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Procedia Structural Integrity 44 (2023) 2082–2089

Structural Integrity Procedia

www.elsevier.com/locate/procedia

XIX ANIDIS Conference, Seismic Engineering in Italy

A Bayesian-based data fusion methodology and its application for seismic structural health monitoring of the Consoli Palace in Gubbio, Italy

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Abstract

Recent earthquakes have demonstrated that monumental structures located in regions characterized by high seismic hazard are particularly sensitive to damage, stimulating a growing attention to the formulation of cost-effective and long-lasting methods for damage assessment. Generally, the evaluation of a healthy or damaged state is data-driven and it can be subjected to a large amount of uncertainty. In order to associate a damage symptom to an actual structural damage, including all the uncertainties involved in the process, a Bayesian-based data fusion methodology is proposed. To this purpose, different sources of information are combined, such as dynamic structural properties extracted from monitoring data (natural frequencies and mode shapes), static response data (crack amplitudes) and visual inspections. More in depth, the proposed procedure comprises three fundamental steps: i) calibration of a finite element (FE) model, partitioned in well-thought-out macro-elements on the basis of engineering judgments and/or numerical simulations and, subsequently, construction of a tuned surrogate model (SM) considering pre-selected uncertain parameters as inputs, such as the Young's modulus, shear modulus, Poisson's ratio and mass density associated to each macro-element; ii) solve the Bayesian-based inverse problem aimed at deriving the posterior statistics of the uncertain parameters over the space of the surrogate model's classes in a computational effective manner by using dynamic data; iii) adjust the posterior distribution on the basis of the information obtained from static data and visual inspections, i.e., data fusion. The suitability of the proposed approach is demonstrated by using the monitoring data pertaining to a monumental palace, located in Gubbio (Italy) and named Consoli Palace, which has been monitored by the Authors since 2017.

Keywords: Bayesian Data fusion, Damage detection, Surrogate model, Structural Health Monitoring, Architectural heritage.

10.1016/j.prostr.2023.01.266

Introduction

Nowadays, the damage identification process of monumental structures located in regions characterized by high levels of seismic risk is a challenging task. Recently, SHM-based approaches are a fast-growing techniques due to their ability to respond to structural changes (Cavalagli etal., 2018, Venanzi etal., 2020) through the post-processing of the data acquired from an array of sensors deployed on the structure. The main goal is to monitor the health of the structure based on measurable response parameters, as these can ultimately become signs of possible damage due to excessive loads, earthquakes, material's degradation and so on. Usually, these data-driven methodologies can be classified as unsupervised approaches. Then, different works in literature have contributed to the development of SHM-based probabilistic approaches for damage detection (Behmanesh etal., 2015, Sun etal., 2020) and semi-supervised methodologies (Ierimonti etal., 2021). Nowadays, the challenge is to make robust decisions considering the complex nature of the real-world applications and the high level of uncertainties during the SHM-based data pre-processing and post-processing. In this context, a fundamental role is played by data fusion, an attractive multi-informative approach aimed at collecting and interpreting data of different nature. According to Hall, 1997, three levels of data fusion can be identified: (i) data-level, consisting of combining data derived from multiple sources with the same physical meaning; (ii) feature-level, consisting of analyzing and processing heterogeneous input data which are then concatenated, also with different physical meaning; (iii) decision-level, consisting of separately addressing the results from different sources and then the final decision is achieved by means of selected combination rules.

Different works in the literature make use of data fusion approaches aimed at quantify a post-event damage (Chatzis etal., 2015 and Li etal., 2020). In light of the brief literature review, this paper presents a real-time decision-level Bayesian-based data fusion methodology for decision making, where SHM is used as a complimentary method to visual inspections. Thus, different sources of information are merged together to achieve a more reliable assessment of the health of the investigated structure. To do so, a high-fidelity model of the structure is constructed to capture the physics involved in the problem. Then, the model is used for identifying damage-sensitive portions on the basis of engineering judgement (EJ) and nonlinear static analysis (NLSA). The material's mechanical characteristics of each damage-sensitive portion are assumed as uncertain. Then, a surrogate twin model is calibrated, i.e., a mathematical relationship between the uncertain parameters and the modal features of the structure. The posterior statistics of the uncertain parameters are evaluated through the Bayes theorem. Given the complexity of structures and the inability to perfectly model all aspects of the system, Bayesian-based results, static measurements and visual inspections are merged together to aid engineers in detecting the onset of damage in real-time.

