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Review on Vibration-Based Structural Health Monitoring Techniques and Technical Codes

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Abstract: Structural damages occur in modern structures during operations due to environmental and human factors. The damages accumulating with time may lead to a significant decrease in structure performance or even destruction; natural symmetry is broken, resulting in an unexpected life and economic loss. Therefore, it is necessary to monitor the structural response to detect the damage in an early stage, evaluate the health condition of structures, and ensure the operation safety of structures. In fact, the structure and the evaluation can be considered as a special symmetry. Among several SHM methods, vibration-based SHM techniques have been widely adopted recently. Hence, this paper reviews the vibration-based SHM methods in terms of the vibrational parameters used. In addition, the technical codes on vibration based SHM system have also been reviewed, since they are more important in engineering applications. Several related ISO standards and national codes have been developed and implemented, while more specific technical codes are still required to provide more detailed guidelines in practice to maintain structure safety and natural symmetry.

Keywords: structural health monitoring (SHM); vibration; frequency domain; time domain; time-frequency domain; technical codes

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1. Introduction

Civil engineering structures are usually designed to serve for 50 years to 100 years, during which they are expected to maintain structural integrity. Unpredicted and unexpected structure failure due to accumulated damages during design life may cause significant life and economic losses; therefore, structural health monitoring (SHM) is very important since it can monitor the structural response, evaluate the structural safety in real time and maintain structure safety and symmetry in nature.

SHM techniques have been developed for many years [1–10]. Generally, the vibration based SHM methods are the most widely adopted. The objectives of these SHM approaches are determining the existence of structural damages, identifying the location and severity of structural damages, evaluating structure safety, predicting the remaining service life of the structure, and making decision of the maintenance strategy, if possible. In fact, the vibration characteristics of a structure are a function of its physical parameters. Structural damage causes change in physical parameters of the structure, and change in physical parameters therefore can be used as an indicator of structure health condition. Through the signal monitored by the sensors installed on the structure, the vibration characteristics can be extracted and the corresponding change can be detected and analyzed. In addition, from the change of vibration characteristics, one can further obtain the change in the physical parameters of the structure to diagnose the structure health condition. Recently, with the rapid development of modern computer technology and the progress of sensor technology and signal processing technology, test signals can be accurately and quickly analyzed and processed. Therefore, vibration-based structural health monitoring technology has become a research hotspot at home and abroad.

Based on these techniques and recently developed IT and sensing techniques, many technical standards and codes on vibration-based SHM have been developed and implemented for engineering applications. For a SHM system that can be used in practice, it usually contains four parts or sub-systems: sensing sub-system, including both a fixed sensor system and a portable sensor, data acquisition and transmission sub-system composing of a data acquisition unit, data transmission network and corresponding software system, data management and control sub-system containing of data management software and control server, and structure performance evaluation sub-system including structural health assessment server, structural health assessment workstation, and corresponding software system.

Although SHM has become an important field in the development of civil engineering disciplines, related technical methods still need to be improved, and there is still a lack of complete technical standards and specifications for vibration-based structural health monitoring. It is difficult for engineers to design suitable SHM system for a given structure based on the existing codes because there is no explicit answer of what kind of sensors to be used, where the sensors to be installed, and how to evaluate the structure health condition by using monitored data. Therefore, this work aims to review both vibration-based SHM techniques and technical codes, and provide a certain reference for the application of technical methods and standard specifications for vibration-based structural health monitoring. In Section 2, the vibration-based SHM approaches are reviewed, and attention will be paid on the more recently developed ones due to the length limit. In addition, the advantages and drawbacks of each approach has been summarized. In Section 3, the developed technical codes including both ISO standards and national codes are reviewed, and the suitable situations that each code can be applied have been reviewed, which may help to find out most suitable SHM method for a given structure. In Section 4, the challenges and future development are discussed.

2. Vibration-Based Structural Health Monitoring Techniques

Generally, in terms of vibration parameters used, vibration-based structural health monitoring techniques can be classified into three categories: frequency domain, time domain and time-frequency domain approaches.

2.1. Frequency Domain Methods for Vibration-Based SHM

Modal parameters including frequency, mode shape, and damping are usually used in frequency domain methods for vibration-based SHM [11–15]. In addition, several Frequency Response Function (FRF) related parameters have also been widely adopted. Compared to time domain methods and time-frequency domain methods, the frequency domain methods can be used in more situations because the frequency domain properties of structure are more stable. Even if the structure is subjected to greatly different loading conditions, the extracted dynamic properties are almost the same, and they only depend on the structure itself. However, it should be noted that the algorithms to extract these properties are not easy to implement and sometimes time consuming.

