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Development of a Noise Filtering Algorithm for Strain Signals Using the Fast Fourier Transform

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Abstract: The purpose of this study is to filter the noise in strain signals based on the fast Fourier transform. The strain signals were measured at an automotive lower arm made from the SAE 1045 carbon steel driven on paving block and asphalt. This technique removed lower amplitude cycles as much as possible due to their contribution to the minimum fatigue damage and simultaneous maintenance of cumulative fatigue damage. The filtering algorithm was able to remove up to 36.2% of the lower amplitude cycles and maintain more than 90% of the fatigue damage. This proved that the algorithm developed was successfully identified and eliminated low amplitude cycles.

Keywords: Fatigue, Frequency, Lower arm, Power Spectral Density

1. Introduction

Fatigue is a type of failure found in many structures and mechanical components under repeated loads. It may also occur at a lower stress than required to break material with a single static load or at stress below the yield strength [1,2]. Its occurrence is associated with the propagation of fatigue cracks [3] and the process is very dangerous because it occurs without any initial indications. There are many factors influencing fatigue and this makes its prediction to be very difficult [4].

In order to predict the fatigue life of a component, the experimental measurement of the strain signal is required [5]. However, the strain signals obtained usually contain noise, affecting the accuracy of the prediction. Noise is extracted using various methods, such as wavelet transforms [6,7]. Unfortunatelly, wavelet analysis is complicated, involving the selection of the mother wavelet, the level, and the order [8,9], so it difficult to use generally. The aim of this study therefore was to remove this noise with a simpler method based on the fast Fourier transform (FFT) which is expected to provide a pure strain signal and, consequently, an accurate fatigue life assessment.

2. Material and Methods

Flowchart of the study is shown in Fig. 1. Strain signals measured at an automotive lower arm driven on paving block [10] and asphalt [11] were selected as the case study. The 46-second paving block strain signal was measured at a frequency of 500 Hz with 23,000 data points while the 160-second asphalt strain signal was measured at 200 Hz with 32,000 data points, as shown in Fig. 2.

Moreover, it is possible to distinguish filters by low pass, high pass, bandpass and band reject. The low pass can be used to filter low frequencies, high pass for high frequencies, bandpass for iterations passing through, and band reject to screen the ones caught [12]. However, since the noise is usually at a high frequency, a low pass was used and a parameter known as Cut-Off-Frequency (COF) was used to determine the filtered frequency level.

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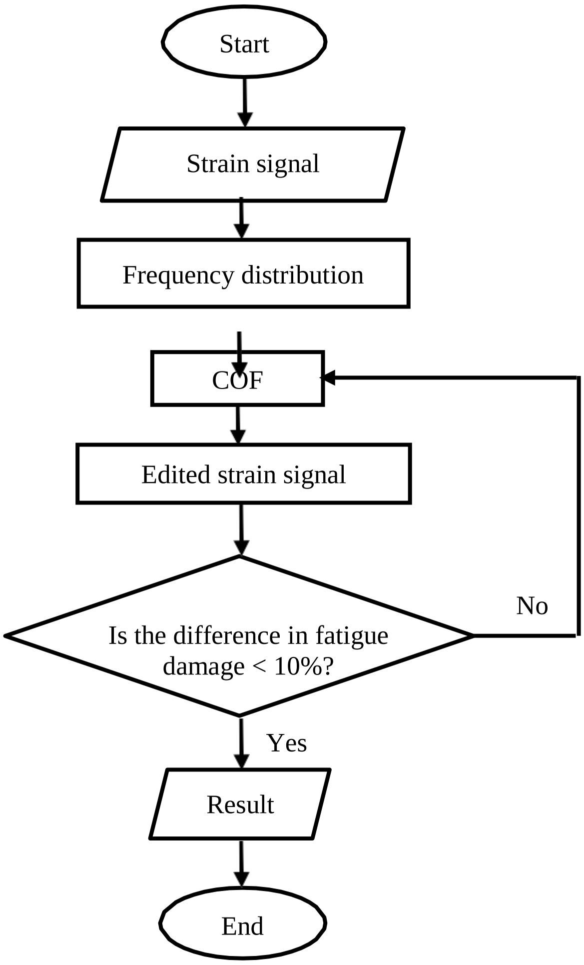