The effectiveness of the proposed approach is demonstrated by analyzing the effects of a low-intensity earthquake occurred on May 2021 on the Consoli Palace, located in Gubbio, central Italy. The palace has been equipped with a permanent SHM system since 2017 and the actual configuration has been enhanced in July 2020 with a dense array of sensors.

The rest of the paper is organized as follows. Section 1 describes the steps of the proposed methodology. Section 2 gives a general frame of the case study, its FE/surrogate model and the installed SHM system. Section 3 highlights some preliminary results. Section 4 concludes the paper.

1. The Bayesian-base data fusion procedure

The Bayesian-based procedure can be divided in two phases: i) the offline phase; ii) the online procedure. Detailed information about each phase are summarized in the following Sections.

1.1. Description of the offline phase

The main purpose of the offline phase is to calibrate a SM which is then used in the Bayesian-based model updating stage to make predictions on the possible damage.

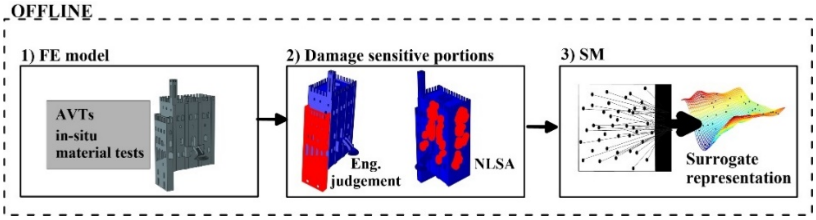


Fig. 1. Schematic representation of the offline phase.

The fundamental steps of this phase are:

1) *Construction of the FE model*. The FE model can be constructed and calibrated on the basis of Ambient Vibration Tests (AVT) and in situ material characterization tests.
2) *Evaluation of damage-sensitive portions*. The building is subdivided in *N* regions **R**={R1, .. , R*j*, .., RN} potentially prone to damage, defined on the basis of NLSA and EJ. Each region is considered homogeneous in terms of material's mechanical characteristics. Vector **K**={k_1(R1), .. , k_j(R*j*), .., k_N(RN)} collects the damage parameters associated to the j-*th* region.
3) *Calibration of a SM*. In order to reduce the computational effort of the analysis, a SM(**K**) is calibrated as a function of the uncertain parameters to be updated. The SM is proposed to present the numerical relationship between FE model, in terms of frequencies and mode shapes, and **K**.

1.2. Description of the online procedure

The online procedure is performed by running the following steps:

1) *Start continuous SHM*. A network of sensors of different nature allows to store acceleration/velocity data, temperature/humidity data and static measurements, such as crack amplitudes and tilt rotations.
2) *Feature extraction*. The SHM data are post-processed and the modal features MF of the structure are evaluated, i.e., fundamental natural frequencies and vibration modes. Furthermore, environmental effects are removed from original signals. For the purpose, the MOSS integrated software (García-Macías etal., 2020) is used, which is an automated tool based on the stochastic subspace identification (SSI) technique.
3) *Novelty detection.* If a novelty is detected go to step 4, otherwise go back to step 1. The novelty at time *t* is related to the estimation of the square Mahalanobis distance T^2 (Hotteling, 1947) of the residual E(t), i.e., $T^2(t) = (E(t) - \bar{E})^T \sum^{-1}(E(t) - \bar{E})^T$, where $\bar{E}$ represents a vector collecting the mean values of the residuals empirically estimated in the training period and $\sum$ the corresponding covariance matrix.
4) *Intermediate analysis.* Perform the Bayesian model updating of the uncertain parameters and proceed with visual inspections. More in detail, the posterior distribution p of the *j*-th uncertain parameter is evaluated as follows:

