Advanced signal processing methodology of vibration response data toward Structural Health Monitoring purposes

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Abstract. This paper outlines a comprehensive and consistent methodology for signal processing analysis of vibration response data, applicable for final structural monitoring and identification purposes. The methodology combines classical and advanced techniques, including, in its pre-processing phase, the adoption of a Time Domain Compression (TDC) technique and the application of an AutoRegressive Moving Average (ARMA) modeling approach. The TDC technique removes lower-quality subsamples from the full data set, resulting in a higher-quality modified signal that may display a weakly stationary character. The ARMA modeling approach enhances the understanding of the response signals by modeling unknown source inputs; as a peculiarity, the inherent polynomial function applied to a white noise source in the model is interpreted as a filtering term that transforms the source into a non-white noise configuration, enabling the effective deciphering of the structure transfer function features. The research is part of a more comprehensive case study concerning the structural evaluation of a historical reinforced concrete arched bridge over the Adda river in Lombardy, Italy. The focus of this paper is specifically on the application of the TDC and ARMA techniques to the signal response data collected from the bridge under operational conditions.

1. Introduction

A promising approach to monitor the current structural health of infrastructures, like bridges, involves the processing of their response data during regular operation under vehicle traffic. The technical literature offers numerous examples dealing with this topic, often utilizing modeling procedures such as the well-known Frequency Domain Decomposition (FDD) [1–5] or AutoRegressive Moving Average (ARMA) models [6–12]. These models assume that the unmeasured operational excitation shall correspond to a White Noise stochastic process. However, in many cases, loading is not continuous and the recorded response is a succession of transient vibrations. It might therefore be useful to propose approaches for a preceding data processing, coming from vibration monitoring systems, to enable the application of sound identification methods, such as those above mentioned, even when the excitation shall not be assumed as a White Noise process.

In this paper, strategies based on a Time Domain Compression (TDC) technique and an ARMA model are presented, as useful means to achieve such an ambitious goal. They are proposed as part of a detailed vibration signal processing analysis approach, which is highly generalisable and able to provide initial insights on the current state of the structure under analysis, without any particular restrictions related to the type of the analyzed signal. The approach is based on established notions and methods from signal processing theory and may be suitable as a preliminary signal analysis treatment, to be beforehand performed.

One of the most telling aim of this contribution is to open up a discussion on the importance of a first signal processing phase, which is here considered as a fundamental part of the structural response interpretation based on data acquisition, as well as representing a field of research whose development shall lead to relevant results in the general field of Structural Health Monitoring (SHM); in the literature, a signal processing dedicated to a preliminary analysis, which shall serve algorithms to pursue structural monitoring and identification goals, is in fact often overshadowed, thereby limiting a full sharing of the endowed research experience.

The vibration signal analysis methodology here proposed was recently initially outlined as part of a case study concerning the structural evaluation of a three-span reinforced concrete arched bridge over the Adda river, in Lombardy (Italy), built in 1917 (Brivio bridge) [25]. Since then, subsequent developments have refined the proposed procedure, particularly in relation to the parts concerning the adoption of the TDC technique and the ARMA method, with the above described purposes. This paper presents first insights into the use of such elaborations.

The paper is structured as follows: Section 2 provides a synoptic description of the proposed signal processing procedure for the vibration response analysis of civil structures. Section 3 presents first results obtained by applying the TDC technique and the ARMA models to vibrational data collected from Brivio bridge. Some final remarks conclude the paper.

2. Robust signal processing procedure for vibration response analysis of structures

The procedure within which this study is placed is meant to be developed on the basis of experimental measurements under operational conditions and based on the following main conceptual steps.

- Analysis of the signals in the time domain, to evaluate their main features. In particular, the evaluation of the possible stationarity of the data is of a main concern. To achieve this, a statistical analysis shall be performed, by looking at the distribution of the instantaneous values, positive and negative peaks, mean value and root mean square value.
- Analysis of the signals in the frequency domain, to identify the dominant frequencies of the recorded signals in the frequency range of interest, by processing both the whole record and peculiar reduced length records, for instance by a Fourier Transform (FT) analysis.

