EVENT DETECTION ALGORITHMS IN PACKAGING VIBRATION TESTING
An analytic review

László Róbert Hári
University of Győr, Hungary
E-mail: hari.laszlo@sze.hu

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Abstract

Goods transported on wheeled vehicles are subjected to road-induced vibrations. Verification of protective packaging is accompanied by random vibration testing in standard procedures, which utilize power spectral density (PSD). Since PSD is time-invariant, it produces stationary Gaussian signals; however, stationarity is hardly the case in road vehicle vibrations (RVV). Various attempts had been presented on nonstationary vibration simulations and unique signal segmentation methods are presented to understand the real nature of RVV.

Key words: Changepoint detection, Nonstationary random vibration, Packaging vibration testing, Road vehicle vibration

1. INTRODUCTION

Since supply chain management is involved in the quality control of products transported, available methods applied for the verification and validation of packaging systems -as a prevention against transport damages- must be summarized. Current paper is distinguished from the following reviews in terms, that here the utilized signal segmentation methods are in scope, which are often inherent the analysis and preceding the simulation of non-stationary vibration simulations.

Road vehicle vibrations (RVV) are often characterized by power spectral density (PSD) functions, which is a wide-spread procedure in packaging vibration testing (PVT) according to standards like International Organization for Standardization (ISO), International Safe Transit Association (ISTA), American Society of Testing and Materials (ASTM) or United States Military Standard (MIL-STD), as discussed in (Lepine, Rouillard and Sek, 2015; Griffiths *et al.*, 2016; Bonnin *et al.*, 2018). PSD profiles are usually averaged from longer time-history records and several journeys. The averaging process moderates the effect of sporadic shocks in the spectrum (Kipp, 2008). Besides, the inverse Fourier transform with uniformly distributed random phase yields a Gaussian distributed random signal, which is stationary with respect to time (Sek, 1996; Rouillard and Sek, 2000). However, stationary signals contradict the fundamental of RVV because the non-Gaussianity is caused by the nonstationary nature of RVV (Rouillard and Sek, 2010). Therefore, an RVV might be represented by the composition of distinct segments with varying duration, and root mean square (RMS). Scholars developed different approaches to decompose RVV into segments and to produce nonstationary signals in change.

Lepine et al. presented the simulation approaches as of date classifying methods on packaging testing purposes, such as standardized methods, time-history replication, non-Gaussian simulations, and nonstationary simulations; appended by transient events and harmonic simulations (Lepine, Rouillard and Sek, 2015). A sufficient simulation method should account for the three modes in RVV: the non-stationarity, transient and harmonic modes, according to ibid. Albeit nonstationary simulation is a well-disputed phenomenon, unfortunately, no definitive method has been developed and validated to identify and characterize the two other modes of transient and harmonic processes.

Fernando et al. reflected on fruit quality deterioration during transportation (Fernando *et al.*, 2018). Id. identified three experimental approaches, such as in-transit experiments, performed in real transit passages under live conditions; transit-simulation experiments, measuring RVV in real-life conditions and deriving vibration profiles to apply in shakers; and simulation experiments, as laboratory studies under controlled circumstances of interest, e.g., standard vibration profile. The discussion of factors on fruit quality deterioration in the context of RVV complements ibid.

The current article reviews in the first place the columns of changepoint detection algorithms applied before nonstationary simulations in PVT. Whereby possible, process flow diagrams are reproduced. The reader can see this evolution through the collocations of time-, frequency-, time-frequency- domain approaches; finally, the contemporary mixed methods are highlighted. Each method is queued in the following manner: (i) *introduction*, (ii) *discussion*, and (iii) *summary*.

2. SEGMENTATION IN THE TIME DOMAIN

Let $x[i]$ denote the i -th element $i = 1, 2, \ldots, N$ of a realization of the $x(t)$ continuous process sampled with an equidistant Δt sampling on $T = N\Delta t$ period. Segmentation aims at finding changepoints within $x[i]$, such that sections can be considered homogenous with respect to a certain criterion in-between and different from adjacent sections. The following methods are established on various measures of $x(t)$ considering only time-domain characteristics.

2.1. Moving statistics

(i) Different moving statistics can be evaluated in windows sliding over the time domain. Common approaches are the moving root mean square, - crest factor, and - kurtosis (κ) (Bruscella, Rouillard and Sek, 1999). If a predictor reaches a predetermined threshold, an event can be detected.

(ii) The moving statistics can be calculated in different window lengths, which might seem an appealing solution, accounting for shorter or longer variations of the given statistic over time. This advantage, however, implies a drawback by defining a justifiable window size, which is similarly true for the threshold values. The reader is referred to (Lepine, 2016) for the sensitivity of factors $x_{rms}, x_{cf}, x_{\kappa}$ in the presence of non-stationarities, shocks, and harmonics.

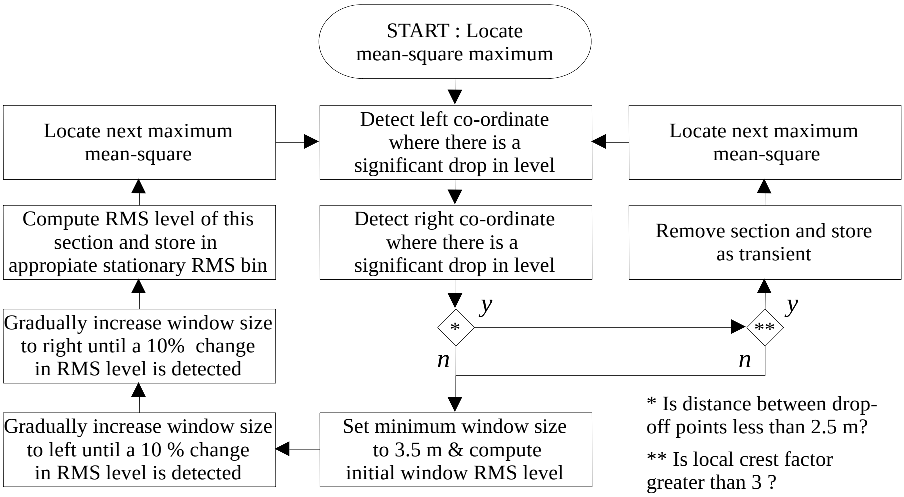
(iii) The moving statistics are heuristic approaches for signal segmentation. Still, it can assert the nonstationary nature of RVV. The simultaneous use of different window sizes of the same statistics can be implemented, as well.