Fig. 1 - Flowchart of the study

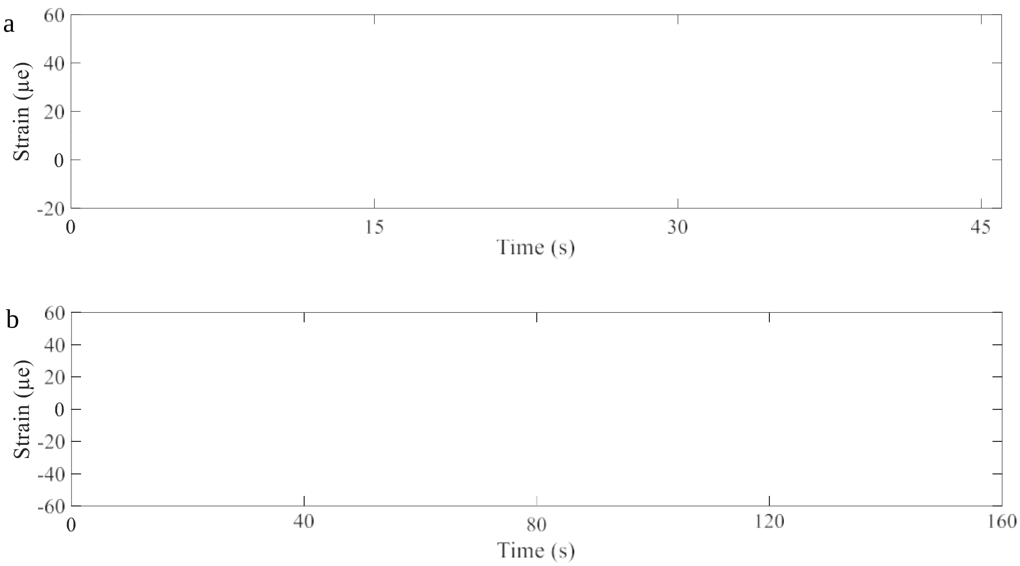


Fig. 2 - The original strain signals: (a) paving block; (b) asphalt

The experiment started with the transformation of the strain signals from time to frequency domain and the Fourier transform *FT* [13] is defined as:

$$FT_{(\omega)} = \int_{-\infty}^{\infty} F_{j(t)} e^{-i\omega t} dt \quad (1)$$

where F_j is the time domain signal, t is time and ω is the angular frequency, defined by:

$$\omega = 2\pi f \quad (2)$$

where f is the frequency. The FFT which was used to break the signal effectively into discrete sinusoidal waves and to reduce the repetition needed in the process of the digital signal conversion was introduced by Cooley & Tukey [14].

Power Spectral Density (PSD) is a frequency analysis used in considering the energy of a signal in the frequency domain providing the strength of the variations in intensity as a function. It is defined as [15]:

$$PSD = \frac{1}{2\pi} \sum_{n=-\infty}^{\infty} F_{j(n)} e^{-i\omega t} \quad (3)$$

The filtered strain signals were validated based on the difference in fatigue damage compared to the original strain signals, which was below than 10%. The Coffin-Manson model [16,17] combines the elastic and plastic strains and defined as follows:

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

where ε is the strain amplitude, σ'_f is the fatigue strength coefficient, E is the material modulus of elasticity, N_f is the number of cycles, b is the fatigue strength exponent, ε'_f is the fatigue ductile coefficient and c is the fatigue ductile exponent. The Morrow model [18] determines the mean stress σ_{mean} by adjusting the elastic strain-life curve, as stated by:

$$\varepsilon = \frac{\sigma'_f - \sigma_{mean}}{E}\left(2N_f\right)^b + \varepsilon'_f\left(2N_f\right)^c \quad (5)$$

Another model used in the consideration of the mean stress is the Smith-Watson-Topper (SWT) parameter [19] which was represented mathematically as follows:

$$\sigma_{max}\varepsilon = \frac{\sigma'^{2}_f}{E}\left(2N_f\right)^{2b} + \sigma'_f\varepsilon'_f\left(2N_f\right)^{b+c} \quad (6)$$

σ_{max} is the maximum stress amplitude. Fatigue damage for each loading cycle D_i is:

$$D_i = \frac{1}{N_f} \quad (7)$$

Then, the cumulative fatigue damage was calculated through the use of the Palmgren-Miner rule [20,21] which was defined by:

$$D = \Sigma\left(\frac{n_i}{N_f}\right) \quad (8)$$

where n_i is the number of applied cycles.

