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Two algorithms for the sorting of unknown train vibration signals into freight and passenger train categories

C. J. Sharp, D. Waddington, J. Woodcock, G. Sica, E. Peris and A. Moorhouse

University of Salford, The Crescent, M5 4WT Salford, UK
c.sharp@edu.salford.ac.uk

The human response to railway noise has been well researched; however, there is a need to further research the human response to railway vibration, freight in particular. To facilitate this, two algorithms have been constructed with the aim of sorting unknown train vibration signals into freight and passenger train categories so that they can be further analysed. 307 known train vibration signals measured close to the railway were analysed to determine which signal properties, if any, are identifiably different for freight and passenger train vibration signals. These data were collected within the Defra funded UK study "Human Response to Vibration in Residential Environments" conducted by the University of Salford. Several signal properties were found to be statistically significantly different for freight and passenger train vibration signals, all of which relate either to the duration of the signal event or its frequency content. These differences were used to successfully create two algorithms that are capable of sorting unknown train signals into freight and passenger train categories at a relatively high level of accuracy. The methodology used in creating the algorithms, their level of accuracy and recommendations for their use are presented in this paper.

1 Introduction

European rail operators intend to increase their market share of goods traffic from 8% in 2001 to 15% in 2020 and so will be relying much more heavily on railway freight transport [1]. Research has shown that increasing levels of transport noise and vibration can induce annoyance and sleep disturbance [2,3]. In addition, it has been shown that annoyance due to vibration is higher at night and that annoyance reactions due to sound are more frequent during evenings and night-time, when freight traffic tends to be more prevalent [4,5]. There is therefore a need to develop measures to ensure acceptable levels of noise and vibration, in order to minimise the level of annoyance and sleep disturbance experienced by residents located in the vicinity of freight railway lines.

The University of Salford has recently completed a research project funded by the Department for Environment, Food and Rural Affairs (Defra, UK), which was successful in determining exposure-response relationships between different vibration sources and local residents [6]. Detailed analysis of the extensive database of case studies, which comprise face-to-face interviews and vibration measurements, will be extremely useful in developing research for the EU FP7 Cargovibes project, which aims to facilitate the expansion of freight traffic on rail. However, vibration measurements were taken over a period of 24 hours, during which time there were many train passes, and no attempt was made to discriminate between different types of passenger trains and freight trains and hence there is currently no way to investigate the different responses that freight and passenger trains may elicit. It would be beneficial to be able to identify freight train signals in the Defra database, and determine a response relationship specific to freight train vibration, so that the effect of a potential increase in vibration due to freight traffic can be better understood.

Therefore, the objectives of the current research are to investigate the differences in the vibration signals caused by passenger trains and freight trains, in an attempt to determine distinguishing factors of vibrations caused by freight trains in particular. These distinguishing signal properties are used to construct an algorithm that is able to sort unknown train vibration signals into freight and passenger train categories for further analysis. An event identification algorithm has already been written as part of the Defra funded project and it could be used in conjunction with the results of the current research to quickly and automatically identify freight train vibration signals in the existing database.

2 Data Extraction and Analysis

2.1 The Existing Defra Database

The work in this report is based on existing measurements taken as part of the Defra funded research project at the University of Salford. The vibration measurement protocol for the project involved long term monitoring at external positions, along with synchronised short term measurements taken within dwellings. The transmissibility calculated between these pairs of measurement positions allowed the estimation of 24-hour vibration acceleration time histories within dwellings.

The vibration measurements were performed in the field using Guralp CMG-5TD strong motion accelerometers with a 100 Hz low pass filter. These measurement devices consist of a tri-axial accelerometer and a digitiser in a self-contained unit. The device has two key properties that made it ideal for the required measurements, one being the low noise floor of the instrument coupled with its 24-bit digitiser, providing a dynamic range that is large enough to cover the required range of vibration magnitudes, eliminating the need for the operator to continually adjust its sensitivity and avoiding the potential of over or under loading due to operator error. The other relevant feature of the Guralp CMG-5TD units is their ability to be time synchronized via the Global Positioning System (GPS), allowing phase locked, full time history measurements to be taken without extensive cabling between instruments.

While the internal measurements were being taken, the operators noted any train passes that occurred during the measurement period on a handwritten log. In most cases the time of the event, and the type of train, were noted.

Using this approach, 149 long term measurements were conducted along with 522 short term internal measurements. The high rate of success in obtaining internal measurements has the benefit of eliminating uncertainties due to interpolation and extrapolation of data.

