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Review for vision-based structural damage evaluation in disasters focusing on nonlinearity

Sifan Wang*[1] and Mayuko Nishio[2a]

[1] *Department of Engineering Mechanics and Energy, University of Tsukuba, 1-1-1 Tennodai, Tsukuba, Ibaraki 305-8577, Japan*
[2] *Institute of Systems and Information Engineering, University of Tsukuba, 1-1-1 Tennodai, Tsukuba, Ibaraki 305-8577, Japan*

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Abstract. With the increasing diversity of internet media, available video data have become more convenient and abundant. Related video data-based research has advanced rapidly in recent years owing to advantages such as noncontact, low-cost data acquisition, high spatial resolution, and simultaneity. Additionally, structural nonlinearity extraction has attracted increasing attention as a tool for damage evaluation. This review paper aims to summarize the research experience with the recent developments and applications of video data-based technology for structural nonlinearity extraction and damage evaluation. The most regularly used object detection images and video databases are first summarized, followed by suggestions for obtaining video data on structural nonlinear damage events. Technologies for linear and nonlinear system identification based on video data are then discussed. In addition, common nonlinear damage types in disaster events and prevalent processing algorithms are reviewed in the section on structural damage evaluation using video data uploaded on online platform. Finally, a discussion regarding some potential research directions is proposed to address the weaknesses of the current nonlinear extraction technology based on video data, such as the use of uni-dimensional time-series data as leverage to further achieve nonlinear extraction and the difficulty of real-time detection, including the fields of nonlinear extraction for spatial data, real-time detection, and visualization.

Keywords: computer vision; damage evaluation; nonlinear structural dynamics; system identification; video data

1. Introduction

Civil structures may sustain mechanical damage during operation due to various dynamic and environmental loads, including traffic, wind, and natural disasters, which result in structural weakening, cracks caused by fatigue, loosened joints, and residual deformation due to yielding. These damages significantly delay the dynamic response, increase large displacements locally or globally, and magnify the catastrophic effects of disaster events. The Emergency Events Database (EM-DAT 2023) recorded over 26,000 mass disasters worldwide from 1900 to 2023, of which about two-thirds were related to natural hazards. These disasters inevitably affect the serviceability of civil structures, adversely impacting their safety. In the past few decades, structural health monitoring (SHM) has attracted much research attention for evaluating mechanical damages on existing structures, with various methods proposed. Most of these methods fall into two categories: local and global damage evaluations (Frigui *et al*. 2018). Since local damage evaluation methods chiefly focus on local and small specific damages, they also fall under nondestructive evaluation (NDE) methods (such as the ultrasonic method). The global damage evaluation methods use the global response of a structure, with the predominant method based on structural vibrations. The fundamental idea of vibration-based damage evaluation methods is that structural damages cause changes in the system properties (mass, damping, and stiffness), possibly leading to detectable changes in the modal properties (resonant frequencies, mode shapes, and modal damping) (Fan and Qiao 2011).

One issue in global vibration-based damage evaluation methods is finding features sensitive to structural damage but not to operational and environmental effects (Ren and Roeck 2002a, b). Some damage features that have demonstrated various degrees of success include natural frequencies (Hou *et al*. 2018, Sarrafi *et al*. 2018, Sha *et al*. 2019, Kordestani and Zhang 2020), mode shape curvatures (Shokrani *et al*. 2018, Altunışık *et al*. 2019), modal flexibility (Wickramasinghe *et al*. 2020), and modal strain energy (Khatir *et al*. 2019). In addition, the vibration-based damage evaluation methods usually begin from time-domain data and then conduct the modal analysis, raising the standard for the signal acquisition procedure. For example, response signals must be collected in a quiet environment, containing as little noise as possible. The time-domain signals should comprise the characteristic segments, with the sampling frequency adhering to the Shannon-Nyquist sampling theorem (Nyquist 1928). Although modal analysis techniques play a dominant role in damage evaluation, they have various limitations. For

*Corresponding author, Ph.D. Student,
E-mail: wang.sifan.xs@alumni.tsukuba.ac.jp
[a] Ph.D., Associate Professor,
E-mail: nishio@kz.tsukuba.ac.jp

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instance, the Fourier transform (FT) is a popular conventional method applicable for extracting modal properties by converting the time-domain data into the frequency domain. However, it cannot predict when or where the damage event occurs due to the complete loss of time-domain information by the transform. Consequently, several signal processing methods, especially time-frequency representations, were developed to address this issue. A short-time Fourier transform (STFT) was proposed to improve this deficiency. However, a higher resolution in both the time and frequency domains could not be achieved simultaneously using STFT once the window size was fixed (Kwok and Jones 2000). Another improved approach for vibration-based damage detection is the wavelet transform (WT). Unlike the STFT, the WT reveals "hidden" aspects of the measured response signal owing to its flexibility in window-length selection (Serra and Lopez 2017). Numerous investigators have applied the WT to detect structural cracks or damage (Abdulkareem *et al*. 2018, Mousavi *et al*. 2021, Chen *et al*. 2021, Fallahian *et al*. 2022). For instance, Pnevmatikos and Hatzigeorgiou (2017) and Wang *et al*. (2019) employed a discrete wavelet transform (DWT) to detect the damage to a frame structure and a shear structure, respectively. The DWT could be used as a damage alarm by engineers when the response signal spikes appear, as they can visually inspect the appropriate region of the structures.

Another approach based on vibration-based damage evaluation involves the detection of nonlinear structural behaviors caused by damage. Most damage scenarios may result in a previously linear structure exhibiting nonlinear behavior (Farrar *et al*. 2007); therefore, extracting such nonlinear behavior is an effective strategy for detecting structural damage. The main challenges in structural damage detection are distinguishing between 1) linear and nonlinear types of damage and 2) nonlinear damage and inherent nonlinearities in a "healthy" structure. An initial linear structural system can generate various nonlinear behaviors because of external and environmental loads. Cracks are a common type of damage that can cause nonlinear behavior (Zhang *et al*. 2018, Smyl *et al*. 2018, Agathos *et al*. 2018). However, not all cracks generate a nonlinear response; they can only be recognized as nonlinear when the cracks subsequently open and close under operational loadings. Otherwise, cracks only change the structural geometry, with the structure continuing to respond as a linear system with different configurations (Farrar *et al*. 2007). Other nonlinear behaviors in engineering structures include crushing, sliding, yielding, fracturing, and boundary-condition nonlinearity (Chiu *et al*. 2015, Swaminathan *et al*. 2015, Chen *et al*. 2019, Shakeel *et al*. 2020, Grotto *et al*. 2022). Identifying and extracting these structural nonlinear dynamic behaviors provide a novel perspective for vibration-based damage detection, having the potential for broad application in SHM. Structural nonlinearity occurs more often during disasters. Disasters like earthquakes, floods, and tsunamis usually involve extreme loads, with most civil structures exhibiting nonlinear behaviors. The technological identification of these nonlinear behaviors is highly promising for detecting structural degradation.