2.1.1. Frequencies and Mode Shapes

Frequencies and mode shapes are the most frequently used modal parameters in SHM methods. When a structure is damaged, its frequencies usually drop accordingly. In particular, the lower frequencies drop slightly while higher frequencies drop a little bit significantly [16]. In addition, temperature change also affects the natural frequency of the structure. The importance of temperature effects for a damage detection method based on relative frequency shift of several weak-axis bending vibration modes of beam-like structures was investigated by Gillich et al. [17]. However, frequencies alone are not usually adopted to identify the local damage since they are global indicator and they do not contain location information. Therefore, they are usually used together with mode shapes, which contain location information and more sensitive to local damages. The extracted mode shapes during monitoring were compared to those measured at the undamaged stage, and the damage indices of MAC and COMAC were proposed to locate and evaluate the local damages:

$$\mathrm{MAC}\left(\varphi_i^{\mathrm{u}}, \varphi_i^{\mathrm{d}}\right) = \frac{\left[\left(\varphi_i^{\mathrm{u}}\right)^{\mathrm{T}} \varphi_i^{\mathrm{d}}\right]^2}{\left[\left(\varphi_i^{\mathrm{u}}\right)^{\mathrm{T}} \varphi_i^{\mathrm{u}}\right]\left[\left(\varphi_i^{\mathrm{d}}\right)^{\mathrm{T}} \varphi_i^{\mathrm{d}}\right]} \tag{1}$$

$$\mathrm{COMAC}\left(\varphi_i^{\mathrm{u}}(x_j), \varphi_i^{\mathrm{d}}(x_j)\right) = \frac{\left(\varphi_i^{\mathrm{u}}(x_j)\varphi_i^{\mathrm{d}}(x_j)\right)^2}{\left(\varphi_i^{\mathrm{u}}(x_j)\right)^2\left(\varphi_i^{\mathrm{d}}(x_j)\right)^2} \tag{2}$$

where φ_i^{u} and φ_i^{d} are the ith undamaged and damaged mode shape, x_j is the coordinate of jth point. It is observed that when φ_i^{d} exactly matches φ_i^{u}, the MAC value should be 1, hence a MAC value close to 1 indicates that the structure is still in good condition, but a MAC value greatly less than 1 means that the structure is damaged. Compared to MAC, COMAC has location information, the COMAC value at x_j close to 1 indicates that the structure is still intact at x_j and the COMAC value at x_j greatly less than 1 means that the structure has damage at x_j.

A lot of research [18–24] has been conducted to identify local damages by using both frequencies and mode shapes since they contain both global and local information of structures, and some improvements have also been proposed so that they can be applied successfully in practice. One direction to improve is to construct the baseline of structure mode shapes more accurately. Finite element (FE) model updating has been widely used for this purpose [25–27]. Conventional FE model updating was constructed for regenerating of baseline of frequencies and mode shapes. The frequencies and mode shapes obtained by FE model were compared to those measured by monitoring system to check the existence of local damages in the building. Then the stiffness matrix (usually, the mass matrix is not included) can be updated so that the updated frequencies and mode shapes can match the measured ones. Finally, the location and severity (stiffness loss) can be obtained by the updated FE model. In fact, the FE model updating can be generalized as a constrained optimization problem:

$$\min_{x_k} \left\| \sum_i w_i(\lambda_{FE,i}(x_k) - \lambda_i) \right\|_2^2 \; s.t. \; x_{lk} \le x_k \le x_{uk} \tag{3}$$

where $\lambda_{FE,i}(x_k)$ is the ith frequency or mode shape obtained by FE model using design parameters x_k, λ_i is the measured ith frequency or mode shape, w_i in the range of 0 to 1 is the weight factor, x_{lk} and x_{uk} are the upper and lower bounds on the kth design variable. There are several standard procedures to solve this kind of constrained optimization problem.

To reduce iteration times and increase computation efficiency, substructure techniques have been developed [28–35]. It divided the whole structures into several small substructures, each of which was treated independently. Then the substructures were assembled to regenerate the global structure by imposing interface constraints. Weng et al. [28] proposed a new iterative substructuring method, which can accurately obtain the eigen-solutions and eigen-sensitivities of structures. Li et al. [30] proposed a sub-structure damage identification method based on frequency domain dynamic response reconstruction, and verified it numerically and experimentally. Papadimitriou et al. [31] proposed the component mode synthesis technology, which can effectively re-analyze in the generalized coordinate space of the accurate component model calculated by using the reference finite element model and the characteristic interface mode. The substructure techniques are usually more effective than conventional FE model updating method since substructure is more sensitive to local damage. The FE model updating methods including substructure techniques are considered as a typical inverse problem in mathematics, where restraint and optimization algorithm are very important.

