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Computational methods for wireless structural health monitoring of cultural heritages

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Abstract. The structural health monitoring of cultural heritages is addressed in this paper. The arising inverse problem is solved through the Learning-by-Examples (*LBE*) paradigm, exploiting data collected by a Wireless Sensor Network (*WSN*). More in detail, low-cost and low-size sensing devices are spread over the scenario to be monitored, allowing environmental data as well as acceleration and vibration information to be acquired and processed by means of a Support Vector Machine (*SVM*) in order to detect the presence/absence of a damage in the monitored structure. The proposed approach has been preliminary validated in a laboratory-controlled environment, demonstrating promising performance.

1. Introduction

Structural Health Monitoring (*SHM*) is a process aimed at the detection and characterization of structural damages in structures of any kind. In particular, literature reports several examples of local Non-Destructive (*ND*) and Destructive Testing (*DT*) methodologies for structural health detection as applied from civil to aerospace engineering structures. In the last years, in fact, there has been an increasing interest in such a science, especially considering the high potential life-safety and the economic benefits, which can be obtained thanks to the understanding of the actual performance and future life of a structure. In addition, *SHM* has also been boosted thanks to the technological evolution in pervasive computing and computer science, which has determined the ability of manipulating big amount of data acquired by several distributed sensors, by applying complex methodological systems to achieve advanced *ND* structural health estimations [1]-[7].

The *SHM* process generally involves the observation of a system over time, which may be performed periodically or continuously in order to sample the dynamic evolution of the environmental characteristics, which may somewhere damage or deteriorate the structure itself. Such systems are indeed oriented to the detection and forecasting of structural damages, potentially enabling the scheduling of preventive maintenance operations. On the other hand, *SHM* is also used to detect

structural damages in case of extreme events such as earthquakes [8]. As an example, Japan is one of the most earth-quakes zone in the world. The costs for structure maintenance is very high, hence a high interest in *SHM* applications has arisen in the last years.

To this end, Wireless Sensors Networks (*WSN*s) represent a widely used technology, thanks to the provided features such as low-cost and easy installation, which allowed a rapid increase in the use of wireless-based systems as an alternative to wired-based networks [5].

In order to perform the structural health analysis and solve the related inverse problem (i.e., by inferring the status of the monitored structure starting from *WSN* pervasive measurements), some tests have to be performed, thus acquiring useful information to be processed for the damage investigation. In such a framework, destructive testing represents a set of investigative techniques, which determine the material mechanical characteristic, such as strength, hardness or toughness, through material breaking. The advantage of this kind of tests, is related to the possibility to determine material features, which cannot be identified with non-destructive tests. At the same time, this advantage represents also one of the main drawbacks of such techniques since the structure to be monitored has to be totally or partially impaired. Accordingly, destructive techniques become more economic for mass produced objects.

SHM is also referred to a wide variety of non-destructive testing [9]. To establish the health status of a structure and to determine its reliability and safety, continuous inspections should be performed. Traditionally, visual inspection or simpler measurements are performed by a technician, but this kind of analyses may not be sufficient since only information about the superficial health status can be collected, neglecting potential internal damages. Hence, sometimes non-destructive testing has to be paired with destructive testing applied to samples of the monitored structures, which have to be removed from the original structure. In this way, destructive testing is conducted in laboratory on the structure samples, in order to evaluate the mechanical properties. As it may be clear, these operations may not always be feasible, especially considering the cultural heritage works.

Nevertheless, the evolution of electronics and computer science, and an increasing interest in these applications, have allowed the study and definition of general approaches in non-destructive techniques, such as systems based on the study of the propagation of mechanical waves [10] or of an induced electromagnetic field inside the monitored structure, or systems based on radar and radio frequency analyses [11][12].

SHM processes can be articulated into four main levels, namely damage detection, damage localization, damage quantification, prognosis on the remaining life time.

Damage detection is the process in charge of identifying the damage in the monitored structure, in general comparing current conditions with respect to a reference status, such as a model or experimental measure [13]. In order to make the discrimination precise and reliable, it is necessary to suppress environmental influence, filtering data from undesired measurement noise and considering additional data acquisition to compensate external influence.

Damage localization, instead, represents the statistical process used to estimate the actual position of the structural damage on the basis of the acquired data. Damage localization is often based on the wave propagation theory, as applied to materials, also exploiting probabilistic approaches to estimate the position of structural damages [14]. In the literature, two main techniques are considered, respectively based on mechanical and electromagnetic waves. Single or multiple damages could be recognized by the use of particular techniques for data manipulation [15]. In addition, environmental condition, especially temperature, impact on the physical characteristics of materials, which actually represent the media where mechanical and electromagnetic waves are propagating. For this reason, also damage localization algorithms need proper data compensation to filter undesired external influences.

