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Application of Mildly Nonstationary Mission Synthesis (MNMS) to Automotive Road Data

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Abstract

This paper describes the Mildly Nonstationary Mission Synthesis (MNMS) algorithm which has recently been developed for the purpose of producing short vibration mission signals which are representative of experimentally measured road data. The MNMS method makes use of the Discrete Fourier Transform (DFT), the Orthogonal Wavelet Transform (OWT) and bump (shock) selection and reinsertion techniques. By performing a wavelet grouping procedure, and by setting trigger levels, the user can produce signals which are shortened by up to a factor of 10 compared to the original road data. The resulting missions are representative of the original data in terms of Power Spectral Density (PSD), Probability Density Function (PDF), RMS value, Crest Factor and Kurtosis value. Mission synthesis results vary depending on the level of nonstationarity present in the original data, but obtained mission signal PSD, RMS, and Kurtosis values are typically within +/- 10% of the road data targets. The MNMS algorithm has been implemented as a Fortran program for DOS-compatible personal computers

1. Introduction

In automotive engineering, vibration mission signals are important because many components are nonlinear, providing different vibratory behaviour depending on the nature of the input excitation used. A common example of this is the person/seat system, whose transmissibility function shows a softening system behaviour, with the principal resonance shifting to lower frequencies as the excitation amplitude at the base of the seat rises [3,4]. Vibration mission signals which summarise in a short test sequence the behaviour actually encountered in the vehicle during driving are commonly used for both laboratory testing and numerical simulation. Unfortunately, it is still common practice to use vibration inputs which are simple recordings made at the seat guide of a reference vehicle when driving over standard test tracks, each track being selected because it was found through experience to excite important vehicle and subsystem resonances. Determining these mission signals has often been a matter of trial and error.

This paper describes the Mildly Nonstationary Mission Synthesis (MNMS) algorithm [5,6] developed during the course of *Brite-Euram Project 4186 SCOOP* [1] for the purpose of assisting engineers to define vibration mission signals for vehicle components such as seats. MNMS is a compression tool which shortens road or test track signals while maintaining unaltered the fundamental vibrational nature of the data. The algorithm uses the Discrete Fourier Transform (DFT), the Orthogonal Wavelet Transform (OWT) and bump (shock) selection and reinsertion techniques. The algorithm provides short data sets which reproduce the original road data record in several statistical metrics including: Power Spectral Density (PSD), Probability Density Function (PDF), RMS value, Crest Factor and Kurtosis. For the purpose of seat vibrational testing, an accurate reproduction of the original road data in terms of Kurtosis is fundamental due to the close correspondence between this metric and the 4^{th} power methods such as the Vibration Dose Value (VDV) [7] commonly used for evaluating comfort.

2. Classification of Road Data

Classical methods of vibration mission synthesis assume that the measured data is both stationary and Gaussian. *By stationary, it is meant that the 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 a Gaussian probability distribution function.* Stationary Gaussian processes are completely described by their Power Spectral Density, which characterises the distribution of vibrational energy in the frequency domain. Classical mission synthesis methods first calculate an average PSD function to the represent the complete road data set, then perform an inverse Fourier transform using the modulus values of the average PSD and random phase angles to produce short time histories. The global 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

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

When deviations from Gaussian behaviour are expected, three global signal statistics are often used to describe the data. The first is 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

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

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

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

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

The *SCOOP Project* consortium included four EU vehicle manufacturers (2 automobile and 2 industrial vehicle) who furnished experimental data from their NVH proving ground circuits. The signals consisted of vertical acceleration time histories measured at the rear 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 pave' surface. Each time history represented steady-state vehicle motion at constant speed. Preliminary analysis of the data from the 11 road surfaces showed that only 2 of the 11 could be considered stationary Gaussian processes. An example of the data from one of the Gaussian road surfaces is presented as Figure 1-a. The 9 remaining data records failed to follow a Gaussian stationary model. Two data records presented highly nonstationary behaviour, as shown in the example of Figure 1-b. Such heavily nonstationary signals are best described as containing one or more large transient events. Their frequency content, RMS and mean value vary over time. The remaining 7 road surfaces were intermediate situations, between 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 (shock events) which occur when the vehicle moves over large road irregularities such as stones or pot-holes. An example of a vibration signal obtained from a mildly nonstationary road surface is presented in Figure 1-c, 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.