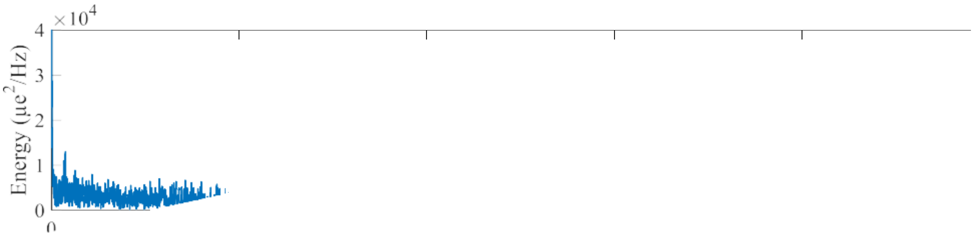
For the fatigue life assessments, the material used was the SAE 1045 carbon steel which is commonly used for car lower arm productions. The properties of this material are listed in Table 1. According to the assessments, the fatigue damage for the paving block strain signal based on the Coffin-Manson, Morrow and SWT models was 1.12E-04 damage per block, 1.24E-04 damage per block, and 1.64E-04 damage per block, respectively, at 1,412 cycles. For the asphalt strain signal, the fatigue damage was 5.68E-04 damage per block, 6.00E-04 damage per block, and 7.10E-04 damage per block at 10,913 cycles.

Table 1 - Mechanical properties of the SAE 1045 carbon steel [12]

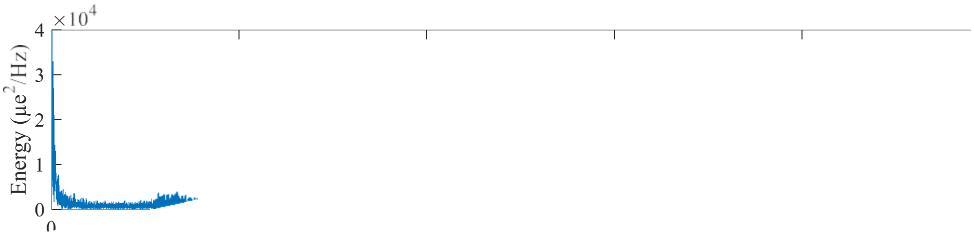
Properties	Values
Ultimate tensile strength, S_u [MPa]	621
Material modulus of elasticy, E [GPa]	204
Yield strength [MPa]	948
Fatigue strength coefficient, σ'_f [MPa]	-0.092
Fatigue strength exponent, b	-0.445
Fatigue ductility exponent, c	0.26
Fatigue ductility coefficient, ε'_f	621

3. Results and Discussion

Fig. 3 presents the frequency spectrums for each strain signal using 1024 sinusoidal discrete. Based on these spectrums, the COFs were identified and 50 Hz was selected for the COF of the paving block strain signal considering the noise were distributed at the area. Therefore, the elimination of lower strain amplitudes was believed not to affect the original characteristic of the strain signals significantly.