Nonlinear behaviors frequently occur in specific locations of a structural system, such as discontinuous parts with stress concentrations, structural member joints, and bearings used for applying boundary conditions, resulting in a high locality. Nonlinear system identification (SI) can be classified into four stages: nonlinearity detection, localization, classification, and nonlinear parameter identification. Among these, nonlinear parameter identification has been extensively researched as the basis for determining the existence of nonlinearity. The basis for judgment frequently includes the superposition principle, anisotropy, harmonic distortion (HD), frequency response function distortion (Simon and Tomlinson 1984, Feldman 1994a, b, Verboven *et al*. 2006, Feldman 2014a, b). Nonlinearity localization, the most complex stage in nonlinear SI, aims to determine the degrees of freedom (in a structure) directly affected by the local nonlinearity. Although certain degrees of freedom in a structure are directly affected by local nonlinearity, all degrees of freedom are influenced indirectly by nonlinearity, making it more challenging to localize the local nonlinearity. Currently, the most prevalent methods are based on the frequency response function (FRF) (Peng *et al*. 2007, Cheng *et al*. 2014) and model updating techniques (Asgarieh *et al*. 2014, Simoen *et al*. 2015). The main goal of nonlinearity classification is to determine the specific form of each nonlinearity in a system, including its type and descriptive form. Determining the nonlinearity type primarily involves identifying its properties, such as hardening or softening characteristics, smooth or non-smooth nonlinearities, symmetric or asymmetric nonlinearities, and whether the nonlinearity belongs to stiffness or damping nonlinearity. Commonly used nonlinearity classification methods are similar to those used for nonlinearity detection. Nonlinear parameter identification, the last stage of nonlinear SI, estimates the unknown properties according to the nonlinear functions determined in the previous three stages. Restoring the force surface (RFS) (Masri and Caughey 1979, Masri *et al*. 1982), reverse path (RP) (Rice and Fitzpatrick 1988, 1991), recurrence plot (RP) (Eckmann *et al*. 1987, Chen *et al*. 2018), nonlinear subspace identification (NSI) (Lacy and Bernstein 2005, Marchesiello and Garibaldi 2008) and model updating are often employed for this purpose. However, most of these nonlinear parameter identification methods have only been evaluated through numerical studies. The application of these methods to actual structures in nonlinearity evaluations during disaster events has not yet been sufficiently studied.

Although these vibration-based methods have achieved great success in damage localization, their recognition accuracy is highly dependent on the quality of the acquired signals. Sensor systems with high precision, resolution, and multipoint synchronization are required for vibration-based damage evaluation approaches (Lee *et al*. 2012, Magalhães *et al*. 2012, Avci *et al*. 2021). However, for large-scale civil structures, vast and intense deployment of sensor networks and data acquisition (DAQ) systems on actual structures is difficult to achieve because of the installation and maintenance costs. Researchers have considered and applied noncontact measurement methods including video stream (Zaurin and Necati 2011), laser vibrometers (Staszewski *et al*. 2012, Tashakori *et al*. 2016) Unmanned aerial vehicles (UAVs) (Kang and Cha 2018), remote sensing technologies (Alamdari et al. 2019) and computer vision (CV) techniques (Yuan *et al*. 2020, Dong and Catbas 2021) to address these difficulties in recent SHM studies. Ribeiro *et al*. (2014) employed a high-speed video camera system to achieve the displacement measurement of a railway bridge deck with a high accuracy of less than 0.1 mm (the distance from the camera to the target being up to 15 m). Video data are expected as applicable to damage evaluation with exceptional advantages, such as low-cost and noncontact data acquisition, high spatial resolution, and multipoint dynamic measurement (Yang *et al*. 2017b). Notably, ideal environments, including good weather conditions during video recording, are required to ensure data effectiveness and accuracy. The scientific quality of video data is sometimes unguaranteed because of non-standardized acquisition and use. The structural vibration data acquired by video cameras are widely unaccepted as a substitute for accelerometers used in laboratory tests. However, video cameras can be regarded as a noncontact SHM strategy in various situations, such as a lack of enough cameras in ideal places to allow for proper visualization (with the captured images not subject to data protection) (Oliveira and Ferreira 2021). The vibration-based damage identification method based on video data is broadly recognized because it is convenient to obtain, and a high identification accuracy for some realistic structures is unnecessary.

In recent decades, when a disaster occurs, people like to share all kinds of video data, i.e., public and personal data on the Internet or other media. These video data contain various pieces of information, not only on the target of the videographer but also on the scene background. It may include the dynamic behaviors of structures during an earthquake and information on the moving properties of media, such as tsunamis, landslides, and water sloshing. These video data have potential usage for damage evaluation during disasters. One benefit is that most video data contain a clock that controls the shooting speed; therefore, no errors occur if researchers try to speed up or slow down the scene. Some studies have demonstrated the potential of using the video data on the Internet to analyze disaster events from a professional perspective. For instance, Ngo and Robertson (2012) used video technology and Google Earth to analyze the flow characteristics in several coastal cities in Japan hit by the 2011 tsunami. Zhai and Peng (2020) employed Google Street View (GSV) images to provide insights into damage assessments following disaster events. In addition, considering the monthly and yearly updating of GSV images, this approach could be utilized by decision-makers to evaluate the recovery progress of a community over time. It is worth considering the use of these shared video data for the damage and condition evaluation of civil structures from the viewpoint of structural dynamics. There is a significant advantage of the data containing information in both the spatial and time domains. Therefore, it is possible to measure dynamic displacements if our sight can easily discriminate small movements at a distance and in situations where a line is visible, such as in a visual image that includes a corner building. Detection of nonlinearity in structural dynamic behaviors can also help detect damage occurrences and their evaluations owing to disaster events.

This paper reviews previous studies and recent directions in video-based structural dynamics analysis to demonstrate the effectiveness of using video data to investigate the nonlinearity of structural vibrations, especially in disaster events. Notably, this study emphasizes video data analysis; therefore, the methods or algorithms of signal processing and the related analysis methods are not comprehensively mentioned and reviewed. The contents are organized as follows. Section 2 introduces the method of video data acquisition and preprocessing, and then video-based linear and nonlinear SIs in laboratory-based studies are reviewed. Section 3 classifies linear and nonlinear dynamic behaviors of civil structures during disaster events by reviewing related studies. Prevalent video data-based damage detection technologies have also been introduced. Section 4 discusses the potential research directions for our future work on structural nonlinearity extraction and visualization based on video data for structural damage evaluation in disaster events.

