Big Data Fractal Analysis for Structural Health Monitoring

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Abstract
The article presents the new fractal analysis of data in the output of automatic Structural Health Monitoring System. The technique displays much better recognition ability of defected zones in the object under monitoring, than simple thresholding technique, usually used for damage prediction. New technique also involves possibility to detect at early damage stage the defects, incipient in the construction's area free of sensors.

Keywords: Structural health monitoring, pattern recognition, multi sensors data, fractal analysis

1. Introduction

Structural Health Monitoring (SHM) is the next step after NDT to provide the safety of complex objects and constructions. While the smart sensor technology is making progress very quickly, the principles of processing of big data, which appear on the output of SHM systems (SHMS), in order for automatic decision making is mostly very primitive. Usually it reduces to the thresholding of current data from sensors over some ultimate values given by designers. The next step should be the extraction of latent information, hidden in current data, from output SHM measurement results and reconstruction of object’s pattern, which characterizes the object’s safety.

There exists a big difference between perceived sensory system signal and its interpretation. In living systems, the signal is perceived by the sense organs, and analyzed and interpreted by the brain of an animal or human. The separation of sensing and interpreting is due to differences in biophysics of sense organs and brain, respectively. Mathematically speaking, if the effects of external stimuli on the sensors is a forward problem, the problem of reconstructing a pattern of danger and risk assessment given measured signals, is inverse one. In animals, this inverse problem solution occurs at the level of "sensation, perception and representation" (I.P.Pavlov). At the root of recreating the pattern of danger there are their cognitive abilities, without which a complete safety system is incomplete. In technical systems where the sensor signals are evaluated quantitatively, the restoration of a danger pattern must be performed by solving the inverse problem using a priori information from past experience. From the standpoint of the Zellner theorem [1] of an optimal signal processing, reconstructed patterns could be optimally obtained from the corresponding input data using the inverse problem solution in a Bayesian formulation. In this presentation we consider the final goals of SHM systems: search for damages and defects in the construction, as well as risk assessment of direct and indirect consequences (a consecutive damage, such as collapse), given measurement multi sensors big data.

2. Basic formulation and situational modeling

Two of the analytical methods to achieve these goals are discussed in this paper. The base system of an object (BSO) is represented as a Markov chain of states, the transition between them is under the influence of various factors and occurs with a certain transition probability, which is estimated previously at the stage of situational modeling. Interaction of SHMS with
BSO is shown in Figure 1. In BSO a dangerous state \( A_r = \{ A_r^k \} \) - where \( r \) - index system state, \( k \) - number of the system element, can appear, while a SHMS displays an instantaneous set of multi sensors measurement results: \( B_q = \{ B_q^i \} \) with \( q \) - index state of instantaneous multi

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\min: -\log P(A_r | B_q) = -\log P(B_q | A_r) - \alpha \log P(A_r) : \{ A_r \in R^k \}
\]

(1)

\( P(B_q | A_r) \) - conditional probability of obtaining a set of sensor data given risky measurement result; \( P(A_r) \) - a priori probability of a risk of damage, \( \alpha \) - regularization factor.

From the first term right in equation (1) it follows the requirement for: a) situational modeling of BSO, b) sensor accuracy enhancement and c) zero state specification. Also the pre-estimate of the probability of dangerous condition and the value of regularization factor follow from considering of the term \( \alpha \log P(A_r) \). Thus it is necessary to increase the likelihood of measured data with some qualitative penalty function implied on the behavior of transition pdf, e.g., smoothness, positivity, total variation, etc.
3. Big Data Fractal Analysis in the output of SHMS

To simplify the above approach, consider the output SHMS data in the rectangular matrix form $A_{MN}$ with the column vector $A_{mN}$ and row vector $A_{nM}$, where $M$ is the number of sensors, and $N$ - number of simultaneous measurements by all sensors at once: $N \gg M$. Usually the threshold analysis is applied to matrix's data to find a state of danger in SHMS, the last is being identified when the value exceeds the ultimate value, e.g. stress, given by designer. During the monitoring process the changes in matrix's term values even in a state of upcoming danger are much smaller than ultimate values. Thus they are being unnoticed and missed within automatic data processing cycle.

The above numerical model formulation means the transformation from $k$-dimensional space of SHMS's parameters values to $mn$-dimensional space of measuring parameters: $B = f(A); R^k \rightarrow R^{mn}$. The new approach consists of using monitoring history (archives) to predict an approximate numerical model. In principle the following known algorithms can be used:

1. Linear and non-linear regression analysis: $a_m = \sum_k b_k (1-d_{k,m}) + \eta_m$;
2. Modeling using latent variables $D$ and transformation function $F$: $A_{mn} = D_{mn}F$;
3. Principal and Independent Component Analysis, PCA and ICA as methods for dimensionality reduction;
4. Method of quickly calculated metamodels with Radial Basis Functions: $f(A) = \sum_{i=1}^{N} q_i \phi((X - X_i))$, dependent only on the Euclidean distance between two variables.

The proposed fractal analysis assumes that in a long measured data matrix one has to sort out the first rectangular square matrix $M\times M$ and to calculate its first eigenvalue. Then by one step shogging the next $M\times M$ matrix is sorted out and analysed for its first eigenvalue, $E_j$ and first value of eigenvector, $V_j$. The procedure is then repeated up to the last measured column. So the scale (fractal) for evaluating of all the time filled up rectangular matrix is square $M\times M$ matrix. The number of such steps and final diagram's points number is thus $(N-M)$. At each monitoring process step one has gets two functions: $E_j(t)$ and $V_j(t)$, which are analyzed in competition with simulated functions $\hat{E}_j(t)$ and $\hat{V}_j(t)$ respectively. Figures 2 and 3 illustrate the application of the above described analysis to the simulated data, in which there are small clusters, exceeding the mean value of the initial matrix only by 10%, what is more than 2 times less, than the variance of the random values in the matrix. The initial matrix was 10x180, filled with the random values in the range 110 ÷130. In the 1-2 rows the random values were raised by 10% starting from column 30 to 100, while in the rows 70÷140 the values were decreased by 10%.

The results are shown in the figures 2 and 3. It is seen that the automatic tracing for changes of the initial matrix's elements values is ambiguous due to the large dispersion of measured data, while the identification of "defected" zones with eigenvalues and eigenvectors are significant.

4. Conclusions

The proposed fractal analysis of big matrix data, arose in the output of automatic SHM system, display much better recognition ability of defected zones in the object under
monitoring, than simple thresholding technique. Admissible values for eigenvalues and eigenvectors should be estimated at the design stage by including the acceptability of indirect consequences and collapses after small damages in the construction. New technique also involves possibility to detect incipient defects at early damage stage.

Fig.2. Elements of simulated matrix's values with two exceeding and decreasing groups of "defected" zones respectively by 10%, comparing to the matrix range of about 20%.

Fig.3. (Overhead): variation of the two eigenvalues' first elements: 1-regular matrix, 2- matrix with "defected" zones; (lower): variation of eigenvector's first elements.

References