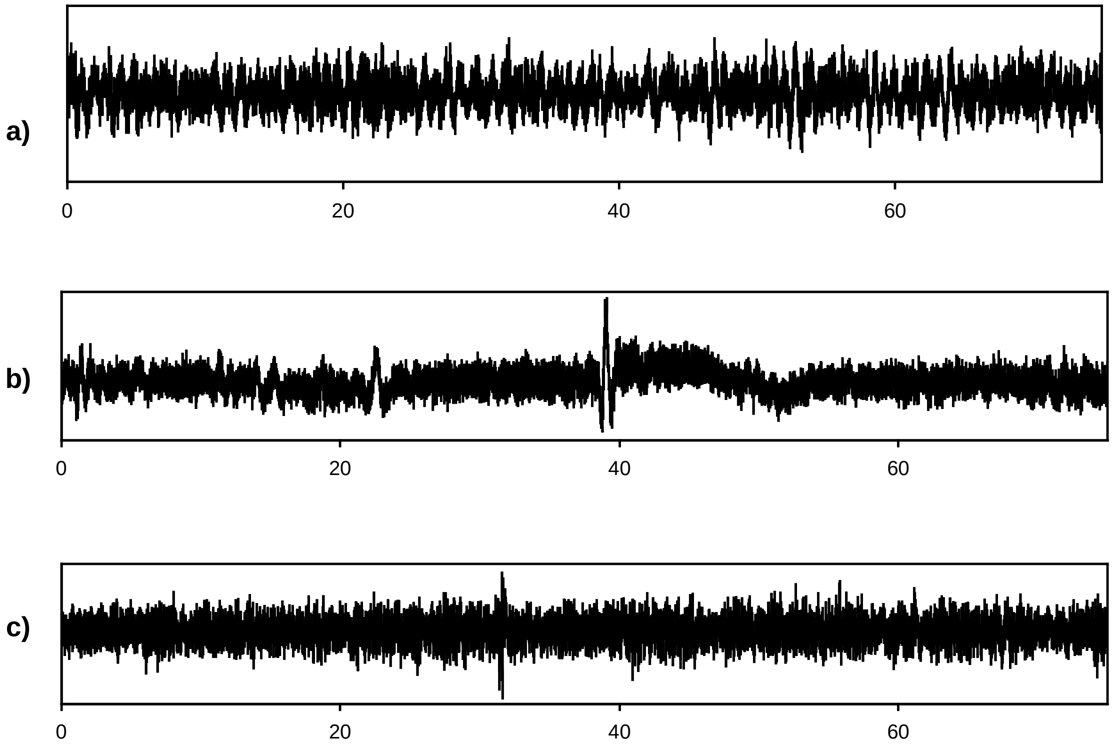


Figure 1) Seat guide vertical acceleration data produced by three road surfaces.

a) stationary Gaussian signal with $\lambda = 0.04$, $\gamma = 3.04$, $CF = 3.9$ (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)

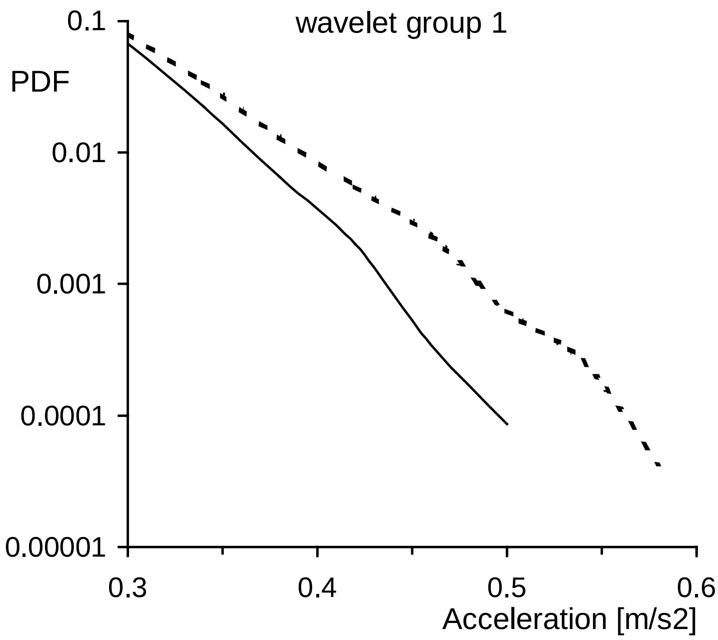


Figure 2) Seat guide vertical acceleration PDF tail for a road signal (- - -) and for its mission signal constructed by means of the method of classical Fourier Series inversion (——)

The presence of small numbers of bump (shock) events can have a large effect on several signal statistics. Figure 2 presents a typical example of a Probability Density Function tail (extreme values of the PDF function) for a seat guide vertical acceleration road signal and for a mission signal constructed using the classical Fourier Series inversion method. Mission synthesis by means of Fourier Series inversion can be seen to produce vibration time histories whose extreme values underestimate those of the original data set. Use of Fourier synthesised test signals leads to an underestimation of the vibrational response and of the fatigue life of the component under evaluation.

3. Mildly Nonstationary Mission Synthesis (MNMS)

The MNMS algorithm was developed for the purpose of synthesising mission signals for mildly nonstationary road surfaces, the most numerous class found in the proving ground data. While starting from a synthetic basis signal constructed by means of classical Fourier Series inversion, the MNMS algorithm performs a series of time history corrections so as to reintroduce bump (shock) events into the short mission signal, thus bringing the PDF tails, Kurtosis and Crest Factor back to values close to those of the original road data. The basic signal processing algorithms used are the Discrete Fourier Transform (DFT) and the Orthogonal Wavelet Transform (OWT). MNMS-specific operations include: grouping of wavelet levels, selection of bump events, counting of bump events, synchronisation of bump events, event reinsertion and event edge smoothing.

3.1 MNMS – Synthetic Fourier Base Signal

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

$$A_k = \sqrt{2\Delta f S(k\Delta f)} \tag{4}$$

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 synthetic signal which serves as the basis for constructing the vibration mission signal. The synthetic signal is calculated from a Fourier Series expansion using a large number N of harmonics

$$y(t) = \sum_{k=1}^{N} A_k \cos(2\pi k \Delta f t + \varphi_k) \tag{5}$$

with phase angles φ_k 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 traditionally used in digital random controllers for shakers and similar test benches [10-12,17,18]. The approach guarantees that the short test signal reproduces the PSD of road data. In the MNMS algorithm the time duration of the synthetic Fourier signal is defined in terms of the requested compression ratio. Values of up to 10 have been tested and found accurate to date.