Constraint is important since FE model updating is generally ill conditioned due to less measurements than unknown parameters to be determined. Hence, the target function to be optimized should include an additional term leading to a convex error function, and the selection of regularization parameters should be determined by specific structures and experience. The Tikhonov regularization is frequently adopted [36–38], and it is proven effective for a lot of practical scenarios, but the identified size of damage is usually larger than expect.

In addition to conventional optimization algorithms, several advanced optimization algorithms proposed for artificial intelligence and pattern recognition have been adopted in vibration-based SHM approaches, such as genetic algorithm [39–43], artificial neural network [44,45], and particle swarm optimization [46,47] and Artificial bee colony algorithm [48,49], etc. Unlike conventional optimization techniques which require established model to optimize parameters, these advanced ones are model-independent. This is actually very helpful in vibration-based SHM system since the measured and monitored data are usually insufficient and contains significant uncertainties, which brings great difficulties in convergence when identifying parameters by conventional optimization methods. However, it should also be admitted that these advanced approaches have their own drawbacks, for example, the computation load of genetic algorithm is very high since it is a global optimizer. In fact, for different types of structures, different optimization techniques should be considered due to various degree-of-freedoms; unfortunately, there is no common sense on how to select the optimization algorithms based on the type of structures.

Recently, machine learning methods become more popular due to the quick development of artificial intelligence [50–58]. It can definitely help to improve the reconstruction of structural model, but the model is a data-driven model rather than the physics-based model in FE model updating methods. Generally, the machine learning methods contains three steps, data acquisition, feature extraction, and feature classification, which are also the most important steps in pattern recognition. Frequencies and mode shapes are usually obtained during data acquisition and pre-processing as input of these algorithms. Feature extraction may depend on "model", which means that the features of undamaged "model" and damaged "model" should be labeled artificially during the training process. Then the algorithms are trained by the labeled data to generate the classifier. This is also known as supervised learning, and artificial neural network, convolutional neural network, and supported vector machine, etc., are the most typical ones. Actually, these methods are quite useful in real vibration-based SHM systems since it does not require regeneration of physics-based models of structures; therefore, it has great potential in the future application. However, it should be noted that there is a huge amount of data to be labeled during the training process, which costs a lot of manpower.

Bayesian methods [59–63] have been proposed and developed to reduce the influence of measurement noise and model errors on identifying local damages, since deterministic methods may fail when the change of frequencies and mode shapes due to damage is concealed by measurement noise or model errors. Bayesian methods use prior information from experiments and experience to construct the posterior probability of uncertainties and identified and evaluated damages accordingly. They are typical probabilistic methods, and they can even help on ill-conditioned inverse problems since they introduce a regularization term by using the probability distributions of uncertainties. However, it is noteworthy that prior information is very important in Bayesian methods, if the prior information is not accurate enough, the damage identification may fail even though the measurement is noiseless and model is perfect. In fact, the Bayesian probability of parameters θ under a given structure response $\mathbf{R}$ is as follows:

$$p(\theta\,|\mathbf{R}) = \frac{p(\mathbf{R}\,|\theta\,)p(\theta)}{p(\mathbf{R})} \tag{4}$$

where $p(\mathbf{R}\,|\theta\,)$ is the posterior joint probability distribution of the structure response under the condition of θ, $p(\theta)$ is the prior probability distribution of θ, $p(\mathbf{R})$ is a standardized constant, and $p(\theta\,|\mathbf{R})$ is the posterior joint probability distribution of θ under the condition of $\mathbf{R}$. It should also be noted that the integral value of $p(\theta\,|\mathbf{R})$ equals to 1.

In practice, the sampling data for generating prior distribution is usually sparse which makes the task difficult; therefore, sparse Bayesian learning [64–69] has been proposed to construct parameterized prior which can accurately construct the prior distribution based on sparse data. Several investigations have been conducted to show the feasibility of Bayesian methods on SHM by using frequencies and mode shapes, however most of which used lab-scale experiments and numerical simulations. Further studies are expected to show the applicability of Bayesian methods on real structures.

The other direction to improve is elimination of the dependency of the baseline or the undamaged model of structures. An assumption was proposed for this purpose: the mode shapes and mode shape curvatures are smooth and no sudden change with respect to location can be found for undamaged structures [70–73]. Once the sudden change of mode shapes or mode shape curvatures is observed, it is believed that the local damage occurs there. It is also proven by some studies that the mode shape curvatures are more sensitive than mode shapes on local damages, especially for early-stage damages. However, the extraction of mode shapes from accelerations or displacements is usually polluted by noise, and the mode shape curvatures obtained by central difference on mode shapes are even less accurate, resulting that the sudden change of mode shape curvatures due to local damages are covered by numerical error. Hence, how to improve the accuracy of mode shape curvature during monitoring should be investigated. On the other hand, the machine learning methods may also be independent on "model", which means that the features from undamaged "model" and damaged "model" do not need to be completely labeled, and the algorithms themselves can identify can classify the features. This is what is called "semi-supervised learning" [58,74] and "unsupervised learning" [75,76]. It is attractive but the identification accuracy needs to improve significantly, otherwise the false alarm will be issued unexpectedly and frequently.

