technical report

An algorithm for mildly nonstationary mission synthesis (MNMS)

J. Giacomin, A. Steinwolf and W. J. Staszewski, The University of Sheffield

1. Introduction

An important technical problem associated with the design, development and testing of vehicle subsystems is the definition of the operating conditions faced in use. Determining vibration missions is critical in the field of automotive NVH because numerous components are nonlinear, providing different vibratory behaviour depending on the nature of the input excitation used. An example of a nonlinear vehicle component is the person/ seat system. Seat transmissibility measurements in the vertical direction typically show a softening system behaviour, with the principal resonance shifting to lower frequencies as the excitation amplitude at the base of the seat rises [4]. Industrial testing methods such as those applied to seats often work around the problem of nonlinearity by using several test signals [3], each one selected to represent a specific road surface which was found through experience to excite important vehicle and subsystem resonances. Determining these mission signals has often been a matter of trial and error.

In the durability field, several algorithms are now available to analyse road data for the purpose of synthesising excitation signals for fatigue testing [9-10,16-17]. Concepts such as rainflow counting, or techniques based on the Wiebull distribution have been successfully applied. No such algorithms have been developed, however, for the purpose of NVH testing or for the human comfort testing. This paper describes an algorithm developed for performing vibration mission synthesis of mildly nonstationary signals. The algorithm is based on the use of the Discrete Fourier Transform (DFT), the Orthogonal Wavelet Transform (OWT) and peak correcting techniques. The software provides short data segments, or mission signals, which are representative of the original road data record in several statistical metrics including: power spectral density, probability density function, Crest Factor and Kurtosis. Crest Factor control with consideration of the Kurtosis value provides realistic signal sequences for seat comfort testing due to the close correspondence between these statistics and methods used for evaluating human comfort such as the vibration dose value (VDV) [6].

2. Classification of Road Data

The vibration mission synthesis algorithm described in this paper was developed as part of a research project [1] which has the objective of defining an experimental procedure for the comfort testing of automotive seats. Several EU manufacturers of automobiles, industrial vehicles and seating systems are members of the project consortium. Four manufacturers (2 automobile and 2 industrial vehicle) furnished data measured on their most frequently used NVH proving ground circuits. The experimental data consisted of vertical acceleration time histories measured at the rear mounting bolt of the outer guide of the driver's seat. One particularly large data set consisted of measurements from 11 different test tracks of five types: speed circuit surface, highway surface, good road surface, country road surface and pavé surface. Each time history represented steady-state vehicle motion of more than one minute when the driver kept the vehicle speed constant. All data was sampled at a rate of 409.6 Hz. Data from the 11 surface set was used to investigate the nature of the induced vibration, and was used during development of the algorithm described in this paper.

Classical methods of vibration mission synthesis typically assume that the measured data is both stationary and Gaussian. *By stationary, it is meant that the various statistical measures of the data do not change within the system response times, and within the time necessary for a good statistical sample. By Gaussian, it is meant that the data can be accurately modelled using the well know Gaussian probability distribution function.* Stationary Gaussian processes are completely described by their Power Spectral Density (PSD) which characterises the distribution of vibrational energy in the frequency domain. Numerous classical mission synthesis methods work in the frequency domain to summarise a signal, then invert with various phase angle combinations

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to produce short time histories for laboratory testing purposes. The overall energy content of the vibration data is typically quantified by calculating the Root-Mean-Square (RMS) value of the signal, which for a zero mean process can be expressed as

$$\sigma = \left\{ L^{-1} \sum_{j=1}^{L} x^2 (j\Delta t) \right\}^{-1/2} \qquad (1)$$

When deviations from Gaussian behaviour are expected, three statistics are often used to describe the extent of deviation from a Gaussian stationary model. The first statistic is the signal skewness, which is defined as the average of the instantaneous vibration values $x(j\Delta t)$ cubed. For a zero mean process, the skewness can be expressed as

$$\lambda = L^{-1} \sigma^{-3} \sum_{j=1}^{L} x^3 (j\Delta t) \qquad (2)$$

A second statistic often used to quantify the deviation from a Guassian stationary model is the Kurtosis, which is the fourth normalised spectral moment. The Kurtosis is highly sensitive to outlying data among the instantaneous values. For a zero mean process, the Kurtosis can be expressed as