Damage quantification approaches allow to estimate the structural degradation and damages as a combination of multiple measures and evaluations. Such a process can be recast as a decision-making procedure, which has to outcome quantitative and detailed damage information [16]. A crucial aspect is therefore represented by the *goodness* of the acquired data, which may improve the actual result

obtained from the damage quantification process. As a comparison, the damage detection process requires lower complexity to estimate a pattern change with respect to a reference situation. On the contrary, damage quantification complexity further grows in order to achieve accurate quantitative damage estimation, considering both required sensors and processing methodology. As an example, damage quantification can be computed by using high performance decomposition methods, which allow a high resolution in damage estimation [17].

After damage detection, localization, and quantification the remaining life time of the monitored structure can be estimated [18]. In general, depending on the structure, a number of damages due to climate solicitation and mechanical stress could be supported [19]. For this reason, an *SHM* system has to properly prevent failures in decision making, thus giving correct suggestions on decide to repair, upgrade or dismantle it. In [20], the authors introduce a two-steps approach. The first step is focused on the detection of low entity damages (called micro-cracks). Multiple micro-cracks could be accumulated by materials. Thus, a probabilistic approach is used in the second step, in order to predict the onset of high entity damages (called macro-cracks), which could permanently damage the materials composing the structure, with potential severe loss of stability and safety.

In general, large set of sensors may be deployed on real sites thus improving the pervasiveness of the monitoring system. In such a scenario, sensors could be of heterogeneous nature, in order to achieve the objective of the structure health estimation. In detail, some sensors deployed at the site should be devoted to measure the actual structure properties, while other sensors may be employed in order to acquire useful information to compensate material properties changes due to the environment conditions.

Cultural heritage monitoring application is mainly focused on artwork maintenance, by exploiting distributed sensing for preserving them. Therefore, in order to preserve paintings, historical structures, frescos and artworks, pervasive monitoring systems can be exploited in order to continuously monitor the cultural heritage and prevent potential damages [21]. In [22], a monitoring system for wooden artworks is proposed with environmental and mechanical measurements. A predictive simulator of stress is also proposed to estimate wood deformation due to environmental conditions.

Therefore, considering the *SHM* for cultural heritage monitoring, this work is aimed at proposing a wireless monitoring system for damage detection, by exploiting the heterogeneous data acquired by distributed *WSN* sensing devices and processed by a machine learning methodology [2]-[7], [23]-[25] in order to determine if potential damages are arising in the monitored structure.

2. System Architecture

The proposed system for *SHM* of cultural heritages is based on the *WSN* paradigm, thus allowing the system to be spread even over large environments, such as museums or exhibition areas. Therefore, a set of *N* sensing devices can be deployed around the scenario in order to sense the heterogeneous parameters of interest at different positions. A data collection device, commonly called gateway node (*GW*) or data concentrator, is used as an interface between the wireless sensor network and the data analysis system.

The data measured by the sensor network, once received by the control unit, are properly acquired and the reception timestamp is appended to the data stream for synchronization purposes, before storing such information in a local or remote database. The choice of storing data into a local or remote database is mainly motivated by the ease of management of big data streams and in turn the ease of recalling whatever subset of saved data for subsequent processing. A multiple database approach may be considered, as well, in order to guarantee data on remote machines and allow the processing of information though computer clouding approaches.

The wireless sensing node is based on the TinyNode device, properly connected to a sensor interfacing board developed ad-hoc for the communication with the selected sensing technologies modules. In particular, the wireless sensing node can be equipped with a temperature and humidity sensor (SHT11 model), a piezoelectric transducer (BM15015-06HC model), and a high resolution three-axis digital accelerometer (LIS3LV02 model).

Figure 1 shows a wireless sensor device as mounted in the selected packaging, which contains the TinyNode device, the sensor interfacing board and the batteries for powering the device. The piezoelectric transducer as well as the accelerometer can be installed outside the packaging for direct contact with the monitored structure.

Figure 1. Detail of the wireless sensor device interface board for sensor equipment.

The sensing nodes communicate among the wireless network in the *ISM* 868 MHz band. This design choice is driven by the low scattering given by the actual operating frequency, which allows the ease deployment of the monitoring system in large environments, without the need of forwarding nodes and/or procedures to allow each sensing device to communicate with the *GW* node.