3.2 MNMS – Wavelet Decomposition and Wavelet Level Grouping

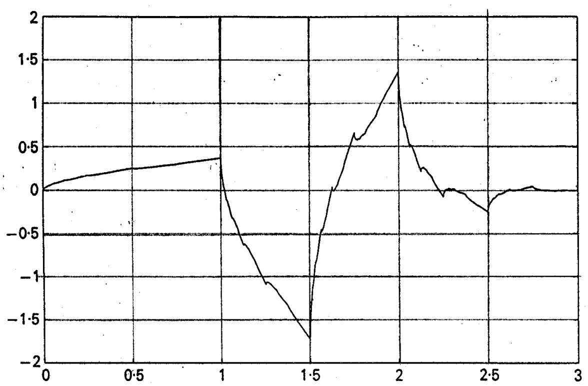
Previous research [13-16] has shown that analysis is greatly facilitated if the vibration time history is first decomposed by means of the Orthogonal Wavelet Transform [2,8,9]. Wavelets are mathematical functions $\psi(t)$ which are used to decompose a signal $x(t)$ into scaled wavelet co-coefficients $W_\psi(a,b)$. The continuous wavelet transform is a time-scale method which can be expressed as

$$W_\psi(a,b) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{a}} \psi^*\left(\frac{t-b}{a}\right) dt \tag{6}$$

where $\psi_{a,b}(t)$ are the scaled wavelets and ψ^* is 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. A natural extension of continuous analysis is the 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

$$W_\psi(m,n) = \int_{-\infty}^{\infty} x(t)\, a_0^{-m/2}\, \psi^*\left(a_0^{-m}, t - nb_0\right) dt \qquad (7)$$

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 for MNMS. The algorithm makes use of wavelet levels, which are signals reconstructed from the wavelet decomposition for a given value of scale a_0^{-m}. Daubechies wavelets functions (see Figure 3) were chosen and the algorithm uses up to 15 wavelet levels for a typical signal sampled at 300-400 Hz and containing a total of 30,000 data points.



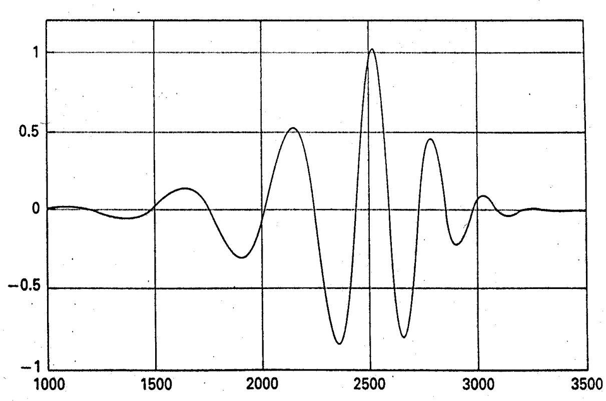


Fig 3) Examples of a Daubechies 4 (left) and a Daubechies 20 (right) wavelet function.

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 aid the identification of bump events in the data, a grouping stage was introduced to permit the user to group levels is such as way as to isolate frequency bands of particular interest. For example, in the case of automobiles, one or more wavelet levels can be grouped into a single wavelet group which covers the low frequency band up to 3 Hz, thus separating out the vibrational energy of the rigid body resonances of the chassis on the suspensions. When synthesising mission signals for seat testing, wavelet groups can be defined to cover frequency bands associated with suspension modes, engine/gearbox modes, chassis modes or tyre modes. 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 4 presents, in the frequency domain, 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 guide of the driver's seat. The experimental measurement was performed while driving over a country road test track at a constant speed of 90 km/h. In this example, the vibrational energy from 0 to 60 Hz covered 15 wavelet levels, which were grouped according to the natural energy distribution of the signal into four wavelet groups labelled 1 to 4. The four sets of wavelet coefficients provide output time histories which separate the vibrational phenomena into four frequency ranges. The need for such band pass filtering depends to some extent on the point of the vehicle being measured and on the road surface, but it has generally been found that such filtering is required to efficiently identify bump events.

