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Introduction

1.1 Structural Health Monitoring: A Quick Review

Structures and civil infrastructure systems, including bridges, buildings, dams, and pipelines, are exposed to various external loads throughout their lifetimes. As they age and deteriorate, effective inspection, monitoring, and maintenance of these systems becomes increasingly important. However, conventional practice based on periodic human visual inspection is time-consuming, labor-intensive, subjective, and prone to human error. Nondestructive testing techniques have shown potential for detecting hidden damages, but the large size of the structural systems presents a significant challenge for conducting such localized tests. Over the past few decades, a significant number of studies have been conducted in the area of structural health monitoring (SHM), aiming at timely, objective detection of damage or anomalies and quantitative assessment of structural integrity and safety based on measurements by various on-structure sensors [1–4]. Most of the SHM techniques are based on structural dynamics, and the basic principle is that any structural damage or degradation would result in changes in structural dynamic responses as well as the corresponding modal characteristics. The SHM process is implemented in four key steps: data acquisition, system identification, condition assessment, and decision-making.

Dynamics-based SHM techniques can be categorized into frequency-domain and time-domain system identification methods. Carden and Fanning [5] presented an extensive literature review of frequency-domain SHM techniques based on changes in measured modal properties such as natural frequencies, mode shapes and their curvatures, modal flexibility and its derivatives, modal strain energy, frequency response functions, etc. Modal properties are obtained using various modal analysis techniques, e.g. the natural excitation technique, frequency

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Dongming Feng and Maria Q. Feng.

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domain decomposition, stochastic subspace identification, the random decrement technique, blind source separation, and the autoregressive-moving-average model-fitting method. All of these methods have achieved satisfactory performance in numerical and experimental studies. For example, Kim and Stubbs [6] proposed a technique to locate and quantify cracks in beam-type structures based on a single damage indicator by using changes in natural frequencies. Lee et al. [7] presented a neural network–based method for element-level damage detection using mode shape differences between intact and damaged structures. Pandey et al. [8] proposed for the first time that mode shape curvature, which is the second derivative of the mode shape, is a sensitive indicator of damage. Feng et al. [9] developed the first neural network–based system identification framework for updating baseline structural models of two sensor-instrumented highway bridges.

Time-domain SHM techniques, rather than working with modal quantities, directly utilize measured structural response time histories to identify structural parameters. The identification in the time domain is often formulated as an optimization process, wherein the objective function is defined as the discrepancy between the measured and predicted responses. In the majority of existing studies, which are referred to as *input–output methods*, the known or measured excitation forces are a prerequisite for obtaining the predicted structural responses. However, it is highly difficult to measure excitation forces such as vehicle loads on bridges. Recently, there have been attempts to simultaneously identify both structural parameters and input forces from output-only identification formulations. For example, Rahneshin and Chierichetti [10] proposed an iterative algorithm – the extended load confluence algorithm – to predict dynamic structural responses in which limited or no information about the applied loads is available. Xu et al. [11] presented a weighted adaptive iterative least-squares estimation method to identify structural parameters and dynamic input loadings from incomplete measurements. Sun and Betti [12] demonstrated the effectiveness of a hybrid heuristic optimization strategy for simultaneous identification of structural parameters and input loads via three numerical examples. Feng et al. [13] proposed a numerical methodology to simultaneously identify bridge structural parameters and moving vehicle axle load histories from a limited number of acceleration measurements.

On the other hand, various filter-type algorithms for online system identification have been extensively studied in the literature, using either input–output or output-only time-domain data. Examples include the extended Kalman filter, unscented Kalman filter, particle filter, and H_∞ filter. For example, Chen and Feng [14] proposed a recursive Bayesian filtering approach to update structural parameters and their uncertainties in a probabilistic structural model. Soyoz and Feng [15] formulated an extended Kalman filter for instantaneous detection of seismic damage of bridges and validated its efficacy through large-scale seismic shaking-table tests. Although these online estimation algorithms have proved to be successful in many applications, they also present challenges. For example, the sensitivity of these methods to initial guess values affects the stability and convergence of estimated parameters to exact ones. In addition, parameter/damage identification methods based on heuristic algorithms – e.g. genetic algorithm, particle swarm optimization, artificial neural network, differential evolution, and artificial bee colony – have gained increasing attention due to their global optimization performance. However, validation of these methods is mostly limited to numerical or controlled laboratory examples rather than real-world structures.