2.2. RMS drop-off distances

(i) Constant RMS sections and transients in the spatial acceleration domain had been separated in (Bruscella, 1997) consisting of 415 km records, which utilize the mean square and kurtosis. The mean square gives an unbiased estimate of the power of a signal $x_{ms} = x_{rms}^2$.

(ii) Due to scanning resolution, the process arrows had been lost. Thus, a subsequent article is used here to visualize the referred process diagram (Rouillard, Bruscella and Sek, 2000)

Figure 1. Flowchart for stationary and transient identification



Source: reproduced from (Rouillard, Bruscella and Sek, 2000).

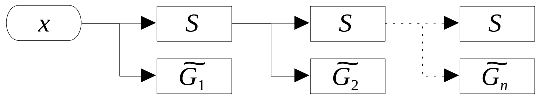
Transients are detected by "*sufficiently short moving mean square drop-off distance*" and "*sufficiently large spatial acceleration local crest factor*." The transient-free road segments are classified into bins of quasi-constant RMS levels [mm/m^2].

(iii) The presented method deploys arbitrary window size, bin widths, RMS levels, and crest factors as *carefully selected* parameters. Id. admit that „*different values may affect the results*" but claim the remaining validity of the procedure.

2.3. Shock extraction method

(i) Shock extraction method is introduced in (Zhou and Wang, 2018). The original signal is decomposed into a series of approximated Gaussian segments and one shock segment. The segmentation is based on the moving crest factor and the one-tenth peak (OTP) value.

Figure 2. The decomposition workflow of Shock extraction method, S referring to *shock*, G_n denoting the n-th *approximately* Gaussian vibration.



Source: reproduced from (Zhou and Wang, 2018).

(ii) The method is further studied in (Zhou and Wang, 2019). Albeit a pseudo code is provided, *ibid*. remains silent about the algorithm. But it is apparent that events with $x_\kappa[k]$ greater than a threshold are extracted. A *code* calculates the optimal threshold valu*e*, such that κ of the remainder part is close to three. Another parameter (*Hsize* max. 0.5 s) is introduced to extract shocks, and ± 0.25 s around the peak location is found to be the duration of a shock. The lower limit on the duration of segments 5 s reflects on vibration table sensitivity. For simulation purposes, segments are simulated as stationary Gaussian signals, concatenated to match the total simulation time. Uniquely, segments are ordered ascendingly according to their RMS, and one shock segment is appended at the end.

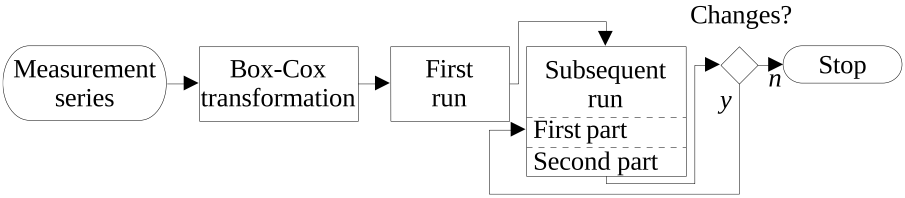
(iii) It is reckoned that OTP is equivalent to drop-off distance; however, a confusing definition is provided: "*a horizontal line drawing from one-tenth of the wave height intersects with the shock spectra, the time distance of those two intersection points is deemed to be the duration t of that shock spectra*" (Zhou and Wang, 2018). It is unclear how the time-domain is interpreted on a spectra; or what wave height points out the estimation's initial point. *Wave* is also underdefined: if the vibration acceleration is meant, OTP is hard to define since shocks tend to fluctuate around an equilibrium. Albeit MCF is often used to index transients, it is not always reliable and is often not appropriate for signals containing strong non-stationarities (Lepine, Rouillard and Sek, 2017). Fatigue life prediction may also be unrealistic since suffered damages may vary by the sequence of high- and low- or low- and high-stress fluctuations (Ibrahim, 2017, p.365).

2.4. Bayesian detector

(i) Thomas (2005) introduced a Bayesian detector to find homogenous sections separated by changepoints within IRI and rutting measurement series from different countries. The resulted segments of the measurement series are considered homogeneous "*with respect to a certain criterion if the associated measurement series can be described by a single first-order autoregressive process*" (ibid.).

(ii) The Box-Cox transformation brings the series closer to the model assumption of normal distribution. The heuristic at-most-one-change (AMOC) algorithm expresses the probability of inserting a changepoint $p(change)$; secondly, selecting the location with the highest posterior support $p(location \mid change)$.

Figure 3. Steps in the execution of the algorithm.



Source: reproduced from (Thomas, 2005).

Heuristics are motivated by placing changepoints sequentially instead of simultaneously to avoid a numerical burden by the binomial coefficient. The *first run* scans the series block-wise, obtaining the probability of the overall existence of a change somewhere. Given a changepoint, the block steps further; otherwise, the block slides to the right with an overlap. Blocks containing one changepoint are further analyzed in *subsequent runs*. The *first part* seeks for additional changepoints between preliminary borders. The *second part* checks the changepoint's actual necessity given the neighboring ones and its correct position. If neither the number nor the location of the changepoints is altered, the algorithm is terminated.