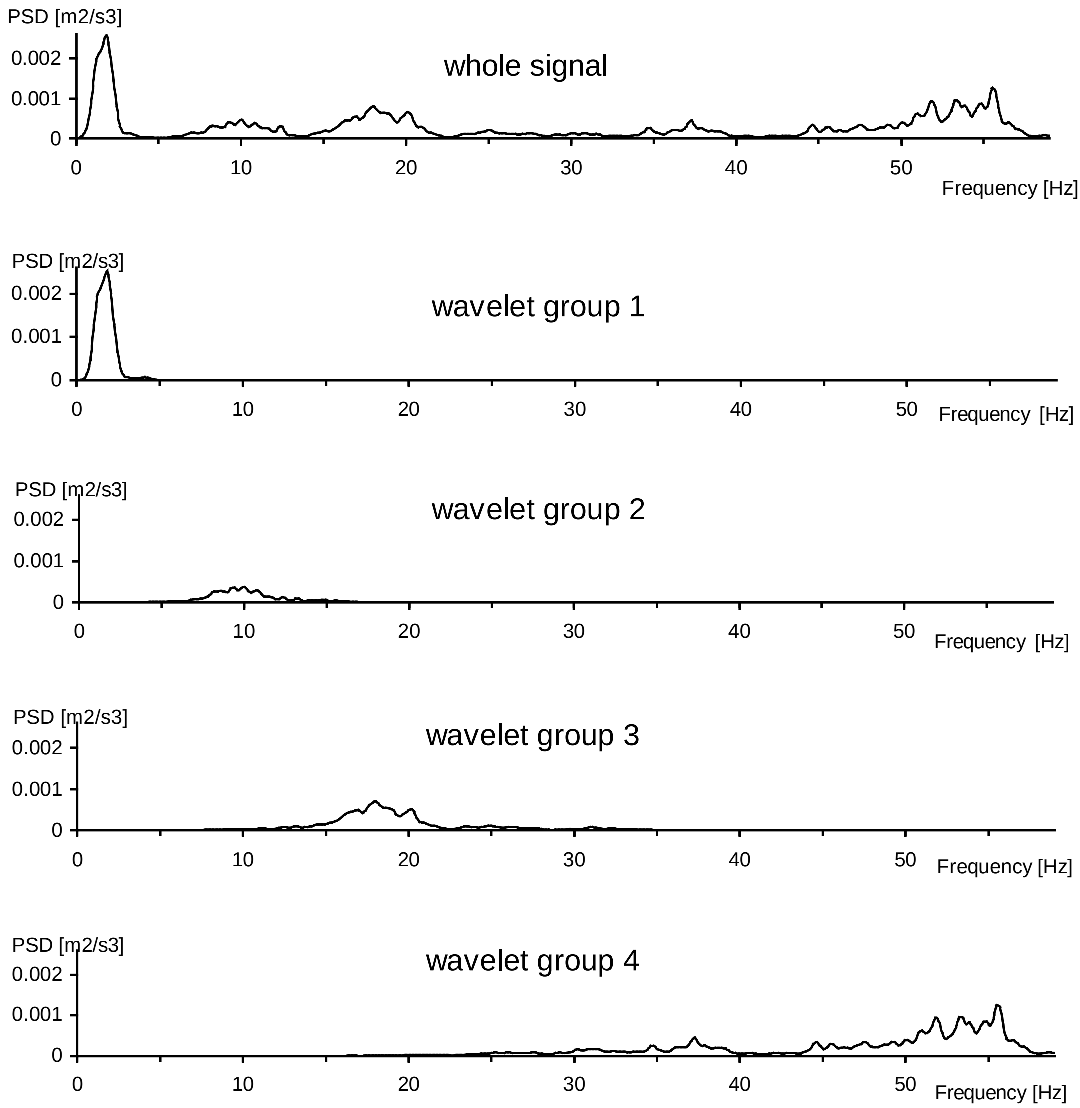


Figure 4) Example of the wavelet grouping procedure applied to seat guide vertical acceleration data. The wavelet levels in the frequency range from 0 to 60 Hz were organised into 4 groups.

3.3 MNMS – Bump Event Selection and Processing

In the MNMS algorithm a wavelet analysis is performed on both the original road data and the short synthetic Fourier signal. A processing stage then seeks to locate the bump events in each wavelet group of the original road data. The high amplitude events are saved to memory, ordered, then reinserted into the synthetic Fourier signal so as to "correct" it, returning the behaviour and statistics to those of the original road signal.

For the purpose of the MNMS algorithm, bump events are defined as high amplitude transient events which can cause the overall time history to deviate from a stationary gaussian model. Bump events are identified by searching the wavelet group time histories for data points which exceed a trigger level prescribed (for each wavelet group) by the user in terms of standard deviations. Wavelet group trigger levels in the range from 2.0 to 4.0 standard deviations have been found to produce accurate vibration missions for most road data signals analysed to date. Once an event is identified which exceeds the trigger level, the time duration of the bump event is determined. To determine the time extent of an individual bump event it is assumed that the event represents the system response to a single isolated impulse. The algorithm checks the monotonic decay envelope of the signal on either side of the peak value and identifies the points where the signal amplitude begins again to increase. The inversion points at which the monotonic decay process ends are taken to signal the time duration of the bump event. The bump start and end points are then taken to be a fixed distance (in data points) from the points of envelope inversion.

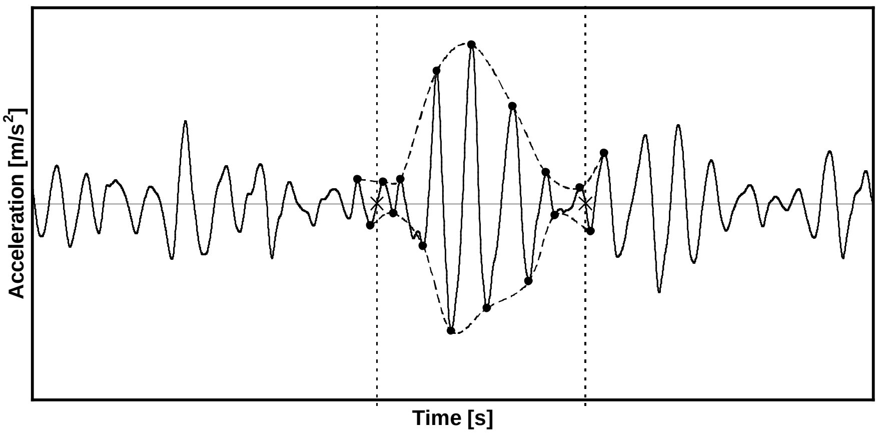


Figure 5) Bump selection by means of trigger level and end inversion check.

In MNMS, the number of bump 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 signal, or if instead it is necessary to introduce bump events into the synthetic time histories. Table 1 presents an example of the results from an MNMS analysis run made for 12 minutes of seat guide vertical acceleration data from an automobile on a country road test track driving at 90 km/h. The number of bump events ($CF \geq 3.5$) counted in the road data and in the synthetic Fourier data are given for four wavelet groups. When comparing the road and synthetic Fourier signals, it can be seen that the results for wavelet groups 2 and 4 are similar, but that groups 1 and 3 present significant differences. Groups 1 and 3 require correction of the synthetic Fourier signal by means of bump event reinsertions.

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 automobile seat guide vertical acceleration data from a country road test track.

3.4 MNMS – Bump Event Reinsertion and End Smoothing

In the MNMS procedure, bump events from a wavelet group of the original road signal are introduced into the same wavelet group of the synthetic Fourier signal with minimum disturbance to the latter. If all bump events extracted from a long record were introduced the correction could be excessive, and the final mission signal could deviate from the original 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. After selecting and determining the time extent of each bump, the bumps are counted and ordered. For each wavelet group, each bump is ranked based on its maximum peak amplitude. 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.