Depending upon the potential stationarity of the data, two different approaches shall then be adopted: being the signals stationary, a conventional analysis may be performed, including sound methods for modal analysis finalities or, being the signals non-stationary, a further study shall be outlined. In the latter case, the procedure shall continue with the following steps (see implemented details in Tables 1-2).

- Design and employment of a TDC algorithm, to try to make the signals stationary in the time domain and then to repeat the statistical and correlation analyses; if then the time-compressed signals are not stationary in the frequency domain, further devoted analyses should be performed, and the procedure shall continue with the following phases.
- Wavelet analysis, to identify the frequency contents, by positioning in the time domain the components of the signals, thus overcoming the spreading characteristics of the information associated with the FT analysis.
- ARMA modeling, as a further approach to investigate intrinsic structural characteristics, which can also be derived from state-space models, within which it is generally easier to incorporate insights into the physical mechanisms of the system than by the direct application of the ARMA models.

Table 1. Synoptic overview of the signal processing procedure for vibrational response analysis of structures – Part I.

Macro-phases	Sub-phases
A) Time domain analysis	• Identification of possible disturbances on the recorded signal • Rough classification of the type of signal • Rough correlation between physical events and signal properties • Estimate of the signal to noise ratio • Determination of the average, rms, positive peaks and negative valleys values of the full record and of significant sub-records (see, e.g., [13]) • Rough evaluation of the dominant frequencies • Identification of unimportant parts of the signal to be discarded and reduction of the signal to the meaningful parts (Time Domain Compressed signal)
B) Statistical analysis	• Evaluation of the statistical distribution of the instantaneous values of the TDC signal • Evaluation of the statistical parameters, first–, second-, third- and forth-order moments, on the full TDC signal and on reduced length sub-records • Identification of the similarity of the above experimental distribution with classical statistical distributions having equal statistical parameters • Rough judgement of the stationarity of the signal, weak stationarity or strong stationarity, local or general stationarity • Correlation between the statistical distribution of the signal and the physical events under study • Evaluation of the statistical distribution of the positive peaks and negative valleys of the TDC signal and possibly of reduced length sub-records with reference to the physical events • Identification of the similarity of the above experimental distribution with classical statistical distributions having equal statistical parameters
C) Correlation analysis	• For each single signal evaluation of the auto-correlation function on the full TDC signal and on significant sub-records • Classification of the type of signal • Verification of the correspondence between correlation parameters and time domain parameters • Rough estimation of possible dominant frequencies • Evaluation of the cross-correlation function among the signals of different measuring channels • Rough estimation of the similarity between different cross-correlation functions • Estimation of the delays in correspondence of the peak values and their interpretation with reference to the physical event

Table 2. Synoptic overview of the signal processing procedure for vibrational response analysis of structures – Part II.

Macro-phases	Sub-phases
D) Frequency analysis	• Calculation of FS, FT, SP, PSD based upon the type of signal of the full TDC record (see, e.g., [14]) • Repeat the above frequency analysis on significant sub-records and find the relationship with the physical event • Identification of the peak frequencies and their correlation with the physical properties of the structure and of the physical event
E) Wavelet analysis	• Choice of the suitable mother wavelet for the specific type of signal to be studied (see, e.g., [15–23]) • Performance of the wavelet analysis on the full TDC record for a stationary signal and on significant sub-records for non-stationary analysis • Evaluation of the dominant frequencies at each level of the wavelet analysis
F) ARMA models	• Based on the results of the previous analysis, evaluate whether the unmeasured input to the structure shall be similar to a white noise disturbance or not • For a white noise unmeasured input, the AR model should be adopted, and the parameters of the system should be evaluated by minimizing the figure of merit • For a non-white noise unmeasured input, the ARMA model should be adopted in order to reproduce a sort of filtering of the white noise, and the parameters of the system should be evaluated by minimizing the figure of merit • When the physical structure is already described by a physical model with lumped parameters, the ARMA model could be derived in the state-space • The obtained transfer functions for the disturbance model may be used as input for more precise dynamic analysis tools such as the Frequency Domain Decomposition (FDD)

3. Brivio bridge case study

The signal processing procedure for vibrational response analysis of structures herein presented has been adopted for a systematic signal processing investigation of collected acceleration responses during an experimental campaign performed on Brivio bridge (1917) between 11 and 13 June 2014 [24].