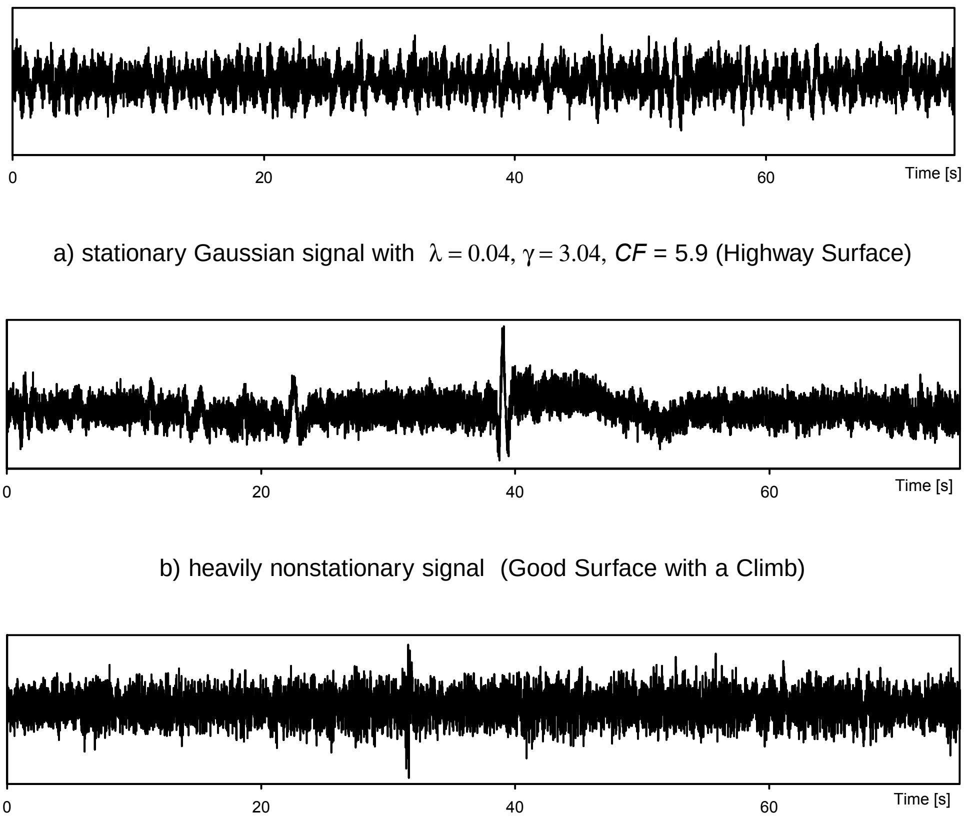
$$\gamma = L^{-1} \sigma^{-4} \sum_{j=1}^{L} x^4 (j\Delta t) \qquad (3)$$

A third statistic is the Crest Factor, *CF,* which is defined to be the ratio between the maximum value found in the time history and the RMS value. For a Gaussian stationary process, the skewness calculated from the vibration data should be close to zero ($\lambda = 0$), while the Kurtosis should result close to three ($\gamma = 3.0$) and the Crest Factor should normally be in the range $3.5 < CF < 4.0$.

Preliminary analysis of the data from the 11 road surfaces showed that only 2 of the 11 could be considered stationary Gaussian random processes. An example of the data from one of the road surfaces which could be considered both stationary and Gaussian is presented in part (a) of Figure 1. The 9 remaining data records failed to match the Gaussian stationary model. Two data records presented strongly nonstationary behaviour, as shown in the example of part (b) of Figure 1. Such heavily nonstationary signals are best described as containing one or more large transient events. Their frequency content, RMS and mean values vary over time. The remaining 7 proving ground road surfaces were intermediate situations, between the purely stationary random and the purely transient. For the purposes of this paper, such surfaces have been classified as mildly nonstationary vibration. *Mildly nonstationary vibration is taken in this paper to mean a random vibration process with stable mean and RMS values for most of the record, but containing a few high peaks due to short duration transients.* The high peaks correspond to bump events which occur when the vehicle moves over a considerable road irregularity such as a pot-hole. An example of a vibration signal obtained from a mildly nonstationary road surface is presented in part (c) of Figure 1, where it can be seen that the high peaks are reflected in the signal statistics by an increase of Kurtosis to $\gamma = 3.23$ and Crest Factor up to $CF = 5.9$ in value.

3. Mildly Nonstationary Mission Synthesis (MNMS)

Vibration mission synthesis for road surfaces which produce large shocks or transients is quite difficult, and is the subject of ongoing research. This paper describes, instead, an algorithm [5] developed for the purpose of synthesising mission signals for mildly nonstationary road surfaces, the most numerous class found in the proving ground data. The Mildly Nonstationary Mission Synthesis algorithm (MNMS) represents one approach to the problem. It is based on well known signal processing algorithms and the use of simple peak correcting. The signal processing algorithms used are: the Discrete Fourier Transform (DFT), the Orthogonal Wavelet



a) stationary Gaussian signal with $\lambda = 0.04$, $\gamma = 3.04$, *CF* = 5.9 (Highway Surface)

b) heavily nonstationary signal (Good Surface with a Climb)

c) mildly nonstationary signal with $\lambda = 0.01$, $\gamma = 3.23$, *CF* = 5.9 (Speed Circuit Surface)

Figure 1. Examples of seat guide vertical acceleration data produced by three different road surfaces.

Transform and correlation functions. The application-specific heuristics include: grouping of wavelet levels, counting of bump events, Crest Factor control and Kurtosis monitoring. The algorithm consists of three processing stages:

- application of the Discrete Fourier Transform to the road data, and use of the resulting spectra to construct a short artificial basis signal which has the same power spectral density as the prescribed road data;
- application of the Orthogonal Wavelet Transform to the road data, and grouping of wavelet levels into a small number of filter banks which subdivide the vibrational energy;
- counting of bump events for each wavelet group in both the original road data and the artificial Fourier basis signal, and peak correction of the basis signal to introduce needed bump events into selected wavelet groups.