Several strategies for reinserting bump events into the synthetic Fourier signals have been developed and tested. Figures 6, 7 and 8 describe the three methods that are currently implement in the MNMS software. The first reinsertion strategy is the *nonsynchronised procedure*. In this procedure each wavelet group is treated as independent from each other group, bump events occurring in one wavelet group time history are not considered to be related to those of another. The bumps are reinserted independently at the point of closest similarity between the bump event and the synthetic Fourier signal. This method can be the most appropriate for road data from vehicle systems having widely spaced (in frequency) modes of vibration and from road surfaces with large single irregularities of varying wavelength. The method was found to provide good results for several of the *SCOOP Project* data sets.

Synchronisation procedure 1 involves the synchronisation of bump events across wavelet groups. The basis for this method is the observation that a single sharp road irregularity will approximate an impulse function. In the frequency domain, energy would be present in the input spectrum up to a critical cutoff frequency. For an input signal of this type, the vibrational energy would spread across many, it not most, wavelet groups. The bump events in the various wavelet groups would therefore be expected to be occurring together, and independent reinsertion of such events would not correctly represent the data. *Synchronisation procedure 1* attempts to solve this problem by reinserting together all bump events which occurred at the same time due to an impulsive input to the vehicle. Wavelet group 1, which spans the lowest frequency range under consideration, is used for the synchronisation check. All bumps from all wavelet groups that are found to occur at the same time as a wavelet group 1 event are bundled together and reinserted into the synthetic Fourier signal as a single event.

A last strategy, named *synchronisation procedure 2*, involves reinsertion into the synthetic Fourier signal of segments of the original time history. This procedure is the most conservative of the bump reinsertion strategies developed. Once all bump events are identified and ranked for all wavelet groups, synchronisation procedure 2 “cuts” the original road data time history, and the whole segment defined by the “cut” is reintroduced into the synthetic Fourier signal. By reinserting the segment of the original road time history, issues regarding the synchronisation of individual bump events are bypassed, thus maintaining unaltered all the original amplitude and phase relationships. Wavelet-based analysis is used to locate the bump events, but reinsertion simply involves transferring a segment of data from the road signal to the closest matching segment of the synthetic Fourier signal. In many cases, this procedure was found to produce the closest match between the global statistics of the final mission signal and those of the original road data.

For all three synchronisation procedures, the road data events are introduced into the synthetic Fourier signal at the point at which the two signals are most similar. 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 in terms of root-mean-square difference at each position. The RMS difference is computed as

$$\sigma_{diff} = \left\{ M^{-1} \sum_{j=1}^{M} [x(j\Delta t) - x_{Fourier}(j\Delta t)\,]^2 \right\}^{-1/2} \tag{8}$$

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. 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, the algorithm can be re-launched to attempt to achieve a more favourable result.

A final operation performed by the MNMS algorithm during bump reinsertion is the smoothing of bump event end discontinuities by means of a 5 point exact-fit polynomial. The polynomial smoothing is performed in order to better merge the bump (shock) event into the synthetic Fourier signal, eliminating any discontinuities produced during segment reinsertion.

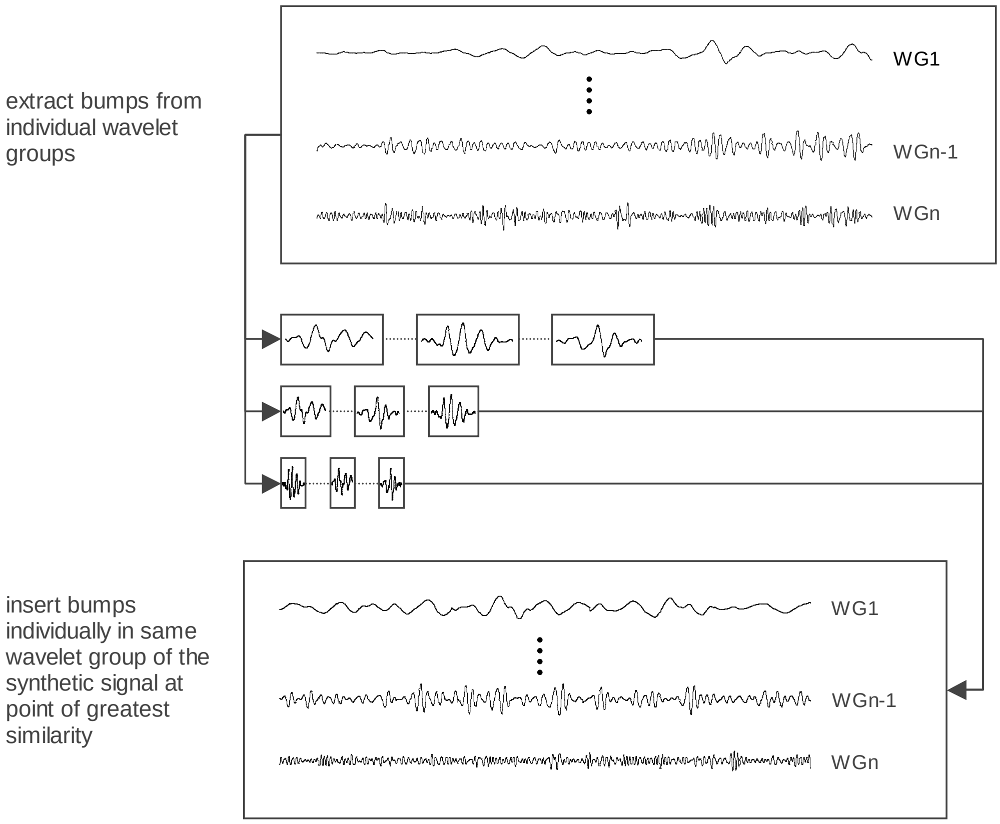


Figure 6) Nonsynchronised bump reinsertion procedure.