$$p\big(k_j \mid \mathbf{MF}, t\big) = c \cdot p\big(\mathbf{MF} \mid k_j, t\big) \cdot p\big(k_j \mid \mu_j(t-1)\big) \tag{1}$$

where μ_j is the mean value of k_j; c is a constant ensuring the posterior distribution integrates to 1; $p\big(\mathbf{MF} \mid k_j, t\big)$ is the likelihood function modeled as a Gaussian distribution with zero mean (Behmanesh etal., 2015, Ierimonti etal., 2021); $p\big(k_j \mid \mu_j(t-1)\big)$ is the prior distribution calculated as the posterior distribution at previous time step $t-1$.

Visual inspections can be numerically quantified by means of a damage index DI, accounting for the importance G, extension K1 and intensity K2 of damage. The index DI can be evaluated as follows:

$$\mathrm{DI}_j = \sum_{i=1}^{m} G_{ji} \cdot \mathrm{K1}_{ji} \cdot \mathrm{K2}_{ji} \tag{2}$$

where m is the number of damages observed in region Rj. The term G could be, 1,2 or 5 on the basis of the observed damage, i.e., absence of damage, local mechanism, global mechanism. The terms K1 and K2, on the basis of the observed extension/intensity, could be 0.2, 0.5 or 1.

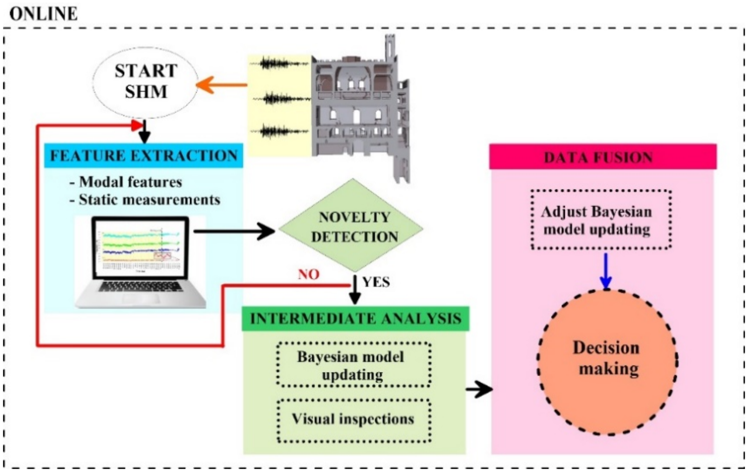


Fig. 2. Schematic representation of the online phase.

5) *Data fusion.* Combine all the information sources as follows:
   i) Evaluate the visual inspection-related DI_j for each region. If $\mathrm{DI}_j > 0$, the region is considered "damaged";
   ii) Evaluate the crack index CI, i.e., assign CI=1 if the crack measurement exhibits a permanent closure or opening, otherwise assign CI=0;
   iii) Define the j-th Bayesian-based Index BI, i.e., assign BI=1 if the updated values are reduced more than or equal to 10 % with respect to the undamaged state, otherwise assign BI=0;
   iv) Calculate the data fusion results by means of the well-known 2-out-of-3 (2oo3) method (majority criterion), named 2oo3 voter and assign 1 if the specific region has the majority of 1, assign 0 otherwise. In the absence of crack/deformation information for a specific region, the value of DI is counted twice.
   v) Adjust the posterior statistics $k_j^{\mathrm{up,VI}}$ by means of a correction coefficient Ψ_j^{VI} which multiplies the posterior distribution k_j^{up}:

$$k_j^{\mathrm{up,VI}} = \Psi_j^{\mathrm{VI}} \cdot k_j^{\mathrm{up}} \quad (3)$$

If the 2oo3 voter is 1 (damaged state) assign $\Psi_j^{\mathrm{VI}} = 1$, otherwise assign $\Psi_j^{\mathrm{VI}} = k_j^{\mathrm{ref}}/k_j^{\mathrm{up}}$

2. The Consoli Palace: SHM system, FE model and corresponding SM

The Consoli Palace is a 60 meters high medieval building, located in Gubbio, Umbria, central Italy. The Palace is built in calcareous stone masonry with a regular and homogeneous texture.