A first stage of the analysis is reported in [25] (following previous and further studies concerning Heterogeneous Data Fusion applications [24, 26], algorithmic FEM model updating [27, 28], and signal denoising [18, 20, 23]). There, the main aim of the analysis was that to produce a "blind test" on the proposed procedure. In particular, the analysis made it possible to identify reliable structural features, such as the dominant frequencies of the structure, and to provide structural interpretations, like for the influences of specific functioning parts and for potential manifestations of a global non-linear behavior. Furthermore, the non-stationarity of the response of the bridge in time was highlighted. The analysis then continued, focusing in particular on the application of the TDC and the ARMA method, in an attempt to overcome the constraints of using sound methods for SHM purposes when the excitation cannot be assumed to correspond to a White Noise process.

First, a TDC procedure was deemed suitable to try to make the signals stationary in the time domain. The adopted criterium was to disregard the parts of the signal having a rms value lower than a fixed percentage of the original rms value. Once the compressed signals were obtained, the statistical and correlation analyses were performed in the time domain; the frequency analysis was then conducted to evaluate the stationarity of the frequency contents.

With reference to the extensive operational experimental campaigns performed on Brivio bridge [24], signals acquired on the upstream side of the central span of the bridge were considered for the current processing. As a starting point, it was decided to process the data coming from two of the channels of the set-up employed during the experimental acquisition campaing (Channel 1 and Channel 2, see [25]). Four cases were in particular studied, by considering different percentages of the original rms value considered as the threshold, varying from 10% to 64%.

In this specific case study, focused on Brivio bridge, all of the compression attempts led to the same conclusions, as in the following.

- The TDC algorithm consistently reduced the length of the original data sets, resulting in final data strings of up to 42% of the original signal length, as in the case shown in Figure 1, where an rms threshold of 64% was set. This represents a beneficial by-product, namely the reduction in the amount of data to be processed and the associated gain in computational time.
- There was no successful effect of the TDC procedure on the stationarity of the signals, although the effect of the TDC made the signals closer to a Gaussian distribution of their instantaneous values (see Figure 2), and their peaks distribution became closer to the Rayleigh distribution of a narrow-band random signal. This potentially provides a more reliable information about the true statistical distribution during the operating life of the bridge, thus allowing a more correct estimation of its fatigue life. The (mere) similarities, however, exclude the perfect superposition of the trends, which would be necessary to assume linearity in the structural behavior.
- The frequency distribution of the original signals and the compressed ones turned out quite similar in shape, except for the absolute value, as it could be expected due to the reduction of the low-magnitude parts of the signals (cfr. Figure 3(a) vs. Figure 3(b)). The fact that the TDC procedure did not alter the frequency content of the original signal is reassuring and expected. It is important to note that, regardless of the specific case study results, it is recommended to always perform this comparison alongside TDC operations to ensure that the acquired signal information content is not altered. This is crucial for accurately interpreting the structural behavior, regardless of the specific case study results.

Since the signal non-stationary character persists even after processing with the TDC technique, the ARMA method was employed for a suitable further signal processing.