2. Video-based structural dynamics analysis

A dynamic analysis of civil structures was conducted to evaluate the effects on the design of critical dynamic loads, such as traffic, wind, and earthquake. Several signal processing and analysis methods for vibration data acquired in actual structures have been developed to validate designs against dynamic loads, evolving into structural condition evaluation methods in SHM. Structural vibration data analysis methods fall under two approaches: time domain and frequency domain. Numerous methods and algorithms wherein the two approaches were successfully applied showed structural SI and structural condition evaluation, including damage detection. Video data containing temporal and spatial information are also applicable to structural dynamic analyses. This section reviews the data acquisition and preprocessing of video data and their applications in identifying linear and nonlinear structural systems.

2.1 Data acquisition and preprocessing

The data acquisition should be designed suitably for analytical purposes. For structural dynamic analysis, the specifications of the video data, such as frames per second (FPS), resolution, and the amount of data, are factors to be addressed. At present, a variety of large-scale annotated visual datasets are available, from image to video data. For instance, it already has well-known video datasets that contain various video categories, such as persons, street signs, cars, animals, food, and windows. However, only a few databases include the information on disaster-related and structural damage, such as the Federal Emergency

Table 1 Video datasets containing disaster information

Dataset	Size of dataset	Types of disaster data
Federal Emergency Management Agency (Tian and Chen 2017)	More than 200 videos	Hurricanes, floods, earthquakes, etc.
20BN-something-something-v2 (Goyal *et al*. 2017, Mahdisoltani *et al*. 2018)	220,847 trimmed videos, 174 action categories	No disaster data, but contain nonlinear events clips, e.g., hitting, dropping down.
YouTube-8M (Abu-El-Haija *et al*. 2016, Lee *et al*. 2019)	More than 1.9 billion video frames, 8 million videos	Fire, building collapse, flood, etc.

Table 2 Number of projects publishing experimental data sets from ASEBI

Types	Total data sets	Open data sets	Ratio (%)
NIED	37	26	70.3
Joint	32	30	93.8
Rental/Private	44	18	40.9
Total	113	74	65.5

Management Agency website (Tian and Chen 2017) in Table 1. Therefore, just a few datasets are currently available for structural dynamic analyses. Some possible methods for obtaining video data adopted in previous studies (Chung *et al*. 2010, Abu-El-Haija *et al*. 2016, Li *et al*. 2019, Aoi *et al*. 2020) are also introduced.

(i) Video data officially shared by institutes: In recent years, there has been an increase in the amount of data obtained by research institutes and government offices being made public. For instance, many earthquake records and experimental data are available on the repository of the National Research Institute for Earthquake Science and Disaster Resilience (NIED). Regarding the structural dynamics against earthquake loads, the Hyogo Earthquake Engineering Research Center of NIED provides the data acquired in some experiments conducted in the 3-D Full-Scale Earthquake Testing Facility called “E-defense”. The system operated by NIED is called as “Archives of E-Defense of Shakingtable Experimentation dataBase and Information (ASEBI)” (ASEBI 2023). The available dataset encompasses digitized measurements, video and photographic imagery, as well as supplementary experimental details, including excitation conditions, sensor specifications and placements, and specimen designs. To date, this website has uploaded over 100 videos of shaking table tests on full-scale structures, including reinforced concrete structures (buildings and bridge piers), wooden houses, steel buildings, and soil-pile foundations, from multiple perspectives, as listed in Table 2 (Horiuchi *et al*. 2022). These data are applicable in analyzing the earthquake response of structures and contribute to the development of seismic design and structural risk analysis.

(ii) Video-sharing platforms on the Internet: Currently, numerous video-sharing platforms exist, and valuable information resources are constantly uploaded. YouTube is one of the most popular video-sharing platforms. A wide variety of video data shot by various people using smartphones or video camera devices is shared on these platforms, including disaster occurrence. These videos, captured during disaster events, may contain information on damage or failure occurrence events in actual structures, and are expected to evaluate these structural conditions by dynamic analysis. Although these video data cannot provide structural vibration data as precise as those available in laboratory tests, they are applicable for observing and understanding the vibrations of structures and structural members under various events.

As mentioned above, while few databases provide videos of structural seismic responses, a vast number of sources may apply to understanding the structural dynamic behaviors under actual disaster events. Many video data applications are expected usage in structural dynamic analysis by adopting appropriate video-processing methods. For instance, the entire collapse process of a structure can be observed, with the mechanism clarified by combining verification with numerical simulations or experiments. In addition, the outcome of actual disaster input loads on structures can be more intuitively recognized, and studies will be conducted to improve structural performance. Data sharing among research institutes through appropriate databases is a promising direction for future progress in this field. Furthermore, video data shared on Internet platforms can help evaluate structural conditions after disaster events.

When using video data for structural vibration analysis, preprocessing is critical to apply a purposeful algorithm appropriately. Although video data shared on the Internet have the potential to extract meaningful information about the conditions of structures, these data may be subject to inconsistency, redundancy, noise, and loss because they are in large amounts and come from a variety of sources. Data preprocessing is applied to solve these issues and comprises four steps: data cleaning, integration, transformation, and reduction (Al-Taie *et al*. 2019). These steps are not separate from one another; instead, they are integral components of data preprocessing. Multiple studies have been conducted on the preprocessing of video data. For instance, Cheng (2021) designed a digital video image preprocessing device using an improved median filtering algorithm and wavelet image denoising. Luengo *et al*. (2020) comprehensively reviewed big data preprocessing techniques, including data reduction methods, imperfect data approaches, discretization techniques, and imbalanced data preprocessing solutions applicable to video data. Big-data processing is a challenging and time-consuming task that requires an extensive computational infrastructure to ensure successful data processing and analysis. For video data, each frame is composed of a three-dimensional (3D) matrix. With the development of high-speed cameras in recent years, video data frequently contain high frame rates, resulting in being viewed as big data and allowing the application of standard big-data preprocessing methods to the video data. Although preprocessing is essential for appropriately analyzing data, most techniques require long processing times. The development of video data preprocessing methods with high precision and low computational cost is still a direction worthy of further investigation.

In addition, video camera technology is experiencing significant development in numerous specifications, such as pixel number, focal length, and zoom function. Especially for dynamic analysis, the specification of FPS, that is, sampling frequency, should be noted from the viewpoint of sampling theory. High-speed cameras have advanced significantly in recent years, reaching specifications higher than 4,000 fps. However, the rise in FPS will unavoidably increase the cost and volume of analytical data. It is crucial to select a camera with an appropriate FPS based on the assumption that the sampling rate is satisfied. Digital imaging sensors capture light at discrete pixel sites. The Moiré pattern (Oster and Nishijima 1963, Oster *et al*. 1964) occurs when the camera lens reduces the scene detail to a lower level than the pixel sites, which leads to an error in target point tracking, thus affecting the dynamic response measurement of structures. To address this phenomenon, the selection of the angle, position, and lens length of the camera is crucial.

