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ScienceDirect

Procedia Engineering 199 (2017) 1894–1899

Procedia Engineering

www.elsevier.com/locate/procedia

X International Conference on Structural Dynamics, EURODYN 2017

Integrated Process of Images and Acceleration Measurements for Damage Detection

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Abstract

The use of mobile robots and UAV to catch unthinkable images together with on-site global automated acceleration measurements easy achievable by wireless sensors, able of remote data transfer, have strongly enhanced the capability of defect and damage evaluation in bridges. A sequential procedure is, here, proposed for damage monitoring and bridge condition assessment based on both: digital image processing for survey and defect evaluation and structural identification based on acceleration measurements. A steel bridge has been simultaneously inspected by UAV to acquire images using visible light, or infrared radiation, and monitored through a wireless sensor network (WSN) measuring structural vibrations. First, image processing has been used to construct a geometrical model and to quantify corrosion extension. Then, the consistent structural model has been updated based on the modal quantities identified using the acceleration measurements acquired by the deployed WSN.

Keywords: Visual Inspection, Dynamic Testing, Model Updating, Image Processing, Automation, Damage Identification

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1. Introduction

Suitable procedures for inspection, maintenance and reconstruction of infrastructure are crucial for a sustainable management in developed countries. Even though the matter has strongly exploited in the scientific community, the raising of innovative technologies in mechatronics, robotics and ICT opens up new perspectives in facing the

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10.1016/j.proeng.2017.09.126

classical problems in the management of infrastructures. The basis to build models useful for decision-making process to assure safe operating infrastructures, is currently under discussion [1] and the adoptable procedures are partially sensible to the available technologies. In this respect, two emerging research fields might significantly impact in the inspection and monitoring of infrastructures: automated machine vision-based inspection integrated in building information modelling (BIM) [2,3] and distributed wireless sensor networks (WSN) [4,5]. In the first area the use of mobile robots and UAV have strongly increased the acquisition of images to sense the spatial characteristics of the environment, permitting the creation of "cloud" of 3D points. Intelligent proximity algorithms are used to convert these points into surfaces that corresponds to the real ones. Consequently, the generation and the management of a three-dimensional (3D) digital representation of physical and functional features of an infrastructure permits to involve the up-to-date concept of BIM. The emerging concept in this area is the use of BIM during the entire life-cycle, starting from creating a virtual 3D model during the design stage – an *as-designed model* – converting it, after construction, to – an *as-built model* – and finally using it for inspection and maintenance management through the development of – an *as-damaged model* [2]. Such scenario determines the condition for the integration of novel structural health monitoring systems using WSN in a BIM environment to permit visualization and management of sensor data, data interpretation and analysis and interaction with classical finite element model for structural behaviour simulation. Moreover, this novel available technology might modify the approach to the development of future Bridge Management System in which a key issue is the organization of data describing the condition of bridges with respect to the evaluation of extension, intensity and evolution of damages [6]. In this respect, in the present paper, a sequential procedure is proposed for bridge condition assessment and monitoring. In Fig. 1 the main steps of the procedures are highlighted. At the first step the acquisition of images in automated manner (UAV, drones, robots, etc) or eventually a laser scanner of the observed bridge permits to construct 3D point clouds from which a geometrical model of surfaces can be created. Such geometrical reconstruction constitutes a basis for the development of a BIM model of the bridge and the associated Finite Element (FE) model furnishes the description of its mechanical and structural behaviour. This first step of the procedure is completed by the acceleration measurements acquired by the deployed WSN which are used to identify the main modal characteristics of the bridge, usable for the updating of FEM. After this initial process, the design of a permanent structural monitoring system can be pursued and automatic or semi-automatic evaluation of the bridge condition [6] based on damage detection can be exploited. The paper deals with the description of an integrated procedure for damage detection based on processing of images and accelerations.