2.2 Data Extraction

The first step in the current work was to create a small subset of known train event signals for analysis from the Defra database. This subset was drawn from periods of the long term external vibration measurements in which details of the type of train pass-bys were recorded by the operator conducting the measurements. Freight train events were found to be much rarer than passenger train events because they tend to occur more regularly at night and all of the periods in which the operators logged the train pass-bys were during the day. Therefore, in order to obtain as many freight signals as possible, the above data extraction was repeated for every measurement log that contained at least one freight train event. This resulted in 307 total events, 53 of which are freight train events extracted from 58 measurement logs spread over 8 sites.

2.3 Signal Property Analysis

Once all of the train events that were successfully identified were manually sorted and categorised, each vibration signal was analysed to determine its signal properties. A Matlab code was written so that all of the vibration signals could be read in turn and several signal properties were calculated for each vibration signal.

A short and a long envelope, defined by the 3dB and 10dB downpoints of the signal respectively, were defined for each event signal (dB re 1×10^{-6} m s^{-2}). To maintain consistency with previous work, all properties were calculated using the 10dB signal envelope [6]. Table 1 shows a summary of the signal properties calculated for each event signal. $x(n)$ is the acceleration time series, N is the number of samples in the series, T is the duration of the event in seconds, $f(m)$ is the centre frequency of bin m and $x_f(m)$ is the magnitude of the signal in bin m.

Table 1: Summary of calculated signal properties

Signal Property	Calculation
Root mean square (m s^{-2})	$x_{rms} = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x(n)^2}$
Equivalent Vibration Level (dB re 1×10^{-6} m s^{-2})	$L_{eq} = 20\log_{10}\left(\frac{x_{rms}}{1\times10^{-6}}\right)$
Vibration Exposure Level (dB re 1×10^{-6} m s^{-2})	$L_E = L_{eq} + 10\log_{10}(T)$
Vibration Dose Value (m s$^{-1.75}$)	$x_{VDV} = \sqrt[4]{\frac{T}{N}\sum_{n=1}^{N} x(n)^4}$
Standard Deviation	$\sigma = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(x(n)-\bar{x})^2}$
Skewness	$S_k = \frac{1}{N\sigma^3}\sum_{n=1}^{N}(x(n)-\bar{x})^3$
Kurtosis	$K_t = \frac{1}{N\sigma^4}\sum_{n=1}^{N}(x(n)-\bar{x})^4$
Spectral Centroid	$C_{spec} = \frac{\sum_{m=0}^{M} f(m)x_f(m)}{\sum_{m=0}^{M} x_f(m)}$

To determine if the signal properties of freight trains are statistically different from those of passenger trains, it is necessary to perform some statistical analysis. A suitable statistical test to use for this purpose is the Student's *t*-test. In particular, since the two samples being compared are independent and do not have the same variance, the *t*-test will be an independent two sample *t*-test assuming unequal variance. The mean signal properties that were found to be significantly different at the 99% confidence level, in the vertical plane and/or both horizontal planes, are the 3dB and 10dB envelope lengths, the Vibration Exposure Level, the Vibration Dose Value, the Kurtosis in the time domain and the standard deviation, Kurtosis and Skewness in the frequency domain.

All of the signal properties that were found to be significantly different relate either to the duration of the signal event or its frequency content. This is not a surprising result, since freight trains tend to have longer pass-bys, resulting in higher Vibration Exposure Levels and Vibration Dose Values, and have different frequency content than passenger trains [6].

3 The Categorisation Algorithms

3.1 The Principles of the Algorithms

Both algorithms were coded entirely in Matlab using a training/testing method. This is a method whereby a set of unknown test signals is analysed and then separated into categories (i.e. freight trains and passenger trains) by calculating certain properties of each signal in the test set and comparing these to the same properties of known examples of freight and passenger train signals that make up a training set. Since only the properties of the signals that are different between freight and passenger trains are of interest in these algorithms, only properties that were found to have statistically different means at the 99% confidence level were calculated.

Two different methods were used when comparing the training and test data. In one algorithm, the signal properties of each test signal are compared to the mean values of all the training freight and passenger train signals. In the other method, a binary probit model is used to predict whether or not a test signal is more like a freight or passenger train signal. The steps taken by both algorithms to categorise unknown signals are as follows:

- Calculate signal properties of known training signals in the training set to determine typical values for freight and passenger trains
- Calculate the same signal properties for unknown signals in the test set
- For each tested signal, determine which of its signal properties are more like freight train signal properties and which are more like passenger train properties (each algorithm uses a different method for this step)
- Decide whether a signal should be categorised as a freight or passenger train signal by the proportion of its signal properties that are deemed more similar to freight train signal properties

3.2 Categorisation Using Mean Value Comparison

For this version of the algorithm, each tested signal is categorised as either a freight train or a passenger train by comparing its signal properties to the mean value of the known passenger and freight train signals in the training set. The first step is therefore to calculate the properties of each signal in the training set and determine a mean value for each property for passenger and freight trains.