2.2 Linear system identification using video data

SI is the process of estimating the unknown properties of a system based on input-output data. Particularly in structural engineering, a system is represented by the equation of motion or the state-space model. The model properties are identified based on resonant properties, such as natural frequencies, mode shapes, and damping ratios. In recent decades, extensive SI investigations in civil engineering were conducted to determine the dynamic structure under the effects of dynamic loads, including vehicle traffic, earthquakes, wind, and collision (Lee and Park 2011, Sirca and Adeli 2012, Salehi and Burgueño 2018, Kuok *et al*. 2022). Furthermore, the steel and concrete elements of structures, such as concrete and steel bridges, suspended bridges, and concrete columns, have also been identified using SI technologies. This research includes the health monitoring of different types of traditional structures and the investigation and control of smart structures, which have become increasingly popular in recent years. Traditional SI methods require data acquisition, such as acceleration, velocity, and displacement. However, when the structure is small compared with the sensor, the additional mass from the sensors may disturb the identification result. By contrast, video data-based technology does not require traditional sensor systems and has recently been employed in SI. The application of video technology to linear SI has been reviewed herein.

Modal parameter identification is required for an accurate condition assessment of the structure. For instance, the natural frequency can be utilized to reflect changes in the cable tension in a cable bridge and achieve model updating by combining mode shape information, which can also be used in nonlinear SI (Xu *et al*. 2018). Phase information is sensitive to some changes, such as the scale and speed of the input image, and is usable for video motion processing, as first proposed by Fleet and Jepson (1990) in 1990. This index is widely used and is continuously being developed. Wadhwa *et al*. (2013) utilized phase-based video-processing technology to achieve small motion magnification, which belongs to output-only modal identification without the need for installing markers or speckle paints on a structural surface, such as digital image correlation (DIC) technology.

Furthermore, the phase-based video motion processing method has been demonstrated to be computationally efficient in extracting local motions that correlate with structural vibrations (Yang *et al*. 2017a). In addition, the proposed method in the research takes advantage of automated, unsupervised, and efficient extraction of the output-only structural modal frequencies, damping ratios, and full-field (as many points as the pixel number of the video frame) mode shapes. In these methods, a video of a vibrating structure is processed in an Eulerian framework, which generates individual videos of the structural vibration at different modal frequencies. Conversely, the phase-based optical flow provides an Eulerian representation of the motion at every pixel of the image space, which does not acquire the full-field spatiotemporal Lagrangian displacement trajectory of the structure (Bhowmick and Nagarajaiah 2020). Hence, Bhowmick *et al*. (2020a, b) proposed a vibrating continuous-edge-based full-field displacement response measurement method. In this technology, Hankel dynamic mode decomposition (Rowley *et al*. 2009, Proctor *et al*. 2016, Arbabi and Mezić 2017) is used to decompose the obtained high-dimensional full-field continuous displacement measurement matrix into inherent sparse low-dimensional linear vibration modes and extract the full-field modal parameters of the structure. The objective of the full-field imaging method is to separate an independent model from a family of unsupervised machine-learning models (Dasari *et al*. 2018). Related research has established that there is a one-to-one mapping between the modal superposition model and the linear mixture model of blind source separation (BSS) techniques, which can perform very efficient output-only modal identification (Yang and Nagarajaiah 2013, Antoni and Chauhan 2013, Brewick and Smyth 2014).

Other techniques based on video data for linear SI have also been developed. A high-speed camera can help achieve the modal identification of simple structures with high accuracy owing to its high frame rate (Chen *et al*. 2015). Furthermore, Zhang *et al*. (2016a) employed a high-speed video and integrated two efficient subpixel-level motion extraction algorithms (the modified Taylor approximation refinement and the localization refinement algorithms) to realize the extraction of the structural vibration signal in real-time. However, high-speed cameras for higher-frequency vibration measurements are extremely expensive, and the sampling frequency of the most affordable digital cameras is limited to 30-60 Hz, which is lower than the requirement of the Shannon-Nyquist sampling theorem for modal analysis. To address this drawback, Yang *et al.* (2017b) proposed a method that exploited the properties of signal aliasing for feasible output-only modal identification with potentially temporally aliased vibration-response measurements. In addition, it is possible to generate a non-ideal field deployment owing to the tiny objective structure, which limits the application of traditional DIC technology. Frame-to-frame keypoint-based technology (Dasari *et al.* 2018) and target-less vision-based displacement sensors (Choi *et al.* 2016) have been proposed to identify full-field structural dynamics in non-ideal operating conditions. The mode shapes and natural frequency identification accuracy reached 0.12 mm displacement and over 99%, respectively.

2.3 Nonlinear system identification using video data

SI for nonlinear structural dynamic systems is the modeling of nonlinear behaviors in system responses originating from time or displacement dependencies. Because the vibration response of a nonlinear structural system exhibits nonstationary properties, various SI methods for linear structural systems are no longer applicable. It is well known that the ability of any nonlinear SI scheme to describe a vast class of structural systems, including various nonlinearities in stiffness or damping (Nelles 2020). The dynamic responses of structures governed by nonlinearities complicate the analytical investigations. This is mainly because the uniqueness and superposition of solutions, which are characteristics of problems governed by linear differential equations, do not exist in the issues governed by nonlinear governing differential equations (Oppenheim 1965, Sathyamoorthy 2017). Owing to their complex internal structures and various nonlinear forms, there is no universal mathematical model for characterizing all nonlinear systems. Consequently, identifying structural nonlinearity is more complicated and crucial than damage detection. Most existing nonlinear SI methods achieve nonlinear localization and nonlinear parameter prediction from the measurement data. The localization of nonlinearities can achieve feature extraction relevant to certain structural damages, such as cracks (Rubio and Fernández-Sáez 2012) in SHM. In addition, it can improve the validity and accuracy of mathematical models of nonlinear systems, realize efficient nonlinear parameter estimation, and reduce the uncertainties of nonlinearities (Zhang *et al.* 2016b).

Despite the difficulties of nonlinear SI, video-data-based SI technology for nonlinear structural systems has great potential because of its noncontact nature, low cost, and high spatial resolution. One method was based on the traditional camera method. For example, Jiao *et al.* (2021) achieved camera motion estimation and vision-based displacement measurement using a newly proposed tracking algorithm that combined the Random Sample Consensus algorithm and Efficient Second-order Minimization technique. Furthermore, an unscented Kalman filter (UKF) (Xie and Feng 2012, Astroza *et al.* 2019, Wu and Chen 2020) was employed to identify the nonlinear SI and demonstrated good results in updating the physical parameters of the nonlinear structure system. In addition, considering that the UKF uses displacement data derived from video data, it demonstrates the accuracy of using video data to quantify the displacement of a nonlinear structural system.