For both frequency- and time-domain methods, vibration-based SHM strategies have proved effective in evaluating the global health state of structures and performing a rapid risk assessment. However, their wide deployment in realistic engineering structures is limited by the prohibitive requirement of installing dense on-structure sensor networks (primarily accelerometers) and associated data-acquisition systems. Contact-type wired sensors require time-consuming, labor-intensive installation and costly maintenance for successful long-term monitoring, which poses many economic and practical challenges. Although wireless sensor technology has addressed several limitations of wired sensors by eliminating cumbersome wiring, data acquisition remains challenging due to the complexity of data transmission, time synchronization, and power consumption, especially when hundreds of wireless sensors are mounted on a large-scale structure to measure dynamic responses. Moreover, one main bottleneck is that conventional on-structure sensors provide sparse, discrete point-wise measurements and thus low spatial-sensing resolutions, which limits the effectiveness of SHM on a large-scale structure. Although such a sensor network with a limited number of sensors may allow for the detection of changes in overall structural dynamics, it is often insufficient for identifying the location or assessing the extent of damage.

To address these practical limitations, the research and engineering practitioner communities have been actively exploring new sensor technologies that can advance the current state of SHM practice. This book introduces the emerging computer vision–based sensor technology.

1.2 Computer Vision Sensors for Structural Health Monitoring

While most SHM studies are based on the measurement of structural acceleration responses, displacement responses more directly reflect overall structural stiffness and thus offer the potential for improved accuracy in the assessment of structural conditions. As shown in Figure 1.1, sensors currently available for measuring structural displacements can be classified as contact types, such as the linear

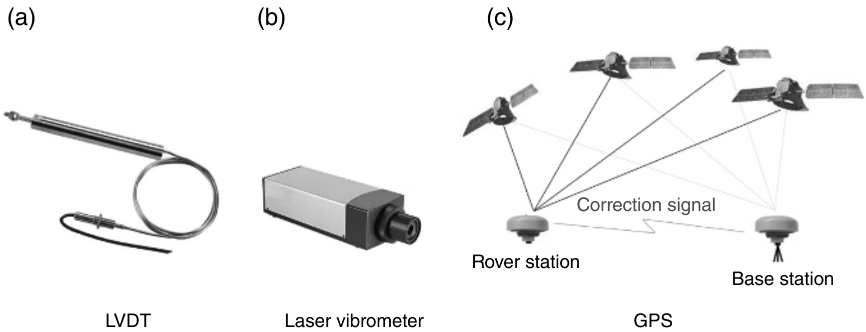

Figure 1.1 Common displacement sensors: (a) LVDT; (b) laser vibrometer; (c) GPS.

variable differential transformer (LVDT); and string potentiometer and noncontact types, such as GPS, laser vibrometers, and radar interferometry systems. These displacement sensors suffer from many limitations for field applications. For example, it is costly and highly difficult, if not impossible, to install an LVDT or a string potentiometer, which requires a stationary reference point; noncontact laser vibrometers are generally accurate but are costly and have a short measurement distance because of safety regulations; GPS sensors are easier to install, but the measurement accuracy is limited; and an interferometric radar system allows remote measurements with good resolution but requires reflecting surfaces mounted on the structure, which can be difficult to install and maintain.

Rapid advances in cameras and computer vision techniques have made vision-based sensing a promising alternative to conventional sensors for structural dynamic displacement measurement and health monitoring. As shown in Figure 1.2, a typical computer vision–based sensor system simply consists of one or more digital cameras and a computing unit such as a laptop or a tablet PC with measurement software installed. Video images of features on a structure, such as rivets and edges, are captured by the camera and streamed into the computer. By processing the digital video images using the measurement software, displacement time histories can be obtained at multiple locations simultaneously. The emerging vision-based sensor offers significant advantages over conventional contact-type and other noncontact-type displacement sensors, as summarized next [16]:

1) In contrast to a contact-type sensor (such as an LVDT or a string potentiometer), which requires time-consuming, costly installation on the structure and physical connections to a stationary reference point, a computer vision sensor requires no physical access to the structure, and the camera can be set up at a convenient remote location. This represents significant savings of both time and cost. For monitoring bridges, for example, no traffic control is required.