2.1.2. Damping

Although damping can also be used for SHM system to monitor the health condition of structures [14,77–81], it is less frequently observed in practice than frequencies and mode shapes since it is more difficult to measure. Frizzarin et al. [77] analyzed the damping by using ambient vibration data to detect damage without baseline, and demonstrated the proposed method by a large-scale concrete bridge model with seismic damage. Mustafa et al. [78] introduced an energy based damping evaluate approach to evaluate the health condition of a truss bridge by numerical simulations. Cao et al. [79] compared damping based damage detection methods by using reinforced concrete structures and fiber reinforced composites, and clarified the factors that influenced the capability of damping on damage detection. Recently, Liu et al. [14] proposed a novel complex eigen-parameter identification method to evaluate the stiffness reduction and damping defect simultaneously on a non-classically damped shear building.

Ideally, the damping change due to local damage can be observed because the cracks may increase the frictions between interfaces. However, the measurement is vulnerable to noise, especially for structures subject to ambient environmental vibrations, so that the change of damping due to local damage is concealed by the measurement error. On the other hand, the damping model is difficult to select or construct whereas which is important in identification of damping. Classical Rayleigh damping which is a combination of mass and stiffness is frequently adopted in practice because it is the simplest damping model. However, it cannot be applied to many structures; therefore, some more advanced damping models have been proposed. It should be noted that for different types of structure, different damping models should be considered. Moreover, damping is a global property for a structure, similar to frequency, so damping itself can hardly be used to identify the location of local damages.

2.1.3. FRFs and Related Variants

FRFs are actually an extension of conventional modal parameters, because they contain the information over the entire frequency range. For different types of structure, the optimal frequency range may be various, which is highly dependent on experience and trial experiments. There is lack of theoretical analysis and numerical simulation investigations of how to select the sensitive frequency range to local damages for different structures. Operational deflection shapes [82–85] and their curvatures, power spectral density [86–88], frequency shift curve, and its curvature [89,90] are the most frequently used FRFs related variants.

FE updating methods can be applied to FRFs and related variants [91]. Conventional FE updating methods are effective in identifying local damages but have lower computational efficiency. Unfortunately, there are less investigations on applying substructure techniques, advanced regulation algorithms and optimization algorithms to FRFs and related variants, because it is difficult to select the sensitive frequency range for a given structure and it is also difficult to converge due to uncertainties in the measurement of FRFs.

Machine learning methods can also be applied to FRFs and related variants [92–94]. Conventional FRFs are curves which can be represented as one-column vectors, hence artificial neural network is suitable for identifying local damages by using FRFs. Usually, principal component analysis is applied to FRFs first to extract the most important components, which are then used as input to artificial neural network. Fourier amplitude spectra is a 2D surface FRFs related variant [95], therefore, convolutional neural network can be applied to it to construct the SHM system. In addition to neural networks, the Dirichlet process clustering [96] can be applied to SHM system to identify early-stage damages on bridges by using FRFs. However, these investigations have been conducted through numerical simulations and lab-scale experimental studies. Whether these machine learning methods based on FRFs and related variants are still effective should be further examined by field measurement. It should also be noted that since the quality of dataset for training is crucial for machine learning methods, therefore, the performance of these methods should be further examined when more FRFs data are available.

2.2. Time Domain Methods for Vibration-Based SHM

Instead of extracting the frequency related properties from the time history of dynamic responses of a structure, the dynamic responses of a structure in time domain can be used for SHM directly. Among them, acceleration and displacement are the most frequently used. The time domain methods usually do not require much calculation resources and therefore are timesaving, but they are used for the structures subject to stabilize environmental excitations because different excitation may cause quite different dynamic response and may cause the methods to fail to identify damages.

2.2.1. Accelerations

FE updating methods can be applied to accelerations for SHM [97], similar to frequencies and mode shapes. Tikhonov regularization [98,99], adaptive Tikhonov regularization [100], and L1 regularization [101] were successfully used to identify local damages based on accelerations. However, the dataset of time history of accelerations is much larger than the dataset of frequencies and mode shapes, hence the convergency is difficult to achieve. Moreover, there is no proven procedures on how to select the certain time history of accelerations, which is now generally dependent on experience.