Another aspect involves the utilization of UAVs for image and video data acquisition. Compared with cameras that need to be fixed to a stationary reference, UAVs can be utilized in a broader range, such as bridges built over mountains, rivers, and high-rise buildings, making it difficult to find an appropriate camera installation location. Additionally, the rapid expansion of the commercial UAVs industry has resulted in enhanced performance in terms of stability and mobility. Commercial-grade off-the-shelf UAVs now include 4K resolution cameras. The use of UAVs to capture aerial images and videos of civil infrastructure offers the possibility of resolving concerns regarding traditional fixed-reference vision-based structural monitoring. Recently, researchers have employed UAVs to measure the displacements of real structures with high accuracy (Yoon *et al.* 2018, Ribeiro *et al.* 2021). The ability of UAVs to detect structural displacement highlights their potential for structural SI. Yoon *et al.* (2017) utilized video data from UAVs and combined the Natural Excitation Technique (NExT) with the eigensystem realization algorithm (ERA) to estimate the natural frequency and mode shapes of a linear system, with a maximum error of only 1% when compared to fixed camera measurements. It is possible to achieve nonlinear SI based on UAVs' video data by utilizing an applicable nonlinear parameter identification technique, such as the nonlinear subspace method, because the displacement recognition accuracy of UAVs is sufficiently high. However, because numerous uncontrollable circumstances, such as strong winds, impair the accuracy of UAV usage in real structures, the viability of its application in real structural nonlinear SI needs to be further verified.

It can be concluded that there are challenges in addressing nonlinear structural systems in video data, although many studies have focused on linear systems. During actual disaster events, large displacements occur in structures, producing various nonlinear events. The emergence of nonlinearity indicated the occurrence of structural damage. The following section discusses the implementation of video-data-based technologies on the actual structure, with a particular focus on damage-detection applications in disaster events.

At the end of this section, the structural SI using the vision-based methods are summarized in Table 3 based on the subset of SI, core technologies, applied excitations, types of source data, and whether the method was used only for experiments or for both experiments and real-life structures.

3. Video data-based structural damage evaluation in disaster event

The application of video data can incorporate these two forms of information because the appearance of nonlinearity encompasses both the occurrence time (time domain) and location (spatial domain). Although the study

Table 3 Review of structural SI using vision-based method, "E" indicates that the study was conducted Experimentally, while "R" indicates that the study was conducted to Real-life structures

References	Subset of SI	Technologies	Excitation	Types of source data	E/R
Wadhwa *et al*. 2013	Motion identification	Phase-based	Impact hammer/ Loudspeaker	video	E
Chen *et al*. 2015	Modal identification	Phase-based	Impact hammer	video	E
Zhang *et al*. 2016a	Motion identification	Maximum cross-correlation algorithm	Driving handle	video	E&R
Choi *et al*. 2016	Motion/ Modal identification	Target-less vision-based displacement sensor	Shaking table	video	E
Yang *et al*. 2017a	Modal identification	Phase-based/ Blind source separation	Impact hammer	video	E
Yoon *et al*. 2017	Motion/ Modal identification	Eigensystem realization algorithm/ UAVs	Band-limited white noise	video	E
Yoon *et al*. 2017	Motion identification	Unmanned aerial system	Traffic loads	video	R
Dasari *et al*. 2018	Motion/ Modal identification	Consensus-based matching and tracking of keypoints	Impact hammer	image	E
Xu *et al*. 2018	Motion/ Modal identification	Correlation-based template matching	Moving load	video	E&R
Bhowmick and Nagarajaiah 2020	Modal identification	Optical flow/ Dynamic mode decomposition	Impact hammer	video	E&R
Jiao *et al*. 2021	Motion identification	Homography estimation/ Unscented Kalman filter	Shaking table	video	E
Ribeiro *et al*. 2021	Motion identification	Linear variable differential transformer/UAVs	Environmental loads	video	E&R

of video data- based structural damage evaluation in disaster events is still at an early stage, video data-based techniques have been considered in some studies because of the low cost and flexibility of data acquisition. Herein, a review of the classification of common nonlinear events in disasters and prevalent damage detection technologies from video data is presented.

3.1 Classification of structural nonlinearities occurred in disaster events

When structural damage occurs in a disaster event, the structural system changes from a linear state to a system with local nonlinearities, which may eventually lead to the instability and collapse of the structure. However, not all types of damage result in a nonlinear response of the system, and some common structural nonlinearity events during disasters are summarized here. The video data obtained from the publicly available YouTube platform contained the dynamic responses of structural and non-structural members in the exterior and interior of various structures during disaster events.

3.1.1 Material nonlinearity

Material nonlinearity is widely observed in disaster event structures because of the inelastic behavior of constituent materials such as concrete and steel when strained beyond their proportional limit, resulting in cracks, crushing, sliding, yielding, and fractures. Reportedly, the 2011 earthquake and tsunami on the Pacific coast of Tohoku that occurred on March 11, 2011, caused 190 thousand buildings to be damaged, among which 45,700 had collapsed as of April 3 that year (Norio *et al*. 2011). Upon searching for the keyword "2011 Japan earthquake" on YouTube, there is a huge amount of video data, mostly from surveillance cameras and mobile phones. Cracks are one of the most common structural damages caused by material nonlinearity and frequently occur during earthquakes. Even if a magnitude 9.0 earthquake struck, several houses would have cracks and not collapse, owing to the Japanese buildings' high seismic fortification intensity. Figs. 1 and 2 show the wall cracks of a structure in Murata Town, Miyagi Prefecture, which is only 120 km from its epicenter. As mentioned in the Introduction, if the wall is not subjected to external loads after cracking, the structural system will not produce a nonlinear response but only result in a change in the geometry of the structure, and the structure will continue to respond as a linear system with a different configuration. Consequently, the cracks in Fig. 1 were not continuously affected by external forces and exhibited opening and closing, with only a linear response generated. In comparison, the cracks shown in Fig. 2 have open and closed forms, resulting in a nonlinear response and exhibiting structural material nonlinearity. For reinforced concrete structures, it may be challenging to observe tiny cracks; however, spalling will occur and finally separate from the steel as the cracks increase. At this point, material nonlinearity in a video can be easily observed. Fig. 3 depicts the damage to a tower in the Turkey-Syria earthquakes in 2023, as evidenced by the spalling of brick in the shear walls; [Video #2] clearly shows the scale of devastation in Turkey-Syria following earthquake. Moreover, once a high-level earthquake continues for an extended period, the cracks in the structure gradually

Fig. 1 Cracks in the wall due to the seismic wave (only linear response is generated because the crack is static) [Video #1]

Fig. 2 Cracks in the wall that open and close under the action of the earthquake (containing nonlinear response due to the opening and closing of the cracks) [Video #1]

Fig. 3 Spalling of the brick shear walls (containing the material nonlinearity) [Video #2]

Fig. 4 Collapse with overturning (containing both material nonlinearity and geometric nonlinearity) [Video #3]

expand until a partial and overall collapse occurs. Fig. 4 presents the collapse process of a couple of shear-wall-building with an overturn, which contains material nonlinearity and strong geometric nonlinearity.