The acquired data are representative of the health status of the monitored structure. In particular, a variation of the sensed parameters is expected in case of a damage, if compared with the damage absence scenario data. Therefore, as a preliminary approach, the damage detection problem is recast as a binary classification problem solved by means of a support vector machine (*SVM*) algorithm [24].

During a preliminary off−line phase, a database of input/output (*I/O*) pairs (i.e., presence/absence of damages in the structure vs. sensed parameters) is setup in order to allow the *SVM* algorithm in determining the decision function, successively used during the on−line phase to perform real-time predictions of the structure health (i.e., detecting the presence or absence of a damage).

More in detail, a set of K *I/O* pairs of data $\left\{\boldsymbol{\xi}^{(k)},\ \chi\left(\boldsymbol{\xi}^{(k)}\right);\ k=1,...,K\right\}$ is generated during the off-line *SVM* training procedure to model the relationship between sensed data $\boldsymbol{\xi}^{(k)}=\left\{\left(T_n^{(k)},H_n^{(k)},\underline{A}_{n,x}^{(k)},\underline{A}_{n,y}^{(k)},\underline{A}_{n,z}^{(k)},\underline{V}_n^{(k)}\right),n=1,...,N\right\}$, where $T_n^{(k)}$ and $H_n^{(k)}$ are respectively the temperature and relative humidity for the n-th node in the *WSN*, $\underline{A}_{n,q}^{(k)}=\left\{a_{n,q,i}^{(k)};i=1,...,I\right\}$, $q=\{x,y,z\}$, $a_{n,q,i}^{(k)}$ being the q-th acceleration component measured by the n-th node at the i-th time instant $t_i\in[0,\tau],i=1,...,I$, τ being the acquisition time window, $\underline{V}_n^{(k)}=\left\{v_{n,i}^{(k)};i=1,...,I\right\}$ where $v_{n,i}^{(k)}$ is the vibration measured by the n-th node at the i-th instant, and the health status of the structure given by $\chi\left(\boldsymbol{\xi}^{(k)}\right)=+1$ when a damage is present, $\chi\left(\boldsymbol{\xi}^{(k)}\right)=-1$ in case of absence of damages.

Therefore, the information carried out by such training set is exploited by the *SVM* algorithm in order to define the following decision function

$$\hat{\chi}(\boldsymbol{\xi})=\operatorname{sgn}\left(\sum_{k=1}^{K}\chi\left(\boldsymbol{\xi}^{(k)}\right)\alpha^{(k)}\ \Omega\left(\boldsymbol{\xi}^{(k)},\boldsymbol{\xi}\right)+b\right) \tag{1}$$

used during the on-line working of the algorithm for predicting the structure health status.

In Eq. (1), $\operatorname{sgn}(.)$ is the sign function, $0\le\alpha\le C$ are the Lagrange multipliers with C being the so-called penalty factor, b is a bias term [23]-[25], while $\Omega\left(\boldsymbol{\xi}^{(k)},\boldsymbol{\xi}\right)=\exp\left(-\gamma\left\|\boldsymbol{\xi}^{(k)}-\boldsymbol{\xi}\right\|^2\right)$ is the radial basis function (*RBF*) kernel function.

3. Experimental Validation

The proposed system has been arranged in a laboratory-controlled scenario at the ELEDIA@UniTN laboratories, University of Trento, Italy. In particular, a set of $N = 10$ wireless sensing devices have been spread around the laboratory areas, as shown in Figure 2, in order to allow the validation of both the wireless monitoring system capabilities, testing the communication performance in different conditions representative of potential real applications (e.g., museum exhibition, ancient buildings characterized by thick walls that impact on the communication range capability), as well as the performance of the *LBE*-based strategy for damage detection.

