The Ability of the Fast Fourier Transform to De-Noise a Strain Signal

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Abstract. This study aims to develop an algorithm for filtering the noise in the fast Fourier transform. It requires the determination of the cycles, based on the rain flow counting method. This design was further applied to remove the lower amplitude cycles in a 600-second strain signal. Therefore, the results indicated that the method was able to remove more than 10% of the lower amplitude cycles at a frequency of 45 Hz. The filtered strain signal maintained the fatigue damage by more than 90% and further upheld its original characteristics. This study concluded that the developed algorithm was able to identify and remove the noise contained in the strain signal.

1. Introduction
Fatigue failure arises when a material is subjected to repeated static or dynamic stresses. It could occur with a load that is lower than what is presumed to break material with a single impact, below the ultimate tensile strength and the yield strength [1,2]. This phenomenon is very dangerous because it occurs without a deformation, hence it is very difficult to predict since it is influenced by many factors [1]. Researchers constantly try to improve knowledge on experimental prediction, in order to not neglect matters that could precedent to this phenomenon, such as mass, stiffness and damping ratio, collectively known as structural parameters.

Data used to assess fatigue life is obtained by conducting experimental measurements [3]; however, they do not come out pure as they contain noise from the movement of other components, which further disturbs this assessment [4]. Previous research by Abdullah et al. [5] utilized the Daubechies wavelet to conducted noise filtering in a strain signal. However, wavelet is complicated by its process of analysis, starting from the selection of the mother wavelet, the order and the level of operation [6,7]. Since the wavelet transform is difficult to apply generally, this study aims to develop an algorithm for noise filtering with a simpler method based on the fast Fourier transform (FFT).

2. Methodology
Fig. 1 presents the noise filtering algorithm developed using the FFT. This study used a strain signal for validating the noise filtering algorithm. The strain signal was measured on an automotive lower arm, driven on a public road for 60 seconds with the mean value of -11 με, as shown in Fig. 2. The strain signal gave the fatigue damage of 1.64E-04 damage per block and the number of cycles of 1,412. The material used for the simulation was the SAE 1045 carbon steel, commonly utilized for fabricating the component and its properties are shown in Table 1.
Figure 1. Flowchart of the algorithm

Figure 2. The original strain signal

Table 1. Mechanical properties of the SAE1045 carbon steel [8]

| Properties                              | Values |
|-----------------------------------------|--------|
| Ultimate tensile strength, $S_u$ [MPa]  | 621    |
| Material modulus of elasticity, $E$ [GPa]| 204    |
| Yield strength [MPa]                     | 948    |
| Fatigue strength coefficient, $\sigma_f'$ [MPa] | -0.092 |
| Fatigue strength exponent, $b$           | -0.445 |
| Fatigue ductility exponent, $c$          | 0.26   |
| Fatigue ductility coefficient, $\varepsilon_{f}'$ | 621    |
The effectiveness of the algorithm depended on the maintenance of at least 90% of the fatigue damage in the filtered strain signal, in order to keep its original characteristics. Prediction of fatigue life is more accurate with the strain-life approach because it considers the formation of plastic events in the local area. One of which is the Smith-Watson-Topper (SWT) parameter \[9\], which further gives an accurate result for a signal with positive mean stress \[10\]. It is defined as:

\[
\sigma_{\text{max}} \varepsilon = \frac{\sigma_f^{'2}}{E} (2N_f)^{2b} + \sigma_f^{'f} \varepsilon_f (2N_f)^{b+c}
\]

(1)

where \(\sigma_{\text{max}}\) is the maximum stress, \(\varepsilon\) is the strain amplitude, \(\sigma_f^{'}\) is the fatigue strength coefficient, \(E\) is the material modulus of elasticity, \(N_f\) is the number of cycles to failure for a particular stress range and mean, \(b\) is the fatigue strength exponent, \(\varepsilon_f^{'}\) is the fatigue ductility coefficient, and \(c\) is the fatigue ductility exponent.

Rain flow cycle counting method \[11\] was used to determine the number of cycles, which involved small cycles, treated as interruptions to larger ones. Furthermore, the strains were rearranged from the maximum peak or the minimum valley, starting with whichever was greater in absolute magnitude. Small cycles were extracted first, leaving the larger ones for the end of the process.

Fatigue damage for each loading cycle \(D_i\) is represented by:

\[
D_i = \frac{1}{N_f}
\]

(2)

The Palmgren-Miner rule \[12,13\] was used to determine the cumulative fatigue damage, as in the following:

\[
D = \sum \left( \frac{n_i}{N_f} \right)
\]

(3)

Fatigue damage ranges from zero (indicating no deterioration) to one, which implies an outright failure.

Signal processing is characterized as the recovery of the procedure, based on physically observed data, usually subject to interference caused by differences in thermal, electrical, or mechanical situations. The random characteristics of these signals implore the importance of statistical techniques in the formulation of models in accordance with system behaviour. Furthermore, the process also requires the development of appropriate techniques to estimate model parameters and evaluate performance \[14\].