3.1 MNMS Processing Stage 1

In the first stage, traditional Fourier analysis is applied to the data to determine the overall Power Spectral Density function. Each frequency line in the obtained PSD is characterised by an amplitude

$$A_k = \sqrt{2\Delta f S(k\,\Delta f)}$$

where S(f) is the underlying power spectral density of the Gaussian signal and $k\,\Delta f$ is the frequency of the harmonic in question. The amplitudes A_k are then used to generate a short artificial signal which serves as the basis for constructing the vibration mission signal. The time history of the short artificial basis signal is calculated from a Fourier expansion with a large number N of harmonics

$$y(t) = \sum_{k=1}^{N} A_k \cos(2\pi k \Delta f t + \varphi_k) \qquad (4)$$

with phase angles φ_κ chosen in a random manner, in line with the traditional assumption of stationary Gaussian behaviour. Constructing a short summary signal by means of Fourier techniques is a basic procedure [11] traditionally used in digital random controllers for shakers and similar test benches [17]. The approach guarantees that the short test signal reproduces precisely the PSD of road data prescribed.

3.2 MNMS Processing Stage 2

The first procedure of Stage 2 performs an Orthogonal Wavelet Transform [2,7,8] of the road data. Previous research [12-15] has shown that signal analysis and synthesis is greatly facilitated if the original vibration time history is first decomposed by means of the OWT. Wavelets are mathematical functions $\psi(t)$ which are used to decompose a signal $x(t)$ into scaled wavelet co-coefficients $W_\psi(a,b)$. The continuous wavelet transform is a time-scale method which can be expressed as

$$W_\psi(a,b) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{a}} \psi^*\left(\frac{t-b}{a}\right) dt \qquad (5)$$

where $\psi_{a,b}(t)$ are the scaled wavelets and ψ^* the complex conjugate of ψ. The basis wavelet $\psi(t)$ can be any of a number of functions which satisfy a set of admissibility conditions [7]. A natural extension of continuous analysis is a discretisation of time b and scale a according to $a = a_0^m$, $b = n\, a_0^n\, b_0$ where m and n are integers, $b_0 \neq 0$ is the translation step. This implies the construction of a time-scale grid, and thus a Discrete Wavelet Transform can be defined by

$$W_\psi(m,n) = \int_{-\infty}^{\infty} x(t)\, a_0^{-m/2}\, \psi^*\left(a_0^{-m}, t - nb_0\right) dt \qquad (6)$$

When the wavelets $\psi_{m,n}(t)$ form a set of orthonormal functions, there is no redundancy in the analysis. The discrete wavelet transform based on such wavelet functions is called the Orthogonal Wavelet Transform. These transforms are particularly convenient in damage detection and other feature selection applications, and have thus been adopted as a basic component of the algorithm described in this paper. The algorithm makes use of wavelet levels, which are reconstructed signals from the wavelet decomposition for a given value of scale a_0^{-m}. Twelfth order Daubechies wavelets have been used in the analysis performed to date. Results from a country road surface are presented in the Figures 2, 3, 4, 5 and 8 of this paper to illustrate the MNMS procedure. For the 30,000 data points and 409.6 Hz sampling rate of the country road surface, 15 wavelet levels were defined which were counted in the direction from high to low frequencies.

The coefficients from the transform are used to construct an individual time history for each wavelet level. This is equivalent to using the wavelet transform as a filter bank, dividing the vibrational energy among the levels. To further aid the identification of bump events in the data, a grouping stage was introduced to permit the user to group levels to cover frequency bands of particular interest. For example, in the case of automobiles, a low frequency band up to 3 Hz can be defined which contains all the rigid body resonances of the chassis on the suspensions. For automobiles, higher frequency bands containing predominately suspension modes, chassis modes or tyre modes can also be defined by grouping the wavelet levels which cover the relevant resonance frequencies. The procedure of grouping wavelet levels into application specific bands is helpful in that it becomes less likely that vibrational energy from one subsystem resonance covers that of others during analysis.

Figure 2 presents an example of the wavelet grouping procedure. The vibration signal is from an accelerometer aligned with the vertical direction, placed over the outer rear mounting bolt of the seat guide of the driver's seat. The measurement was performed during driving over the country road test track at a constant speed of 90 km/h. The vibrational energy from 0 to 60 Hz covered 15 wavelet levels, which were grouped according to the natural energy distribution (in frequency) of the signal into four wavelet groups labelled 1 to 4. The wavelet coefficients from the levels contained in each group were used to construct a time history for each group. The time signals from wavelet groups 2 and 1 are presented, along with the complete original time history of the measurement in Figure 3. The selective filtering provided by the wavelet groups separates the vibrational phenomena, and the behaviours of the different wavelet groups are typically quite different in accordance with the subsystems whose resonances fall within the frequency band considered. In the data segment shown in Figure 3, wavelet group 2 is relatively free of bump events while wavelet group 1 presents a sharp bump event in the neighbourhood of .45 seconds. Comparison of the wavelet group 2 and 1 time histories to the overall signal suggests that the level 1 bump event would have been difficult to identify without wavelet filtering of the original signal.