Next, the same properties calculated for each training signal are calculated for each of the unknown test signals. For each test signal in turn, each calculated property is compared to the mean value of that property for freight trains and for passenger trains, determined from the training set. If the property of the signal is closer to the mean of the freight train signals, it is assigned a value of 1 and if the property is closer to the mean of the passenger train signal it is assigned a value of 0. The assigned value for each property is then summed for each train signal and converted to a percentage score, resulting in a value between 0% (when all calculated properties are closer to the passenger train mean properties) and 100% (when all calculated properties are closer to the freight train mean properties), with most signals having a value somewhere in between.

The final step is to sort each signal into the freight train or passenger train category. All of the signals that have a percentage score above a certain categorisation cut-off value (e.g. 50%) are sorted into the freight train category and all other signals are sorted into the passenger train category.

3.3 Categorisation using a Binary Probit Model

For this version of the algorithm, a binary probit model is constructed for each signal property, with a resulting predicted probability that a signal is a freight train signal as a function of the signal property [7].

Signal properties are calculated for each vibration signal in the training set, after which a binary probit model is derived. The binary probit model allows the regression of a continuous independent variable on a binary dependent variable to be calculated. In this case, the continuous variable is one of the signal properties calculated for each vibration signal and the binary variable is whether the signal comes from a freight train (1) or a passenger train (0).

Figure 1 shows the application of the binary probit model to the 3 dB envelope length in the vertical plane. The passenger train signals (Pr(y = 1) = 0) are clustered at the lower end of the duration spectrum than the freight train signals (Pr(y = 1) = 1), which are more spread out and have a greater proportion at the higher end of the spectrum.

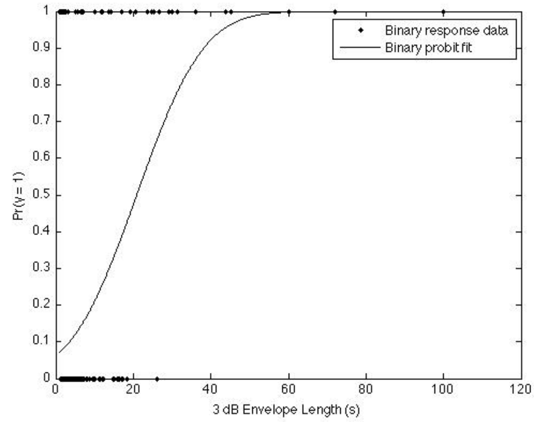

Figure 1: Example of binary probit model for 3 dB envelope length in the vertical plane

Next, a binary probit cut-off value (e.g. Pr(y = 1) = 0.5) was defined above which a signal property is determined to be more likely to belong to a freight train than a passenger train. If a signal property is such that the probability according to the binary probit model is above this critical value, it is assigned a value of 1. Otherwise, it will be assigned a value of 0. These values are then summed in the same way as for the comparison of means algorithm, and a percentage score is determined as before. Again, the final step is to categorise the test signals into freight train signals and passenger train signals, by sorting all the vibration signals that have a percentage score above a specified categorisation cut-off value (e.g. 50%) into the freight train category and the rest into the passenger train category. As with the comparison of means algorithm, the definition of the categorisation cut-off value will have an effect on the accuracy of the algorithm. In addition, the definition of the binary probit cut-off value will have an effect on the algorithm's accuracy.

3.4 Investigating the Critical Value for the Comparison of Means Algorithm

For each signal tested in the comparison of means algorithm, the percentage of calculated signal properties that are deemed more similar to freight train signals than passenger train signals is calculated. A categorisation cut-off value for this percentage is then defined above which signals are classified as freight train signals, and below which signals are classified as passenger trains. The accuracy of the algorithm is therefore dependent on this critical value. Figure 2 shows a plot of the accuracy of the algorithm as a function of the categorisation cut-off value. The total accuracy is defined as the percentage of all tested signals (both freight and passenger) correctly categorised, the freight train accuracy is the percentage of all tested freight signals correctly categorised and the passenger train accuracy is the percentage of all tested passenger train signals correctly categorised.