Fatigue signals are generally characterized by statistics representing their features. Therefore, a number of statistical parameters were used to monitor patterns and classify random signals. The parameters usually used include the mean, standard deviation (SD), root-mean square (r.m.s.), and kurtosis. For a signal \(F_j\) with the number of data \(n\), the mean value \(\bar{x}\) is estimated using:

\[
\bar{x} = \frac{1}{n} \sum_{j=1}^{n} F_j
\]

(4)

SD was used to determine how data were distributed in a sample and the number of average variabilities in a data set. SD can be stated as follows:
\[
SD = \sqrt{\frac{1}{n} \sum_{j=1}^{n} (F_j - \bar{x})^2}
\]  

(5)

r.m.s. was used to estimate the total amount of energy in a discrete data \( F_j \). This is expressed by:

\[
r.m.s = \sqrt{\frac{1}{n} \sum_{j=1}^{n} F_j^2}
\]  

(6)

Kurtosis is a statistical parameter that is sensitive to spikes in the data with a discrete equation as follows:

\[
K = \frac{1}{n(SD)^2} \sum_{j=1}^{n} (F_j - \bar{x})^4
\]  

(7)

Frequency analysis was performed to convert a time signal into the frequency domain, to be used in obtaining information. It is further distinguished into four types, which include a low and high pass for filtering minimal and enormous frequencies respectively, also, band pass, to filter iterations that pass through, while band rejected screens that get caught [8]. Since noise was generally presented at high frequencies, low pass was used in this study.

The Fourier transform \( FT \) [15] is defined as:

\[
FT(\omega) = \int_{-\infty}^{\infty} F_j(t) e^{-i\omega t} dt
\]  

(8)

where \( F_j \) is the time domain signal, \( t \) is the time and \( \omega \) is the angular frequency, defined by:

\[
\omega = 2\pi f
\]  

(9)

where \( f \) is the frequency.

According to Figliola & Beasley [16] and Kreyszig [17], the discrete Fourier transform is the main equipment in the frequency domain analysis, where time signals are converted to a set of points. This apparatus is however quite difficult to implement because it involves repeated addition and multiplication operations. Therefore, the FFT was introduced by Cooley & Tukey [18], which effectively breaks a signal down into discrete sinusoidal waves and reduces the repetition required in the digital signal conversion processes.

In addition, the spectrum analysis was performed using the power spectral density (PSD), taking into account the energy of a signal in the frequency domain further showing the strength of the variations in intensity as a function. It is expressed as [19]:

\[
PSD = \frac{1}{2\pi} \sum_{n=-\infty}^{\infty} F_j(n) e^{-i\omega n}
\]  

(10)

3. Results and Discussion

Based on the frequency distribution presented in Fig. 3, the cut-off frequency (COF) applied was 40 Hz, 45 Hz and 50 Hz since the noise was distributed there. Filtering at 50 Hz was able to remove almost 6\% of the cycles and maintained the fatigue damage of 96.5\%. At 45 Hz, it maintained 1,268 cycles,
ensuring the removal of 10.2% of lower amplitude cycles, which further reduced to 8.4% or changed of the fatigue damage to become 1.5E-4 damage per block. Clarifying at 45 Hz was selected as the optimum value since the fatigue damage deviation was observed to be more than 10% at 40 Hz, which was detrimental to the original behavior of the strain signal.

The 3-D histogram obtained from filtering at 45 Hz shown in Fig. 4 clearly shows that some cycles at the lower ranges (Fig. 4.a) have been removed; hence they did not appear in Fig. 4.b. Therefore, this proved that the developed algorithm was able to identify and remove low amplitude cycles. The removed cycles did not change the statistical parameter values in any way. The original and filtered strain signals provided similar values, which were the mean of -11 με, SD of 2 με, r.m.s. of 12 με and kurtosis of 3.3. Furthermore, the energy maintenance, determined by calculating the area under the PSD [8], was also considered as seen in the plot in Fig. 5 that filtering at 45 Hz reduced the energy by 11%. However, this reduction did not significantly influence the fatigue damage and the original signal characteristics.
4. Conclusion

An FFT-based algorithm for noise filtering was developed in the current study. Based on the results, this process was able to remove more than 10% of the lower amplitude cycles and maintained more than 90% of the fatigue damage. The cycles were removed up to 44%. This was due to the strain signal, which was a non-stationary, with a kurtosis value of 3.3. A non-stationary signal changes with time, while the time information in the FFT was lost when the analysis was performed, hence it was not relevant to apply this for non-stationary signals [20]. However, the purpose of this study was achieved as the technique did not change the strain signal significantly as removed high frequencies were produced by low amplitude cycles obtaining a minimal effect on the fatigue damage.

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