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Vibration-based structural health monitoring: Challenges and opportunities

M.P. Limongelli
Politecnico di Milano, Milan, Italy

ABSTRACT: In the last twenty years vibration-based methods for Structural Health Monitoring (SHM) have received increasing attention by both academics and operators, due to undoubtable advantages they provide for damage identification purposes. These are mainly related to the capability of providing continuous information about the global state of the structure without a prior knowledge about the location of possible damages and without the need to access the damaged portion of the structure. These methods rely on the fact that a damage inducing a loss of stiffness results in a change of the dynamic behavior therefore, structural responses to forced or ambient vibrations can be used to retrieve information about these changes. Despite the large amount of literature published on these methods, their experimental validation is often limited to highly controlled laboratory conditions or numerical simulations. The validation of the algorithms on real damaged structures is often hampered by the unavailability of data and this constitutes indeed a challenge for the implementation of these techniques at the operational level. In the first part of this paper the possible drawbacks related to the effect of uncertainties related to the effect of environmental sources, noise in hardware systems for the acquisition and transmission of structural responses and approximations in the adopted models. Another aspect that has slow down the practical diffusion of these methods, and generally of SHM techniques, is the difficulty to quantify their benefits prior to their implementation. This has sometime restraint the operators from investing on them, despite the several advantages these systems offer in terms of maintenance optimization and emergency management. In the paper some recent research efforts on several aspects related to the development and implementation of these methods are illustrated.

1 INTRODUCTION

The general purpose of Vibration-Based Method (VBM) for Structural Health Monitoring (SHM) is to monitor the performance of structures using their response to vibrations recorded using permanent networks of sensors. This enables to follow the structural performance so that that efficient remedial actions to counter deterioration, damage, extreme loads and unintended use may be identified and implemented in a timely fashion, before they pose a threat to the structural integrity, or reduce the functionality of the asset.

Vibration-based damage identification methods allow assessing structural damage states mainly induced by stiffness losses. One of the major advantages of these methods is the possibility to detect damage at a global level, using sensors not necessarily deployed close to the – unknown – location of damage. Different levels of refinement in the identification of damage are possible, depending on the amount of information provided by the recorded responses.

Detection, that is the identification of the existence of damage, might be possible based on a single sensor able to capture meaningful characteristics of the structural response, e.g. the natural frequencies of the modes sensitive to damage.

Localization requires a higher number of sensors deployed at several locations along the structure.

The assessment of damage, that is the estimation of its severity, usually necessitates a finite element model that allows to map the responses recorded on the structure to different damage types and scenarios through the physical model of the real structure.

The main idea behind Vibration-Based Methods (VBM) for damage identification is that losses of stiffness affect the dynamic behavior of the structures, therefore they can be identified through analyses of the changes of the modal parameters between the current and a reference state. It is noted that VBM are not indicated to identify damage due the strength reduction unless a correspondent reduction of stiffness is caused.

The structural response to ambient (e.g. due to wind or traffic) is measured and used to extract 'damage features', that is parameters sensitive to damage that can be, for example, modal or operational parameters. The variation of one or of a combination of several of these parameters is assume as damage indicator. In literature have been proposed both model-based and response-based methods to perform damage identification (Limongelli et. al 2016).

Model-based methods use finite elements (FE) models, updated using measured responses. Usually in a first phase the model is calibrated using the response of the structure in the reference state. The parameters of the model are corrected so that the simulated responses agree with the test results.

Usually the objective function is defined in terms of the difference between the analytical and experimental results and minimized by adjusting the parameters of the FE model. In the 'inspection phase' the calibration of the FE model is repeated and new values of the model parameters are computed. In reference (Mottershead & Friswell 1993), is reported a survey of Vibration-Based Methods to update FE models. In order to overcome the problems related to the large computational effort related to the update of FE models, several approaches based on substructure methods, neural networks or surrogate models have been proposed. (Fang & Perera 2009, Gao et al. 2012, Torkzadeh 2016).