ARMA models constitute a very powerful tool for the identification of a system through the determination of the parameters of a black box. Beyond the signal analysis, ARMA models can be seen as a first stage for the identification of the physical parameters of a structure, starting from its response to known, but not necessarily measured, inputs. In the general formulation of the AutoRegressive Moving Average process with eXogenous input (ARMAX) models, response $y(t)$ and input $u(t)$ are both measured, while there are also unmeasured inputs $e(t)$. However, when both the input and output are measured, there are many other direct modeling procedures and mathematical tools that can be used besides ARMAX models. ARMA models are particularly useful when only the response of the structure is measured, and all inputs are considered as unmeasured term $e(t)$, which is taken into account in the Moving Average part of the model. The general theory is developed by considering that $e(t)$ is represented by a white

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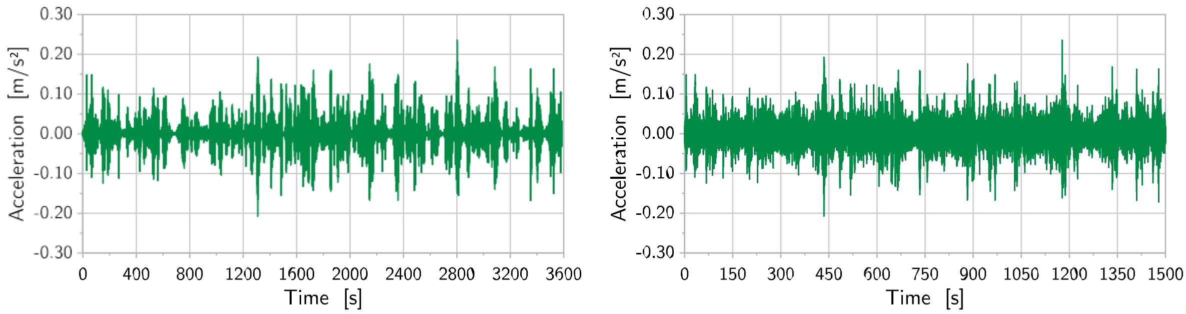
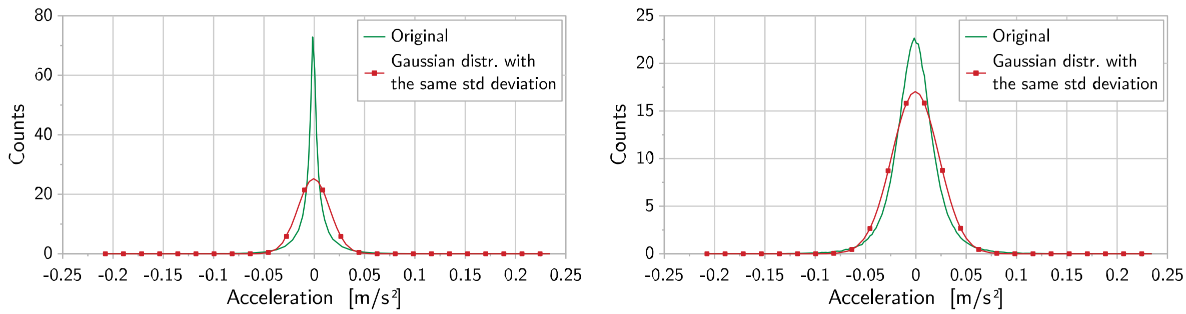


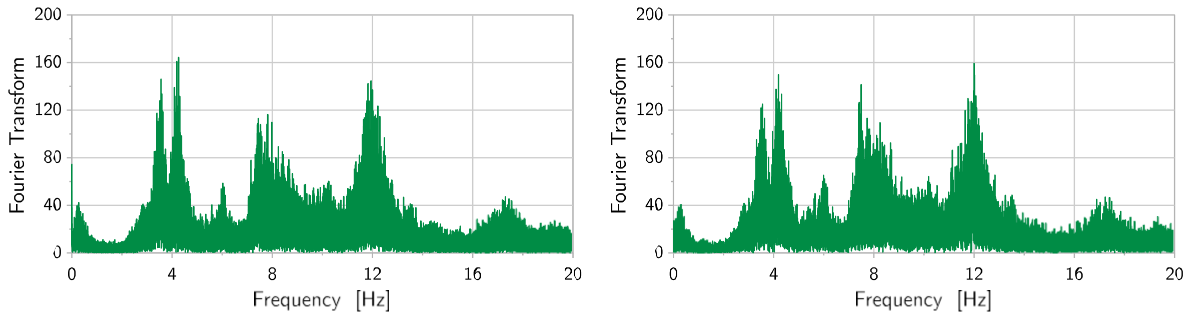
(a) Original signal. (b) Compressed signal.