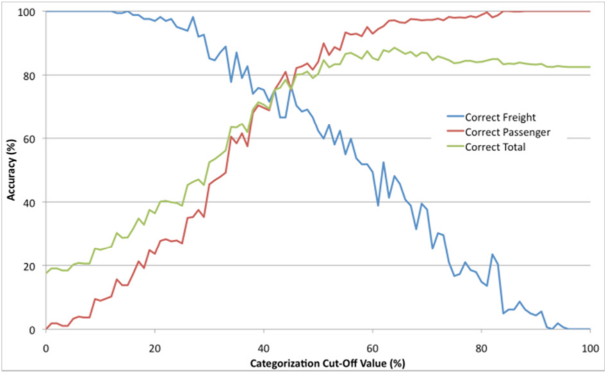

Figure 2: Percentage accuracy of comparison of means algorithm as a function of the categorisation cut-off value

Clearly, the categorisation cut-off value has a very significant effect on the accuracy of the algorithm, with the percentage of freight trains correctly identified being very high at low categorisation cut-off values, whilst the percentage of passenger trains correctly identified is extremely low, and vice-versa. The highest overall accuracy is therefore somewhere in between, at a categorisation cut-off of approximately 60%. At this cut-off value, the overall accuracy is approximately 85% and the accuracy for passenger and freight trains is approximately 95% and 50% respectively. In this case, the lower percentage accuracy for freight train identification does not have such a significant effect on the overall percentage accuracy, since there are relatively fewer freight trains than passenger trains in the training and test sets. Depending on the application, it may be more important for the algorithm to have similar accuracy for both freight train and passenger trains. In this case, a cut-off value of approximately 40% would be more appropriate. Although this gives a lower overall percentage accuracy, it has the advantage of the overall, freight and passenger train accuracy all being approximately the same at around 70%, making the algorithm much more consistent.

3.5 Investigating the Critical Values for the Binary Probit Model Algorithm

In the binary probit model algorithm, for each signal property, a binary probit model is created. A critical point in this model is then defined above which signal properties will be classified as similar to freight train signal properties. Then, as with the comparison of means algorithm, a categorisation cut-off value is defined above which signals are categorised as freight train signals. Figure 3 shows a plot of the percentage accuracy of passenger train signals that are correctly identified, as a function of the categorisation cut-off value and the probit cut-off value.

The percentage of passenger trains correctly identified is 0% when both the categorisation cut-off value and the probit cut-off value are 0. This is because all of the signal properties will be found to be more similar to freight train signals, since they will have values that are above 0 on the probit model. In addition, all of the signals will be classified as freight train signals because they will have percentage scores equal to or higher than 0%. In contrast, when the categorisation and cut-off values are at their maximum of 100% and 1, the percentage of passenger trains correctly identified is 100%. For any given categorisation cut-off value, the percentage of passenger trains correctly identified increases with the probit cut-off value, since higher probit cut-off values mean that fewer signal properties are assumed to be similar to freight train signal properties. Similarly, for any given probit cut-off value, the percentage of passenger trains correctly identified increases with increasing categorisation cut-off value, since a higher categorisation cut-off value means that a signal must have more properties that are similar to freight train signals for it to be classified as a freight train. Figure 4 shows the percentage of freight trains correctly identified as a function of the cut-off values.

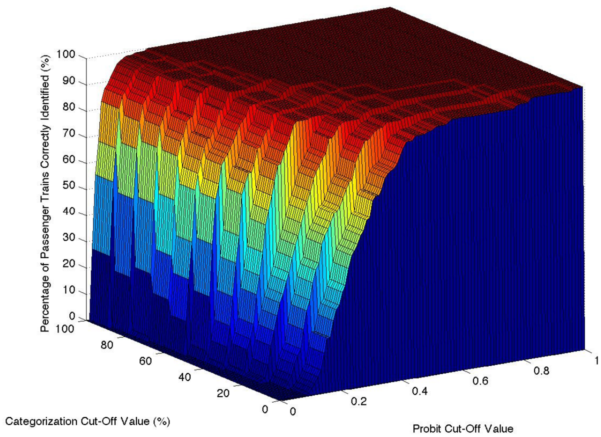

Figure 3: Percentage of passenger trains correctly identified by the binary probit algorithm, as a function of the categorisation cut-off value and the probit cut-off value

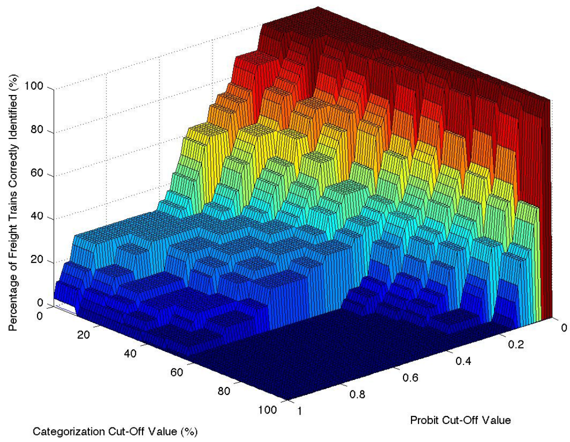

Figure 4: Percentage of freight trains correctly identified by the binary probit algorithm, as a function of the categorisation cut-off value and the probit cut-off value

