On the use of Machine Learning to Detect Shocks in Road Vehicle Vibration Signals

The characterisation of transportation hazards is paramount for protective packaging validation. It is used to estimate and simulate the loads and stresses occurring during transport which are essential to optimise packaging and ensure that products will resist the transportation environment with the minimum amount of protective material. Characterising road transportation vibrations is rather complex due to the nature of the dynamic motion produced by vehicles. For instance, different levels of vibration are induced to freight depending on the vehicle speed and the road surface; which often results in nonstationary random vibration. Road aberrations (such as cracks, potholes, speed bumps…) also produce transient vibrations (shocks) that can damage products. Because shocks and random vibrations cannot be analysed with the same statistical tools, the shocks have to be separated from the underlying vibrations. Both of these dynamic loads have to be characterised separately because they have different damaging effects. This task is a challenging because both types of vibration are recorded on a vehicle within the same vibration signal.

This paper proposes to use machine learning to identify shocks present in acceleration signals measured on road vehicles. In this paper, a machine learning algorithm is trained to identify shocks buried within road vehicle vibration signals. These signals are artificially generated using nonstationary random vibration and shock impulses that reproduce typical vehicle dynamic behaviour. The results show that the machine learning algorithm is considerably more accurate and reliable in identifying shocks than the more common methods approaches based on the crest factor.

1 Introduction

At some point in the supply chain, all products and goods are transported by road freight. This mode of transportation contains some risks for shipment integrity. For instance, the imperfections of the road induce shocks and vibration to the vehicle. Distribution packaging is designed to protect freight from such transport hazards. However inefficient packaging poses a significant problem that costs hundreds of billions of dollars, not to mention the additional environmental impact as a result of solid waste [1]. On the other hand, excessive packaging increases the shipment weight and volume which proves to be costly throughout the supply chain. To overcome these issues, packaging must be optimised to offer just the necessary level of protection.

The characterisation of vehicle vibration is essential to optimise packaging because it can be used to produce accurate simulations of the loads and stresses occurring during transport. Due to the nature of the dynamic interaction between the road surface and road vehicles, the resulting motion is often complex and cannot be characterised by simple statistical means. For instance, different levels of vibration are induced to freight depending on the vehicle speed and the variation in road surface roughness resulting in highly nonstationary random process. Also, randomly-occurring road surface aberrations (such as large cracks, potholes, speed bumps, drains, rail crossings…) produce shocks that can be harmful to shipments. These randomly-occurring nonstationary and transient events generated during road transportation co-exist and need to be identified, separated and analysed separately in order to achieve an accurate and realistic characterisation and simulation of road vehicle vibration.

The nonstationary random component of the road vehicle excitation has been investigated by many researchers [2-16]. Limited research has been undertaken into the characterisation of shocks during road transportation despite being as important as the random component when simulating vehicle vibration. Accurate simulations should include representative distributions of shock occurrences and amplitudes [17]. The characterisation of these distributions is challenging because the shocks are superimposed onto nonstationary signals which makes them difficult to identify. The methods currently used to characterise shocks often rely on moving crest factor analysis [7, 18-23]. This approach is not always reliable and is often not appropriate for signals that contain strong nonstationarities.

This paper presents a machine learning algorithm that is able to identify shocks that are superimposed (buried) in random road vehicle vibration signals. The basics of machine learning and the selected algorithm are first introduced, which is then followed by a learning process used to develop the classifier. The classifier validation and comparison with methods based only on the crest factor is also presented.

In this paper, shocks are defined as sudden and severe accelerations of a finite and measurable duration. As the excitation is brief, shocks are principally composed of the natural frequencies of the system (i.e. the road vehicle).

2 Machine learning

Machine learning is a branch of Artificial Intelligence that involves teaching (or training) a computer program to solve a problem. Once the training process is completed, the program can solve similar problems to those used for learning using the relationship that was learnt during training. One type of machine learning is called classification where the analysed data is divided into discrete classes. The classifiers are developed based on the workflow presented in Figure 1. It starts with a learning dataset which is a set of data where the classes are known. For vehicle vibration, this is an acceleration signal where the locations of the shocks are known. This dataset is processed to reveal different data behaviours and characteristics in a format compatible with the learning algorithm. This is where machine learning is different to other classification approaches because it can base its prediction on several different signal processing methods. For instance, it combines nonstationary and shock analysis technique to distinguish transient events (shocks) from signal intensity variations. Once the processing is completed, the data is randomly partitioned into two sets: the training set and the validation set. Both sets have the same proportion of each class. The training set is used to train the algorithm and develop the classifier. The trained classifier is then validated using the validation set.