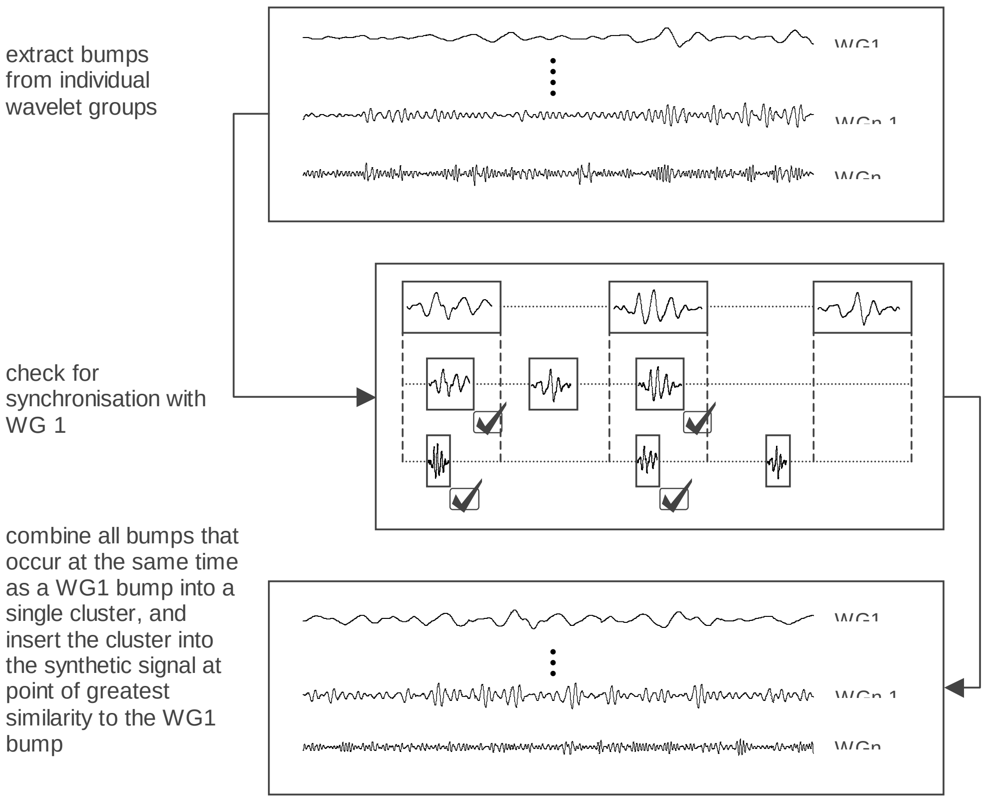


Figure 7) Synchronisation procedure 1.

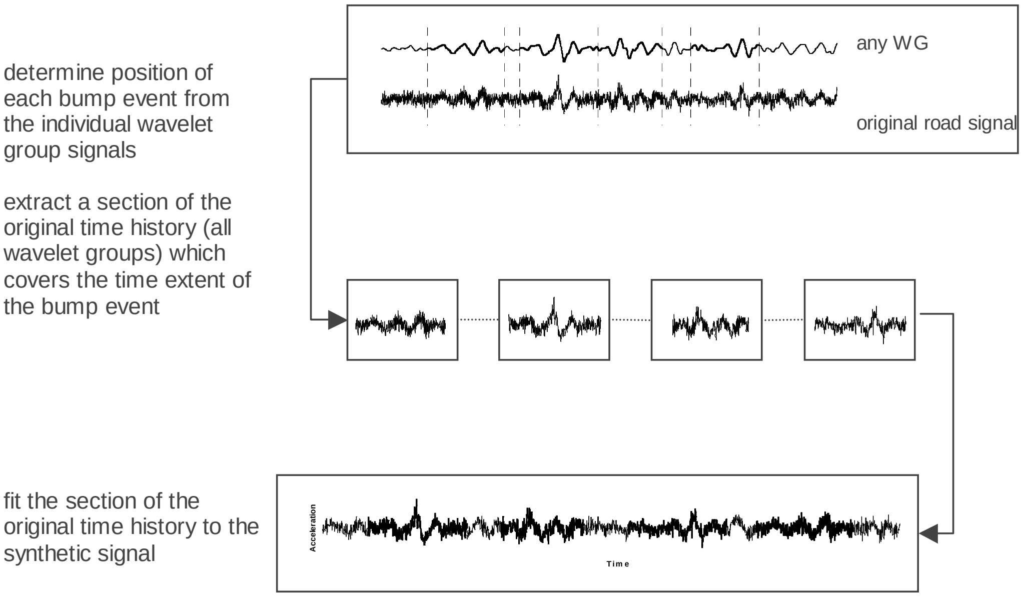


Figure 8) Synchronisation procedure 2.

read ASCII file of road data

calculate and visualise the PSD of the road data

perform and visualise the wavelet decomposition of the road data

group wavelet levels into a small number of wavelet groups (by means of saved settings or by user interactive selection)

set bump trigger levels (by means of saved settings or by user interactive selection)

set compression ratio, synchronisation method and random number seed (by means of saved settings or by user interactive selection)

Fourier synthetic signal generation at desired compression ratio

wavelet decomposition of the Fourier synthetic signal

bump selection on each wavelet group

bump ordering from smallest to largest based on peak amplitude

cross-correlation analysis to determine the reinsertion point where the synthetic signal and bump are most similar

reinsertion of selected bumps

smoothing of end transitions at each bump reinsertion point

calculation of global statistics of the corrected synthetic signal

Figure 9) MNMS Algorithm Flowchart

4 Mission Synthesis Results

Figure 9 presents the flow chart for the complete MNMS algorithm in its current form. User inputs can be performed either directly from terminal or by means of a parameter file. The program is written in Fortran, and runs on DOS-compatible PCs. Figure 10 presents the PSDs of mission signals obtained for a seat guide vertical acceleration data set from a 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 mission signal was within +/- 7% of the corresponding wavelet group in the road data. The results obtained for this example data set are representative of the results obtained for other road data sets, and can thus be considered typical. Computer runs times are of the order of a few minutes.