(a)



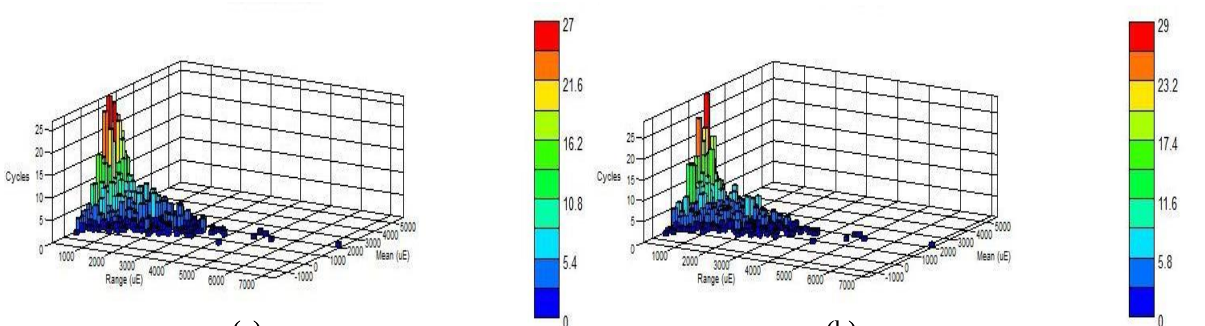
(b)

Fig. 3 - Frequency distributions in the range of 0 to 100 Hz: (a) paving block, (b) asphalt

Moreover, in order to maintain these original characteristics, the filtered strain signals should have 90% of the fatigue damage [22-25]. However, for the 50 Hz filtered paving block strain signal based on the Coffin-Manson, Morrow and SWT models it was found to be 1.08E-4 damage per block, 1.20E-4 damage per block, and 1.58E-4 damage per block, respectively. This shows a removal of approximately 3.7% of the fatigue damage and 6.6% of the cycles to maintain 1,319 cycles. This led to the reduction of the COF to 45 Hz which later produced 1.01E-04 damage per block, 1.13E-4 damage per block, and 1.50E-4 damage per block, or a reduction of the fatigue damage up to 9.8%. This shows a removal of 10.2% of the cycles to retain 1,256 cycles. This COF was selected as the optimum because it filtered at a lower frequency of 40 Hz and reduced the fatigue damage up to 16.1%, affecting the original behavior of the strain signal.

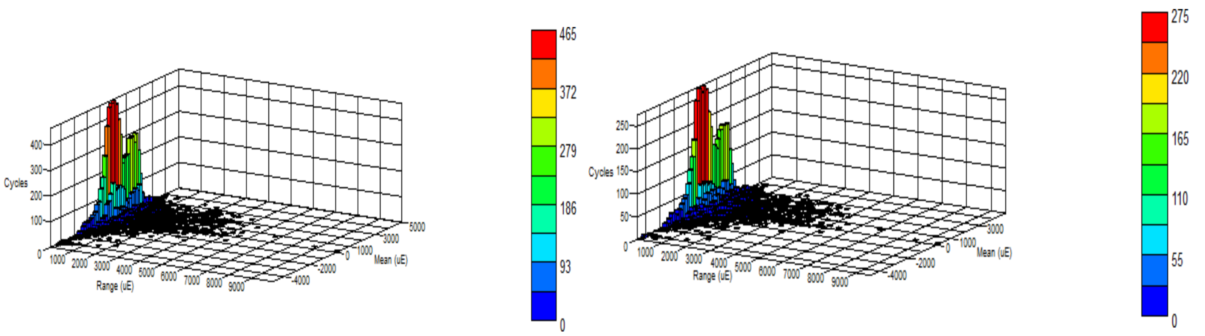
However, for the asphalt strain signal, the COF started at 95 Hz and produced 5.4E-04 damage per block, 6.7E-04 damage per block, and 6.7E-04 damage per block for the Coffin-Manson, Morrow, and SWT models, respectively. This removed up to 5.5% of the fatigue damage and 30.2% of cycles to retain 7,622 cycles. Since the fatigue damage removed was below 10%, the COF was further decreased to 90 Hz which later produced 5.2E-04 damage per block, 5.5E-04 damage per block, and 6.5E-04 damage per block, or a reduction up to 9.1%. This removed 36.2% of cycles to retain 6,958 cycles. This COF was selected as the optimum because it filtered at 85 Hz and produced fatigue damage deviation of more than 12%.