An alternative to model-based methods are the so-called response-based methods that, instead of physical (FE) models use models based only on the measured response of the structure.

Damage-sensitive features are extracted from measured data and their changes between the current and the reference states are used to identify damage. Several vibration-based methods that rely only on recorded responses have been proposed in literature. In references (Fan & Qiao 2011) a comprehensive survey is reported.

Comparing the two families of methods– response-based and model-based – two main differences emerge: model-based methods are more demanding due to the need of building and updating the numerical model. However, they allow a more detailed description of damage, including also quantification and prognosis. For prognosis, of course, a forecast model of the degrading processes is needed. Response based methods are easier to implement for real time damage identification, but usually limited to damage detection and localization.

2 CHALLENGES

Despite in the last decades a large research effort has been devoted to VBM and a number of successful applications have shown their efficacy for the monitoring of the structural health, their large-scale implementation for continuous monitoring is still challenged by practical and theoretical issues that still need investigations.

2.1 *Uncertainties*

A first issue is related to the accurate computation of the damage features. In real world conditions, due to several sources of epistemic and aleatory uncertainties, the vibration-based damage features can exhibit changes even if no damage occurs.

2.1.1 *Influence of environmental and operational sources*

Modal parameters, often used as damage features, may be affected by environmental or operational variability. It has been shown that variations of temperature and humidity (moisture content) can induce daily or seasonal variations of the modal frequencies that easily exceed 5%–10% (Peeters & De Roeck, 2001). Therefore, changes of the damage features due to temperature can mask or mistakenly denounce damage.

Operational variability due to traffic (mass and velocity of vehicles, may also induce variations of the modal parameters higher than 5% (Kim et al. 2012) particularly for bridges with small mass ratio between the structure and the vehicles.

In order to avoid mistakes in the identification of damage, either the effects of environmental and operational variability must be eliminated from the measured responses, or damage features not affected by these sources should be considered.

Several techniques based on regression models or pattern recognition have been proposed in literature to remove the effect of temperature.

Regression models can be used when data about the variability of the sources (e.g. temperature or traffic) are available. Information on the inputs may be extracted by deploying a small number of sensors tracking environmental agents or traffic/train crossing loads, along with the array of vibration sensors monitoring structural response.

In these cases, linear, multilinear or polynomial (Ding et al. 2011) regression models are fitted to the variable relationship. If data about the environmental or operational sources are not available, output-only methods (unsupervised learning) must be used.

These methods aim to eliminate the influence of operational factors based on measured responses and/or extracted features (Kullaa 2011). Methods such as the Principal Component Analysis (PCA) (Magalhães et al 2012) or its nonlinear ramifications (kernel PCA, Factor Analysis) have been employed to solve the problem. These methods search and discard patterns thus revealing the influence of the unobserved input variables.

Operational sources of variability include mainly traffic for bridges, moving machines (as lifts) or users for buildings. Due to the relevant variation of the mass, modal parameters can change, leading to a wrong identification of damage in a healthy structure. Velocity and number of vehicles can be another source of variation of modal parameters (Brady, 2006, O'Brien 2009) that can hamper a correct identification of damage.

2.1.2 *Instrumental uncertainty*

Beside the already mentioned environmental and operational sources of variability of the damage features, other sources of uncertainties are due to instrumental errors.

Measured accelerations can be affected by systematic errors related to the characteristics and implementation of the monitoring hardware: accelerometers, data acquisition system (DAQ) and cables.

These can be errors related to the characteristics of the sensors (cross sensitivity, low ratiometricity, sensitivity to temperature) or related to the implementation (calibration, mounting, alignment) and bias error. Systematic errors affect uniformly all the recorded signals and specifically their accuracy, that is their capability to provide a measurement close to the real value. Systematic errors can be removed by calibration of the instrumentation.

Measured signals are also affected by random errors introduced by the precision of the sensors, intended as their capability to provide equal values for repeated measurement of the same quantity.