3.3 MNMS Processing Stage 3

When Fourier based techniques are used for mission synthesis, the Power Spectral Density of the original data is preserved in the mission signal, but deviations from the Gaussian stationary model are normally lost. Figure 4 illustrates this situation by presenting the wavelet group 2 and 1 time histories for the road data and for a Fourier synthesised signal of the same PSD and time extent. Wavelet group 2 is similar for both the road data and the synthetic Fourier signal, but the situation is different for wavelet group 1, where the road data has more than twice the number of high amplitude bump events as the synthetic signal. Figure 5 further highlights the differences by presenting the tails of the Probability Density Functions (PDFs) for the wavelet group 2 and 1 times histories. From Figure 5 it can be seen that the mildly nonstationary road data of the country road surface produced a wider PDF function than the standard Gaussian model of the synthetic Fourier data. Accurate construction of short mission signals requires that the high valued bump events of the road data be introduced into the synthetic Fourier signals. Stage 3 of the MNMS procedure consists of routines for counting bump events for each wavelet group in both the original road data and the synthetic Fourier signal, and peak correction of the artificial basis signal to introduce needed bump events.

In stage 3 each wavelet group of the road data is analysed separately to locate and count all bump events. *For the purpose of the MNMS, bump events are defined as high amplitude transient events which can cause the overall time history to deviate from a stationary gaussian model.* Formally, a point is considered a bump event if the road data signal is at a local maximum or minimum, and the wavelet group time history exceeds a prescribed value which is unlikely to be reached often if the data follows a stationary gaussian model. Experience suggested that this boundary value could be conveniently expressed as a Crest Factor of 3.5. In the MNMS, the number of bump

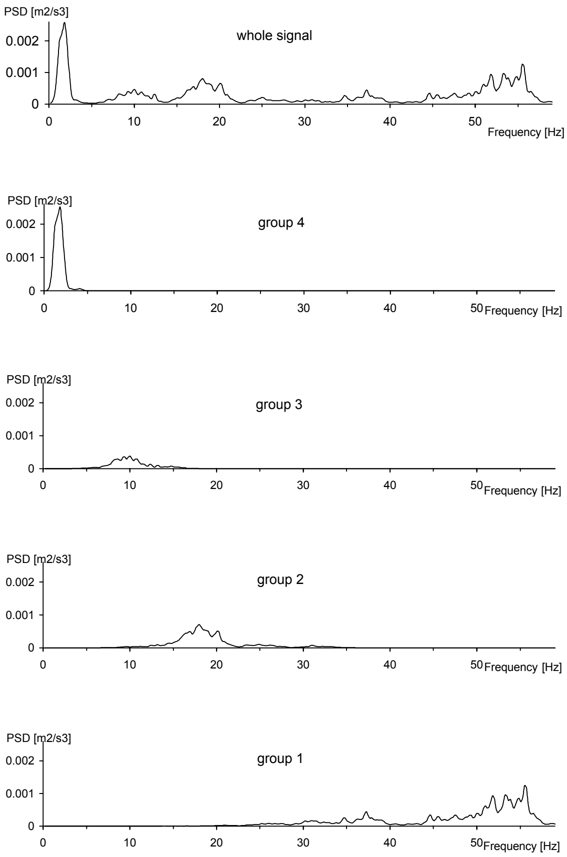


Figure 2. Example of the wavelet grouping procedure applied to the seat guide vertical acceleration data. The wavelet levels in the frequency range from 0 to 60 Hz were organised into 4 groups.