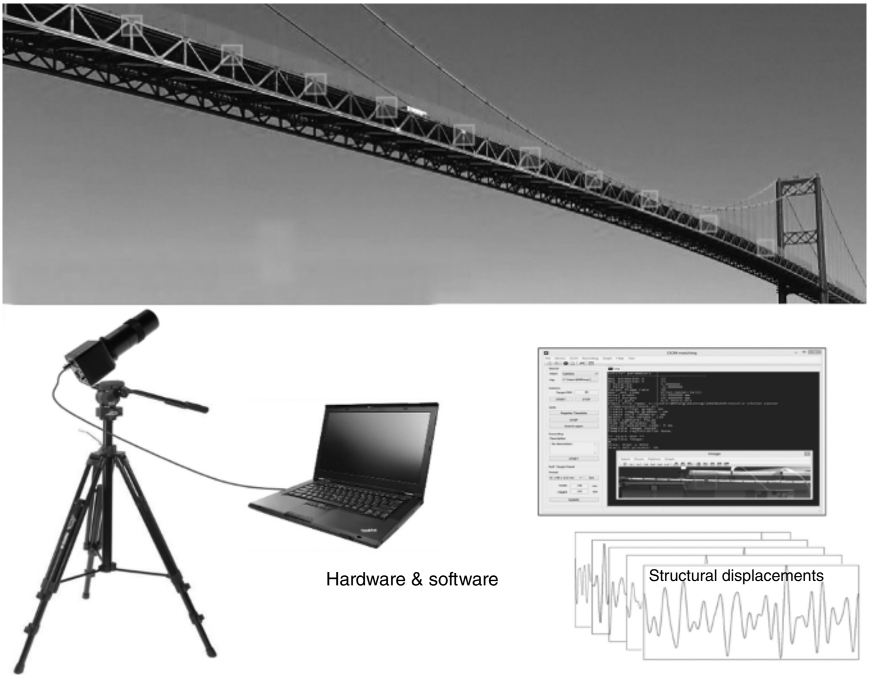

Figure 1.2 Vision-based remote displacement sensor.

In addition, each contact-type sensor measures one-dimensional (1D) displacement, but a single computer vision camera can measure two-dimensional (2D) displacements simultaneously.

2) Compared with a noncontact GPS, which requires installation on the structure (but not a stationary reference point), a vision-based sensor is far more accurate and less expensive. Depending on the cost, the GPS measurement error is typically in the range of 5–10 mm: more than an order of magnitude larger than that of a vision sensor.
3) Unlike a noncontact laser vibrometer, which must be placed very close to the measurement target due to the limited allowable laser power, a vision sensor can be placed hundreds of meters away (with the help of an appropriate zoom lens) and still achieve satisfactory measurement accuracy.
4) In contrast to conventional displacement sensors, almost all of which are point-wise sensors, a single vision sensor can simultaneously track structural displacements at multiple points. More importantly, one can easily alter the measurement points after video images are taken, offering unique flexibility for achieving better SHM results.

A comparison between commonly used vibration sensors and vision-based displacement sensors is summarized in Table 1.1.

Table 1.1 Comparison of sensors for measuring structural vibrations.

Sensors	Measure	Pros	Cons
Wired or wireless accelerometer	• Acceleration	• Suitable for continuous monitoring • Hardware easily available • Sensitive to high-frequency vibrations	• High cost of sensor system • High cost of installation and maintenance • Contact sensor • Single-point measurement • Additional mass on the structure may affect output
LVDT	• Displacement	• Hardware easily available	• Difficult and costly to install • Contact sensor • One-dimensional measurement • Single-point measurement
Laser vibrometer	• Velocity or displacement	• Noncontact • Accurate	• High cost of sensor system • Not suitable for continuous monitoring • Limited measurement distance
Computer vision sensor	• Displacement	• Noncontact, continuous monitoring • Low-cost industrial or consumer-grade video cameras • Two- or three-dimensional measurement • Multiple flexible measurement points on the visible object surface	• Accuracy affected by weather, light, and camera motion

About 10 years ago, the research community started to develop computer vision–based sensor technology for displacement measurement of large-size structures in controlled laboratory and challenging field environments. Modal analysis can be performed on the displacement data to extract natural frequencies and the mode shapes of a structure. Moreover, by analyzing the measured displacement time histories and modal analysis results, analytical models and parameters of the structure can be updated, damage detected, and structural integrity assessed. The adoption of vision sensors can significantly reduce the testing cost and time associated with conventional instrumentations. For example, Poozesh et al. [17] pointed out that testing a typical 50 m utility-scale wind turbine blade requires approximately 200 gages (costing \$35 000–\$50 000) and about three weeks to set up a conventional strain gauge system, while by contrast, a multicamera system could streamline the blade-testing process by eliminating the sensor instrumentation and reducing the setup time to two days.