3.1.2 Geometric nonlinearity

Geometric nonlinearities are associated with large-amplitude vibrations of thin structures such as beams, cables, plates, and shells because of their relatively low bending stiffness (Kaewunruen *et al*. 2020, Colin *et al*. 2020). In recent years, the number of applications in real-world engineering challenges has increased owing to the more prevalent usage of lightweight and thinner structures (Touzé *et al*. 2021). Linear structural analysis requires both material and geometric linearity and assumes linear-elastic constitutive behavior and minor displacements.

In contrast, the most common form of structural geometric nonlinearity in engineering is the change in structural stiffness owing to a change in the shape or reconfiguration of loads.

In addition, it should be noted that when geometric nonlinearity arises in the structure, material nonlinearity often occurs simultaneously because the large structural deformation usually causes the material to enter a plastic stage. Material nonlinearities associated with excessive deformation (geometric nonlinearity), such as steel yielding, can cause structures to behave nonlinearly under dynamic loads. Because yielding does not affect the stiffness or mass distribution of a structure in general, once the force has been removed, this type of damage is difficult to identify. When a structure is dynamically loaded, yielding is accompanied by permanent deformation, possibly leading to a nonlinear system response if it has a subsequent impact on neighboring components (Farrar *et al*. 2007). Below, three real-world structural geometric nonlinear events from YouTube during disasters are presented.

Fig. 5 shows the buckling of a timber-framed house support column owing to seismic loads. This large deformation causes geometric nonlinearity because the stress distribution in the column changes. In the video analysis, it is observed that the mainshock induced residual deformation in the timber columns, resulting in structural damage. Furthermore, the aftershock led to structural vibrations characterized by geometric nonlinearity.

To gain insight into the manifestation of geometric nonlinearity in structural vibration during powerful earthquakes, an in-depth analysis of [Video #4] reveals compelling observations from a shaking table experiment conducted by NIED. The video prominently illustrates the behavior of an 18-story steel frame building, particularly emphasizing geometric nonlinearity as it emerges following column yielding. The opening video of such phenomena is crucial for enhancing the understanding of earthquake-induced structural behavior and informing resilient design practices for earthquake-prone regions.

3.1.3 Boundary-condition nonlinearity

Structural nonlinearities also arise owing to nonlinear boundary conditions, such as the presence of nonlinear springs and partial slipping. Boundary-condition nonlinearities mainly emerge from two phenomena. First, the contact between two separate surfaces, such that they are mutually tangential. Second, a single component is split into two or more separate components by an external force. Nonlinear analysis with nonlinear boundary conditions is more complex than nonlinear analysis, which considers

Fig. 5 Buckling of a timber-framed house support column (containing geometric nonlinearity due to the continuous upper structural gravity) [Video #1]

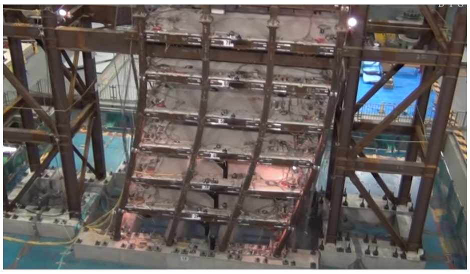


Fig. 6 Yielding and collapse of an 18-story steel frame building (containing geometric nonlinearity due to the large deformation) [Video #4]

Fig. 7 Damages of the support column (containing boundary-condition nonlinearity. At the same time, the change of boundary conditions will lead to the redistribution of the internal forces of the upper structure. Therefore, it will also cause nonlinear behavior in the upper structure) [Video #5]

Fig. 8 Separation of the building boundary and ground (containing the boundary-condition nonlinearity) [Video #5]

only geometric nonlinearity. Ye *et al*. (2020) demonstrated the necessity of considering the nonlinearity of the boundary conditions in the vibration analysis of curved beams and, for the first time, in studying transverse vibration.

Moreover, changes in the boundary conditions are typical in real-world engineering structures when large external loads are applied. When the boundary conditions change, the structure typically exhibits strong nonlinearities in terms of the stiffness and load redistribution. Furthermore, material nonlinearity often emerges simultaneously with boundary-condition nonlinearity because the failure of constraints causes a high-stress concentration with yielding.

Here, the occurrence of nonlinearity in the boundary condition is shown in videos that captured the vibrations of building structures in the 2011 earthquake off the Pacific coast of Tohoku. Fig. 7 shows the failure of the foot of the support column of the building, resulting in a change in the constraints and nonlinear boundary conditions. The building is separated from the ground, as shown in Fig. 8, due to the seismic wave effect. At this time, the boundary conditions of the building were changed because the constraints in the horizontal direction were released, and nonlinear boundary conditions occurred. In addition, the obvious relative sliding of the two boundaries under the action of aftershocks can also be clearly observed in [Video #5]. Although the emergence of nonlinear boundary conditions generally requires large seismic loads, once they occur, the structural conditions become severe, possibly leading to the collapse of the entire structure. To evaluate the occurrence of boundary-condition nonlinearity, analysis techniques based on video data exhibit exceptional advantages because the entire occurrence process can be observed based on video data.

3.2 Damage detection from video data

Most existing vibration-based damage detection methods are post-processing techniques in which the damage is detected by applying an algorithm to the already acquired vibration data. However, these methods cannot detect damage in real-time. In particular, with the use of video data, it becomes difficult to achieve real-time detection owing to the limitations of the computational cost and complexity of the algorithm. Many video-data-based damage detection methods sacrifice the analysis speed to achieve higher detection accuracy, even though high-speed analysis is often required in structural condition evaluations. In addition, because most recent video cameras realize the specification of a high FPS and generate a large amount of image data, data storage and processing time must also be considered (Khuc and Catbas 2017). Several methods for structural dynamic analysis based on video data have been proposed in recent SHM studies (Feng *et al*. 2015, Pan *et al*. 2016, Feng and Feng 2016). However, video data-based algorithms for real-time analysis require higher computational efficiency to process large amounts of data.