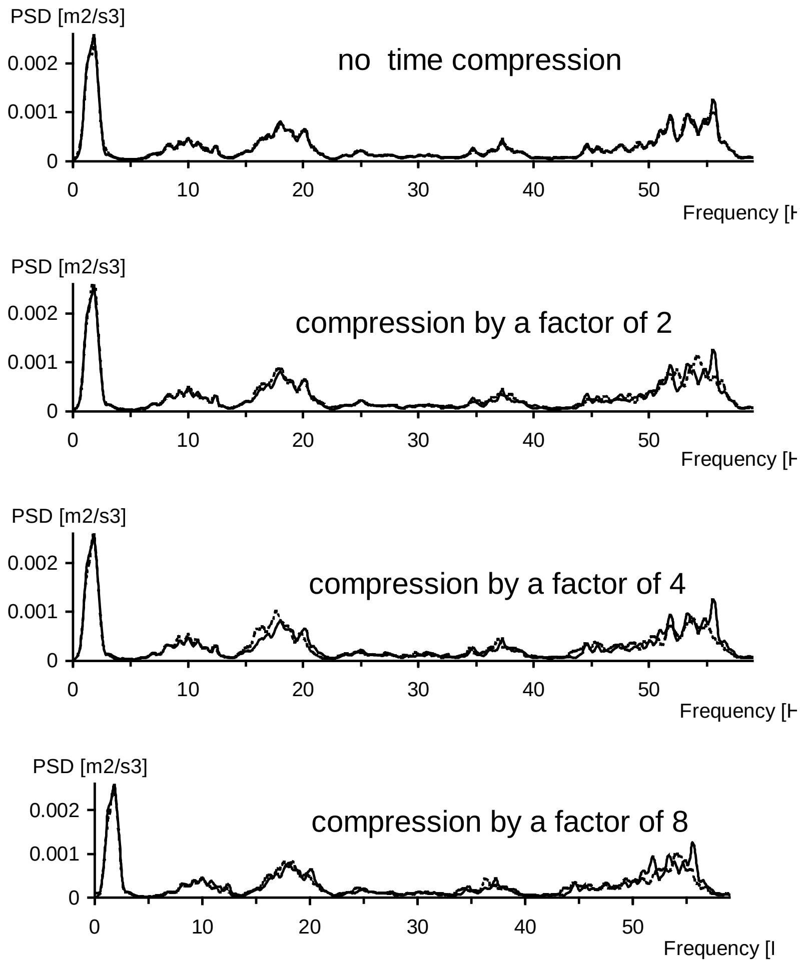


Figure 10) PSD comparison between the final mission signals (- - -) for the seat guide vertical acceleration data and the original road data (——) for compression ratios of 1, 2, 4 and 8.

In order to illustrate the effect of the compression ratio on final mission signals, results from two data sets are presented below. The first data set is from a Renault automobile measured over a relatively stochastic road surface. The data set contained only a few bump (shock) events, and was thus very close to the base definition of a mildly nonstationary signal. The Renault data set was sampled at 300 Hz and was 109.2 seconds in length (32,766 data points). It was decomposed into 8 wavelet levels which were grouped into 5 wavelet groups. Bump trigger levels in the range from 2.2 to 4.2 were set for the various wavelet groups. The second data set presented below was from a BMW automobile measured on a road surface with numerous shock events. The data set was sampled at 256 Hz and was 120.0 seconds in length (30,720 data points). It was decomposed into 9 wavelet levels which were grouped into 4 wavelet groups. Bump trigger levels in the range from 2.2 to 4.5 were set. The BMW data set can be considered much more nonstationary than the Renault data set. The global statistics of the two data sets are presented in Table 2.

Global Statistic	Renault Data Set	BMW Data Set
RMS	0.17	0.37
Kurtosis	3.54	4.60
Skewness	0.13	-0.06
RMQ	0.23	0.54
Positive Crest Factor	5.60	5.99
Negative Crest Factor	-4.09	-5.65

Table 2) Global statistics of selected Renault and BMW data sets.

Figures 11 and 12 present MNMS performance summaries at various compression ratios. Each data point represents the average of five individual MNMS runs. The plotted curves include the value of the original road data set, the value obtained from the nonsynchronised procedure, the value obtained from synchronisation procedure 1 (sync_1) and the value obtained from synchronisation procedure 2 (labeled sync_2). From the Kurtosis plots it can be seen that all three synchronization methods achieved good results for compression ratios in the range from 2 to 10. The mission signals obtained for the Renault data set, which contained only a small number of bump events, were very close to those of the original road data set. In terms of signal global statistics, the results for the BMW data set, which contained numerous large bump events, can be seen to fall somewhat short of the road data set. The reader is reminded, however, that the achieved Kurtosis values were nonetheless greater than the value of 3.0 that is produced by the classical method of Fourier Series inversion. From the Crest Factor plots it can be seen that the values achieved by the MNMS mission signals fall short of the value calculated from the original data at compression ratios of 1, and that performance tends to drop monotonically with increasing compression ratio due to greater difficulties with finding optimum reinsertion points with increasing number of bump events.