Machine learning methods can also be applied to accelerations and variances for SHM [102–108], including both supervised and unsupervised methods. Although research showed that the machine learning methods can locate and evaluate local damages successfully in lad-scale experiments and numerical benchmark studies, no evidence have been provided that they can also be applied to real structure in practice. On the other hand, unlike frequencies and mode shapes which are only dependent on the structure itself, the accelerations are highly dependent on environmental excitations. The environmental excitations are always varying with respect to time, therefore it is quite difficult for the training algorithms in machine learning methods to differentiate the change of accelerations due to local damage and that due to environmental excitations.

Bayesian methods are also applicable when accelerations are used [109,110], and they show great potential in application to real structures. Research work has been conducted through experimental and numerical study. It should be noted that since the prior information is important to the Bayesian methods, hence the change of operational conditions should be considered carefully. For example, the traffic load of a bridge may increase with the economy development, therefore the prior information constructed previously may change with respect to time.

Statistical time series methods [111,112] are proposed especially for time history of dynamic responses, which usually fit time series models such as autoregressive model, autoregressive with exogenous model, and Mahalanobis squared distance, etc. All of them show their distinguishing advantages, but they still have their own limitations. For autoregressive model and autoregressive with exogenous model, it is difficult to determine the model order, which is currently highly dependent on experience. For Mahalanobis squared distance method, the data from the undamaged structures under various conditions is required, which is almost impossible for old building and structures. Statistical moment of accelerations can also be used to identify local damages of structure, Yang et al. [113,114] proposed a fusion of statistical moments by combining the fourth-order statistical moment of displacement with the eighth-order statistical moment of acceleration for the damage identification of structures. However, the order of moment to be selected is highly dependent on experience since different structures may have various statistical moments sensitive to damages, which limits the widely application of statistical moment. Temperature also plays an important role in SHM approach in time domain. Hios et al. [115] proposed a new stochastic global model method based on statistical hypothesis testing, and determined a functional hybrid model that can describe temperature-dependent dynamics. OBrien et al. [116] used temperature data to validate damage indicators based on measured data collected under uncontrolled traffic conditions, and showed that temperature can be used as a proxy for damage since stiffness of concrete structure is dependent on temperature.

2.2.2. Displacements

Generally, the methods that can be applied on accelerations can also be applied to displacement [117]. However, the displacement is usually not directly measured during monitoring [118]. In principle, acceleration measurement can be doubly integrated to give displacement, but this process is notoriously error-prone due to unknown initial conditions such as integration constants and low frequency noise of measurement that is amplified in an inverse square manner. In reality, the displacement at the measured location can only be recovered from field measured acceleration in an approximate sense, depending on the frequency characteristics of the contributing activities.

In the SHM system, one strategy to resolve the issue of unknown initial conditions makes use of the basic fact in structural dynamics that initial condition effects decay exponentially with time. Thus, one can start the numerical integration process before the main event to be captured, so as to allow a 'burn-in' time for the (unknown) initial condition effect to die down to negligible level during the main event that matters. On the other hand, the presence of noise especially in the low frequency regime presents a major difficulty. In addition to amplification of low frequency noise during numerical integration, data acquisition hardware typically has 'pink' noise in the low frequencies, i.e., with PSD inversely proportional to frequency. Integrating the 'raw' measured acceleration will often lead to significant systematic over-estimation of displacement, in many cases a 'flying off' trace of time history. In particular, a constant error in the acceleration gives a linear trend in the velocity and a quadratic trend in the displacement. One basic strategy is to suppress the noise by a causal filter with parameters designed to significantly attenuate the frequency components in the data below and above specified cut-off frequencies. Acceleration data is filtered before numerically integrated to give velocity data, which is filtered again and then integrated to give displacement data. Filtering produces distortion in the acceleration data and hence the integrated displacement. This will need to be controlled and verified in the development of SHM system.

2.3. Time-Frequency Domain Methods for Vibration-Based SHM

In addition to time domain and frequency domain dynamic properties, the properties in both time domain and frequency domain can also be used for SHM due to the development of advanced time-frequency analysis. Compared to time domain and frequency domain methods, the amount of time-frequency domain methods is much fewer. The time-frequency domain methods are more powerful because it contains the information of stable frequency domain properties and can further show the change with time. However, it is admitted that they require a lot of calculation resources and space for data storage.

Short time Fourier Transform, Wavelet Transform [119], and Hilbert-Huang Transform [120] including empirical mode decomposition are the most widely used time-frequency analysis methods. Usually, only the measured accelerations or dynamic strains are required for these methods, and the high frequency components may change significantly once the local damage occurs. Therefore, it is not necessary for these methods to construct the undamaged model for the monitored structure. This is a very attractive advantage of these methods; however, it is noteworthy that the time-frequency methods can only locate the local damages but cannot evaluate the severity of local damages. Further investigations of applying time-frequency domain methods on real structures are expected in the near future.

3. Current Technical Codes Related to Vibration-Based Structural Health Monitoring

In this section, the current technical standards and codes related to vibration-based structural health monitoring are reviewed, including both ISO standards and national codes.