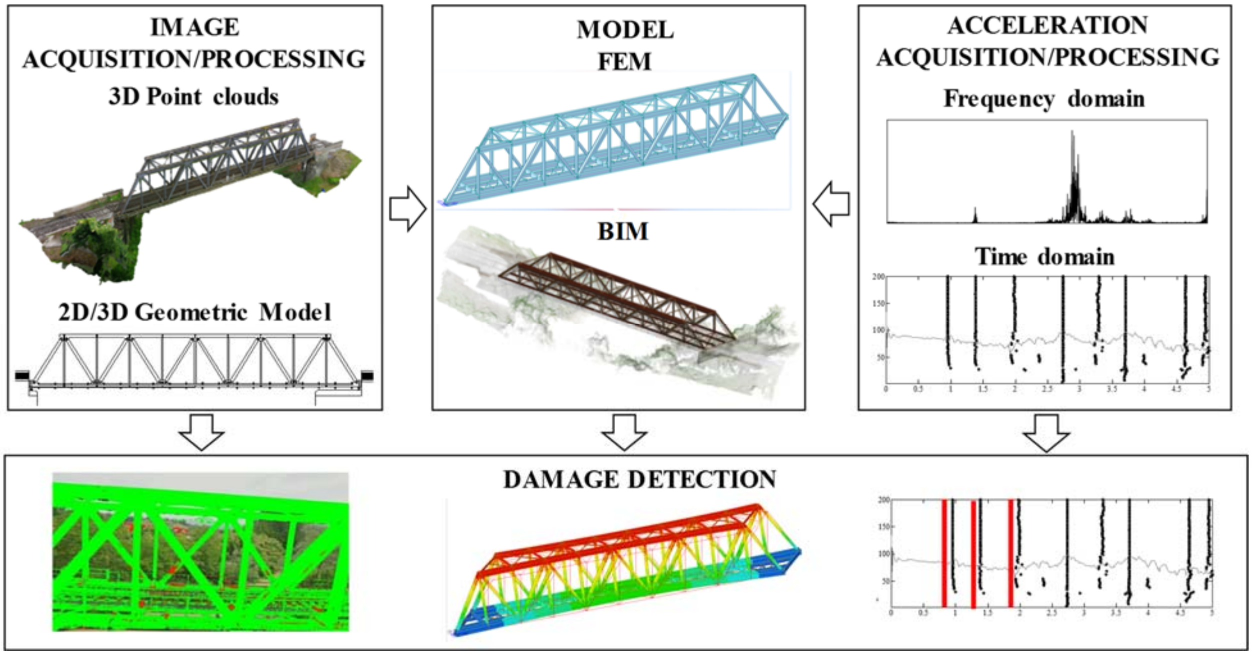


Fig. 1. Block diagram of an integrated procedure for damage detection.

2. Image acquisition and processing

Damage detection by visual image processing requires the recognition and identification of both the observed object with respect to the background and the specific defect.

The first step for the acquisition and image processing is data collection, assuming the use of either an automatic or semi-automatic system, being ground (mobile robot) or Unmanned Aerial Vehicle (UAV), to collect images of the object to be analyzed. The second step is the data processing using a selected digital algorithm technique. In the last two decades, several techniques have been developed to recognize objects; one of the most used is based on the Haar wavelets. The Haar wavelets are natural set basis functions, which encode differences in average intensities among different regions [7]. This approach requires a training of an object detector by means of a process of learning [8], with a database of positive and negative images. The greater is the database the best will be the overall outcome in recognition. Nevertheless, in the presence of small differences, an object cannot be recognized, even with a large database. This means that a Haar based detector requires learning every kind of object to be recognized in order to achieve the object detection. Furthermore, the training is a time expensive procedure.

Another approach is related to finding correspondences between two images of the same scene. The search procedure for finding discrete image correspondences can be divided into three main steps: first, “points of interest” are selected at distinctive locations in the image, such as corners, blobs, and T-junctions. Second, it requires that a feature vector represent the neighborhood of every point of interest. This descriptor has to be distinctive and, at the same time, robust to noise, detection errors, and geometric and photometric deformations. Third, the descriptor vectors are matched among different images [9]. This approach requires a sample image in which the object to be detected is present, in order to be compared to the acquired image. If there are not enough common “points of interest”, even taken from different prospective, this method cannot produce good result.