(iii) The method is a fast iterative algorithm that needs to undergo further experimentations (Lepine, Rouillard and Sek, 2015). Sometimes the method can get into an endless cycle of recurrent partitions. The approach objectively allows probability-based decision-making, even though various coefficients need to be determined.

2.5. Random Gaussian sequence decomposition and the modulation function

Charles formulates the idea of Random Gaussian Sequence Decomposition, as non-Gaussian RVV can be decomposed into random Gaussian distributions (Charles, 1993); Lepine reports (Lepine, Rouillard and Sek, 2015). The idea is worked out later by Rouillard (Rouillard, 2007a). Sek in [5] summarizes other procedures of environment descriptions recommended by Charles. Rouillard uses Hilbert transform to obtain the magnitude of a vibration signal (Rouillard and Sek, 2000). The reduced form of the magnitude is called vibration intensity, which can describe the statistical characteristics of an RVV. Id. introduces a different form of data reduction technique in (Rouillard and Sek, 2002) by a so-called dynamic bin width. Followingly id. works out the RGSD (Rouillard, 2007a) and later presents a cumulative-sum/bootstrap algorithm to find stationary segments in an RVV (Rouillard, 2007b). The synthesis of non-Gaussian RVVs is presented by id. in his thesis (Rouillard, 2007c), which is currently under permanent embargo; still, the research (Rouillard, 2007d) is published in the same year, presenting RGSD with the changepoint detecting algorithm and introduces the concept of modulation function. Id. introduces different distributions to characterize the nonstationary nature of RVV in (Rouillard, 2009).

2.5.1. Reduction of the analytic signal

(i) Rouillard and Sek (2000) hypothesize that a nonstationary random vibration signal can be modeled as the amplitude-modulated version of a steady-state random signal. Given a time-series a, the analytic signal $\tilde{a}$ is obtained by Hilbert-transform. The magnitude M of the $\tilde{a}$ is reduced and named vibration intensity (VI), which can be later used for amplitude modulation of a stationary Gaussian series.

(ii) Two methods are given for data reduction: *a*) M_{i+1} is eliminated, if $\left|M_i - M_{i+k}\right| < \Delta M$, where the selected magnitude bin is denoted by ΔM. Thus, consecutive M_i can be thought redundant, where those are between a tolerance limit; *b*) the *VI* can be further compressed according to VI probability density PDF_{VI}.

(iii) Ibid. is concerned in first place with reduction of *M*; however, *a*-*b*) are also apprehensible as segmentation methods, albeit ΔM and PDF_{VI} bin width are subjective parameters.

2.5.2. Dynamic reduction of the analytic signal

(i) Segmentation with peak-valley considerations is presented in (Rouillard and Sek, 2002) to characterize the non-stationarity of RVV. Given a signal and its Hilbert-transform, the magnitude of the analytic signal is obtained. The magnitude is smoothed and fed to an algorithm to detect quasi-stationary sections. The algorithm reduces the number of points in M but utilizes a dynamic segmentation bin width and considers the peaks and valleys, Mpv.

(ii) The absolute difference $\left|dM\right|$ between current VI_n and the subsequent $i+1$ -th magnitude peak/valley Mpv_{i+1} is computed. The *dynamic segmentation bin width* VI^b is, simply put, a bin size to differentiate regions on the magnitude axis. If $\left|dM\right|$ is greater than the actual bin size corresponding to VI_n, a new segment is initiated at the investigated Mpv_{i+1} being the new initiative VI. If the difference is smaller than the actual threshold, the Mpv_{i+1} is included in the VI average and Mpv_{i+1} is discarded. An operation "$*I$" is not discussed.

(iii) The smoothing algorithm needs a window width, but the parameter is not introduced. Neither the identification of Mpv_{i+1} is discussed, nor the derivation of VI^b is available, whereas $b = 0.5$ exponent is found to produce *very satisfactory results*.

2.5.3. Random Gaussian sequence decomposition

RGSD is a theoretical framework proposed by Charles and implemented by Rouillard (Rouillard, 2007a). The fundamental hypothesis covers that RVV is composed of zero-mean Gaussian processes with varying standard deviation. It is *tested* by comparing the sum of Gaussian estimates against the PDF of the original

RVV. The algorithm does not provide changepoints within a measurement series; thus, it cannot indicate stationary segments' place and duration.

2.5.4. CUSUM – Bootstrap algorithm

(i) Rouillard presents a changepoint detection algorithm to find the length of stationary segments in RVV (Rouillard, 2007b). Instantaneous magnitude computed by Hilbert transform is subjected to a cumulative sum-bootstrapping method. The algorithm assesses the probability of a changepoint being present, thus deals with amplitude-type non-stationarities. A variety of RVV measurements and simulated time-domain signals were used to derive a distribution of segment lengths.

(ii) In lack of a process diagram, the script is quoted here (ibid.):

1. The instantaneous magnitude of vibration is computed using the Hilbert Transform.
2. Compute the cumulative sum of the instantaneous magnitude vector normalized with respect to the mean magnitude.
3. Apply the bootstrap algorithm sequence whereby the entire instantaneous vibration vector is randomly re-samples *a number of times* and the cum-sum re-computed for each re-sampled vector.
4. The maximum and minimum envelopes from the bootstrap samples are computed.
5. The largest extremum of the original record is detected and identified as a change-point. Its value is compared with that of the bootstrap sample (…).
6. The change point is identified as significant or valid if the ratio of the largest extremum to the bootstrap extremum exceeds a predetermined value. In all cases studied, the ratio threshold of 5.5 was identified as *adequate* (…).