ISO has four technical committees related to building and construction: TC 59 (Committee on Architecture and Civil Engineering), TC 98 (Committee on Fundamentals of Structural Design), TC135 (Committee on Nondestructive Testing), and TC268 (Committee on Urban and Community Sustainable Development). TC 59 including its SCs has published 124 ISO standards of which 33 under the direct responsibility of ISO/TC 59 (Table 1), TC 98 including its SCs has published 23 ISO standards (Table 2), TC 135 including its SCs has published 97 ISO standards of which 1 under the direct responsibility of ISO/TC 135 (Table 3), and TC 268 (including its SCs) has published 26 ISO standards of which 10 under the direct responsibility of ISO/TC 268 (Table 4). The ISO standards published by ISO/TC135 are all about non-destructive testing, including detailed procedures of different non-destructive testing methods. They are not reviewed herein since they are more relevant to damage detection rather than SHM system.

In fact, the codes published by ISO TC 59 do not only specify the general principles to determine requirements of structural performance, but also provides a general approach to assess the structural safety based on structural performance. They are a very important framework of a SHM system, but they lack details on how to implement in real engineering projects. The standards published by ISO TC 98 focus more on reliability and show the requirements and procedures to assess structure health condition based on structural reliability. They also provide approaches and procedures to prepare national and organization codes. However, structural reliability is more abstract, and it contains more complicated mathematical models, which is difficult to be applied in real SHM projects. The regulations published by ISO TC 268 focus on smart building and sustainable development. They provide the foundation on how to construct smart community infrastructures. Of course, the SHM system is helpful to construct smart community infrastructures and maintain sustainable development. Therefore, they provide the future work scope for current SHM systems, but they lack more details on how to construct a SHM system for an existing building.

Table 1. Published ISO standards by TC 59's SCs.

Subcommittee	Subcommittee Title	Published Standards	Standards under Development
ISO/TC 59/SC 2	Terminology and harmonization of languages	4	2
ISO/TC 59/SC 8	Sealants	30	14
ISO/TC 59/SC 13	Organization and digitization of information about buildings and civil engineering works, including building information modelling (BIM)	18	5
ISO/TC 59/SC 14	Design life	10	1
ISO/TC 59/SC 15	Framework for the description of housing performance	8	2
ISO/TC 59/SC 16	Accessibility and usability of the built environment	1	1
ISO/TC 59/SC 17	Sustainability in buildings and civil engineering works	12	3
ISO/TC 59/SC 18	Construction procurement	8	3

Table 2. Published ISO standards by TC 98's SCs.

Subcommittee	Subcommittee Title	Published Standards	Standards under Development
ISO/TC 98/SC 1	Terminology and symbols	2	0
ISO/TC 98/SC 2	Reliability of structures	8	2
ISO/TC 98/SC 3	Loads, forces, and other actions	13	0

Table 3. Published ISO standards by TC 135's SCs.

Subcommittee	Subcommittee Title	Published Standards	Standards under Development
ISO/TC 135/SC 2	Surface methods	14	2
ISO/TC 135/SC 3	Ultrasonic testing	24	3
ISO/TC 135/SC 4	Eddy current testing	7	0
ISO/TC 135/SC 5	Radiographic testing	26	0
ISO/TC 135/SC 6	Leak testing	4	0
ISO/TC 135/SC 7	Personnel qualification	7	1
ISO/TC 135/SC 8	Thermographic testing	4	2
ISO/TC 135/SC 9	Acoustic emission testing	10	3

Table 4. Published ISO standards by TC 268's SCs.

Subcommittee	Subcommittee Title	Published Standards	Standards under Development
ISO/TC 268/SC1	Smart community infrastructures	16	15

3.1. Standards Published by ISO/TC59

3.1.1. ISO 11863:2011

ISO 11863:2011 (ISO/TC 59/SC 15) [121], specifies the basic requirements and principles to determine and check the basic requirements of structural performance. This is very important to a SHM system since it can help to restrain the scope of the SHM system and select proper vibration parameters to be monitored. It also specifies the thresholds for capability, which is in fact essential for a SHM system since automated alert algorithm highly depends on the pre-defined thresholds. In addition, it provides guidelines on assessing the difference between designed and measured capabilities, which is helpful to generate the maintenance strategy in SHM system. However, it does not provide any detailed feasible procedures for any specific structures. Therefore, it is difficult to construct a SHM system for a specific building or structure by just following ISO 11863. For example, it requires "the threshold level is a minimum level of demand", but the statement is quite general because for different buildings or structural components the requirements may be quite different, hence it is difficult to be applied in real application directly.