Another approach is related to Color Detection Techniques, since colors allow fast processing and are highly robust to geometric variations of the object pattern and viewing direction [10]. A digital image can be described by 2D matrix of elements that are associated to a specific color space, which is a specific organization of colors representing the image. A color detection technique can determine an object by a suitable model (classifier), which defines explicitly through a number of rules the correlation among the color components [11]. These rules are a function of the used color space to represent the image. The most used color space is RGB, where each color is represented by a triple of components (Red, Green and Blue) which are added together. In the last decades, this method has been used for many applications and in particular, for face recognition [12], since this technique can avoid problems related to the illumination issues by applying a normalized color space.

In the present research, a color detection technique has been used for the image processing, and then each image can be represented by a RGB color space with 8-bits, since every color space component is discretized in a range of values from 0 to 255. A suitable relation among components has been chosen to detect object (in this case the bridged structure) and defects (the superficial defect), and it can be represented by the following condition

$$\begin{aligned}&(R_{min} < R < R_{max}, G_{min} < G < G_{max}, B_{min} < B < B_{max})\ and\\&(\mathrm{G} - \mathrm{G}_{Rmin} < \mathrm{R} < \mathrm{G} + \mathrm{G}_{Rmax})\ and\\&(\mathrm{B} - B_{Gmin} < \mathrm{G} < \mathrm{B} + B_{Gmax})\end{aligned} \qquad (1)$$

Assuming the availability of images taken by automatic system (UAV) and mobile robot, they are used for the image processing. In particular, in the studied case of bridge recognition of defects, the limiting values in eq. (1) of chromatic ranges have been determined by a pre-processing procedure. Then, an automatic procedure using eq. (1) in the analysis of each pixel permits to recognize structural components and defects. In the presented example the limiting values used to identify the components are reported in Table 1.

For the image processing, a software has been developed in VB.NET environment and uses the EMGU library [13]. Emgu CV is a cross-platform image-processing library closely related to OpenCV because Emgu CV is a .NET wrapper to OpenCV. The Emgu CV library spans many areas in computer vision, including plant product inspection, medical imaging, user interfaces, camera calibration, stereo vision and robotics. Because computer vision and machine learning often go hand in hand, Emgu CV also wraps a full, general-purpose machine-learning library from the OpenCV image-processing library [13].

In Figure 2 the original images (Fig.2a,e) and the outcomes after post processing are shown for object detection,

Table 1 – Values for parameters of Eq. (1) to identify structural components and defects.

	R_{min}	R_{max}	G_{min}	G_{max}	B_{min}	B_{max}	G_{Rmin}	G_{Rmax}	B_{Gmin}	B_{Gmax}
Objects	20	190	30	200	20	200	15	15	15	15
Defects	90	220	50	180	40	170	-5	60	5	40

