^{-m/2} \psi^*(a_0^{-m}, t - nb_0)dt \tag{2}$$

where a and b are the scale factors and Ψ is the mother wavelet. The Wavelet-based energy coefficient enables the detection of fatigue damage significantly before the component is exposed to fatigue failure

In the automotive industry, the components imposed under service loadings are commonly evaluated using the stress-life and strain-life approach. Stress-life commonly used for high cycle fatigue analysis, meanwhile strain-life always used in low cycle fatigue analysis. The strain-life approach consists of converting the loading history, geometry and material properties input into a fatigue life prediction. Nowadays, Coffin-Manson, Morrow, and Smith Watson Topper (SWT) are the most famous approaches in strain-life analysis for life assessments. The Coffin-Manson strain-life model is mathematically defined as:

$$\varepsilon_a = \frac{\sigma'_f}{E}(2N_f)^b + \varepsilon'_f(2N_f)^c \tag{3}$$

Where ε_a is the total strain amplitude, σ'_f is the fatigue ductility coefficient, c is the fatigue ductility exponent, and E is the modulus of elasticity. Nevertheless, the Coffin-Manson relationship only considers the damage calculation at zero mean stress. The damage parameters are usually developed to consider the mean stress effects on fatigue behaviour, such as the Morrow and Smith-Watson-Topper (SWT) models. The Morrow strain-life model is mathematically defined as:

$$\varepsilon_a = \frac{\sigma'_f}{E}\left(1 - \frac{\sigma_m}{\sigma'_f}\right)(2N_f)^b + \varepsilon'_f(2N_f)^c \tag{4}$$

In addition, the SWT strain-life model is defined according to this formula:

$$\varepsilon_a \sigma_{mak} = \frac{\sigma'^{2}_f}{E}(2N_f)^{2b} + \sigma'_f\,\varepsilon'_f(2N_f)^{b+c} \tag{5}$$

The strain-life approach is often applied in the analysis of ductile materials with the low fatigue life and for materials with some plasticity at high fatigue life.In this study, fatigue loading is variable amplitude type. Therefore, it is necessary to utilize a cumulative damage rule for the strain-based fatigue life prediction. The widely used Miner's rule was established deterministically as

$$D_{TOT} = \sum_i \frac{\eta_i}{N_{fi}} = 1 \tag{6}$$

where D_{TOT} is the total damage, N_{fi} is the fatigue life of some materials according to the respective stress level, and n_i is the number of load cycles in fatigue test. The critical damage is assumed to be 1. The damage per cycle can be calculated as

$$D = \frac{1}{N_{fi}} \tag{7}$$

Methodology

The fatigue strain signal from various road surface conditions is important for fatigue analysis especially for automotive components. The reason for performing the VAL testing is to extract the information of fatigue strain signals under complex loadings based on rough rural road conditions. Therefore, to extract the fatigue feature of the VAL, there is a need to conduct actual road tests. The VAL testing procedure is shown in Figure 1. The strain gauge is attached at the critical region of the coil spring during the service loading. This is to ensure the strain signal is accurate; the attachment point was polished to a mirror reflection. Then, the strain gauge was connected to the data acquisition and computer for signal measurement and monitoring. A sampling rate of 500 Hz was considered so that the essential components of the signal were not lost during measurement [10].