3.1.2. ISO 15928-1:2015

ISO 15928-1:2015 [122] shows a general method on assessment of the structural safety performance of buildings, in which the principles on how to evaluate the design and construction of buildings are provided. It mainly focuses on the design and construction stage of buildings; therefore, it is helpful for generating SHM systems during construction. Although the idea of evaluating the structural safety performance of building during design can be shared in constructing SHM systems for operation stage, it should also be noted that design of building and design of monitoring system for building are quite different. Therefore, the evaluation processes outlined in this code cannot be directly used for design of monitoring system during operation. Moreover, it only shows that the evaluation "may be carried out by analysis, testing, service experience or a combination of the above" [120] without any details. The details of design of building provided in Eurocode 1-9, or other national standards are important supplementary standards, however they are not covering the design of monitoring system.

3.2. Standards Published by ISO/TC98

3.2.1. ISO 4356:1977

ISO 4356:1977 [123] establishes the basic principles that should be adopted when setting up national standards, regulations and recommendations for the deformation of buildings at the limit states of serviceability. Traditionally, measurement of deformation is usually considered as static measurement rather than dynamic measurement. However, recently developed signal processing techniques can be used to reconstruct the time history of displacement by integrating accelerations twice. In fact, deformation of structural components is quite important in monitoring; when the deformation approaches the threshold at limit states of serviceability, an alert should be issued by the SHM system. Although this code was drafted for the purpose of building design, it can also be used as guideline for design of monitoring system since it provides the basic principles to determine the deformations of buildings at the serviceability limit states, which can also be considered as the base for answering the critical question that how to evaluate the health condition of the building based on the monitored data.

3.2.2. ISO 13822:2010

ISO 13822:2010 [124] provides general requirements and procedures for the assessment of existing structures based on the principles of structural reliability and consequences of failure. Although it is applicable to the assessment of any type of existing structure of any material that was originally designed, analyzed, and specified based on accepted engineering principles and design rules, it only provides very general requirements and procedures without any specified methods. In addition, it mainly focuses on routine visual inspections, including visible deformations and surface defects like cracks and spalling, but limited information of vibration parameters is required in this code. There is no doubt that it is helpful to generate SHM systems of buildings. However, it is noteworthy that the regular inspection and real time monitoring is a little bit different, e.g., the former requires experienced technician while the latter depends on pre-installed sensors.

3.2.3. ISO 2394:2015

ISO 2394:2015 [125] presents a risk- and reliability-informed foundation for decision making of maintenance strategy by considering design and assessment of structures for the purpose of developing code. It is certainly helpful for building SHM systems by answering the critical question that how to evaluate the health condition of buildings based on the monitored data and how to plan maintenance strategy and build automated alert system based on evaluated condition. However, there is only the basic idea without any detailed procedures for specific buildings and the vibration parameters to be monitored.

3.3. Standards Published by ISO/TC268

3.3.1. ISO 37104:2019

ISO 37104:2019 (ISO/TC 98/SC 2) [126] provides general guidance on how to implement and maintain sustainable development management systems in accordance with ISO 37101 principles, which can be applied to cities and other forms of settlement. It should be noted that SHM is important for sustainable development since it can help buildings to extend their life. Therefore, this code should be paid attention to when designing the SHM system, so that the designed SHM system can fulfill the requirements of sustainable developments.

3.3.2. ISO 37105:2019

ISO 37105:2019 [127] specifies a descriptive framework for a city, including a structurally related basis for a city or community. When more buildings have installed SHM systems, it may help to generate sustainable cities. Therefore, this code should also be followed to achieve the objective.

3.3.3. ISO/TS 37107:2019

ISO/TS 37107:2019 [128], provides a top-level maturity model for Smart Sustainable Communities (MMSSC) which can be used for self-assessment of individual cities and communities. A simple way to assess community's maturity in adopting the good practices is sketched. In fact, with the development of IoT, the SHM systems can also be connected to form a network which may perform as an important of smart sustainable communities. Hence, this code is helpful for integrate multiple SHM systems in the future.

3.4. National Codes

Several national codes on SHM have been published in the past two decades. In North America, Intelligent Sensing for Innovative Structures of Canada published the first guideline for SHM, "Guidelines for Structural Health Monitoring" [129] in 2001, in which the techniques of both static and dynamic structural testing, periodic regular inspection, and continuous monitoring were presented and summarized. The Federal Highway Administration, U.S., published guidelines for SHM of bridges and tunnels, "Development of a Model Health Monitoring Guide for Major Bridges" [130] and "Tunnel Operations, Maintenance, Inspection, and Evaluation Manual" [131], where the regular visual inspection is the most important method. The International Federation for Structural Concrete also published "Monitoring and Safety Evaluation of Existing Concrete Structures" as a guideline for SHM of existing concrete structures [132], whereas the vibration-based SHM methods are less important than the quality and durability evaluation of concrete.