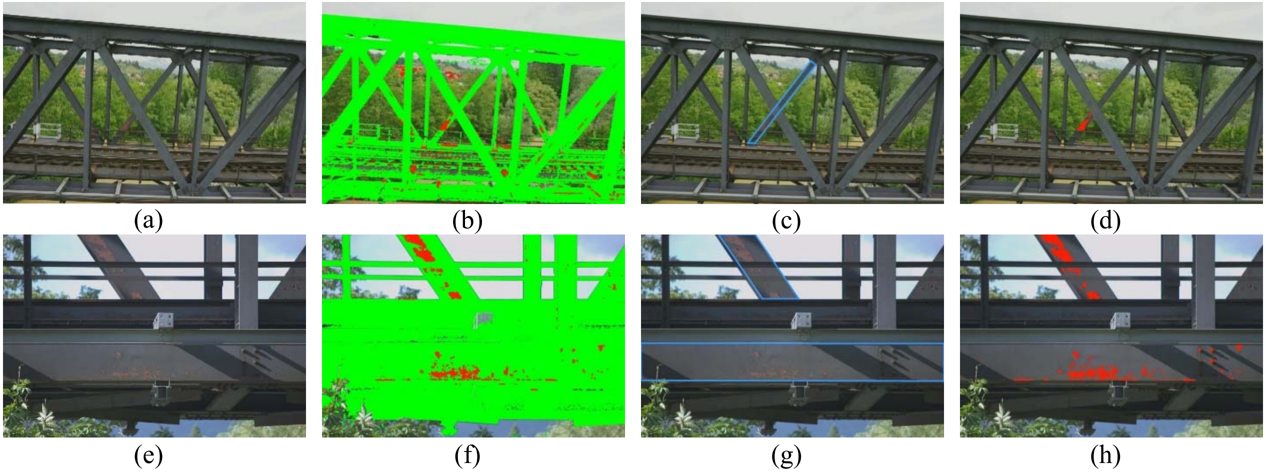


Fig. 2. Image processing: (a), (e) the original image; (b), (f) structural component and defect; (c), (g) manual component selection; (d), (h) component defect evaluation.

marked with green pixels (Fig. 2b,f), and for the defect detection, marked with red pixels (Fig. 2d,h). Specific structural components can be also analyzed by a manual selection (Fig. 2c,g).

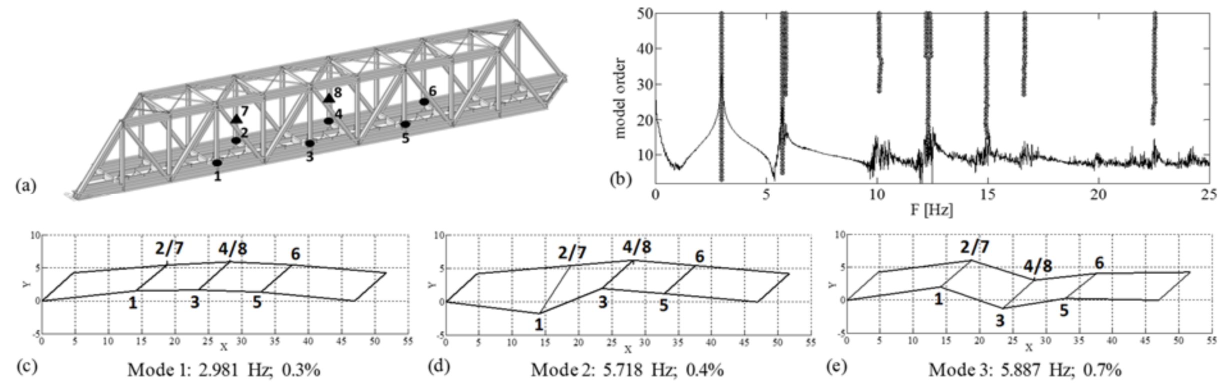
Table 2 reports a summary of the numerical results obtained through the developed image processing procedure applied to two selected images related, for example, to superficial corrosion of a steel bridge (Fig.2a,e). The developed software is able to determine the structural components, with them to select a particular one, and then to quantify automatically the defect extension (percentage) with respect to the component area (last column , Table 2) .

Table 2 – Numerical results obtained with the developed software for corrosion defect extension evaluation.

	Structure/component area [pixel]	Defect area [pixel]	Defect Percentage [%]
Fig. 2b	4695447	145417	3,1
Fig. 2c,d	80942	9197	10,2
Fig. 2f	7204346	209662	2,8
Fig. 2g,h	1758264+318641	110055+81783	5,9+20,4

3. Acceleration measurements, model prediction and updating

The availability of the WSN used in a recent monitoring [5] has permitted to acquire acceleration measurements on the basis of previous experience in the field [14]. Indeed, a one-day experimental tests campaign has been carried out to identify the modal characteristics of the main modes involved in the structural dynamics of the studied railway bridge. Expected global modes for the given railway steel bridges were flexural (vertical or transverse) and torsional. Moreover, the presence of local modes should be taken into consideration especially in steel structures because they can potentially influence the expected global modes [15] and fatigue behavior.



(c) Mode 1: 2.981 Hz; 0.3% (d) Mode 2: 5.718 Hz; 0.4% (e) Mode 3: 5.887 Hz; 0.7%

Fig. 3. Experimental tests: (a) stability diagram, (b) experimental layout, (c)-(d) first three modes identified.