The record is bisected at a valid changepoint, and resulting segments are subjected to the same CUSUM-bootstrap procedure until no more changepoints are identified, or a minimum segment length is reached. It is worth noting that CUSUM here refers to the cumulative sum of differences between each value and the total mean of the series [1]:

$$c_k = \sum_{i=1}^{k} (x_i - \overline{x}_i), \tag{1}$$

for $i = 1, ..., k$. The validity of candidate changepoints must be quantified, for which bootstrapping is applied. Certain factors are unknown, such as the number of replications for the reference set or whether a resampling [2] with- or without replacement is implemented. Usually, bootstrapping is applied to derive the significance level of a changepoint being present in x, such as

[1] An upward- or downward trend in c_k indicates values tending above or below the overall average, respectively. Sudden changes in trend imply sudden shift or change in the mean (Taylor A., 2000).

[2] Bootstrapping and permutation are resamplings with and without replacement, respectively (Kowalewski and Novack-Gottshall, 2010).

$$\tilde{p} = \frac{1}{R}\#\left[\underline{\hat{c}}_x > \underline{\underline{\hat{c}}}_R\right], \tag{2}$$

where $\tilde{p}$ is the estimated p-value, R is the number replications, $\#[\bullet]$ denotes number of elements, such that $\underline{\hat{c}}_x$ extremum is greater than extrema from $\underline{\underline{\hat{c}}}_R$ in replications $r = 1,...,R$. Id. uses a different approach:

$$\underline{\hat{c}}_x > 5.5 \cdot \underline{\underline{\hat{c}}}_R, \tag{3}$$

–seemingly heuristically, since the 5.5 multiplier is found *adequate.* Against too many changepoints, individual thresholding was necessary instead of significance levels.

(iii) Albeit the algorithm skips the possibility of significance levels, and some factors are hidden, several RVV signals subjected to this algorithm had produced consistent estimates on the probability density function of segment lengths by considering amplitude-type non-stationarities.

3. SEGMENTATION IN THE FREQUENCY DOMAIN

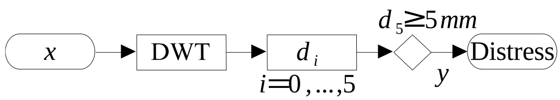
Following methods consider spectral characteristics, for which Fourier-, wavelet -, and Hilbert-Huang transform is often favored. Their introduction is set aside here due to the limited space available, and the reader is referred to actual references.

3.1. Wavelet decomposition

(i) Wei et al. introduce a wavelet decomposition procedure, retrieving supplementary information to pavement roughness indices (Wei, Fwa and Zhe, 2005). Id. investigates the capability of wavelets in the detection of local pavement distresses and provides the following algorithm.

(ii) International roughness index (IRI) signal given in the distance domain is decomposed by DWT into frequency sub-bands d_i. A suprathreshold amplitude in the sub-band d_5 indicates possible surface distresses for field inspection.

Figure 4. Wavelet decomposition



Source: individual representation from (Wei, Fwa and Zhe, 2005).

(iii) The decomposition given Daubechies wavelet (DB3) is found proper until the fifth sub-band. The specific number of sub-bands shows that the necessary number of decomposition levels must be investigated per application, just like the threshold's justifiability. Unfortunately, the detection capability has been presented only on IRI series having artificial distresses. Despite the manual transients in the signals, the article served as initial points in later research to investigate the wavelets in high-sampled time-series, such as vertical acceleration vibrations.

3.2. Separation by filtering

(i) Rouillard et al. present separation by filtering in (Rouillard and Richmond, 2007) for railcar vibration environment. Shocks are removed in frames from the time-domain signal via thresholding. Filtering in the frequency domain is introduced as an alternative approach, for which different assumptions are necessary. The simulation superimposes intermittently occurring structural vibrations (transients or shocks) onto the rigid-body random vibrations.

(ii) A numerical lowpass filter separates the rigid-body- and structural vibrations at the cut frequency. Id. *believes* that impulsive vibrations can be described by their "*amplitude and their statistical likelihood of occurrence*" given their similar characteristic. It is assumed that *a*) rigid-body motions are bandlimited up to a cut-off frequency and intermittent vibrations lie within a different frequency band; *b*) rigid-body motions have the same frequency characteristics, i.e., quasi-stationarity throughout the record. Finally, the similar characteristics of impulsive vibrations must be investigated -unfortunately, no guidance is provided.

(iii) From a simulation perspective, this is the Shock-on-random method. Shocks are simulated according to their amplitude PDF and triggered by a random clock. Random vibration is modeled as a steady-state Gaussian signal from the average rigid-body PSD. Here the author presumes that assumptions *a*-*b*) are closely related to the investigated scenario of railcar vibrations, whereby those cannot be guaranteed in RVV.

3.3. Intrinsic mode functions

(i) Rouillard introduces the Hilbert-Huang transform (HHT) for the analysis of railcar vibrations aimed to describe prevalent frequency-type non-stationarities (Rouillard and Sek, 2005).

(ii) By HHT, the random signal is sifted into intrinsic mode functions (IMF), and the analytic signal from each IMF is computed. The absolute value of the analytic signal corresponds to instantaneous magnitude. Id. assumes that modes 1-4 represent higher, modes 5-7 represent lower frequency components, and modes 8-12 are ignored, describing *very low* frequencies. It is concluded that the method has a special significance in the simulation of railcar vibrations since it may be well advantageous to simulate these two processes separately. The superior resolution of IMF is highlighted, and a spectrogram is presented, but methods for changepoint detection are not offered.

(iii) The paper successfully corresponds to the introduction of HHT in PVT; however, no process is offered to identify changes in the spectrogram.