2.1 Classifier training

In machine learning, data is king. The classifier prediction accuracy is proportional to the quantity of data used in its training. In the case of the detection of shocks in a road vehicle vibration signal, it is unrealistic to gather significant amounts of data on real vehicles to train a classifier because that requires a survey of many kilometres of road profile to know exactly where the aberrations are and to drive a vehicle exactly on the surveyed path. It is more appropriate to use synthetic acceleration signals that mimic typical road vehicle vibration as there are no length limitations and the signal components are accurately known a priori.

The nonstationary component of the signal is synthetised with a technique similar to the one used by Rouillard [16]. The technique modulates a Gaussian signal to create a nonstationary random signal (Figure 2). First of all, a Gaussian signal is synthetised from a Power Density Spectrum (PDS) of a signal measured on a real road vehicle. Only the shape of the spectrum is required at the beginning because the signal will be rescaled subsequently. Therefore the PDS (P_{xx}) is normalised with the signal's RMS value:

$$\hat{P}_{xx}(f) = \frac{P_{xx}(f)}{\sum P_{xx}(f)\Delta f} , \qquad \text{(eq. 1)}$$

where Δf is the frequency resolution of the PDS. This normalized PDS is then transformed to an amplitude spectrum with a random phase ϕ uniformly distributed between -180° to 180°:

$$X(f) = \sqrt{\left(P_{xx}(f)\Delta f\right)} e^{j\phi} . \qquad \text{(eq. 2)}$$

This spectrum is then transformed into the time domain using the inverse fast Fourier transform. The resulting time signal is Gaussian random signal with an RMS value of 1. The signal becomes nonstationary when multiplied by a modulation function representing the variation in the RMS value of the signal (Figure 2).

A two degrees of freedom model of the vehicle, known as the quarter-car model, is used for the synthesis of the shocks. The model is composed of a sprung mass M_s, an unsprung mass M_u, two springs k_s and k_u and two dampers c_s and c_u, illustrated in Figure 3. The numerical values of the components for the model represent typical values used by Cebon [24] for a “quarter-car” truck model, shown in Table 1. The model input $x(t)$ is the road profile and the output $\ddot{y}(t)$ is the vehicle body acceleration. The FRF of the model (Figure 4) shows that the first peak is less damped than the second. The response decreases after the second peak and its magnitude is less than 10 % of the maximum value above 30 Hz.

The shocks are the quarter-car’s response to impulse functions at the road surface, i.e. short Hanning functions (raised single-period cosines). This impulse function can be attributed arbitrary amplitudes and duration ranging, in this case, between 5 to 40 mm and 0.5 to 1.6 s, respectively, to represent a range of different types of road aberrations and vehicle’s response spectra. These shocks are then superimposed onto the nonstationary signal to represent realistic road vehicle vibrations (Figure 2). The signal is composed of 100 shocks randomly distributed within its 1000 s duration. The predictors are computed from this signal; half of it is used to train the classifier (500 s and 50 shocks) and the other half for the validation. The position of the shocks is defined by the step function. Values other than zero mean there is a shock in the signal.

2.2 Predictors

Machine learning prediction performance depends on the data processing prior to the training phase. This processing reveals different signal characteristics, called predictors. In order to detect the shocks superimposed in a nonstationary random signal, the predictors come from a range of relevant analysis techniques used to characterise both the shock and the nonstationary vehicle vibration such as moving Root Mean Square (RMS) values [6, 16, 21-23], moving crest factor [7, 18-23], the Hilbert Huang Transform (HHT) [10-12] and the Discrete Wavelet Transform (DWT) [8, 13-15].

2.2.1 Moving RMS

The moving RMS can be used to characterise the nonstationary nature of vehicle vibration signals. The major shortcoming of this predictor is its sensitivity to its window time T, i.e. the segment length used to compute the RMS values,

$$m_{\mathrm{RMS}}(t)=\sqrt{\frac{1}{T}\int_{0}^{T} x(t+\tau)^{2}\,d\tau}\,. \qquad \text{(eq. 3)}$$

As shown by Rouillard [6], window lengths between 0.5 s to 4 s result in different moving RMS functions. A shorter window is better to detect the short transient events but is ineffective for long Gaussian changes and vice versa for a longer window. Therefore there is no ideal window size. Fortunately, machine learning classification has the capability to use multiple predictors. The moving RMS predictors are not limited to one window length and four different window lengths (0.5, 1, 2, and 4 s) are used. These windows are computed forward to take into account the response of the system. In other words, at one moment, the RMS values represent the signal intensity of the next T seconds. Figure 5 shows an example of the 0.5 s and 4 s moving RMS predictors applied on signal.