Furthermore, Figs. 4 and 5 show the 3-D histograms of the fatigue distributions at the optimum COF for the paving block and asphalt strain signals, respectively. The histograms proved some cycles in Figs. 4a and 5a were eliminated not to appear in Figs. 4b and 5b. This shows the algorithm developed was able to detect and remove low amplitude cycles. Moreover, the effect of the filtering towards energy was also considered. Figs. 6 and 7 provided the PSD graphs of the original and filtered strain signals for the paving block and the asphalt, respectively. From the comparison, the PSD areas for the paving block and asphalt were found to have reduced by only 0.1%. These reductions did not influence the fatigue damage and the original characteristic of the strain signals.



(a) (b)

Fig. 4 - The fatigue distributions of the paving block strain signal: (a) original; (b) filtered



(a) (b)

Fig. 5 - The fatigue distributions of the asphalt strain signal: (a) original; (b) filtered

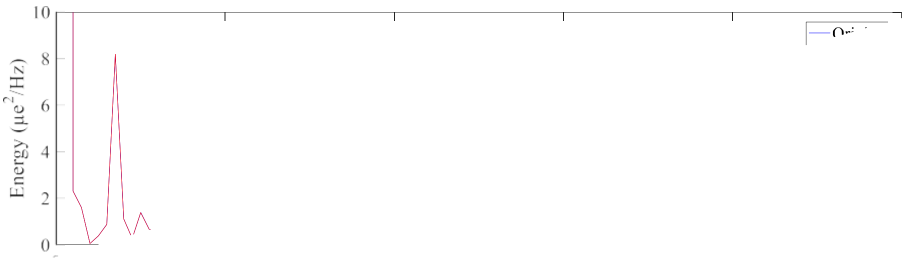


Fig. 6 - PSD of the original and filtered paving block strain signals in the range of 0 to 100 Hz

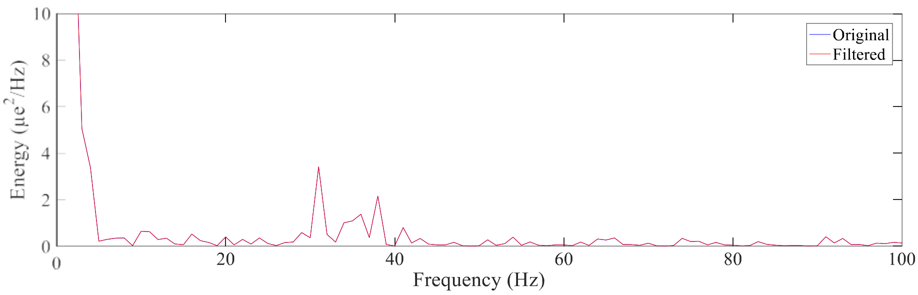


Fig. 7 - PSD of the original and filtered asphalt strain signals in the range of 0 to 100 Hz

4. Conclusion

The purpose of this study was to remove the noise in the strain signals measured at an automotive lower arm made from the SAE 1045 carbon steel. Through the use of the FFT-based filtering algorithm developed, the paving block strain signal was filtered at a frequency of 45 Hz to remove 10.2% of the cycles and maintain 90.2% of the fatigue damage. Meanwhile, the asphalt strain signal was filtered at a frequency of 90 Hz to eliminate 36.2% of the cycles and retain 90.9% of the fatigue damage. Therefore, the algorithm can be applied simply to de-noise a strain signal without affecting its original characteristics significantly.

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References

[1] Ye, X. W., Su, Y. H., & Han, J. P. (2014). A state-of-the-art review on fatigue life assessment of steel bridges. Mathematical Problems in Engineering, 1-13.

[2] Zakaria, K. A., Abdullah, S., & Ghazali, M. J. (2016). A review of the loading sequence effects on the fatigue life behaviour of metallic materials. Journal of Engineering Science and Technology Review, 9: 189-200.

[3] Beaurepaire, P., & Schuäller, G. I. (2011). Modelling of the variability of fatigue crack growth using cohesive zone elements. Engineering Fracture Mechanics, 78: 2399-2413.

[4] Idris, R., Abdullah, S., Thamburaja, P., & Omar, M. Z. (2018). Entropy-based approach for fatigue crack growth of dual-phase steel. International Journal of Integrated Engineering, 10: 1-7.