Precision depends mostly by instrumental noise that determines the minimum resolution of the sensors, that is the smallest detectable variation in acceleration.

It is possible to reduce both types of uncertainties by choosing high-performance sensing, acquisition and transmission devices and accurately installing them however the investigation of methods to reduce the effect of noise through processing or measured data is the focus of several research groups (see for example Yue 2015, Liu 2016)

2.1.3 *Model uncertainty*

Model uncertainty depends on the mathematical model that is used to relate the measured quantity (e.g. acceleration) to the damage feature,

It includes errors due to signal processing, (for example signal truncation when dealing with assumed infinite length of the recorded signals), errors due to the assumptions connected with the mathematical model (for example that the excitation is a broadband stochastic process - white noise - not strictly and always verified in case of ambient vibrations), errors due to non-linear structural behavior whenever this is not accounted for in the considered model; errors included by the necessary simplifications related to the representation of the structure through a finite element model.

Most of these uncertainties can be reduced if large set of measures can be collected on the structure.

2.2 *Validation on real benchmarks*

One of the main issues in the research field of VBM is the validation on real structures of the algorithms proposed by researchers.

The number of monitored structures is still quite low and usually, due to economic constraints, a small number of sensors is deployed on them.

Beside this, many of the instrumented structures have never experienced damage and, in some cases, even if data exist, they are not freely available for research purposes. Due to all these facts, the algorithms proposed in literature for damage identification are often verified using data simulated using numerical models or scaled laboratory specimens tested under controlled conditions and damage artificially simulated.

These conditions eliminate several sources of uncertainty that, as mentioned in one of the previous sections, can severely affect the performance of damage identification algorithms. For this reason, many of these method and the relevant damage indicators, cannot exceed a value of the Indicator Readiness Level, IRL = 6. (Limongelli & Orcesi, 2017, Limongelli et al. 2018) The maximum value of this index is IRL=9 for methods and indicators that can be routinely employed for quality checks of structures.

In the last years, several forced and/or ambient vibration tests have been performed on full scale structures artificially damaged for research purposes.

Data have been recorded using quite dense networks of sensors and made available to the scientific community. Some examples of benchmark on forced vibration tests on damaged structures are reported in references (Farrar & Cone 1995, Moaveni et al 2010, Dilena 2014).

wo examples of ambient vibrations tests on a damaged bridge are reported in references (Reynders & De Roeck 2015, VCE 2009, Sirigoringo et al 2013). In these cases, damage was artificially inflicted through progressive cuts of one structural element (e.g. a pier or a beam) or of the prestressing cables.

Therefore, even if these cases are much close to real conditions with respect to a numerical model with simulated damage, they cannot be really considered real case studies.

Further research developments would largely benefit from the availability of responses measured on benchmark structures permanently instrumented with extensive sensor networks and exposed to natural degradation and damage.

2.3 *Return over investment*

Permanent monitoring systems are usually installed on strategic or landmark structures but suffer from non-scalability due to the not negligible cost of instrumentation devices, installation, and maintenance.

Further to this, the difficulty to estimate the return on investment before their implementation, creates some reluctance in the stakeholders - from owners and managers to sensors producers - to invest on these systems.

A further issue is related to the lack of incentives in the technical codes that usually do not allow to account for the presence of a structural monitoring system in the design of new bridges or in the retrofit of existing ones. Monitoring systems are thus perceived by stakeholders more as a cost rather than an effective benefit.

Recently the research project COST TU1402 on ‘Quantifying the Value of Structural Health Monitoring’ (Thons et al. 2017) has proposed a framework based on the concept of Value of Information from the pre-posterior Bayesian decision analyses, to support the cost/benefit analyses of a monitoring system before its deployment.

In this approach, the benefit associated with the information from monitoring is assessed for forecasted values of the monitored parameter.

An optimization problem is solved for each forecasted value to identify the actions corresponding to the lower risk (in this case lower cost/benefit ratio connected with the design of the monitoring system).