It should be noted that computer vision sensing has been attracting attention and gaining popularity in two major areas of structural engineering: (i) vision-based sensors for displacement measurement and their SHM applications for modal/parameter identification, damage detection, force estimation, and model validation and updating; and (ii) visual monitoring of structural surface for defect detection and condition assessment, including the use of unmanned aerial vehicles (UAVs) and machine learning techniques. The emphasis of this book is on the former application.

1.3 Organization of the Book

The goal of this book is to encourage the application of the emerging computer vision–based sensing technology not only in scientific research but also in engineering practice such as field condition assessment of civil engineering structures and infrastructure systems. This book may serve as a textbook for graduate students, researchers, and practicing engineers. Thus much emphasis has been placed on making computer vision algorithms and their applications in structural dynamics and SHM easily accessible and understandable. To achieve this goal, throughout the book, MATLAB computer code is provided for most of the problems that are discussed. Even though the book is conceived as an entity, its chapters are mostly self-contained and can serve as tutorials and reference works on their respective topics.

Chapter 2 introduces fundamental facts about computer vision sensor systems and algorithms and software for measuring displacement time histories from video images. General principles are presented, including various template-matching techniques for tracking targets and coordinate-conversion methods for converting image pixel displacements to physical displacements. Vision sensor software packages are developed for real-time multipoint displacement measurement based on two representative template-matching techniques: upsampled cross-correlation (UCC) and orientation code matching (OCM).

Chapter 3 presents a wide range of tests conducted in both laboratory and field environments to evaluate the performance of the vision-based sensor system for dynamic displacement measurement. The accuracy of the measured displacement time histories is evaluated by comparing vision sensor results from tracking high-contrast artificial targets or low-contrast natural targets on the structural surface with those obtained with conventional reference sensors. The robustness of the vision sensor is examined against adverse environmental conditions such as dim light, background image disturbance, and partial template occlusion. The vision sensor system is also tested on outdoor in situ structures, including a pedestrian bridge, a highway bridge, two railway bridges, and two long-span suspension bridges. Dynamic displacements induced by various excitations are measured during the daytime and at night from different distances with and without artificial targets installed. These tests confirm the efficacy of the computer vision sensor system for measuring structural dynamic responses in outdoor environments.

Chapters 4–7 demonstrate the use of measured displacement data for SHM. **Chapter 4** compares modal analysis results based on displacement response data with those from conventional acceleration data. Furthermore, the identified modal parameters are used to update structural parameters such as the stiffness of a three-story frame structure and to detect damage in a beam structure.

Chapter 5 describes a model-updating approach for railway bridges, which is based on time-domain optimization of analytical models using in situ measurement of the bridge displacement time histories under trainloads. A finite element model of the bridge is developed, considering the train-track-bridge dynamic interaction. A sensitivity analysis investigates the intrinsic effects of parameters of the train, track, and bridge subsystems on the dynamic response of the bridge. The model-updating approach is applied to a short-span bridge to identify train parameters such as speed as well as bridge structural parameters such as stiffness. The computer vision–based model updating approach can be developed into an effective tool for long-term SHM of short-span railway bridges.

Chapter 6 explores a method for simultaneous identification of structural parameters and unknown excitation forces by using only displacement response (i.e. output-only), as in reality it is often highly difficult to measure excitation forces (i.e. input). Numerical analysis investigates the accuracy, convergence, and robustness of the identified results. Laboratory experiments on a beam structure accurately identified the hammer excitation forces as well as the beam stiffness from the beam displacement response measured by a single camera, validating this output-only method and demonstrating its potential for low-cost, long-term SHM.

Chapter 7 presents the application of the computer vision sensor for cost-effective estimation of tension forces in cables, the most important component in cable-supported bridges and roof structures. Compared with the existing vibration method based on acceleration measurements, which requires the installation of sensors on the cable, noncontact computer vision measurement of the cable vibration represents significant time and cost savings. This computer vision–based method is implemented in two engineering projects to estimate the cable forces of the cable-supported roof structure of the Hard Rock Stadium in Florida and the suspender forces of the Bronx-Whitestone Bridge in New York. Satisfactory agreement is found between cable forces measured by the vision-based sensor and conventional accelerometers.

Chapter 8 provides an overview of the achievements made thus far in computer vision sensor technology through a state-of-the-art literature review as well as a summary of this book. It also discusses challenges and opportunities, which the authors hope will inspire continued research on an extended adoption of computer vision technology for solving civil and structural engineering problems.

Appendix A further introduces the fundamentals of digital image processing using MATLAB, including digital image representation, noise removal, edge detection, and discrete Fourier transform.