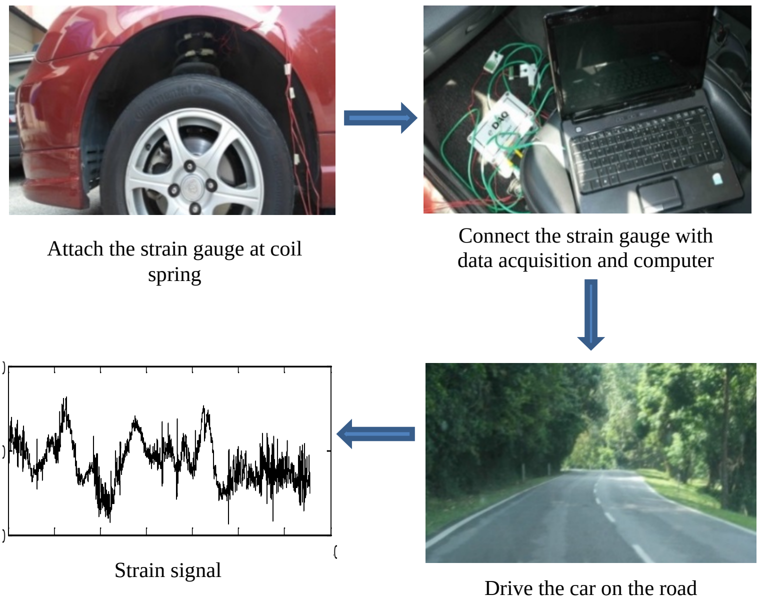


Figure 1 : A diagrammatic process flow for fatigue strain signal collection

Data segmentation of the processes divides the data into certain sections or segments after the extraction process, using a wavelet transform analysis. The obtained strain signals from the data were analysed with the wavelet coefficient plot using the time-scale representation. The wavelet coefficient is associated with the energy coefficient plot for the input values in the fatigue data extraction. The segment extraction was done using the wavelet transform analysis in order to divide the data into segments after the low amplitude was removed, as shown in Figure 2. The feature extraction for every segment was analysed and calculated the Kurtosis, wavelet-based energy coefficient and fatigue damage. All the values of these parameters were then normalised and served as the input in the classification process.

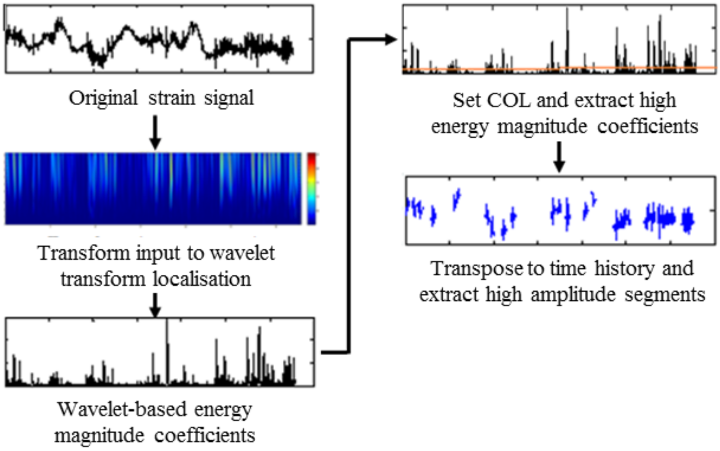


Figure 2 : A diagrammatic process flow of the Wavelet transform based fatigue data editing method

Classification is an application of machine learning; which is creates the classifier based on observing the examples and supervised learning. The artificial neural network is a huge class of similar processing structures that are useful in specific categories of complex problems. The Multi Layered Perceptron (MLP) with back-propagation for training was used in the classification [11]. The ANN has a number of neurons that are connected by weight links that pass the signals from one neuron to another neuron.

Figure 3 shows a schematic diagram of a simple perceptron with 3 input nodes, 5 output node, and a hidden layer. Back propagation, which is the one of the famous training algorithm for MLP, is a gradient descent technique to minimize the errors for a particular training pattern. The back propagation training algorithm has some drawbacks, but this method was used because it is simple and reliable.

For the ANN classification, the input layers have 3 nodes comprising of the features consisting of kurtosis, wavelet-based energy, and fatigue damage that were extracted from the high amplitude segments of the strain signal. An algorithm with momentum is used to train the neural networks during the training process. A selection of the number of epochs is provided prior to training which the training is expected to converge.

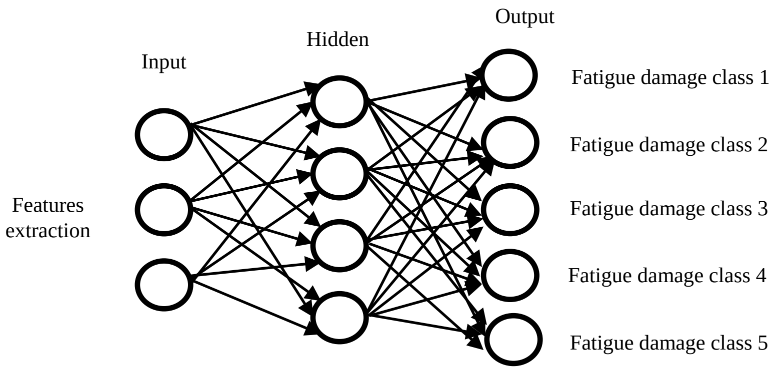


Figure 3: Concept approach diagram for simple perceptron with 3 input nodes, 5 output nodes, and a hidden layer.

The outputs are then compared to what they should actually be, and the error is factored into adjusting the condition criteria that future inputs need to meet. The output layers have 5 nodes denoting the different classes of fatigue damage. Each node gives the level of the classification. The lower class represents lower fatigue damage and the higher class represents higher fatigue damage. The verification is initiated during training by comparing the predicted output with different datasets of strain signals. Once the verification is matched, then the classification is verified.