The risk corresponding to each forecasted value is established through probabilistic models (likelihood functions) accounting for the uncertainty associated with future performances of the monitored system and with the precision of the monitoring techniques (COST TU1402).

Accounting for the uncertainty connected with the forecasts, the final solution of the problem is chosen as the action corresponding to the minimum average cost, over all the possible forecasts, each weighted according to its probability of occurrence (likelihood functions).

One of the bottlenecks in the application of the preposterior analyses is the knowledge of the likelihood functions.

When the monitoring system is not yet installed, they can be inferred from data recorded on similar monitored systems, if available.

Also, in this regard, hold the remarks reported in the previous sections related to the importance of benchmarks of damaged structures to retrieve the distributions of the damage indicators in different structural states.

3 OPPORTUNITIES

3.1 *Sustainable management over life cycle*

The final aim of monitoring systems is to ensure an appropriate level of safety for users, maintaining the quality of the environment, as well as minimizing asset life-cycle costs. This concept spans a very wide range of activities which, through different technologies and algorithms, supply information about the performance of existing and new structures over their life-cycle.

Data gathered through acquisition systems are converted into information by the joint use of algorithms for data processing and models that relate the structural response to the structural state. Information can then support decisions about the asset management all over the life cycle, leading to the reduction of life cycle management cost, reduced use of non-renewable resources, increase of safety.

Data provided by monitoring must support the assessment of the structural performance of the monitored bridges under several loading conditions (both operational and extreme) and feed decision making procedures related to maintenance or emergency management.

The information that must be extracted from data and used for decision making, depend on the goal of monitoring. To this respect an important issue is the integration of the collected data into Bridge Management Systems (BMS) through the use of damage indicators obtained processing the measured data and that provide information about possible damage scenarios (Limongelli 2010, Dilena 2014, Domaneschi et al. 2016), or about parameters that can be used to calibrate performance models able predict the remaining service life of the bridge.

3.2 *Big data, machine learning, artificial intelligence*

An important issue related to data collected by permanent monitoring systems is that, even small systems, produce large amount of data.

The concept of 'Big Data' is described by 3Vs: Volume, Variety, Velocity that is large volumes of data from a variety of data sources are available at high velocity. The amount of data flow can be an issue for the storage and processing of data that can hardly be handled and interrogated using traditional techniques.

On the other hand, large amounts of data increase the chances to reduce the uncertainties and to have a reliable estimation of the damage features, provided a proper processing of these data is carried out.

Large amount of data may reveal correlations and dependencies that allow predictions of the future structural performance, thus fostering and informed and rational decision-making.

Thanks to improvements in sensing capabilities, processing power, storage capacity, software programs and quality of internet connections, the capability of capturing, collecting, sharing, storing and processing massive amount of data is steadily increasing giving the opportunity to take advantage of very large Volumes of a wide Variety of data collected and analyzed at high-Velocity.

Big Data can be supplied to Machine Learning (ML) algorithms that can 'learn' from data without having been explicitly programmed for that purpose. ML algorithms and statistical models detect patterns based on data mining, pattern recognition and predictive analysis.

With respect to traditional algorithms they are much more effective to deal with uncertainties, , in situations where large and diverse datasets (i.e. Big Data) are available.

Due to the large volumes of data, the analyses and the detection of the correlations and relationships between thee data might be prohibitive using traditional methods. Machine learning algorithms, such as for example Artificial Neural Networks, are based on the training of a model using available data (Farrar & Worden 2013). If data about different performances of a bridge are available (for example the response of the bridge in different damage states) 'supervised' algorithms based on regression, classification and pattern recognition, can be used.

If only data relevant to a reference state, for example the undamaged, are known, 'unsupervised' algorithms that detect deviations from the reference state, without providing further information about the damage state (e.g. type or severity) can be used.

Machine learning, together with pattern recognition and deep learning, are branches of the so-called Artificial Intelligence (AI) techniques that can be defined as the ability of a machine to mimic intelligent human behavior, seeking to use human-inspired algorithms to solve problems (Penadés et al. 2016, Amezquita-Sanchez et al. 2016).