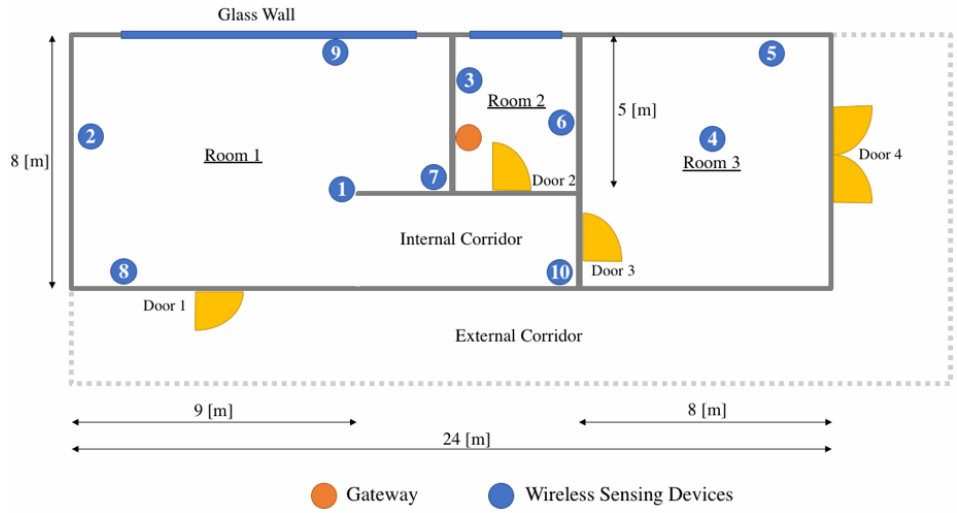

Figure 2. Experimental validation scenario, wireless sensing devices position.

Each device has been equipped with the sensing modules described in the previous section and in particular an acquisition time $\tau = 1[\text{sec}]$ for the acceleration and vibration modules has been considered. Experimental testing is currently under development in order to define an exhaustive set of *I/O* pairs of data to be used for the off-line training of the *SVM* in order to obtain good generalization capabilities of the proposed detection system. In particular, different structures are under analysis to characterize their properties and behavior under different environmental and stress conditions.

Figure 3. Experimental validation, wireless sensing device applied to wood structure.

Some preliminary results have demonstrated the potentialities of the proposed system in structural damage detection on the basis of non-destructive analysis performed with low cost and reduced size wireless sensing devices.

More in detail, a preliminary training set consisting of $K = 100$ *I/O* samples has been generated by dropping objects of different weights onto some monitored wood structures (e.g., representative of a painting frame, Figure 3) in order to simulate anomalous vibrations, deformations, and mechanical stresses of different nature. Moreover, a test/validation set of $M = 50$ samples, evenly distributed (as

for training data) between "damaged" and "undamaged" labels, has been considered to assess the prediction accuracy of the trained *SVM*. Concerning the optimal setting of the parameters of the adopted binary classifier, a standard 5-fold cross-validation approach has been employed on the available training data [2][25], the optimal values being determined as $C = 10^2$ and $\gamma = 10^{-1}$ for the penalty factor and the *RBF* kernel width, respectively. Under such a configuration, the time required to train the *SVM* (once training data have been experimentally collected) has been lower than 10 seconds using a standard laptop and a non-optimized software implementation.

The proposed system showed an appreciable capability in detecting the presence or absence of the applied stress to the wood structure, allowing an acceptable degree of discrimination (i.e., a classification accuracy of about $\Gamma = 67\%$) between class -1 ("absence of a damage") and class $+1$ ("presence of a damage"). Of course, higher detection accuracies are envisaged in the next experimental campaigns by considering a better and more rigorous approach to generate training data, as well as by increasing the number of training samples, *K*. Moreover, it should be remarked that, differently from many state-of-the-art works [8][9][13], the developed monitoring system is based on the exploitation of low-cost sensing devices.

4. Conclusions

SHM represents an interesting technique for cultural heritage monitoring with specific focus on maintenance and preservation of buildings and artworks. In particular, the damage detection has been formulated as an inverse problem, solved through a *LBE*-based approach applied to the data acquired by a distributed monitoring system able to measure different heterogeneous physical parameters. The experimental validation is currently under development, and preliminary results demonstrated the potentialities of the proposed system. It is understood that such results have been obtained with inexpensive off-the-shelf hardware and considering sub-optimal approaches for building the training set, testing the on-line accuracy of the system, and calibrating it in order to enhance robustness to noise and environmental changes that are expected to occur in real-world deployments. Current and future work will be devoted to additional analysis and testing of several structures in order to improve the generalization capabilities of the system. Moreover, an in-depth analysis of the sensitivity of the *SVM* accuracy to relevant parameters such as C, γ, and K will be object of careful investigation. Finally, the use of advanced dimensionality reduction techniques (i.e., feature-selection/feature-extraction) will be investigated in order to determine the most relevant input features/sensed parameters, improve the overall detection and monitoring accuracy, as well as reduce the number of necessary training samples, mitigating the negative effects of the so-called "*curse of dimensionality*" [2].

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