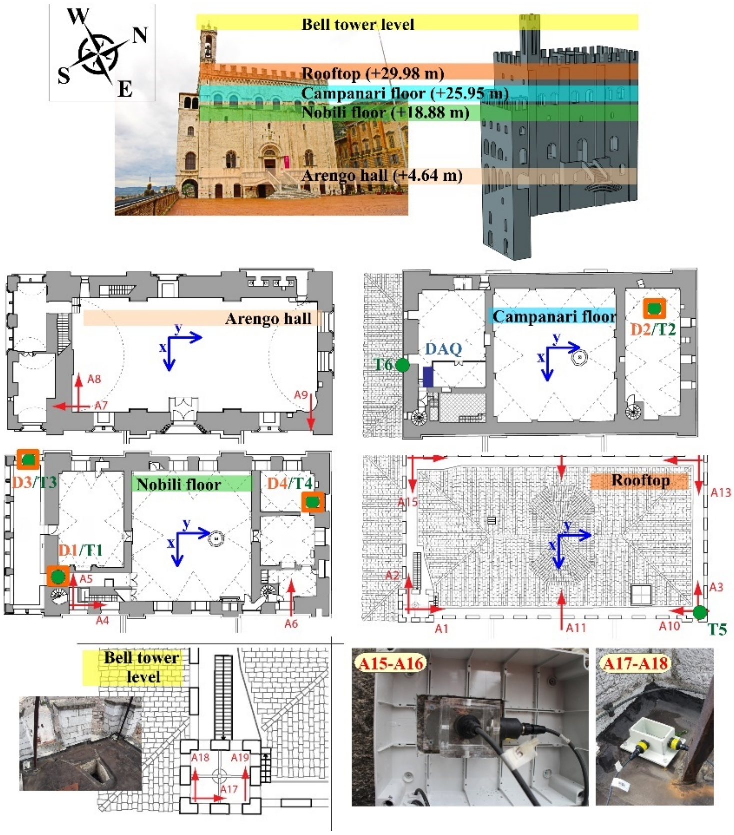
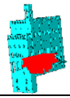
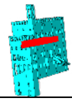
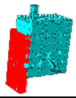
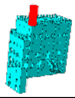
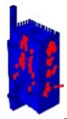
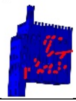
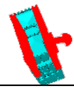


Fig. 3. The Consoli Palace and its SHM system.

The current configuration of the SHM system (Figure 2) was activated by the Department of Civil and Environmental Engineering of University of Perugia in July 2020 and comprises: (i) No. 1 NI CompactDAQ-9132 data acquisition system to which sensors A1-A12, C1-C2 and T1-T2 are wired; (ii) No. 1 wireless gateway to which sensors C3,C4,T3-T6 are connected; (iii) No. 12 PCB393B12 unidirectional accelerometers A1-A12 wired to the NI CompactDAQ-9132 through NI 9234 acquisition modules, installed as reported in Fig. 3; (iii) No. 4 S-series linear variable transducers (LVDTs), denoted as C1-C4, wired to the DAQ acquisition system by means of a NI 9219 acquisition modules; (iv) No. 6 temperature sensors T1-T6. With the main objective of evaluating the dynamic characteristics of the building including the rooftop and the bell tower dynamic behavior, an AVT was carried out on May 7th 2021 by adding channels A13-19 (Fig. 4). Following AVT results, the first 5 principal vibration modes are selected for the numerical simulations: Fx1, a global flexural mode along the East-West direction (f_1=2.32 Hz); Ly1, a local mode which pertains to the bell tower along the North-South direction (f_2=2.99 Hz), Lx1, a local mode which pertains to the bell tower along the East-West direction (f_3=3.54 Hz); Fy1, a global flexural mode along the North-South direction (f_4=3.75 Hz); T1, global torsional mode (f_5=4.2 Hz).