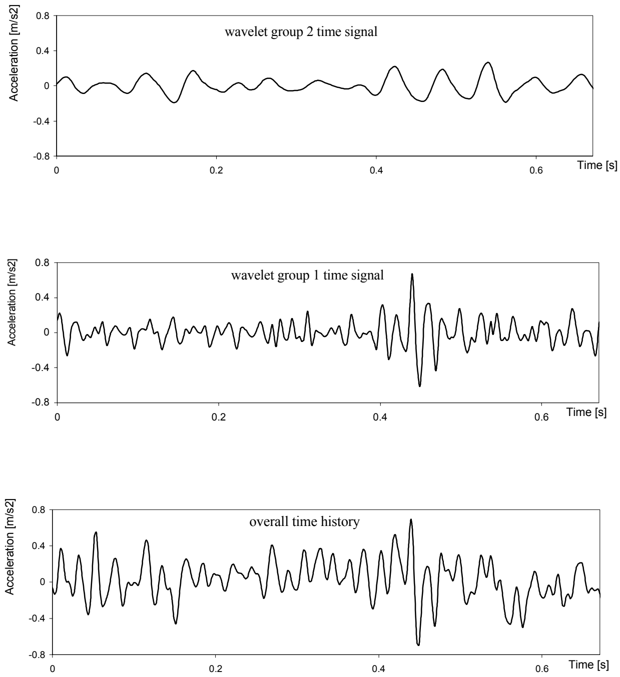
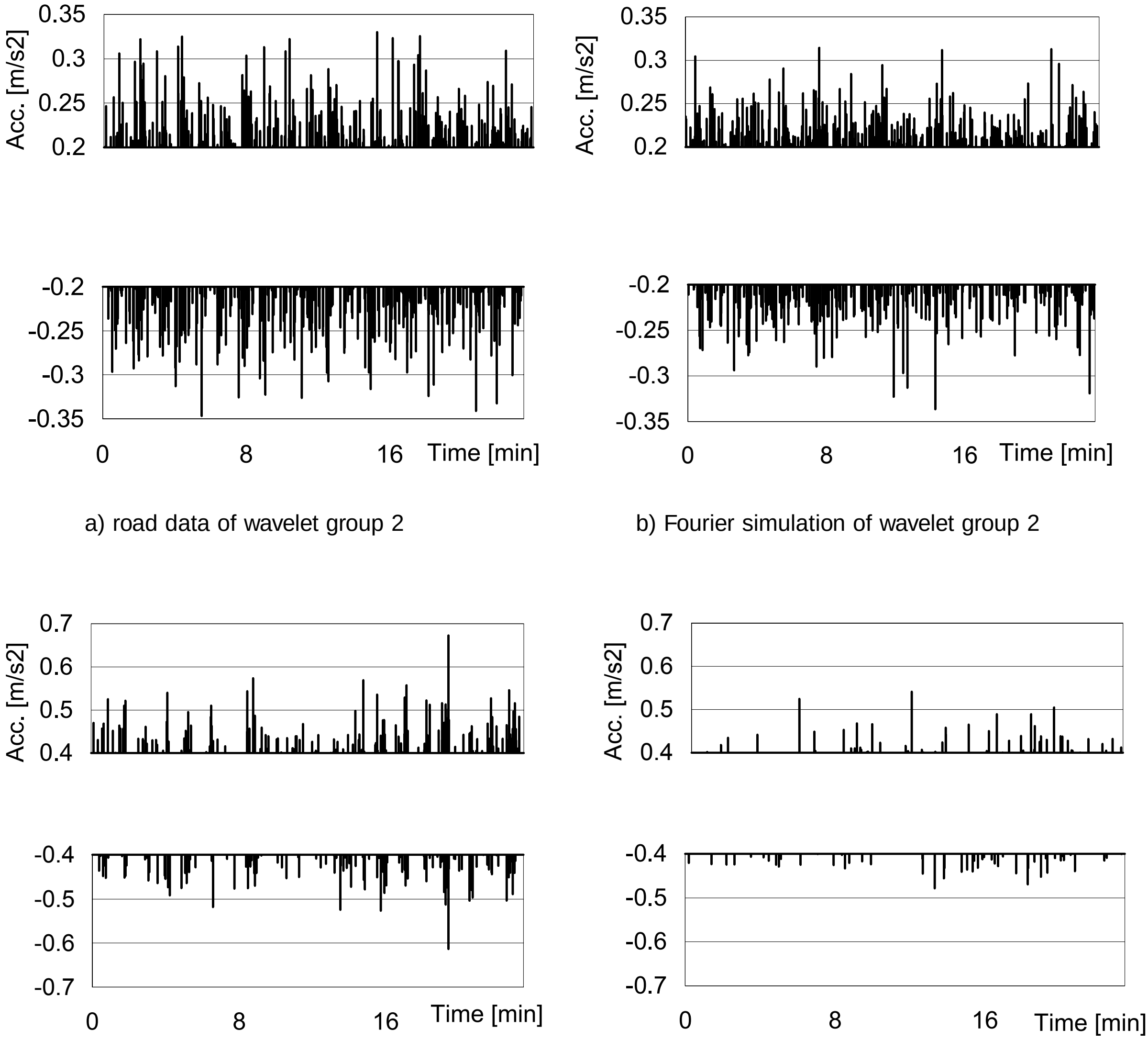


Figure 3. Example of the orthogonal wavelet decomposition of the seat guide acceleration time histories. The time signals of wavelet groups 2 and 1 are compared with the overall time history.

events in the road data and in the synthetic Fourier data are compared for each wavelet group to decide whether the Fourier data is an accurate representation of the original data, or if it is necessary to introduce bump events to correct the time histories.

Table 1 presents the number of bump events ($CF \geq 3.5$) counted in the road data and in the synthetic Fourier data for all four wavelet groups of vertical seat guide acceleration for the country road surface for 12 minutes of data measured at 90 km/h. Wavelet groups 2 and 4 are similar in both the original road data and in the synthetic Fourier representation, but groups 1 and 3 present significant deviations from a Gaussian stationary model, which requires the introduction of bump events to produce a representative mission signal.

In the MNMS procedure, needed bump events from a



a) road data of wavelet group 2

b) Fourier simulation of wavelet group 2

c) road data of wavelet group 1

d) Fourier simulation of wavelet group 1

Figure 4. Comparison for wavelet groups 2 and 1 between the experimental road data and the Fourier reconstructed synthetic time histories having the same PSD.