Results and Discussion

The Examples of VAL strain signals from the road test are shown in Figure 4. Figure 4(a) represents the data from SAESUS [12] and Figure 4(b) from the rough rural area. Basically, the road test consists of rough rural road in order to classify the fatigue damage. For this overall VAL strain signal, the SAESUS data created the highest range of strain amplitude values compared to rough rural road. This may due to the numerous potholes on the road and the rough road surface. For the rough rural road, the range of amplitude values of the strain generated was much smaller than SAESUS as this road was mostly of good surface compared to SAESUS.

Statistical analysis is concerned with reducing a long time signal into a few numerical values that describe it behaviour. In order to find the spikiness of the data, the kurtosis values are calculated. The kurtosis value for SAESUS was found to be at 4.28 and for rough rural area at 3.07. Based on these results, these two data are non-stationary because a kurtosis value of higher than 3.0 indicates the presence of more extreme values than that which should be found in a Gaussian distribution. The difference of the kurtosis value on the SAESUS data is higher than the rough rural road because the road surface represented a noisier and higher range of strain amplitude.

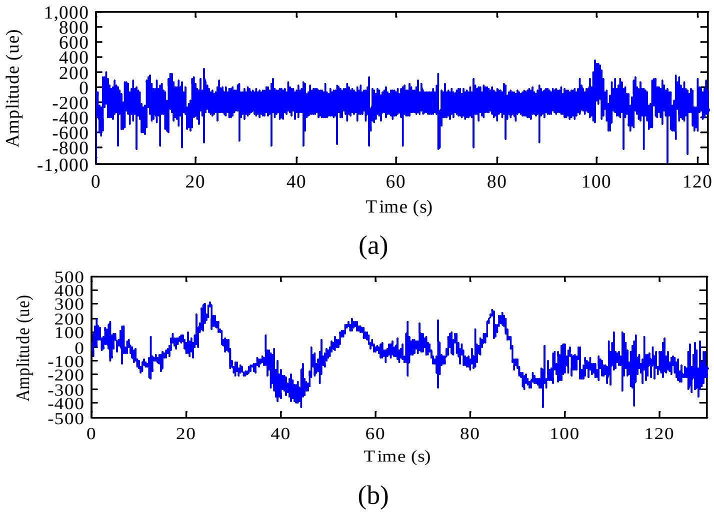


Figure 4 : Strain time history collected based on road conditions
(a) SAESUS (b) Rough rural area road

Subsequently, the strain signal was used to conduct the damage analysis based on the fatigue strain-life model and wavelet transform analysis. Figures 5 and 6 show the fatigue damage magnitude, damage distribution, cycle range and wavelet-based energy plots for the SAESUS and rough rural road data. Based on the fatigue damage magnitude and distribution, the SAESUS data contributed higher fatigue damage, with damage values at 4.80×10^{-3} compared to the rough rural road data at 2.48×10^{-4}.

Figures 7 (a) and (b) show the plots of the ANN classification for the SAESUS and rough rural road datasets. The classifications for these two data have been done based on the generated index of 1 to 5. Table 1 shows the results for the classification of SAESUS and rough rural road. The SAESUS data consists of 21 samples with 100% accuracy and the rough rural road data consists of 20 samples with 100% accuracy.

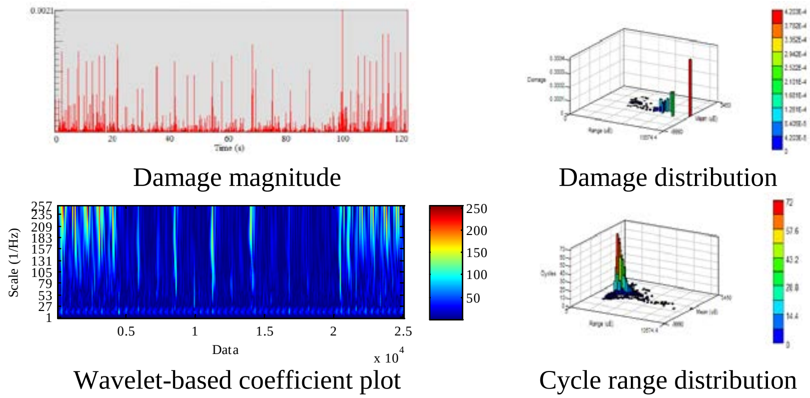


Figure 5 : The distribution of damage and Wavelet-based energy coefficient for SAESUS