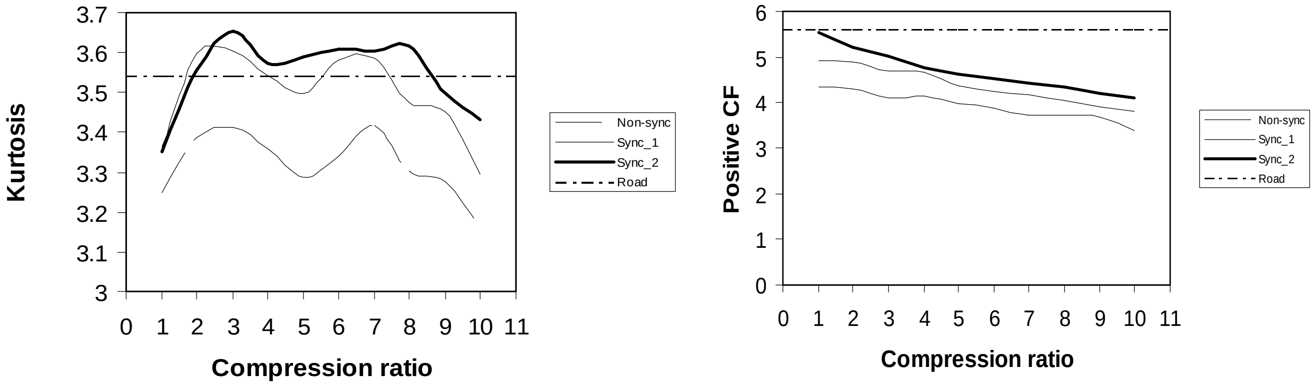


Figure 11) Kurtosis and Crest Factor variation (average of five runs) as a function of the signal compression ratio for a data set from a Renault automobile.

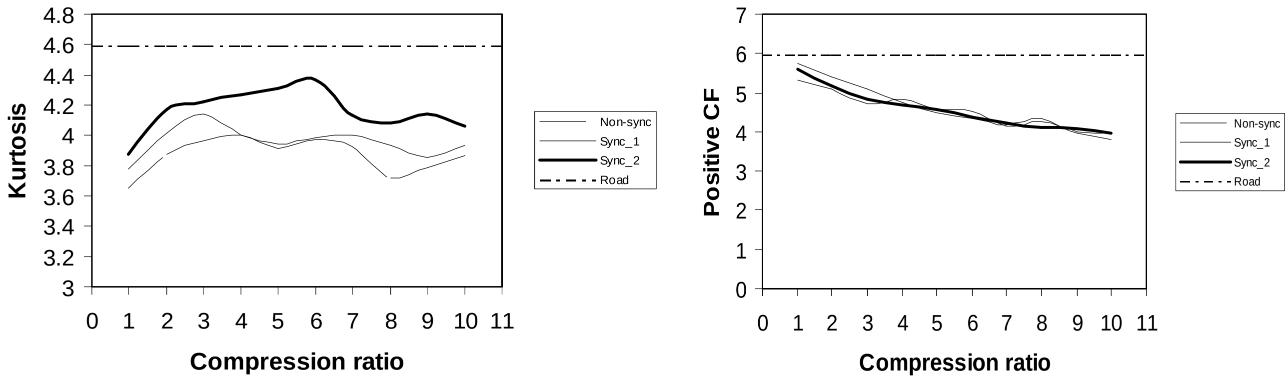


Figure 12) Kurtosis and Crest Factor variation (average of five runs) as a function of the signal compression ratio for a data set from a BMW automobile.

5. Conclusions

Observation of experimental data from the test tracks of four European vehicle manufacturers suggested that vibration signals could be grouped into three categories: stationary Gaussian vibration, heavily nonstationary vibration and mildly nonstationary vibration. The case of mildly nonstationary vibration was the most common found in the proving ground data. The Mildly Nonstationary Mission Synthesis (MNMS) algorithm represents one method of summarising such vibration records so as to obtain short mission signals that can be used for experimental or numerical testing purposes.

The MNMS algorithm makes use of the Discrete Fourier Transform, the Orthogonal Wavelet Transform and bump (shock) event selection and reinsertion techniques. By performing a wavelet grouping procedure, and by setting wavelet group trigger levels, the user can produce mission signals which are shortened by up to a factor of 10 compared to the original road data. The resulting missions are representative of the original data record in terms of Power Spectral Density, Probability Density Function, RMS value, Crest Factor and Kurtosis value. Mission synthesis results vary depending on the level of nonstationarity present in the original data, but mission signal PSD, RMS and Kurtosis values are typically within +/-10% of the road data targets. The algorithm has been implemented as a Fortran program which runs on DOS-compatible personal computers

Research is currently under way to establish a simple procedure for determining the optimal wavelet group trigger levels to use for a given data set, and to establish what maximum compression ratios can be achieved for data from automobiles, vans and heavy lorries. Research is also under way to establish the effect of bump event scaling (increasing the size of individual shocks) on the global signal statistics. Bump event scaling could be used to control the severity of the mission signal, and could have important applications in areas such as accelerated fatigue testing. Current activities are investigating the average rate of growth of the global mission signal statistics as a function of the multiplying scale factor used to increase the bump events before reinsertion in the synthetic Fourier signal.

A new EPSRC funded research project launched at Sheffield University will also add a clustering and 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. The objective is to define for each road signal the alphabet of bump (shock) features present. Besides providing a tool for data analysis, such a clustering and classification stage will provide the basis for an intelligent black-box recorder for long-time testing and monitoring applications.

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