4. SEGMENTATION IN THE TIME-FREQUENCY DOMAIN

Following methods operate in the time-frequency domain. Typical choices are continuous wavelet- and Hilbert-Huang transform, whereby short-time Fourier transform is rarely used in the presented methods.

4.1. Wavelet-based Gaussian Decomposition

(i) Griffiths et al. developed the Wavelet-based Gaussian decomposition (WBGD) to decompose RVV into series of segments with different kurtosis, which can be separately simulated and concatenated to obtain a nonstationary random vibration in total (Griffiths, 2012; Griffiths *et al.*, 2016). The approach uses the continuous wavelet transform (CWT), evaluating the frequency spectra' variation through time.

(ii) The process can be articulated along the following ideas. Given a vibration signal y_m and its power spectral density $S_{y,m}$, an equivalent stationary Gaussian vibration x_m can be derived. The CWT of each signal is obtained by a complex wavelet, resulting in positive and negative absolute coefficients $C_{y,m}(a,b)$ and $C_{x,m}(a,b)$. A decomposition envelope DE is derived from the extrema through the translation b of $C_{x,m}(a,b)$. Regions of $C_{y,m}(a,b)$ outside DE are candidates of non-Gaussian regions; in turn, inlying regions are considered Gaussian parts. "*The data windows surrounding locations that exceed the envelope are extracted from the vibration signal*," here at shortest 1 s. Out- and inlier regions $C_{y,m}^{O}(a,b)$ and $C_{y,m}^{I}(a,b)$ are concatenated, forming two signals, and their wavelet coefficients are inversely transformed, yielding y_m^O, and y_m^I, respectively. If the kurtosis $\beta_2(y_m^O)$ is smaller than a threshold β_{2T}, the vibration signal $y_{m=1}$ is replaced by the outlier y_m^O, and the decomposition is repeated from *1-7)* yielding $y = y_1^I \square ... \square y_M^I \square y_M^O$. The iteration continues until the iteration limiting number M is reached or $\beta_2(y_m^I) < \beta_{2T}$. The second stage of iteration might begin to form:

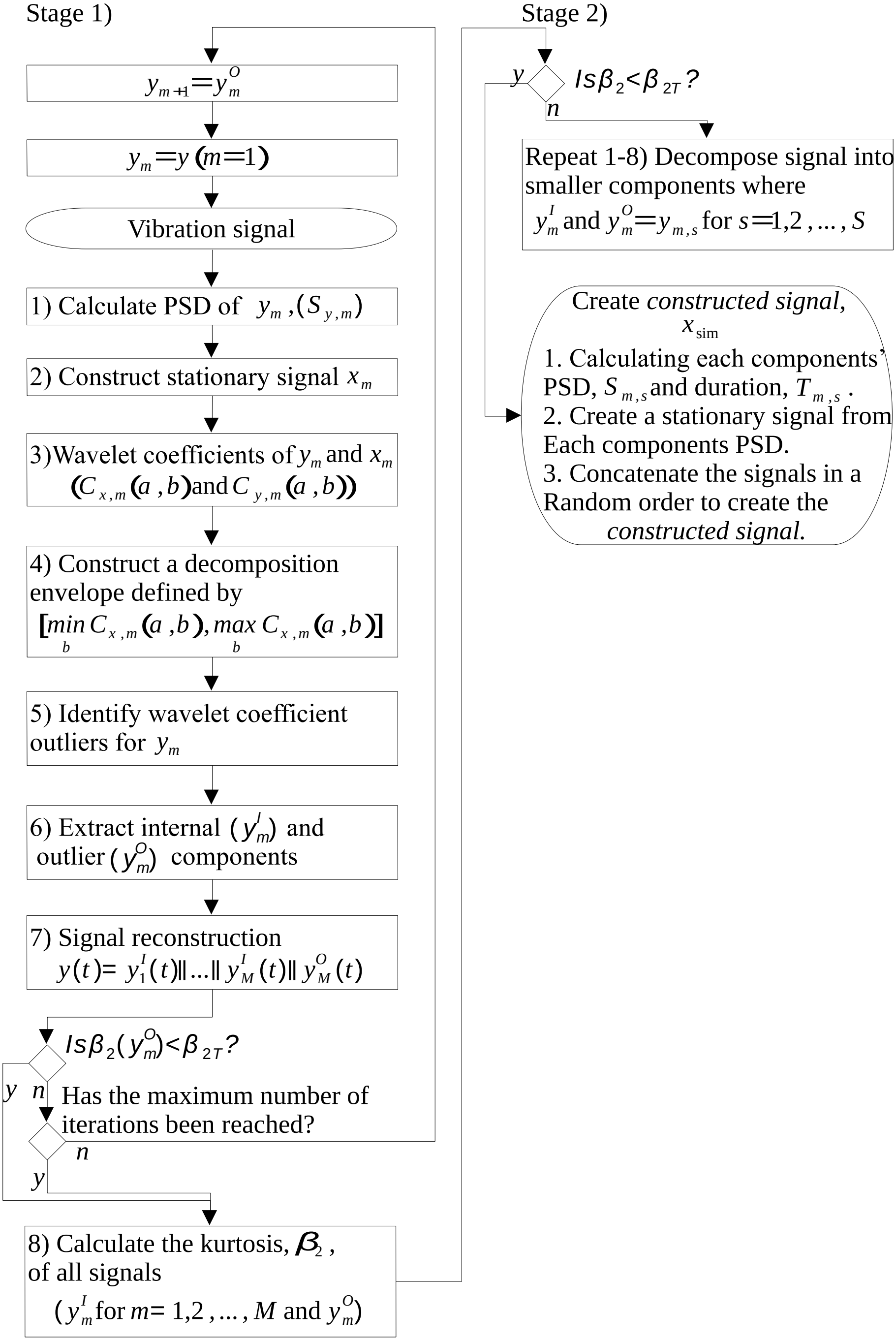
$$y_{i_1}^{I}(t) = \sum_{i_2=1}^{S} y_{i_1,i_2}^{I,I}(t) + y_{i_1,S}^{I,O}(t), i_1 = 1,...,M \tag{4}$$

$$y_M^O(t) = \sum_{i_2=1}^{S} y_{M_1,i_2}^{O,I}(t) + y_{M,S}^{O,O}(t) \tag{5}$$

Steps *1-8*) are repeated given a supra-threshold kurtosis or until the iteration limiting number S per component i_1. Through simulation, final components can be simulated by individual $S_{m,s}$ corresponding to the duration $T_{m,s}$ ordered in a desired sequence.