Figure 1. Record of signals acquired on Span 2, upstream side, Channel 2, before (a) and after (b) application of Time Domain Compression to the original record; from the abscissa it is possible to appreciate the reduction of the time-lenght of the signal.



(a) Original signal, kurtosis = 18.33. (b) Compressed signal, kurtosis = 6.7.

Figure 2. Distribution of instantaneous values of the records acquired on Span 2, upstream side, Channel 2 vs. Gaussian (normal) distribution. After application of Time Domain Compression to the original record the experimental distribution remains leptokurtic, although there is an evidence of a reduction in kurtosis.



(a) Original signal. (b) Compressed signal.

Figure 3. FT plot of signals acquired on Span 2, upstream side, Channel 2. The frequency content of the signal is displayed not to be altered by the application of the Time Domain Compression.

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noise, but in practice this is a rare case. As it is well known by definition, a white noise process may follow any kind of probability distribution, not necessarily a Gaussian distribution, thus from this point of view $e(t)$ is suitable to represent the excitation of vehicle traffic or any other kind of excitation of a structure. Nevertheless, one of the properties of white noise, from where the name, is that the frequency distribution of the signal is flat all over the frequency field, but in many cases the dynamic excitation displays a frequency distribution in a limited range with peaks and valleys.

To overcome this problem, in the ARMA model $A(z)y(t) = C(z)e(t)$, the Moving Average part of the model may be seen as a filtered white noise representing the unmeasured inputs to the system $v(t) = C(z)e(t)$, where $A(z)$ is the polynomial of the Auto-Regressive part and $C(z)$ is the polynomial of the Moving Average part of the ARMA model in the Z–transform space. Therefore, the theory of the ARMA models can be adapted to the case where the unmeasured inputs are neither white noise nor stationary processes, as in the case at hand, and consistently the term $1/A(z)$ can be interpreted as the model transfer function.

In the present work, a Matlab environment [29] is adopted for delivering a self-implementation of the numerical analyses with the ARMA models. When dealing with real structures, the physical system is well approximated by a multi-variable output system, but the fit of the model gets worse when more outputs are included. If there are difficulties obtaining good models for a multi-output system, it might be wise to model one output at a time. Generally speaking, it is thus preferable to work with state-space models in the multi-variable case, since it is easier to deal with the model structure complexity. An ARMA model configured in the state space was therefore considered, for the intended purposes.

The application of the ARMA model was performed on several sub-records of the time-compressed bridge response signals, selected according to appropriate criteria, e.g. based on high peak values, high rms values or local stationarity.

From the results of the ARMA processing, the following main remarks hold.

- The suspected non-stationarity of the recorded data looks confirmed and the resulting Frequency Response Functions (FRFs) turn out to be strongly dependent upon both time location and length of the processed record.
- For a non-stationary signal the use of the FRFs produced by the ARMA models is more suitable than the FRFs obtained by the averaging process of the full original record through the computation of the Power Spectral Densities. This is because the ARMA model permits the identification of parameters that accurately represent the time domain response of the system, resulting in a better fit for subsequent modal analysis algorithms, also on very short time-length samples (as in the case of single recorded transients).
- The FRFs obtained by the ARMA models can be fed as input to the sound algorithms for the subsequent modal analysis, such as the FDD.

Figure 4 depicts the FRFs achieved by the present ARMA implementation on two sub-records of the time compressed signals of the data recorded from Channel 2 in the central upstream side span of Brivio bridge [25]. When observing them, the difference between the FRFs is clearly visible. Specifically, Table 3 shows the peaks frequencies from Figure 4, where differences are similarly visible depending upon the processed part of the record.