2.2.2 Moving Crest Factor

The moving crest factor is the ratio between the signal $x(t)$ and the moving RMS value of a window length T,

$$\mathrm{CF}(t) = \frac{x(t)}{\sqrt{\frac{1}{T}\int_0^T x(t+\tau)^2\,d\tau}} \quad \text{(eq. 4)}$$

Theoretically, the crest factor ratio increases with the presence of a transient event. Therefore they can be detected when the crest factor is above a certain threshold. As opposed to the moving RMS predictor, the moving crest factor predictor is more accurate when using a longer moving window. This is because a longer window averages out the effect of the shock at the crest factor's denominator without affect its numerator, which results to a greater sensitivity to shocks. However, a too long window has been shown to misclassify a short RMS variation as a shock. Four Crest Factor predictors with window lengths of 8, 16, 32 and 64 s are used in the machine learning classifier. An example of the 8 s and 64 s crest factor predictor is shown in Figure 6.

2.2.3 Hilbert-Huang Transform (HHT)

The HHT is an adaptive time-frequency analysis method that provides different types of predictors from vehicle vibration signals [25, 26]. In simple terms, the HHT divides the signal into different narrow banded components. These components, called Intrinsic Mode Functions (IMFs), provide information that can be useful for the classification. For instance, the IMFs are directly used as predictors for their amplitude and instantaneous frequency functions which reveal other details from the signal [10, 11]. Figure 7 shows, for illustration purposes, IMF 1, 5 and 9 of a signal along with IMF 5's amplitude and instantaneous functions.

2.2.4 Digital Wavelet Transform (DWT)

The DWT is another time-frequency (or more specifically time-scale) analysis method that provides predictors which are more sensitive to signal changes and can be useful for transient detection [13]. The DWT coefficients issued from the Daubechies 10 wavelet analysis are directly used as predictors. Figure 8 shows an example the DWT predictors of four different scales of signal.

During the DWT analysis, the signal sampling rate is halved for every scale. The number of scales is limited to 12, so the largest scale has a frequency range up to 0.25 Hz (for a sampling rate of 1000 Hz) which can be considered to be refined enough for road vehicle vibration analysis purposes. This resampling also causes the number of coefficients to decrease at every scale. To create predictors with sampling rates that match the original signal and the other predictors, the coefficients a_n are replicated to match the sampling rate of the signal, as shown in Figure 9.

2.3 Support Vector Machine Classifier

There is a vast variety of machine learning classification algorithms available today. The Support Vector Machine algorithm was selected because it has good accuracy in classification when the data has only two classes as is the case for shock-on-random signals. During the learning phase, this algorithm finds a hyperplane that maximise the distance between the two classes' data points represented in all their dimensions (predictors). The new data points are then classified using this hyperplane as a classification test. Kernel transformations can be used on the data when there is no single hyperplane that can separate the classes. Without going into too many details, these Kernels functions transform the data into a space where the classes are more distinct. Mathematical details on Kernel functions can be found in Kinani and Oudadess [27]. Preliminary investigations have shown that more accurate predictions are obtained with a Gaussian function used as a Kernel transform. Gaussian Kernel transformation is therefore applied with the Support Vector Machine algorithm used in this paper. Refer to [28-31] for more details on SVM.

3 Validation

The second half of the synthetic signal is used to validate the machine learning classifier and to compare its performance with detections based on the moving crest factor alone. There are many ways to assess the performance of classifiers depending on their application. The True Positive Rate (TPR) is used in this paper to assess the classifier's ability to correctly detect shocks. It is expressed as the proportion of true shocks detected over the total number of shocks in the signal by the classification,

$$\mathrm{TPR} = \frac{\sum \text{true shock}}{\sum \text{shock}} \;. \qquad \text{(eq. 5)}$$

Conversely, the False Positive Rate (FPR), or fall-out, represents the proportion of incorrectly detected shocks over signal segment length without shocks,

$$\mathrm{FPR} = \frac{\sum \text{false shock}}{\sum \text{no shock}} . \qquad \text{(eq. 6)}$$

These two values are inherently related; while the sensitivity of a classifier can be adjusted to increase the TPR, the FPR will also increase. This relationship for a specific classifier is given by the ROC (Receiver Operating Characteristic) curve which is used to select the optimal operating point, i.e. the optimal TPR and FPR values. This point is obtained using the minimax criterion [32] which minimises the cost function:

$$\Re = C_m\left(1-\mathrm{TPR}\right)p_1 + C_f\,\mathrm{FPR}\left(1-p_1\right) \qquad \text{(eq. 7)}$$

where C_m and C_f are respectively the cost of a misdetection and a false detection and p_1 is the probability of having a shock in the signal. For any shock probability, the optimum operating point is the closest point on the ROC curve to the minimax equation:

$$C_m\left(1-\mathrm{TPR}\right) = C_f\,\mathrm{FPR} \;. \qquad \text{(eq. 8)}$$

For the sake of the classifiers assessment, in this paper both misdetection and false detection have been attributed the same cost.