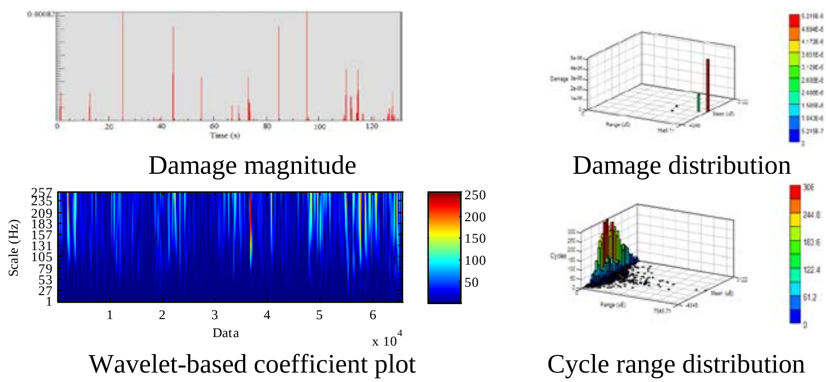
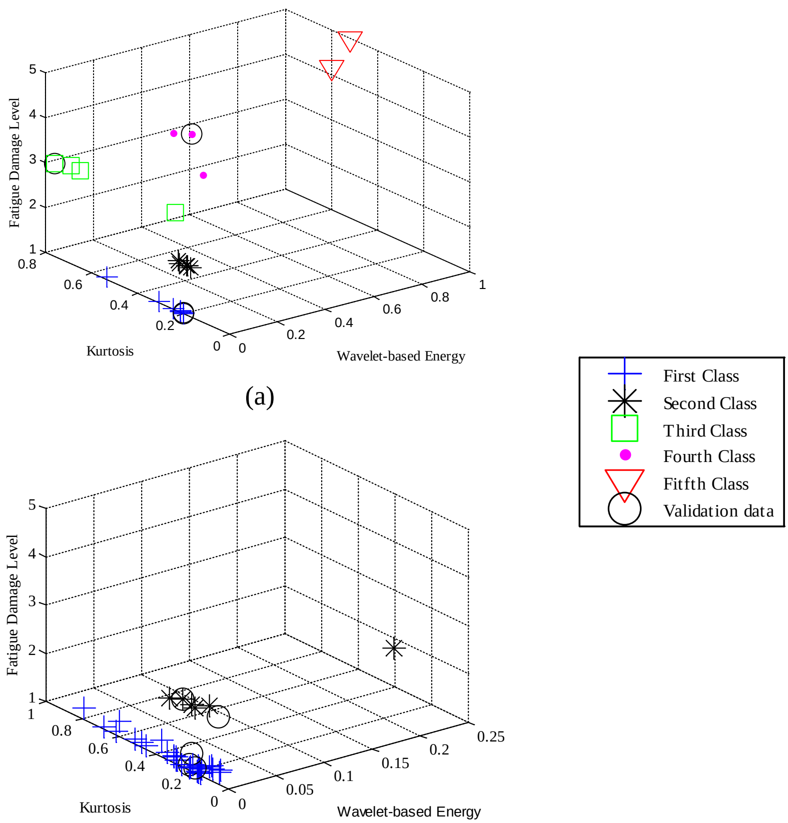


Figure 6 : The distribution of damage and Wavelet-based energy coefficient for rough rural road

Table 1 Classification results for SAESUS and Rough rural road

Data	**No. of Samples**	**Training Samples**	**Validation Samples**	**Accuracy %**
SAESUS	21	16	5	100
Rough Rural Road	20	15	5	100



(a)

(b)

Figure 7 : Distribution of features extraction based on ANN classification; (a) SAESUS, (b) Rough rural road

Based on the plots, the data for SAESUS is scattered at all classes from class 1 to class 5. Meanwhile, the data for rough rural road was only scattered at class 1 to class 2. According to their classification, it can be suggested that SAESUS contributed higher fatigue damage compared to the rough rural road and was more inclined to the fatigue failure. This is due to the VAL strain signal, whereby the SAESUS data created the highest range of strain amplitude compared to the rough rural road. This is because of the numerous potholes on the road and the rough road surface. For the rough rural road, the range of the strain amplitude values generated was much smaller than SAESUS because this road was mostly of good surface conditions compared to SAESUS as shows in Figure 4.

Conclusion

The fatigue damage magnitude and distribution for SAESUS data contributed higher fatigue damage at 4.80×10^{-3} compared to the rough rural road data at 2.48×10^{-4} because of the damaging segment in data. Based on fatigue damage extraction using Wavelet Transform, The SAESUS data contributed 21 damaging segments compared to rough rural road data which is contributed 20 damaging segments. These results suggested that the SAESUS data obtained the higher number of damaging segments compared to the rough rural area data. The present study demonstrated that ANN can be used to classify the fatigue damage of coil springs. The classification classifies the classes of low fatigue damages to higher fatigue damages into five classes. Based on the classification, the level of fatigue damage for SAESUS and rough rural road datasets were determined with 100% accuracy. SAESUS data scattered all in five classes compared to the rough rural road, which only had scattered data in classes 1 and 2. It is suggested that the fatigue damage for SAESUS is more higher compared to rough rural road.

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