In situations where the signals, such as those obtained from Brivio bridge, are highly non-stationary, it is recommended to apply the illustrated procedure to each individual transient signal. This approach allows for a more refined frequency analysis, resulting in the acquisition of Frequency Response Functions that can be used for a more accurate modal analysis.

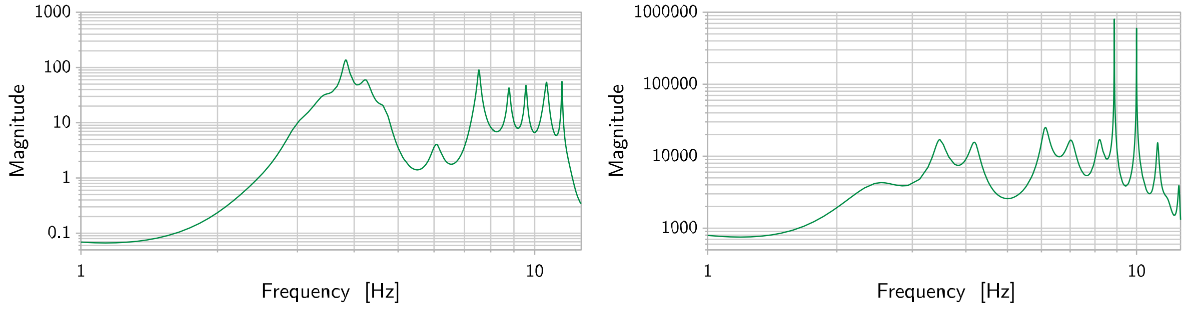

Figure 4. Magnitude plot of transfer function $(1/A(z))$ for ARMA in the subspace model, Channel 2, Span 2, upstream side: (a) first half of the signal (750 seconds); (b) second half of the signal (750 seconds).

Table 3. Peaks frequencies of the transfer function $(1/A(z))$ for ARMA in the subspace model, Channel 2, Span 2, upstream side, for the first half of the signal (Figure 4(a)) and the second half of the signal (Figure 4(b)).

[Hz]	1	2	3	4	5	6	7	8	9	10	11	12
Fig. 4(a)	3.83	4.23	6.07	7.53	8.78	9.57	10.62	11.49	13.55	17.35	19.08	19.78
Fig. 4(b)	3.48	4.18	6.13	7.02	8.87	–	10.00	11.20	–	–	–	–

4. Conclusions

The combination of consolidated statistical signal processing analyses with advanced techniques herein presented provides a devoted methodological procedure to extract reliable structural properties of current condition assessment toward Structural Health Monitoring and intervention purposes, outlining a robust and efficient management monitoring platform.

The considered approaches and whole methodology are validated on the specific case study of Brivio bridge (1917), as discussed in contribution [25] and in this paper. The presented results allowed to derive effective observations regarding the current structural behavior of the bridge, while the study of the devised methodology shall highlight its general applicability with reference to other structural configurations as well.

The current research on such a specific case study has recently focused on the application of the TDC method and the ARMA method in an attempt to enable the employment of identification methods regardless of whether the excitation may be assumed to be a White Noise process or not. Specifically, in the first attempt here reported, the application of TDC to original acceleration acquisitions did not alter the signals, neither in terms of frequency content nor from a statistical point of view. The benefit of data compression is confirmed, although it does not seem to have altered the non-stationary characteristics of the signal, at least in this application to the Brivio bridge case study. The application of the ARMA method has confirmed the non-stationarity of the recorded data, as the resulting Frequency Response Functions (FRFs) turn out to be strongly dependent upon both time location and length of the processed record. Nonetheless, this approach yields FRFs that are more suitable for post-processing the acquired signals, compared to those obtained by averaging the entire original recording through the computation of the Power Spectral Densities. These improved FRFs are proposed as an optimal solution, from a theoretical standpoint, in the case of non-stationary input signals, making them highly applicable even when working with short-duration samples such as single transients.

Applications of the ARMA models are currently envisaged, as described above, toward the above mentioned specific scopes, and more generally for the investigation and interpretation of the behavior of civil structures via signal processing analysis.

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