y_M^O is likely to contain most of the high-level shock events, which can be further decomposed in the second stage arriving at $y_{M,S}^{O,O}$, which still encompass most of the non-Gaussian characteristics, constituted by mainly the high-amplitude events. "*These segments will have highly non-Gaussian distributions, thereby strengthening the limitation that the wavelet decomposition method will always produce one Gaussian approximation that is highly non-Gaussian*" (Griffiths, 2012, p.190).

Figure 5. Wavelet-based Gaussian decomposition



Source: reproduced from (Griffiths *et al.*, 2016).

(iii) WBGD operates in the scale-translation domain and iteratively partitions the CWT of an RVV into quasi-Gaussian- and remaining parts concerning the kurtosis. The main idea to highlight here is that a section is labeled as Gaussian if its CWT fits within the CWT extrema of a Gaussian equivalent at any iteration stage.
The simulated signal has a good match in PSD and kurtosis to the measured RVV, albeit the RMS distributions of the original and simulated signals are significantly different, although it is expected by id. (Griffiths *et al.*, 2016, pp.788-789); however, it remains inconsistent with other empirical studies concerned with the RMS distribution of Gaussian segments.

4.2. Hilbert amplitude spectrum

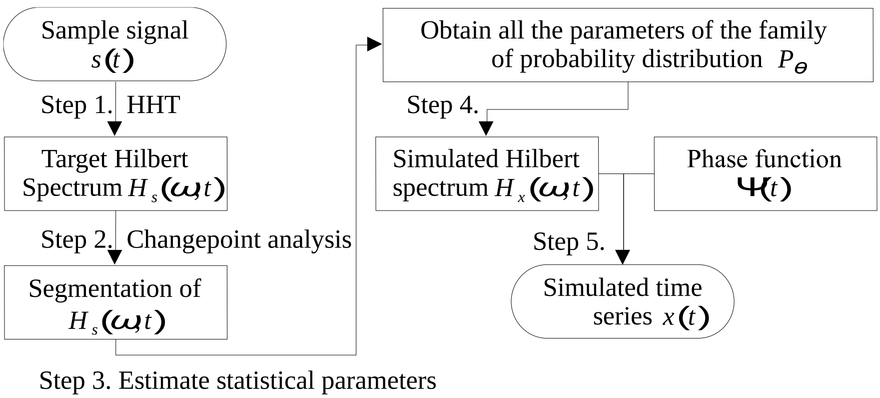
(i) Mao et al. presented their method based on the Hilbert amplitude spectrum to characterize and simulate nonstationary random vibrations (Mao *et al.*, 2015). Note that the current section chooses slightly different notations for readability.

(ii) Given an $s(t)$ sample, the Hilbert-Huang transform yields the $H_s(\omega,t)$ time-frequency domain. The CUSUM approach is responsible for changepoint detection per each frequency section over time. The instantaneous magnitudes between changepoints are fitted by five different distributions P_θ as gamma, exponential, Rayleigh, log-normal, and Weibull distributions for $\theta:\{G,E,R,LN,W\}$. The Kullback-Leibler divergences for P_θ of inst. magnitude within segments $h(\omega_i,t)$ are calculated:

$$\delta KL_\theta(P_\theta \,\|\, h(\omega_i,t)) = \int P_\theta \log_{10} \frac{P_\theta}{h(\omega_i,t)}\, dt \geq 0\,, \tag{6}$$

and averaged through segments of each frequency yielding $\overline{\delta KL_\theta}(\omega_i)$. The idea to highlight here is that each frequency section is characterized by one family of fits having the lowest $\overline{\delta KL_\theta}(\omega_i)$.

Figure 6. Flow diagram of simulation method



Source: reproduced from (Mao *et al.*, 2015).

By simulation, random variables are generated according to P_θ, and in conjunction with a phase function $\Psi(t)$, finally $x(t)$ can be simulated.

(iii) Further improvements might be obtained by choosing the *best-from-the-five* fits directly in each segment. This can be justifiable if $\overline{\delta KL_\theta(\omega_i)}$ are biased by the outlier δKL_θ. Besides, the method is capable of segmentation in the time-frequency domain, but as the virtue of the fitted distributions, it can also be considered a *random* simulative approach.

5. MIXED-METHODS

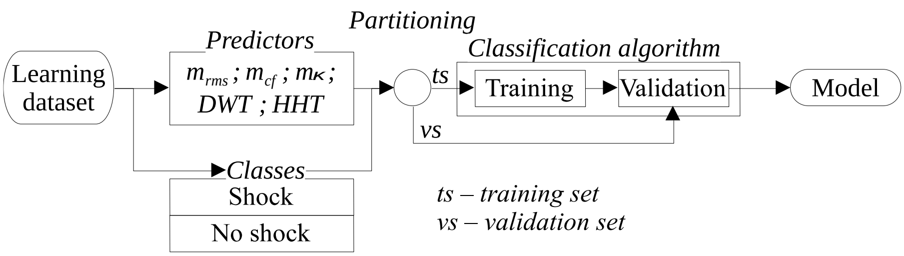
Here an algorithm is referred to as a mixed-method if it can consider time- and frequency domain characteristics simultaneously.