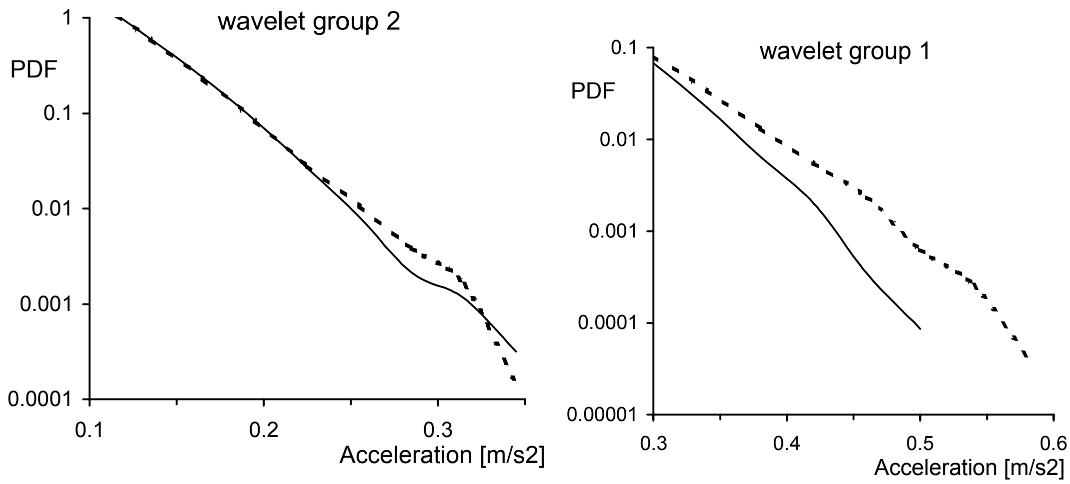


Figure 5. Examples of the PDF tails for the original road data (- - -) and for the synthetic Fourier basis signal (——) for wavelet groups 2 and 1

Wavelet Group Number	**1**	**2**	**3**	**4**
number of bump events in road data	365	122	151	15
number of bump events in Fourier signal	150	78	51	14
ratio of the above two lines (rounded off)	2.5	1.5	3.0	1.0

Table 1. Bump event count ($CF \geq 3.5$) for the automobile seat guide vertical acceleration data from the country road test track

wavelet group of the original road data are introduced into the same wavelet group of the synthetic Fourier signal with minimum disturbance to the latter. The events found in all automobile road data analysed were found to consist of rapid transients which oscillated for two or more cycles before becoming lost in the background vibration. The events were found to take some time to develop from the background vibration and, then, to be accompanied by a decay process which depended on the level of system damping. Thus it was decided to introduce several cycles of the bump event into the synthetic signal, both preceding the peak value and subsequent to it.

If all bump events extracted from long road data record were introduced into the short mission signal, the correction would be excessive, and the final mission signal would deviate from the original data in several statistics. It was therefore decided to introduce a number of bump events selected to be in direct proportion to the signal compression ratio. During the process of bump event counting, a ranking based on the size of the maximum peak value is performed for the events found in the particular wavelet group of the original road data. All identified bumps are ranked in descending order according their peak value. Having ranked all bump events, and having specified a compression ratio of *n*, bump events are selected by moving down the ranking list with a step equal to *n.* In so doing, bump events of various intensities appear in the mission signal (corrected synthetic signal). Each of them will be also a representative of *(n-1)* other bumps of close height not included into the vibration mission. Closeness of road and mission statistical characteristics is ensured by the fact that probability of appearance of a particular bump existing in the vibration mission is equal to the probability of appearance of *n* bumps of similar height in the road record which is *n*-times longer than the vibration mission.

In order to reduce the impact of bump correction on the PSD of the synthetic Fourier basis signal, each selected bump event is introduced at a location in time where the synthetic signal most closely resembles the bump event. This location is determined by means of a correlation procedure in which the bump event is moved along the whole time history of the synthetic signal and compared with it in terms of root-mean-square difference at each position. The root-mean-square difference is computed as

$$\sigma_{diff} = \left\{ M^{-1} \sum_{j=1}^{M} [\, x(j\Delta t) - x_{Fourier}(j\Delta t)\,]^2 \right\}^{-1/2} \tag{7}$$

Where M is the number of data points of the bump event. The point with the lowest RMS difference (highest correlation) is selected as the insertion point, and the bump event of time extent $M\,\Delta t$ then substitutes the similar event of time extent $M\,\Delta t$ of the synthetic signal. When all required bump events are introduced, the synthetic Fourier signal can be considered to be upgraded to mission signal status, and the total sum of all wavelet group time histories produces the final mission signal. Selection by the user of a large compression ratio can make it difficult for the algorithm to provide an optimal mission signal, therefore the MNMS procedure produces at the end of each run not just the mission time history, but also the PSD plots, Crest Factor values, RMS values and Kurtosis values for each wavelet level of both the original road data and the mission signal for comparison purposes. If significant deviations occur in any of the metrics due to an unfavourable combination of phase angles during Fourier signal generation, and MNMS algorithm can be re-launched to attempt to achieve a more favourable result.

4 Mission Synthesis Results

Figures 6 and 7 present the flow chart for the complete MNMS algorithm in its current form. Operations listed as user inputs are either performed directly from terminal or inputted by means of a parameter file. The program is currently written in Fortran, and runs on DOS compatible PCs. Figure 8 presents the PSDs of the mission signals obtained for the seat guide vertical acceleration data of the country road surface at 90 km/h using compression ratios of 1, 2, 4 and 8. The PSDs at all compression ratios are close to those of the original data, and well within the variance of the PSD estimate itself. The Kurtosis value of each wavelet group of the final mission signal is within +/- 7% of the corresponding wavelet group in the road data. The results obtained for the country road surface are representative of the MNMS results obtained for other data sets, and can thus be considered typical. The MNMS algorithm introduced nonstationary bump events into the data to correct the high amplitude characteristics of the signal, while at the same time maintaining the overall spectral characteristics. The run times for the 4 compression ratios illustrated (1, 2, 4 and 8) were 24 minutes, 12 minutes, 6 minutes and 3 minutes respectively.