For a classification based purely on chance (guessing), the ROC curve is a diagonal going from (0, 0) to (1, 1) where TPR equals FPR, shown in Figure 10. Any classifier with an ROC curve above this diagonal perform better than guessing, as is the case for both the crest factor and the machine learning classifiers. The Area Under the ROC curve (AUC) is a common method used to assess the classifier performance [33, 34]. The ideal classifier has an AUC of 1 and a classifier only based on chance has an area of 0.5.

3.1 Crest Factor detection

The detection performance of the machine learning classifier is compared with the most commonly-used detection method, the moving Crest Factor. This method is simple; a shock is detected when the Crest Factor is above a certain predetermined value. The Crest Factor value depends on the window length (eq. 4). As there is no clear indication in the literature on the optimal window length [7, 18-23], a performance comparison was performed using window lengths between 2 s to 64 s, shown in Figure 10. Table 2 shows that, for the type of typical RVV signal used here, the crest factor performs best with a window length above 32 s.

3.2 Machine learning performance

At the optimal operating point, the machine learning classifier shows better performances than the crest factor classifiers, except for a 32 s crest factor window size which has a slightly better TPR than the machine learning (3% increase) but a significantly higher FPR (50 % increase), as shown in Table 2. The machine learning's AUC is 13% higher than the best crest factor classifiers. Figure 11 shows that the machine learning classifier has a better performance at the first portion of the ROC curve, i.e. when the TPR is below 0.95. Above this point, both classifiers have similar performance (FPR above 0.80).

Figure 12 shows the maximal acceleration distributions of the shocks present in the signal and the detections made with the machine learning and crest factor methods. For maximal accelerations below 10 m/s^2, both methods have more shock occurrences than there exists in the signal. The machine learning performs better in this area. Its distribution is closer to the real shocks distribution which means there are fewer false detections than with the crest factor detections. Above 10 m/s^2, there is less discrepancy between all the distributions. The machine learning method missed and falsely detected slightly fewer shocks than the crest factor approach. The general shape of those distributions shows that most of the false detections are below 9 m/s^2 and the most missed detection are around 10-11 m/s^2.

4 Conclusion

Detecting shocks buried in random road vehicle vibration signals allows accurate characterisations of the load and stress induced in freight during transportation which is essential to optimise protective packaging systems. The comparative study presented in this paper showed that the most popular current method to detect road vehicle vibration shocks, the crest factor, can be replaced by more effective methods based on machine learning. Classifiers based on the crest factor only with different window lengths and operating points using the minimax criterion. Machine learning outperformed these classifiers in all cases except the 32 s window length, which has similar a TPR but higher FPR and lower AUC.

Compared to the classic detection methods, machine learning has the ability to integrate many predictors (prediction parameters) in its process. This overcomes many issues related to the classic method, such as the window length selection to compute the crest factor, because it can integrate more than one window length. In this paper a total of 64 predictors were used using several techniques such as the moving RMS, crest factor, HHT and DWT. These predictors can be refined and optimised to increase to accuracy of the machine learning algorithm. Furthermore, the algorithm itself can also be optimised. A support vector machine classifier was used, but other classifier types can also be investigated for this application. While the classifier presented in this paper is not a definitive method to detect shocks buried in road vehicle vibration signals, it is a clear demonstration that machine learning methods can provide more accurate shock detections than the moving crest factor methods. Before establishing a new detection method, machine learning algorithms need to be applied on real vehicle signals and assess how the real vehicle's shock response spectrum which may vary between shocks could affect the detection. Further research should also assess the specificity of the machine learning algorithms. For instance, does the algorithm have to be trained for every truck type or model or load type? These are the main challenges to the shock detection using machine learning that will be addressed in future research.

5 References

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6 Tables

Table 1: Components of the two degrees of freedom model of a typical truck [24]

Component	Value
M_s	8900 kg
M_u	1100 kg
k_s	2 000 kN/m
k_u	3 600 kN/m
c_s	40 kN s/m
c_u	4 kN s/m

Table 2: Classifiers' performance comparison at the optimal operating point

Method	TPR	FPR	AUC
Crest Factor 2 s	0.64	0.55	0.55
Crest Factor 4 s	0.64	0.40	0.66
Crest Factor 8 s	0.64	0.33	0.70
Crest Factor 16 s	0.62	0.29	0.73
Crest Factor 32 s	0.79	0.40	0.74
Crest Factor 64 s	0.72	0.32	0.74
Machine Learning	0.77	0.20	0.85