All the aforementioned techniques aim to process recorded data in the most effective way in order to retrieve directly, or using numerical or analytical models, reliable, accurate and precise indicators of the structural state.

4 CONCLUSIONS

In this paper challenges and opportunities related to the use of vibration-based method for health monitoring of structures are outlined.

Challenges still exist related to the influence of uncertainties on the outcomes of SHM systems and to the difficulties related to the estimation of the return over the investment of such systems, before their installation. Both topics are the focus of intense research activities.

The availability of large amount of data allows to implement innovative techniques for their analyses thus reducing the effect of uncertainties and improving accuracy, precision and reliability of results.

This enables the optimization of maintenance interventions and of emergency management under natural and man-made hazard.

Several procedures and algorithms for damage identification have been proposed in literature but their performance has never been verified on real structures.

The availability of ambient vibration responses recorded on benchmark damaged or degraded structures would largely benefit the research efforts in this domain.

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REFERENCES

Amezquita-Sanchez J., Valtierra-Rodriguez M., Aldwaik M. & Adeli H. *Neurocomputing in civil infrastructure*. Sci Iran Trans C Chem Chem Eng 2016;23:2417.

Brady, S.P., O’Brien, E.J. & Znidaric, A. Effective of vehicle velocity on the dynamic amplification of a vehicle crossing a simply supported bridge. *J. Bridge Eng*. 2006, 11, 241–249.

COST TU1402. Memorandum of Understanding for the implementation of a European Concerted Research Action designated as COST Action TU1402: Quantifying the value of structural health monitoring. European Cooperation in the field of Scientific and Technical Research. *COST 059/14.*

Dilena M., Limongelli M.P. & Morassi A. (2014). “Damage localization in bridges via FRF interpolation method”. Mechanical Systems and Signal Processing, 52–53, pp. 162–180.

Ding, Y.L. & Li, A.Q. (2011). Temperature-induced variations of measured modal frequencies of steel box girder for a long-span suspension bridge. *Int. J. Steel Struct*, 11, 145–155.

Domaneschi M., Limongelli M.P. & Martinelli L., (2016) “Wind-driven damage localization on a suspension bridge”, *The Baltic Journal of Road and Bridge Engineering*, 11(1), pp. 11–21. doi:10.3846/bjrbe.2016.02.

Fan W. & Qiao P., (2011). Vibration-based Damage Identification Methods: A Review and Comparative Study. *Structural Health Monitoring*. Vol 10(1): 83–29 Fan W, Qiao P 2008. Vibration-based damage identification methods: a review and comparative study. Structural Health Monitoring; 10(1) p.83–29.

Fang, S.E. & Perera, R. (2009). A response surface methodology based damage identification technique. *Smart Mater. Struct.* 18, 065009.

Farrar C.R. & Cone K. M., “Vibration testing of the I-40 bridge before and after the introduction of damage,” in *Proceedings of the 13th InternationalModal Analysis Conference*, pp. 203–209, Nashville, Tenn, USA, 1995

Farrar C. & Worden K. (2013). Structural Health Monitoring: a machine learning perspective. J. Wiley & Sons Ltd.

Gao, H.Y., Guo, X.L. & Hu, X.F. (2012). Crack identification based on Kriging surrogate model. *Struct. Eng. Mech*. 41, 25–41.

Kim, C.W., Kawatani, M. & Hao, J. Modal parameter identification of short span bridges under a moving vehicle by means of multivariate AR model. *Struct. Infrastruct. Eng*. 2012, 8, 459–472.

Kullaa J. (2011). Distinguishing between sensor fault, structural damage, and environmental or operational effects in structural health monitoring. *Mechanical Systems and Signal Processing*, 25(8):2976–2989.

Limongelli M.P., (2010), “Frequency Response Function Interpolation for Damage Detection under Changing Environment*”. Mechanical Systems and Signal Processing*, 24, Issue 8, pp. 2898–2913.