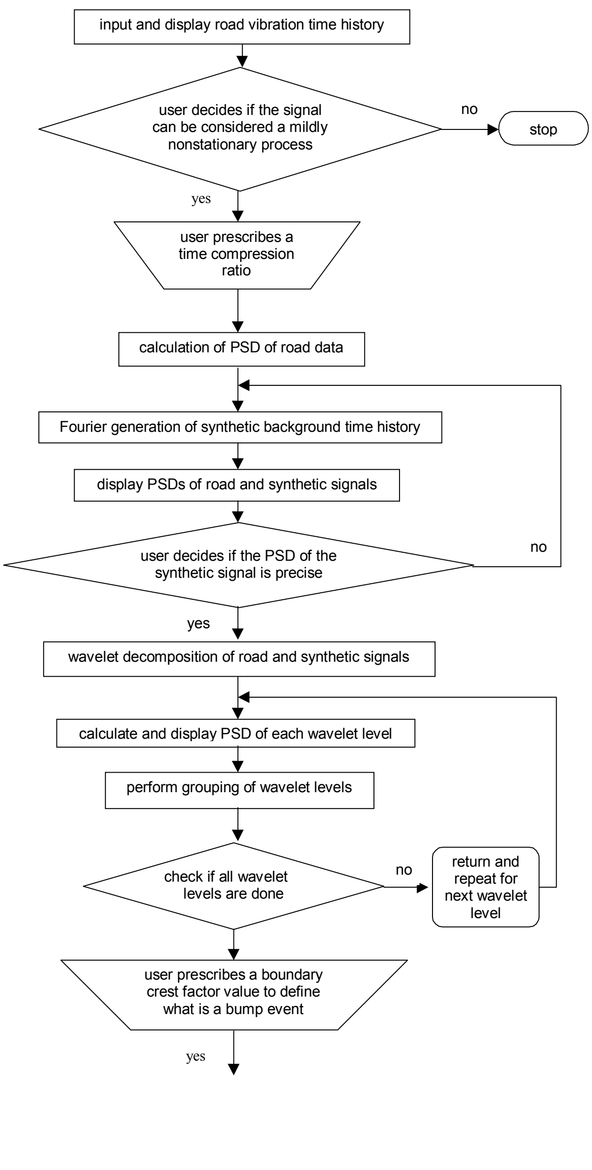


Figure 6. Flow-chart of MNMS algorithm (Fourier generation and wavelet grouping)

Whilst the MNMS algorithm has been found to be robust over all the data sets analysed to date, the statistical properties of the final mission signal are checked for deviations from the originally prescribed road data. Two possible sources of error in the final signal statistics are:

- inaccurate determination of the mission signal PDF at high compression ratios due to the small number of data points involved;
- Crest Factor and/or Kurtosis differences due to lack of bump event co-ordination across wavelet levels.

The first point is relative to the process of comparing an obtained mission signal to the original road data. As the compression ratio requested by the user increases, the time extent of the final mission signal is reduced. Cases have been observed where the time extent of the mission signal is very short, thus including very few bump events. The accuracy of the estimated probability density function tails is reduced in such cases due to the small number of data points involved. This sampling problem is unavoidable when large compression ratios are chosen in conjunction with a short road data record. When this situation occurs, the differences in the PDF tails between the originally prescribed data and the mission signal cannot be accurately evaluated.

The second point is a procedural issue which is the subject of further investigation. The MNMS algorithm in its current form performs all operations on a wavelet group by wavelet group basis. The corrections assume independence of the signal properties of each wavelet group, which is not rigorously the case when vehicle resonances fall in more than one wavelet group. Mission signals synthesised to date have corresponded closely in their statistics to the prescribed road data time histories. Nevertheless, MNMS results are being monitored to identify any future cases where the assumption of wavelet group independence causes the mission signal quality to degrade.

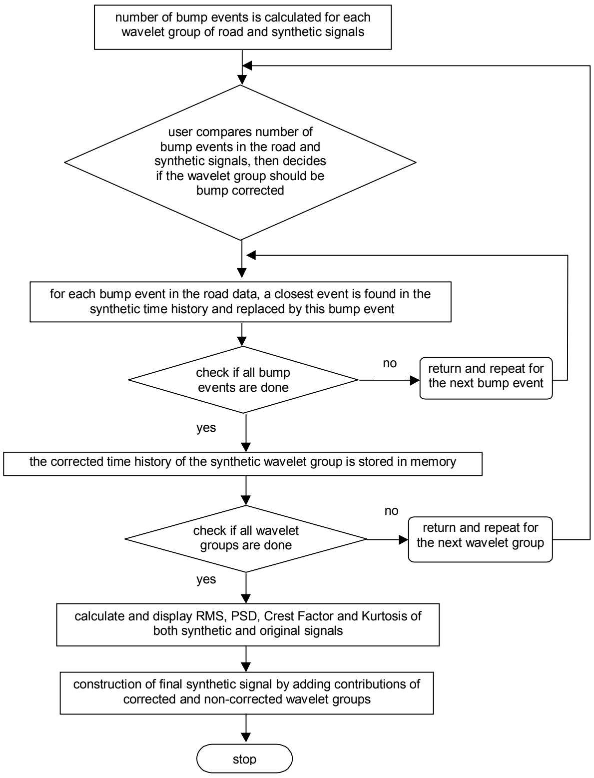


Figure 7. Flow chart of MNMS algorithm (bump extraction and synthetic signal correction)