Therefore, many recent studies have adopted deep

Table 4 Review of structural damage detection using vision-based method, "E" indicates that the study was conducted Experimentally, while "R" indicates that the study was conducted to Real-life structures. In the last column, "I" indicahpgtes that the method was used for damage Identification and "D" indicates that it was used for damage Degree identification

References	Damage types	Technologies	Accuracy (%)	E/R	I/D
Cha *et al*. 2018	Concrete cracks/Medium steel corrosion/ High steel corrosion/Bolt corrosion/ Steel delamination	Fast-RCNN/ Blind source separation	84.7-90.6	R	I
Huynh *et al*. 2019	Bolt-loosening	RCNN/ Hough line transform	30-100	E&R	I&D
Zhai and Peng 2020	Building-level damage/Location-level damage	Google street view/ Deep learning	72.3	R	I&D
Wang *et al*. 2020	Glazed tiles damage	Mask-RCNN	97.5	R	I&D
Yuan *et al*. 2021	Bolt-loosening	Mask-RCNN/UAV	93.9	R	I
Kumar *et al*. 2021	Concrete cracks and spalling	YOLO-v3	94.2	E	I
Dunphy *et al*. 2022	Construction joint/Cracks/Pitting	Generative adversarial networks/CNN	76.9	R	I

learning, which enables classification and regression tasks with feature extraction from high-dimensional data to prevent manual extraction and classification of features from video images (Wang *et al*. 2020). Among these, convolutional neural networks (CNN) have been widely used for video-based real-time damage detection because they are suitable deep learning methods for dealing with high-dimensional matrix data. For instance, Huynh *et al*. (2019) employed a regional convolutional neural network (R-CNN) and Hough line transform (HLT) to achieve bolt-loosening detection and demonstrated the potential to achieve quasi-real-time bolt-loosening monitoring of massive, bolted connections through an experiment on a box girder bridge. In another study by Yuan *et al*. (2021), a mask region-based convolution neural network (Mask R-CNN) was adopted to detect bolt looseness having 8 fps processing frame rate. Although the processing speed could not be achieved in real time owing to the high computational cost of deep learning, quasi-real-time monitoring with an accuracy of up to 97% or even 100% was achieved in some specific cases. A faster R-CNN was also used to detect concrete cracks, bolt corrosion, paint peeling in steel structures; and corrosion in steel members (Cha *et al*. 2018). YOLO (Redmon *et al*. 2016) has also been widely used in damage detection because it is a well-known algorithm for the localization and classification of objects within an image. Although YOLO is still optimized and updated annually and has been updated to YOLO-v7, YOLO-v3 (Redmon and Farhadi 2018) is still the most widely used version based on Google Scholar data and has been used to detect structural damage. The network uses image data as input and returns the outputs of the bounding box parameters and class probabilities. Kumar *et al*. (2021) used YOLO-v3 to detect cracks and spalls in concrete structures in real-time with an accuracy of approximately 94% and an execution speed of 30 fps. However, the use of deep learning techniques for video data-based damage detection is affected by several factors of data quality and network parameters, such as video resolution and the size of the region of interest (ROI). When the resolution of a video image is excessively high, it is difficult to achieve real-time detection because of the large amount of computation required.

From the viewpoint of damage detection, a competitive advantage of the video data-based method is that it contains both damage location information (spatial domain) and damage time information (time domain). In addition, because of the popularity of video data and the diversification of access channels, research on real-time damage detection based on computer vision and deep learning has developed rapidly.

At the end of this section, the structural damage detection using the vision-based methods are summarized in Table 4 based on damage types, core technologies, and whether the method was used only for damage detection or for both damage detection and damage degree detection.

4. Discussions for structural nonlinearity evaluation from video data

Studies on nonlinear structural dynamics based on video data are still in the early stages, as reviewed in the previous sections. Moreover, most existing studies have focused on the identification of nonlinear systems, and the approach to structural nonlinearity detection and its application to evaluate the structural condition after disaster events, which cause large displacements of structures, have not been extensively studied. Here, some potential directions and a discussion in the research on structural nonlinear extraction based on video data and visualization are proposed based on existing technologies.

4.1 Potential approaches for nonlinearity event detections

In the research on structural nonlinear feature extraction based on acceleration time-history data, much research based on uni-dimensional time series has been performed (Farrar *et al*. 2016). Methods for direct feature extraction from image data are relatively limited, and only methods based on deep learning (DL) are mostly applied. In machine learning, the task of detecting certain targets from video or image data is referred to as objective detection. CNN-based methods are also frequently developed for recognition tasks in SHM. (Dunphy *et al*. 2022). Generally, the most important phase in machine learning is the training process, which typically requires a large amount of appropriate data. If we could acquire sufficient video data on structural nonlinearity events, it would become possible to develop a machine-learning model for nonlinearity event detection and classification. However, there is insufficient training data regarding events of structural nonlinearity occurrences because such events that cause structural nonlinearities, such as disaster events, are rare. Therefore, feature extraction based on computer vision and signal processing methods is important for detecting and evaluating structural nonlinearity events from video data.

The first involves judging nonlinearity events and determining their location. Popular nonlinear processing methods (e.g., force surface restoration and nonlinear subspace identification) are also applicable for nonlinear damage identification based on video data. Such methods usually require dynamic physical parameters of the system, such as acceleration, velocity, displacement. These parameters can be obtained by analyzing image data (many researchers have realized the identification of dynamic physical parameters based on video data) can be used as input. Then, nonlinear identification technologies can be employed to achieve nonlinearity identification. Notably, such methods usually achieve only nonlinear discrimination and order identification in the system. However, it is difficult to determine the nonlinear order of nonlinear damage that occurs in real-world structures. Therefore, the mutual verification of multiple techniques is necessary to demonstrate the feasibility of this idea. These ideas are based on uni-dimensional time-series data analysis. However, this procedure is complex and time-consuming, and the data collection and calculation accuracy heavily influence the final recognition result. In recent years, researchers have promoted nonlinear recognition technology to a higher dimension, implying that multidimensional image data, such as weighted recurrence networks, can be directly analyzed and processed (Brandes 2001, Newman 2005, Yang and Chen 2014). Technology based on computer vision has developed rapidly in recent years.

Among these, the optical flow method has significant advantages for feature extraction. Optical flow is an algorithm used to identify target motion characteristics (Chaudhry *et al*. 2009, Khaloo and Lattanzi 2017). In SHM, the motion characteristics (displacement, velocity, or acceleration) of the damaged area, compared to those of the undamaged area, usually show an apparent change. The optical flow method is expected to directly identify these changes based on video data to achieve feature extraction. The current study is still in its early stages and deserves further investigation because the direct processing of spatial data places greater demands on the algorithm.