5.1. Machine learning classifiers

(i) Lepine presented a continuous contribution to PVT by studying machine learning classifiers (MLC) to detect shocks in RVV. The foundation of MLC is presented in the thesis (Lepine, 2016). The support vector machine (SVM) had been compared to the moving crest factor via receiver operating characteristics (ROC) in (Lepine, Rouillard and Sek, 2017). Four different MLC (decision tree, k-nearest neighbors, bagged ensemble, SVM) are investigated by synthetic RVV in (Lepine and Rouillard, 2018). Ibid. is constituted by a detection enhancement algorithm (Fig. 8.). The above MLC are further analyzed, and validation by real RVV is proposed in (Lepine, Rouillard and Sek, 2019).

(ii) RVV measurements with registered shocks are mostly unpractical. Thus artificial RVV might be generated (Lepine and Rouillard, 2018). The synthesis mimics natural RVV as far as the dynamic model is accurate. Different predictors are used, such as $x_{rms}, x_{cf}, x_\kappa$, DWT, instantaneous amplitudes, and frequencies of the IMF from HHT.

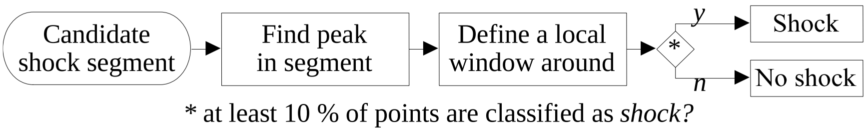
Figure 7. The workflow of the classification algorithm



Source: reproduced from (Lepine and Rouillard, 2018).

The validation and calibration of MLC hold several possibilities, such as ROC curves, the distribution of absolute peak acceleration of shocks can be compared among the validation signal and detections, the purpose-developed pseudo energy ratio - fall-out (PERFO) curves. Optimal operating point (OOP) definition has various possibilities; however, OOP by synthetic calibration is inadequate for real RVV applications in (Lepine, Rouillard and Sek, 2019). In consequence, a synthetically setup MLC may not be directly suitable for real-world applications. Definition of *shock* also has special considerations as of application, e.g., "*sudden and severe accelerations of a finite and measurable duration*" (Lepine, Rouillard and Sek, 2017); or "*a sequence of data points instead of individual data points*" together with the "*detection has to overlap at least 75% of the shock duration to be considered true*" in the validation (Lepine, Rouillard and Sek, 2019). The enhancement algorithm covers a window size in (Lepine and Rouillard, 2018). All data in the window is classified as a shock if it contains "*at least 10% of data points".*

Figure 8. Detection enhancement algorithm



Source: individual representation from (Lepine and Rouillard, 2018).

(iii) A "*considerably more accurate and reliable*" detection performance of the MLC is claimed against the conventional moving crest factor (64 s), producing 13% better area under the ROC curve (AUC index) (Lepine, Rouillard and Sek, 2017) –but one should consider the numerical expenses of this improvement. Development of performance assessment methods is presented, such as ROC - and PERFO curves, distribution of absolute maximum accelerations of shocks. Furthermore, the definition of *shock* might be necessary to adjust. Since inconsistencies are shown for synthetically setup MLC in real-world applications, validation on real-world RVV was proposed (Lepine, Rouillard and Sek, 2019). Consequently, the on-site measurements with a precise indication of shock-inducing instances are hardly avoidable. Additional validation of the MLC must be undertaken for the general implementation of MLC to specific RVV (ibid.).

6. DISCUSSION

A concise appraisal platform is provided in Table 1, discussing various aspects of the dilemma of adaptability. Each method is investigated by a) reproducibility, b) heuristics, c) subjective thresholds and d) accompanying simulations, discussed in the followings. A method is considered reproducible a) if it can be translated into programming languages solely on the published information, given the same dataset is on-hand. For instance, a method being silent about sub-steps in the reference cannot be considered reproducible in the author's recognition. Point b) corresponds to the need for manual parameters and settings in the approach.

Table 1. Appraisal matrix of segmentation methods proposed before non-stationary simulations or introduced as standalone methods

Domain	Segmentation method and first reference	a) Reproducible?	b) Avoid of heuristics?	c) Avoid of subjective thresholds?	d) Accompanied by simulation?
Time	Moving statistics (Bruscella, Rouillard and Sek, 1999) [1]	●	○	○	○
	RMS drop-off distances (Bruscella, 1997)	●	◐[2]	●	●
	Shock extraction method (Zhou and Wang, 2018)	○[3]	◐[4]	○	●
	Bayesian detector (Thomas 2005)	●	○	●	○
	Reduction of analytic signal (Rouillard and Sek, 2000)	●	◐[5]	●	●
	Dynamic reduction of analytic signal (Rouillard and Sek, 2002)	●	●	◐[6]	●
	CUSUM—Bootstrap algorithm (Rouillard, 2007b)	●	◐[7]	◐[8]	●
Frequency	Wavelet decomposition (Wei, Fwa and Zhe, 2005)	●	◐[9]	○	○
	Separation by filtering (Rouillard and Richmond, 2007)	●	●	○	●
	Intrinsic mode functions (Rouillard and Sek, 2005)	●	◐[10]	◐[11]	○
Time-frequency	Wavelet-based Gaussian Decomposition (Griffiths, 2012)	●	◐[12]	●	●
	Hilbert amplitude spectrum (Mao *et al.*, 2015)	●	●	◐[13]	●
Mixed	Machine learning classifiers (Lepine, 2016)	◐[14]	●	◐[15]	●