Limongelli M.P., Chatzi E., Dohler M., Lombaert G. & Reynders E. (2016). Towards extraction of vibration-based damage indicators. *8th European Workshop On Structural Health Monitoring (EWSHM 2016)*, pp. 546–555. 5–8 July 2016, Spain,

Limongelli, M.P. & Orcesi, A.D. (2017) A proposal for classification of key performance indicators for road bridges. 2017; *IABSE 2017*, September 19–23, Vancouver, Canada.

Limongelli, M.P. Orcesi, A.D. & Vidovic, A. (2018). The Indicator Readiness Level for the classification of Research Performance Indicators for road bridges. 2018; *IALCCE 2018*, 28–31 October 2018, Ghent, Belgium.

Liu X., Jin B., Bai Q.Y., Wang D. & Wang Y. Distributed Fiber-Optic Sensors for Vibration Detection. *Sensors.* 2016;16:1164 doi: 10.3390/s16081164.

Magalhães F., Cunha A. & Caetano E. (2012). Vibration based structural health monitoring of an arch bridge: From automated OMA to damage detection. *Mechanical Systems and Signal Processing*, 28:212–228,

Moaveni B., He X., Conte J.P. & Restrepo J.I. Damage Identification Study of a Seven-Story Full-scale Building Slice

Tested on the UCSD-NEES Shake Table. *Structural Safety* 2010; 32(5), 347–356.

Mottershead, J.E. & Friswell, M.I. (1993). Model updating in structural dynamics: A survey. *J. Sound Vib*. 167, 347–375.

O'Brien, E.J., Rattigan, P., Gonzales, A., Dowling, J. & Znidaric, A. Characteristic dynamic traffic load effects in bridges. *Eng. Strucut*. 2009, 31, 1607–1612.

Peeters, B. & Roeck, G.D. One-year monitoring of the Z24-Bridge: Environmental effects versus damage events. *Earthq. Eng. Struct. Dyn*. 2001, 30, 149–171.

Penadés-Plà V., García-Segura T., Martí J.V. & Yepes V. A review of multi-criteria decision-making methods applied to the sustainable bridge design. *Sustainability* 2016;8:1295.

Reynders E. & De Roeck G. (2015). Vibration-based damage identification: The z24-bridge benchmark. *Encyclopedia of Earthquake Engineering*, M. Beer, I. A. Kougioumtzoglou, E. Patelli, and I. S.-K. Au, eds., Springer Berlin Heidelberg, 1–8

Siringoringo D., Nagayama T., Fujino Y. & Nagayama T. "Dynamic Characteristics of an Overpass Bridge in a Full-Scale Destructive Test". *Journal of Engineering Mechanics*, Vol. 139, No. 6, June 1, 2013. ©ASCE, ISSN 0733-9399/2013/6-691–701, (2013).

Thöns S. Limongelli M.P., Mandic Ivankovic A., Val D., Chryssanthopoulos M., Lombaert G., Döhler M., Straub D., Chatzi E., Köhler J., Wenzel H. & Sørensen J. (2017). Progress of the COST Action TU1402 on the Quantification of the Value of Structural Health Monitoring. *Proc of the IWSHM 2017.* The 11th International Workshop on Structural Health Monitoring. September 12–14, 2017, Stanford, California, USA.

Torkzadeh, P., Fathnejat, H. & Ghiasi, R. (2016). Damage detection of plate-like structures using intelligent surrogate model. *Smart Struct. Syst*. 18, 1233–1250.

VCE. Vienna Consulting Engineers. (2009). Progressive damage test S101. Flyover Reibersdorf. *Report nr. 08/2308.*

Yue H., Zhang B., Wu Y., Zhao B., Li J., Ou Z. & Liu Y. Simultaneous and signal-to-noise ratio enhancement extraction of vibration location and frequency information in phase-sensitive optical time domain reflectometry distributed sensing system. Opt. Eng. 2015; 54:047101. doi: 10.1117/1.OE.54.4.047101.