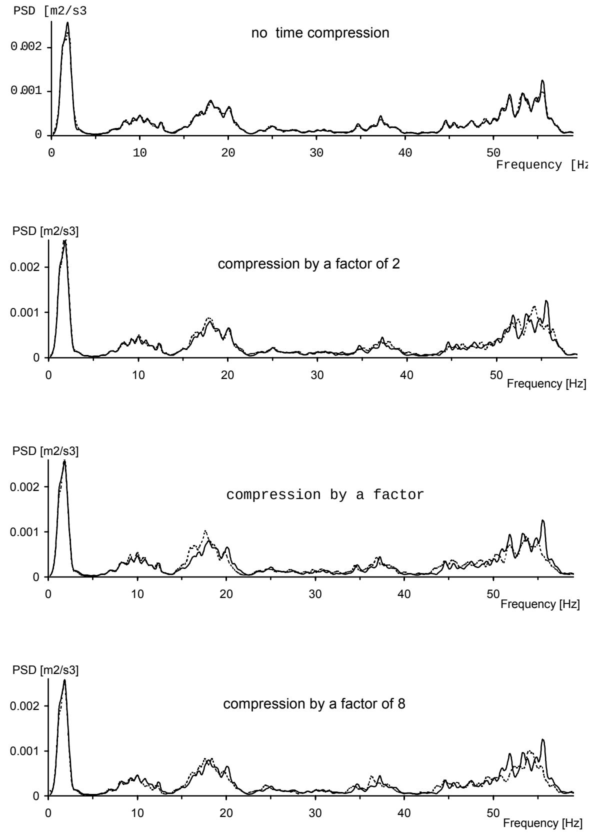


Figure 8. PSD comparison between the final mission signals (- - -) for the seat guide vertical acceleration data and the original road data (——). Compression ratios of 1, 2, 4 and 8 are presented.

5. Conclusions

Examination of experimentally measured vibration data from the most commonly used test tracks of a major European manufacturer of automobiles showed that the records could be grouped into three categories: stationary Gaussian vibration, heavily nonstationary vibration and mildly nonstationary vibration. The final category, that of mildly nonstationary vibration, was the most common case found in the proving ground data, accounting for 7 of the 11 surfaces analysed. The Mildly Nonstationary Mission synthesis algorithm (MNMS) represents one possible method of summarising such vibration records so as to obtain a short mission signal which can be used for experimental or numerical testing purposes.

The MNMS algorithm uses the Discrete Fourier Transform, the Orthogonal Wavelet Transform with the 12^{th} order Daubechies wavelet, a wavelet grouping procedure, a bump counting procedure and peak correction with Crest Factor control to condense experimentally measured vibration data into short test sequences. The mission signals obtained are representative of the original data record in terms of PSD, Crest Factor and Kurtosis value. Compression ratios of up to 8 have been achieved for seat guide vertical acceleration data from automobiles, without compromising the statistical quality of the resulting mission signal. Research is continuing to establish what average, and what maximum compression ratios can be achieved for data from automobiles, vans and heavy lorries.

Two areas requiring attention on the part of the user have been defined. The first regards the problem of comparing the obtained mission signal to the original road data when the road data record is very short, or the required compression ratio is very high. In such cases, one or both of the signals is short in duration, thus it is not possible to perform an accurate PDF comparison due to the small number of data points in the sample. The second area requiring attention is the lack of coordination between wavelet groups. There is a potential risk of mission signal degradation in the presence of closely spaced modes of vibration which simultaneously effect more than one wavelet group. While potentially of concern, there has been little evidence of mission signal degradation in the results obtained to date.

Future research will add a classification stage to the MNMS algorithm to analyse the structure of each bump event and to cluster bump vectors so as to provide a complete documentation of the road features. Classification is expected to be achieved by means of non-linear principal components analysis or a neural clustering network. The combination of event analysis and mission synthesis would serve as an intelligent black-box recorder for testing and monitoring applications.

Acknowledgements

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Engineeering and the new deal

Helping people find jobs and improving their chances of staying in work is key to the Government's Welfare to work strategy. Since April 1998, the New Deal programme has been vital in turning this strategy into reality, helping thousands of young and long term unemployed people find jobs.

A large part of the success of the New Deal initiative is dependent on participating employers. Under New Deal, a signed-up employer receives practical help with recruitment. If the job qualifies as a subsidised New Deal vacancy, they will also receive a contribution towards a structured training programme for the employee and assistance with wages.

So how can New Deal help the engineering industry? As New Deal candidates are selected according to their skills and matched appropriately to vacancies within the industry, employers can use New Deal as an introductory period for Modern Apprenticeships or other recognised training within the industry.

Through New Deal, companies have access to a pool of motivated, employable candidates. Employers have total control over the selection of prospective employees and can also take advantage of a short risk free period of up to three weeks called a 'work trial'. Offering choice and flexibility, the work trial provides both employers and prospective employees with the opportunity to make sure that the right person is matched to the right job.

The low "red tape" aspects of administering New Deal have also added to its popularity among employers.

Says Jacqueline Wainwright-Strachan from Expression Signs of Distinction: "New Deal allowed us to choose employees which matched our requirements. To enable us to get to know the new recruit(s) our advisor offered