In Europe, the Structural Assessment, Monitoring and Control of European Union developed "Guideline for Structural Health Monitoring" [133] in 2006 to present the basic regulations and procedures of SHM, including determination of actions, structural condition analysis, design and operation of monitoring, numerical analysis and general damage identification. It is comprehensive and provides a framework for the following standards and codes. The Russian Federation also published its national code, GOSTR 53778-2010, "Building and structures, technical inspections and monitoring regulations" [134], where regular visual inspections, modal testing methods, condition classification, and grading system were presented. Similar to the Federal Highway Administration, U.S., the German administration also published the codes for SHM of bridges and tunnels, "Quality assurance for structural maintenance, surveillance, checking and assessment of bridges and tunnels, monitoring of bridges and other engineering structures", [135] where checking procedures and methods were presented. However, it was drafted in German, so it is not so easy for engineers in other countries to understand.

In Asia, "GB50982-2014 Technical Code for Monitoring of Buildings and Bridge Structures" [136], was published by Ministry of Housing and Urban-Rural Development of China. It has nine chapters and covers the basic requirements for SHM systems and general monitoring methods, and specific methods for high rise buildings, long-span spatial building, bridge structures, and other structures. For each type of structure, the requirements of SHM system for both construction stage and operation stage are provided. The monitored data are mostly vibration related, in addition to temperature and humidity. This is a comprehensive technical code on SHM, and its supplementary codes "Application and Analysis of Technical Code for Monitoring of Buildings and Bridge Structures" has also been published. However, it should be admitted that it can be improved by including more advanced vibration-based SHM techniques reviewed in Section 2 and more details about the sensor selection and arrangement.

4. Challenges and Future Development

Many vibration based SHM techniques have been proposed and developed recently, which have been reviewed in Section 2, however, their real applications in practical buildings and structures are rare. Some challenges are summarized as follows:

(1) Although various damage indicators and damage indexes based on vibration parameters have been proposed, it should be admitted that the sensitivities of them are not high enough to detect damage at early stage. Usually, the vibration parameters related to lower vibration mode can be measured more easily and accurately, but unfortunately those related to higher vibration mode are more sensitive to minor local damages. Considering that higher vibration modes can be hardly extracted if only ambient environmental excitation exists, damage index more sensitive to local damage at early stage by using lower vibration modes should be investigated in the future.
(2) The uncertainties of damage detection and evaluation in a SHM system are usually inevitable due to measurement noise, non-ideal boundary conditions, and ambient environmental vibrations. It increases the difficulty in extracting modal properties and calculating damage indicators and sometime the damaged signal can be concealed by the uncertainties. The statistical signal or statistical damage index may be investigated to reduce the uncertainties during monitoring.
(3) Data transmission, processing, and storage should also be paid attention to although it is usually be ignored in many research works. In fact, it is very important for a practical SHM system in real applications. The collection of the same type of data should be simultaneous, and they should be transmitted to the local server or cloud server smoothly. The requirements of hardware should be investigated in the future so that the proposed vibration based SHM methods can be applied better in practice.
(4) Currently, the benchmarks of SHM systems are lab studies and numerical studies, which are quite different from actual buildings and structures. Therefore, it is necessary to generate a benchmark study by using real building or structure. In fact, a data sharing platform is desired to examine the proposed SHM approaches, which may be helpful for the development and improvement of vibration based SHM methods in the future.

On the other hand, it can be concluded that although there are some ISO standards and national codes relevant to vibration based SHM system, unfortunately they cannot answer the following critical questions well:

(1) What monitoring methods should be used for a given building?
(2) What types of sensors should be used and where are they installed?
(3) How can the health condition of the building be assessed based on the collected data?

The above issues are important and unavoidable in SHM, since a properly designed SHM system should provide early warning to potential structural collapse to ensure the safety of building and residents' lives. Therefore, it is important to fill the gap in ISO standards and national codes to clearly specify which monitoring methods should be adopted for a specific building, where to install the sensors, how to evaluate the health condition of structures based on the collected data, and how to plan maintenance strategy and predict the remaining life of the building or structure.

5. Conclusions

The vibration-based SHM techniques and related ISO standards and national codes have been reviewed. The advantages and drawbacks of each method as well as the applicability of each standard or code have been presented. For different types of structure, different vibration-based SHM techniques should be selected. There is no universal approach for all types of structures and all kinds of damages. Although the standards, codes, and regulations have provide basic requirements and principles of a SHM system, it is still difficult for engineers to answer questions such as what types of sensors are to be used, where to install them, and how to use the monitored data to evaluate the structure health condition and predict the remaining life for a given structure. Therefore, it is necessary to develop such a code of SHM system construction that can be applied to real civil engineering structures.

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