Legend: ● - *yes;* ◐ - *conditionally yes;* ○ - *no*

[1] *Noting, that it is a cross-disciplinary technique.*
[2] *Apart from the moving window size.*
[3] *Since "pseudo code flow" remains unexplained e.g., "Hsize".*
[4] *Apart from unexplained steps, the algorithm seems to work autonomously.*
[5] *Accepting the selected magnitude bin* ΔM*, as a data driven solution.*
[6] *The threshold value itself is derived from a subjective parameter (dynamic segmentation bin width* VI^b*).*
[7] *Apart from Eq. (3) above.*
[8] *Apart from Eq. (3) above.*
[9] *Accepting, that type of wavelets and the level of decomposition are inherent to DWT.*
[10] *Since the number of IMFs separating low- and high frequencies are only "assumed".*
[11] *If the "assumed" number of IMFs -separating low- and high frequencies- are accepted.*
[12] *Accepting,* that *type of wavelets and the level of decomposition are inherent to CWT.*
[13] *Accepting, that significance limits in hypothesis testing have traditional uses.*
[14] *Accepting, that machine learning classifiers are "grey-boxes", and its skills depend on the training.*
[15] *Since some predictors are moving statistics.*

While some algorithms are designed for heuristic solutions (e.g., to avoid computational overflow) and others had to *experiment* with the methods itself in those days, one now can have preferences toward data-driven solutions, as well. However, the new adoption of such techniques and some form of heuristics does not mean obsoleteness. Question c) investigates unexplained threshold values, while a few of them have traditional uses noted in the table notes. Finally, question d) reflects mainly on the early adoption of the segmentation methods in the simulations. Papers devoted only to detection still possess an important place in the *history* of technology. In conclusion of the appraisal platform, it is advised to perceive the legend entries of Table 1. as *state-switches* or *toggles* instead of *scores*. The following paragraphs discuss and summarize the above methods.

Moving statistics have the longest history because of simple implementation, thus, an early introduction to the discipline, as well. The window size and the threshold value often need heuristics to arrive at a sufficient solution. RMS drop-off distance partially uses such techniques thoroughly investigated in the thesis. Shock extraction method is a young algorithm, mostly relying on older approaches. It is not easily implementable, until new insights in the algorithm are provided. Bayesian approaches represent a traceable procedure with transparent insight into decisions. Its performance must be presented on high-sampled datasets, as well. Section of Random Gaussian Decomposition, incl. subordinative methods have the strongest establishment in the research of packaging vibration testing. However, a few details are only provided on a seemingly investigatory basis.

Frequency characteristics are often in the interest, relying on Fourier-, wavelet- and Hilbert- transforms. Apart from theories applied to arrive in this domain, distinctive approaches can be mentioned here. Wavelet decompositions present a good resolution in time (DWT) and in time-frequency (CWT) representations. Mainly contributing to the promotion of the theory, Wavelet decomposition (Wei, Fwa and Zhe, 2005) *per se* uses thresholds to find transients. Separation by filtering is a well-established method, leaving the cut-frequency the only investigatory parameter beside general necessities (e.g., windowing) in discrete Fourier transform. Albeit no changepoint detection had been presented above in regard to Intrinsic mode functions, it is still regularly used nowadays because of its superior resolution. Wavelet-based Gaussian decomposition (Griffiths, 2012) presents a unique approach, utilising CWT. The concerns addressed in terms of simulated signals must be investigated on an individual basis before implementation. Hilbert amplitude spectrum by Mao et al. (2015) is successful both in segmentation and simulation.

MLC applications show promising results, but only in a costly manner. The presented PVT applications show good accuracy on shock detection; presumably, further developments are ahead.

In summary, moving statistics are recommended only in an explanatory phase of the analysis. For detection in time domain, the CUSUM—Bootstrap- along with the Bayesian approaches are favourable. The sample of frequency domain approaches is smaller; thus, any of the three procedures can be easily tried. Both time-frequency domain method produces transparent results, therefore those encompass preferably successful implementations.

Hence, a favorable algorithm is numerically parsimonious, utilizes as few heuristics and subjective thresholds as possible -preferring data-driven solutions. It provides a transparent decision making and above all it remains reproducible. The author is of the opinion that the non-stationary state-changes, transients and harmonic components are best observable in the time-frequency domain and therefore the author's future research will elaborate on multiple comparison procedures (e.g., by paired- or two sample *t*-tests) among consecutive time-slices of the short-time Fourier transform plane.

7. CONCLUSION

It is agreed that packaging systems set up a safety factor in the assurance of the transported goods' quality. However, different costs can be associated to over- and underinsurance of the shipment. Therefore, the academic community developed various vibration simulation methods beneath standardized procedures, each containing unique signal segmentation practices.

Standardized methods in PVT remain in position for the expected conformability toward standards. Concurrent new methods emerge to account for the deficiencies of PSD-based methods, viz. the produced random vibrations are stationary and Gaussian. No universally accepted method for RVV simulations exist as pointed out by Lepine, Rouillard and Sek (2015), who also addressed some segmentation techniques. In line with this, the applied changepoint detection algorithms -including new ones- present a wide toolbar. Harmonic excitation in RVV is still hardly discussed; the above approaches can partially address the phenomena. Thus, the discussed methods mainly apply to transient event- and nonstationary segment border detection. Unfortunately, some algorithms are hardly reproducible, which does not facilitate the acceptability of proposed methods and delays improvements in standards.

The amplitude- and frequency type non-stationarities in RVV can be simultaneously approached from the time-frequency domain. Frequency modulation detection is less discussed than amplitude disturbances, as apparent from the number of methods. Numerically parsimonious methods are mostly heuristics, based on window statistics and thresholds, which may produce satisfactory results, given the corresponding parameters are justifiable. Sophisticated signal processing methods still often encounter some form of subjective thresholds. Therefore, data driven approaches are favorable.

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