The FE model is built in the Abaqus environment and an isotropic material is assigned to each region. The non-linear behavior of the material is reproduced by using the well-known concrete damage plasticity (CDP) model, as detailed by Ierimonti etal. (2021). Damage-prone regions are selected by means of NLSA and EJ. The different selected regions (1-9) with a brief description are reported in Table 1. Each region allows to define a one-parameter dependent model (k_j), which is defined as the multiplier of the Young's Modulus. Then, the Kriging model is used to calibrate the SM, i.e., the numerical relationship between k_j and the building's MF. To do this, 1000 FE-based samples are simulated by varying each k_j between 0.3 and 1.

Table 1. Selected damage-sensitive regions.

Region	Description	EJ/NLSA	Representation
R1	Arengo floor and the underlying areas	EJ	
R2	Nobili arched ceiling	EJ	
R3	rooftop and its annexes	EJ	
R4	loggia	EJ	
R5	bell tower	EJ	
R6	potential cracking patterns x	NLSA	
R7	potential cracking patterns y	NLSA	
R8	vertical walls along the x direction	EJ	
R9	vertical walls along the y direction	EJ	

3. Results

For the application of the proposed methodology, SHM data recorded between April 22nd and May 29th of 2021 are analyzed in order to highlight the possible consequences related to the seismic sequence occurred on May 2021, with epicenter in Gubbio and a strongest shock of magnitude Mw 4.0 at 07:56 UTC (May 15th). The main ground acceleration a_g recorded by the “Gubbio Parcheggio Santa Lucia” GBSL station is illustrated in Fig. 4. After the main shock, the MOSS (García-Macías and Ubertini, 2020) post-processing tool has revealed an anomaly in the structural behavior, consisting of the following permanent frequency decays FD: FD(f1)=1.3 %; FD(f2)=2.7 %; FD(f3)=2.3 %; FD(f4)=1.1 %; FD(f5)=1.4 %.

As a preliminary result, the proposed procedure is applied considering regions R5 and R6. For data fusion purposes, the following information are considered: static measurements recorded by sensor D2, Bayesian model updating, visual inspections.

After the May seismic sequence, sensor D2, measuring the amplitude of an existing crack involving the north wall, exhibited an evident shift with a closure of about 0.09 mm with no sign of recovering over time. In light of this, an index CI=1 is assigned to those regions potentially subjected to damage due to the permanent modification of the existing crack pattern, i.e., R6.

Figs. 5 a)-b) illustrated the Bayesian-based results, i.e., the posterior statistics of the uncertain parameters k_5 and k_6. From these results it points out that R5 probably remains undamaged and BI=0 is assigned (reduction of the mean value of the posterior distribution lower than 10 %), while R6 is potentially damaged (reduction of the mean value of the posterior distribution higher than 10 %) and BI=1 is assigned.

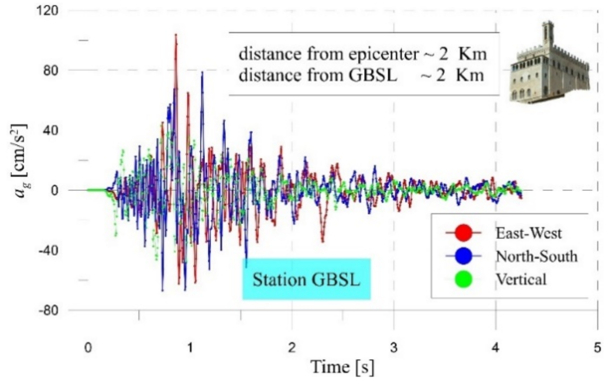


Fig. 4. The May seismic sequence recorded by the station GBSL.

Then, Figs 5 c) and d) illustrate the results of visual inspections, which concern R6, i.e., the crack visible from the Arengo floor in correspondence of the North wall openings, scored with G=1, K1=0.2 and K2=0.2. Finally, the data fusion results are highlighted in Figs. 5 e)-f), comparing the k_5 and k_6 posterior values before data fusion (w/o VI) and after data fusion (VI). Results in terms of DI, CI, BI and 2oo3 voter are summarized in Table 2.