[5] Rahim, A. A. A., Singh, S. S. K., Abdullah, S., & Nuawi, M. Z. (2018). Strain signal characterisation using 4^{th} order of Daubechies wavelet transform for fatigue life determination. International Journal of Integrated Engineering, 10: 21-25.

[6] Kharrat, M., Ramasso, E., Placet, V., & Boubakar, L. (2014). Acoustic emission in composite materials under fatigue tests: effect of signal-denoising input parameters on the hits detection and data clustering, 31st Conference of the European Working Group on Acoustic Emission (EWGAE). Dresde, Germany.

[7] Liu, W. Y. (2017). A review on wind turbine noise mechanism and de-noising techniques. Renewable Energy, 108: 311-320.

[8] Tang, B., Liu, W., & Song, T. (2010). Wind turbine fault diagnosis based on Morlet wavelet transformation and Wigner-Ville distribution. Renewable Energy, 35: 2862-2866.

[9] Jiang, Y., Tang, B., Qin, Y., & Liu, W. (2011). Feature extraction method of wind turbine based on adaptive Morlet wavelet and SVD. Renewable Energy, 36: 2146-2153.

[10] Putra, T. E., Abdullah, S., Schramm, D., Nuawi, M. Z., & Bruckmann, T. (2014). Application of the wavelet transforms for compressing lower suspension arm strain data. Applied Mechanics and Materials, 663: 78-82.

[11] Abdullah, S., Putra, T. E., Nuawi, M. Z., & Nopiah, Z. M. (2011). Vibrational fatigue analysis of a strain loading using the frequency and wavelet filtering methods. Key Engineering Material, 462-463: 124-129.

[12] nCode. (2018). GlyphWorks. Sheffield: nCode International, Ltd.

[13] Fourier, J. (1878). The analytical theory of heat. Cambridge: The University Press.

[14] Cooley, J. W., & Tukey, J. W. (1965). An algorithm for the machine calculation of complex fourier series. Mathematics of Computation, 19: 297-301.

[15] Wijker, J. (2009). Random vibrations in spacecraft structures design: theory and applications. New York: Springer Science+Business Media B.V.

[16] Coffin Jr, L. F. (1954). A study of the effects of cyclic thermal stresses on a ductile metal. Transactions of the ASME, 76: 931-950.

[17] Manson, S. S. (1965). Fatigue: a complex subject - some simple approximation. Experimental Mechanics, 5: 193-226.

[18] Morrow, J. (1968). Fatigue design handbook. Warrendale: Society of Automotive Engineers.

[19] Smith, K. N., Watson, P., & Topper, T. H. (1970). A stress-strain function for the fatigue of materials. Journal of Materials JMLSA, 5: 767-778.

[20] Palmgren, A. (1924). ”Die Lebensdauer von Kugellagern”. Zeitschrift VDI, 68: 339-341.

[21] Miner, M. A. (1945). Cumulative damage in fatigue. Journal of Applied Mechanics, 67: A159-A164.

[22] Putra, T. E., Abdullah, S., Schramm, D., Nuawi, M. Z., & Bruckmann, T. (2015). Generating strain signals under consideration of road surface profiles. Mechanical Systems and Signal Processing, 60-61: 485–497.

[23] Putra, T. E., Abdullah, S., Schramm, D., Nuawi, M. Z., & Bruckmann, T. (2017). Reducing cyclic testing time for components of automotive suspension system utilising the wavelet transform and the Fuzzy C-Means. Mechanical Systems and Signal Processing, 90: 1–14.

[24] Putra, T. E., Abdullah, S., Schramm, D., Nuawi, M. Z., & Bruckmann, T. (2017). The need to generate realistic strain signals at an automotive coil spring for durability simulation leading to fatigue life assessment. Mechanical Systems and Signal Processing, 94: 432–447.

[25] Husaini, Putra, T. E., & Ali, N. (2018). Fatigue feature clustering of modified automotive strain signals for saving testing time. International Journal of Automotive and Mechanical Engineering, 15: 5251-5272.