On this basis the setup has been defined using eight wireless sensor nodes, MEMSIC Imote2, completing the network with the communication platform, MEMSIC SHM-A sensor board. The latter is characterized by an advanced 16-bit data acquisition system while the sensor by a MEMS tri-axial accelerometer (ST microelectronics LIS344ALH). The sensors nodes were placed in the positions where are not expected zero-modal components of the main modes evaluated through a FE numerical model previously developed. For this reason, three accelerometers were attached to the structure in correspondence of about one and two thirds of the bridge's length and also in the mid-span, on both side of the deck. Moreover, the seventh and eighth accelerometers were placed in two vertical structural elements, at the height of about 1.5 m and in correspondence of one-third and half of the bridge's length. Fig. 3a illustrates the complete experimental layout. Deck vibrations have been acquired in two conditions: (1) environmental noise and (2) under a train passage. The measured data have been processed using both time- (Stochastics Subspace Identification, SSI) and frequency- (Power Spectral Densities) based procedures. For sake of brevity, Fig. 3b summarizes only the results obtained applying the SSI in which stability diagram permits to identify three main modes. The first mode presents a high lateral deformation at 2.981 Hz (Fig 3c) while the second and third modes are very similar and vibrating at 5.718 Hz and 5.887 Hz (Fig 3d and 3e), respectively. In the latter modal shapes, the lateral deformation presents a cross point near the mid-span of the bridge. A view from above shows the modal shapes and, even if not apparently visible from the modal components of the sensor nodes 7 and 8, all modes manifest a significant cross-section distortion. The caption of Fig. 3 reports also the identified modal damping ratios for each mode in terms of percentage. These evaluations are within standard values reported in literature for steel bridges. Finally, Table 3 data permits a comparison between the identified and numerical frequencies, the latter ones evaluated by the predictive FE model developed before the experimental campaign, evidencing that even before the model updating the agreement is very good.

4. Damage evaluation and identification

The proposed procedure permits to use the acquired information to determine a suitable damaged steel bridge model to evaluate damage effects on the structural behavior. Both vibration/distortion induced fatigue damages and corrosion were considered because generally occurring in different typologies of steel railway bridges.

Table 3 – Comparison between the identified and numerical frequencies [Hz].

	Environmental noise			Passage of a train		
Mode	Identified	Numerical	Δ %	Identified	Numerical	Δ %
1	2.98	2.91	-2.35	3.00	2.91	-3.00
2	5.72	5.92	3.50	5.71	5.92	3.67
3	5.89	5.98	1.53	5.82	5.98	2.75

The adopted approach has evidenced the possibility of considering the combined effect of corrosion and fatigue. Indeed, on the one hand, the optimized FE models obtained from the updating procedure using acceleration measurements, it permits to evaluate a stress history from dynamic analysis calculations of the structural response in each structural element in order to perform the fatigue analysis according to well-established procedure [16]. On the other hand, the valuable description of the real geometric features of the bridge components and in particular of the paint loss and corrosion extensions is strongly enhanced by the use of automated tools for the acquisition of images and their post-processing. Corrosion effects in the bridge dynamics has been taken into account through the counterpoised double effect due to loss of mass and stiffness reduction [17]. A precise modelling of the surface extension affected by the defect has been made possible using the proposed image processing method while the intensity (thickness of the defect) associated to the identified area is still an objective of on-going research through the exploitation of active infrared thermography.

5. Conclusions

A procedure to integrate information furnished by available technology has been proposed with the aim of evaluating the combined effect of fatigue and corrosion in steel railway bridges. A proposed technique of image processing has permitted to evaluate corrosion extension on the bridge components. Acceleration measurements are used to identify modal characteristics of the bridge in order to obtain an optimized updated FE model in which the area affected by corrosion are modelled as mass loss and stiffness reduction. The updated damaged model is used to extract stress history for fatigue analysis taking into account the real extension and impact of corrosion.

Acknowledgements

The research leading to these results has received funding from the Italian Government under Cipe resolution n.135 (Dec. 21, 2012), project *INnovating City Planning through Information and Communication Technologies*.

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