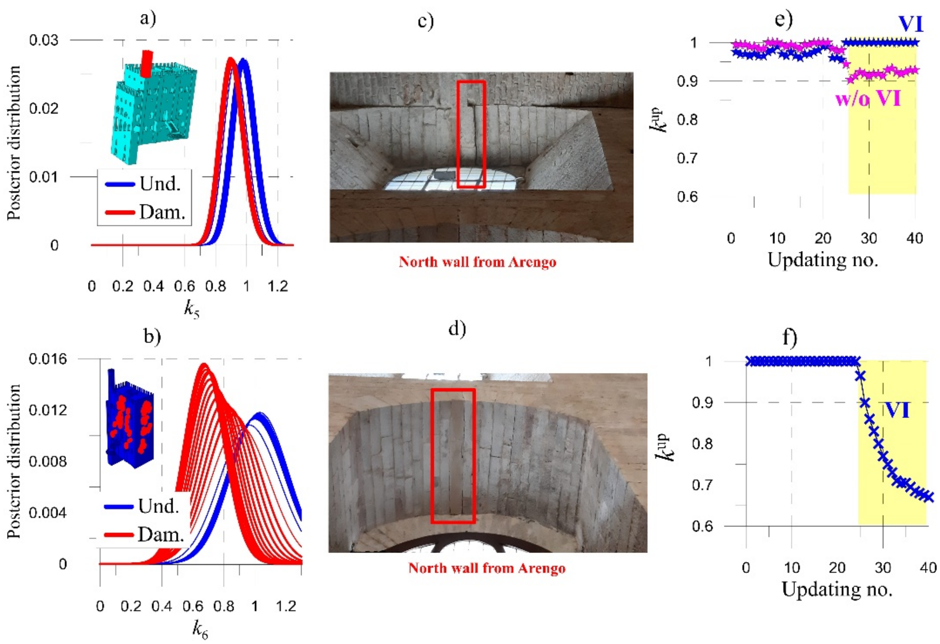


Fig. 5. Analysis results: a)-b) Bayesian based posterior statistics; c)-d) results of visual inspections associated with R6; e)-f) Posterior value of k_5 and k_6, adjusted after data fusion.

On the one hand, the null value of the 2oo3 voter competing to R5 confirms that the bell tower hasn't suffered any damage following the May seismic sequence. On the other hand, the 2oo3 voter = 1 of R6 confirm a possible permanent, but very limited (according to the low value of DI), damage associated to a main earthquake loading along the weak axis of the building.

Table 2. Selected damage-sensitive regions.

Region	DI	CI	BI	2oo3 voter
R5	0	-	0	0
R6	0.04	1	1	1

4. Conclusions

The present paper has presented the results of a Bayesian-based fusion methodology by making use of dynamic and static SHM monitoring data, FE/surrogate modelling, EJ and visual inspections.

The case study building is the Consoli Palace (Gubbio, Umbria, Italy), a monumental masonry building equipped with a permanent dense array of sensors, monitored by the Department of Civil and Environmental Engineering of University of Perugia since 2017. The proposed procedure is applied by using the SHM data before and after the low-intensity seismic sequence which affected central Italy in May 2021. A computationally-effective FE model and a twin surrogate model able to reproduce the dynamic behavior of the Palace as a function of selected uncertain parameters has been used for the purpose. The uncertain parameters are associated with damage-sensitive regions within the building, picked by means of NLSA and EJ. Then, an on-line data fusion approach is proposed by linking the SHM static measurements (crack lengths), the Bayesian-based updating and the results of on-site visual inspections enabling to continuously identify a possible damage over the selected regions. The data fusion results allow to explore all factors that potentially constrain decision making, evaluate options accurately and establish intervention priorities in a structured context (selected damaged-prone regions), avoiding the possible detection of false alarms.

Acknowledgements

The Authors would like to acknowledge the support of the PRIN 2017 project, "DETECT-AGING" funded by the Italian Ministry of University and Research (Prot. 201747y73L).

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