The percentage of correctly identified freight trains is at a maximum of 100% when the categorisation cut-off value and probit cut-off value are both at their lowest value of 0% and 0. This is because all signals will have signal properties that are greater than the value at which the probit model is 0. In addition, all signals will be classified as freight trains since they will have a categorisation percent score greater than 0%. The opposite can be said for the highest categorisation cut-off and probit cut-off values of 100% and 1 respectively, at which the percentage of freight trains correctly identified is 0%. The percentage of total trains correctly identified can be seen in Figure 5.

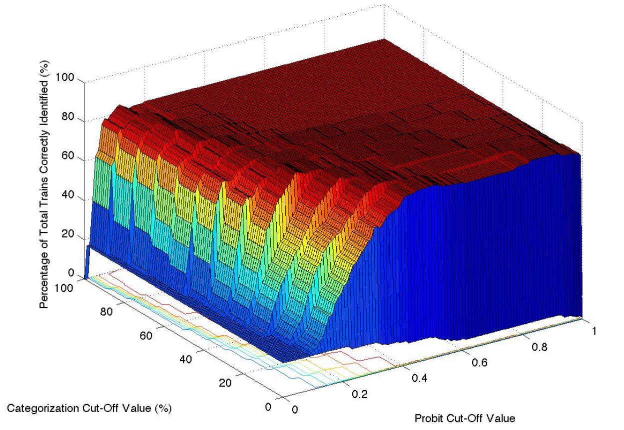

Figure 5: Percentage of total trains correctly identified by the binary probit algorithm, as a function of the categorisation cut-off value and the critical probit cut-off value

The highest percentage of total trains correctly identified is approximately 85% and occurs when the categorisation cut-off value is around 40% and the probit cut-off value is around 0.4. However, despite the high percentage of total trains correctly identified at these cut-off values, the difference between passenger and freight train identification accuracy is severe, with their percentage of correct identifications being approximately 98% and 30% respectively. More consistent identification accuracy occurs when the categorisation cut-off value is around 25% and the probit cut-off value is around 0.25. At these cut-off values, the percentage of total trains, freight trains and passenger trains correctly identified are all approximately 80%. As with the comparison of means method, this more consistent accuracy comes at the cost of decreased overall accuracy.

4 Conclusions

The results of the current research have indicated that there are indeed signal properties that are significantly different for freight and passenger train signal properties. The properties that are significantly different depend either on the duration of the signal events, or their frequency content. Freight trains tend to have envelopes of greater duration, and hence have higher Vibration Exposure Levels and weighted Vibration Dose Values (in the horizontal plane at least). In addition, their Fourier spectra tend to have a lower Skewness and Kurtosis than passenger trains, meaning that more of the energy lies to the left of the mean and that the probability distribution of the Fourier spectra are less “peaky” than for passenger trains. These significantly different signal properties were successfully used to construct two algorithms for categorising unknown vibration signals into freight and passenger train categories.

The two algorithms use slightly different methods to categorise the unknown vibration signals, but both use similar principles of training using known vibration signals before testing the unknown signals. The comparison of means method has a lower overall accuracy. For this reason, it is recommended that the binary probit model algorithm be used, since it has an average accuracy of percentage trains correctly categorised of approximately 80%. Although not present in this paper, an investigation into the ratio of sizes of the training and test sets was performed. It was found that the binary probit model algorithm has a consistent accuracy for training set sizes that are at least 10% the size of the signal set to be tested, whereas the accuracy of the comparison of means algorithm sharply decreases with training sets that are smaller than 25% of the signal test set size.

Although neither algorithms are able to accurately categorise 100% of the tested signals, the signals that are sorted into the wrong category are sorted in this way because they have signal properties that are more similar to the incorrect category and, therefore, the human response to that signal may be the same as if it did actually belong in that category. Furthermore, there is potential to improve the accuracy of the algorithms by combining the two methods, or by further examining the properties of the signals that are incorrectly categorised.

With further work, the accuracy of the algorithms could be improved, however, even at its current level of accuracy, the binary probit model algorithm may prove extremely beneficial for the categorising of unknown vibration signals, allowing a greater understanding of the human response to specific railway traffic sources.

Acknowledgements

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