Not only nonlinear damage identification and localization but also the identification of the occurrence time of nonlinearity events has great engineering significance because it can more accurately reflect the entire damage process. However, most nonlinear SI methods do not contain time-domain information. To address this issue, two ideas are presented to identify the occurrence times of nonlinear events. The first idea is a sliding window (Chen and Yang 2016) which is a self-defined window that can show the center point data at each time point by sliding the window along the time axis, thereby making the time domain visible. The second idea is that using damage indices to determine singularity points is a widely used approach, such as the wavelet packet energy change rate (Liu *et al*. 2021) and singular value entropy. This has a good recognition effect in the identification of the occurrence time of nonlinearity events. However, the application of these indicators requires the conversion of image data into uni-dimensional sequence data. The direct analysis of a 2D image or 3D video data must be further considered.

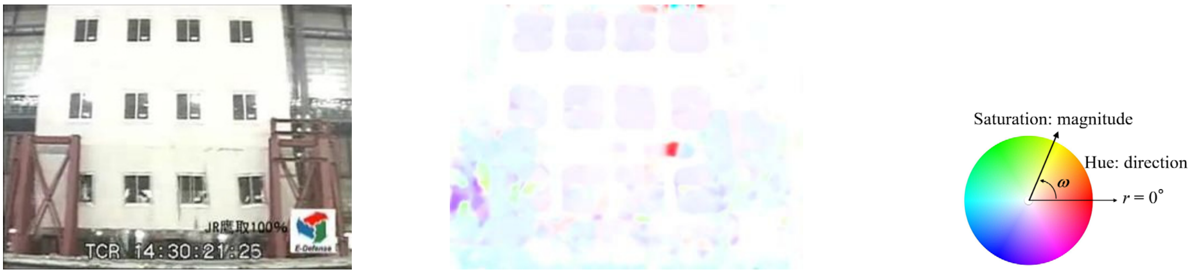
4.2 Discussions to feature extraction in the use of video data by optical flow method

To discuss the potential applicability of the optical flow method to the nonlinear feature extraction in time and spatial domains, one case study was conducted to finalize this review study by using video data of the seismic response of a building structure. The video data was acquired in a shake-table test conducted in the E-defense facility, which is a large-scale 3D shake table in Japan, and the data was opened by the NIED, Japan [Video #6]. The structure for testing was a full-scale 4-story steel building, and it oscillated on a shake table until it collapsed by applying the *Takatori* waveform, one of the recorded earthquake waveforms in the Kobe earthquake that occurred in 1995. The length of the video data was 175 seconds, and the resolution and FPS of the video data were 320×240 pixels and 30 fps, respectively. In this test, the seismic excitation caused cracks and collapse of the building's external wall when the intensity of the earthquake input reached a maximum of approximately 800 gal. The occurrence of cracks is a nonlinearity event that must be extracted, and it belongs to material nonlinearity.

The authors are working on a study that focuses on extracting nonlinearity in structural vibration in video data by the optical flow method. There are several algorithms for deriving the displacements of objects in the optical flow methods; here, we apply the Farneback method for discussion (Farnebäck 2003). The Farneback method is one of dense optical flow algorithms that exhibits accurate estimations both in magnitude and direction of displacement vectors, as well as computational cost efficiency. The displacement vector per time that normally depends on frames per second are derived for every pixel in a whole image.

Fig. 9 demonstrates an application of the Farneback optical flow to a video data of E-defense shaking table test of a steel frame building. There are events of cracking wall board, and they cause phenomena of their open and close responses during the excitation. The output of Farneback optical flow is a contour figure in a whole frame, where saturation and hue in HSV colormap indicate magnitude

(a) The frame before crack occurrence events at the wall board



(b) The frame in a significant crack occurrence event at the wall board

Fig. 9 The visualization results based on the optical flow algorithm

and direction of the vector, respectively (Smith 1978, Lee *et al*. 2021). The RGB color space represents colors as combinations of red, green, and blue channels, where each channel can have values in the range [0, 1]. Here, we used MATLAB function of "estimateFlow" to calculate the Farneback optical flow. Even in oscillation of the building under seismic excitation, there is no significant disturbance in vector field during no event of significant cracking on the wall board, as shown in Fig. 9(a). On the other hand, in the time of large crack occurrence in wall board at the lower right of image, the adjacent area of red and light blue, opposite hue in color, emerged as shown in the red rectangle region of Fig. 9(b). This indicates that the vector field of displacement is disturbed by the crack occurrence event. This might be applicable for detecting nonlinearity event extraction in the video data. However, video and image data obtained during disaster events often contain a large amount of irrelevant information, such as non-damaged parts, window areas in the NIED video, and non-structural parts. As a result, even after the realization of the nonlinear existence identification of image data, further precise localization of nonlinear events and classification of nonlinear types remain essential directions for future studies.

5. Conclusions

This paper presents a comprehensive review of the study of structural nonlinearity extraction based on video data. Video data applications to SI and damage evaluation during disaster events were reviewed. Many studies have demonstrated that video data-based technologies have been widely used for parameter identification (e.g., frequency, mode shape, damping ratio) of dynamic systems and have shown high accuracy compared to traditional sensor measurements. However, the application of this technology in the field of nonlinear SI is still relatively limited and is in its infancy. At present, the commonly used methods for nonlinear SI based on video data start from the obtained system's physical or modal parameters, which are then combined with nonlinear processing methods (e.g., the unscented Kalman filter and nonlinear subspace method) to achieve a nonlinear SI.

Furthermore, structural nonlinear events occur frequently during disasters. In this study, we reviewed and categorized the most prevalent nonlinearity events that occur in structures during earthquake disasters from videos shared on an Internet platform. In addition, studies on video data-based damage detection applications were reviewed. A competitive advantage of the video data-based method is that it contains damage location information (spatial domain) and damage time information (time domain). The direct analysis of video data can provide rich damage information.

Finally, potential research directions in the nonlinearity extraction of structures, damage detection, and visualization were discussed based on existing technologies, such as video data processing and deep learning. According to the NIED shake-table test video data analysis example, feature extraction based on the optical flow method has potential applicability, although some disturbing detection areas should be improved. Notably, several influential factors affect the output accuracy of video data-based nonlinearity evaluation if appropriate concerns are not considered in video data collection and processing. Nevertheless, technology based on video data still has great potential for development because the access channels of video data have diversified, and the data's richness provides a good foundation for the proposal of more advanced analysis technology.

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Video data

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[2] https://www.youtube.com/watch?v=EXJKaQF0Rzw
[3] https://www.youtube.com/watch?v=vm4xx6P56H4
[4] https://www.youtube.com/watch?v=Cqa-skpgVEI
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