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Artificial Intelligence based monitoring system for historical building preservation

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***Abstract* – The historical heritage requires particular systems to preserve its state of conservation. In this regard, the Structural Health Monitoring (SHM) systems they are fundamental in conjunction with suitable algorithms that allow the automatic detection of possible critical events that would ruin the state of conservation of the building. In this paper is proposed the use of a SHM system based on the analysis of the Acoustic emission in conjunction with an K-nearest-neighbor (KNN) Artificial Intelligence (AI) Algorithm for the classification of the data. Fundamental, in the use of the Classification algorithms based on AI, is the use of suitable features. In this regard, these features are estimated by using the Gutenberg–Richter law, typically used in the analysis of the earthquake. This permits to correlate the characteristic of the magnitude acoustic emission due to an event in the building with the number of the events.**
Experimental test will be used for the training and the test of the proposed architectures.

I. INTRODUCTION

The preservation of the historical heritage building is an important task that require innovative system to be performed. In this field, interesting advantages are provided by the use of Structural Health monitoring systems (SHM) [1]–[8]. Among the SHM systems particular interest is devoted to the systems that provides the information about the state of the building by using the Acoustic Emission (AE) signals analysis. In fact, a damage in historical building, for example generated by a compression or a stress of the building, generate a localized releasing of internal energy that can be felt as an AE in the following called crack and represented in Fig1.

Due to their origin the cracks are diffusely used in the online SHM system to determine the damage evolution [4], [6], [16], [7], [9]–[15].

The main problem in the analysis of AE in a SHM system is the signal loss. I fact, due to the non-homogeneous characteristics of the material in which the propagation of the AE is performed the arrival time and the attenuation can be different respect that obtained in a homogeneous material. This can cause that the acquisition system of the SHM do not recognize the AE events obtaining a signal loss. To overcome this problem several solutions are proposed in literature. In particular, in [12], [17] the input signal are connected to the SHM system by a multi-triggered acquisition system [18].

An important topic, once the AE is acquired, is the analysis of the signal in order, to detect or identify a critical event which can affect the state of the historical structure.

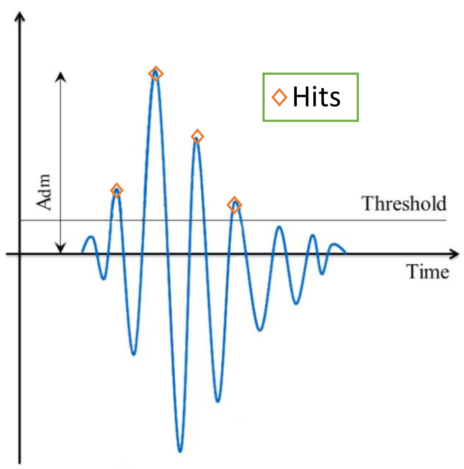

Fig. 1. AE in a concrete sample due to a stress representation.

The identification can be done by using thresholds empirically defined by the experience of the operator [19] or an automatic identification based on artificial intelligence algorithms. These algorithms are based on the pattern recognition of some features estimated on the signal [20]–[29]. With this aim in the paper is proposed the use of the Gutenberg–Richter law (GBR) [30] adaptation to evaluate the features that make up the pattern that will be recognized. In fact, in previous paper [17], [19] is demonstrated as the GBR law can be used to determine the damage in concrete structure by using the AE signals information and in particular critical damages.

The same features are used to train the Machine Learning algorithm so is not necessary a threshold defined by the experiences of the operator.

Among the Machine learning algorithm the k Nearest Neighbour Classifier [31] is chosen for the classification of the AE feature because it is particularly suitable for online classification applications.

The paper is organized as follows: in Section II, the GBR law modification is analyzed; in Section III, the k Nearest Neighbour Classifier is summarized; in Sections IV, the experimental results are presented; finally, the conclusions are drawn.

II. ADAPTATION OF THE GUTENBERG–RICHTER LAW

In order to empirically identify some relationship between variable parameters referring to the geographical area where the earthquake occurs and the earthquake itself the GBR law play a main role [32]. This law is based on the analysis of magnitude-frequency relationship and uses all magnitude values of earthquakes in a region and not just the highest ones. The analytical expression of this law is:

$$log(N) = a + bM \tag{1}$$

where N is the number of the events, M is the magnitude of the events, and *"a"* and *"b"*, so called b-value, are two empirical constants. The constant "a" depends on the seismicity rate, and varies significantly from area to area. Instead the earthquakes number determines the constant *"b"*. The "maximum-likelihood estimation" (ML) methodology, was used in order to identify the b-value:

$$b = \frac{log(e)}{M_{av} - M_{min}} \tag{2}$$

where M_{av} is the average of the observed magnitudes, and M_{min} is the minimum or the considered threshold magnitude.

The fracture process in concrete generates Acoustic emissions (AE). These last are elastic waves, and permits to analyze the fracture process by their amplitude distribution. Among various parameters, the most important one is the b-value obtained from the amplitude distribution data of AEs according to the Gutenberg-Richter law [19]. The AEs recorded during the test are oscillating damped waves very similar to the waves that are generated during earthquakes. These waves are characterized by a decreasing amplitude up to the noise threshold. Starting from these considerations, it is possible to transform the formulation enunciated by Gutenberg-Richter adapting it to AE as following:

$$log(N) = a - bA_{dm} \tag{3}$$

where N is the number of the hits over the noise threshold of a singular AE analyzed during the process, A_{dm} is the maximum amplitude of AE signal, and "a" and "b" are two constants. Constant "a" can be obtained for each test carried out, by considering that in the earthquake the maximum magnitude generates a b-value tending to 1. In our analysis, the critical events recognized on an AE have to generate a b-value equal to 1. Therefore, for the critical events the a-value can be obtained by the (3) as:

$$a = log(N) + A_{dm} \tag{4}$$

Then the feature used in the proposed classifier are a-value and A_{dm}.

III. K-NEAREST NEIGHBOUR ALGORITHM

The *K-Nearest Neighbour* (kNN) belong to the supervised learning algorithm among the machine learning techniques.

In the KNN the classification of the input data is based on the closest training example in the feature space [31]. In Fig. 2 is represented a typical classification problem solved by KNN. The algorithm determines the distance *L* in the feature space of unknown object from the other object previously classified in the training phase. Usually, among the distance definition, the Euclidean one is used:

$$L = \sqrt{\sum_{i=-1}^{N} (P_i - T_i)^2} \tag{5}$$

where N is the number of features, P_i is the *i-th* feature of the object to be classified, and T_i is the *i-th* feature of one of the object pre-classified used in the preliminary training of the algorithm.

In the example there are objects belonging to two class. If k is equal to 5 the 5 nearest objects are taken into consideration, determining the classification area shown in the figure with the solid line. At this point the algorithm consider the neighbor object class as a vote for the classification of the unknown object. Then the object is classified on the basis of the majority vote of its 5 nearest neighbors. If k is 11 then the dashed line area is considered. Typically, is considered k equal to 1 for which the classification is made to the nearest neighbor.

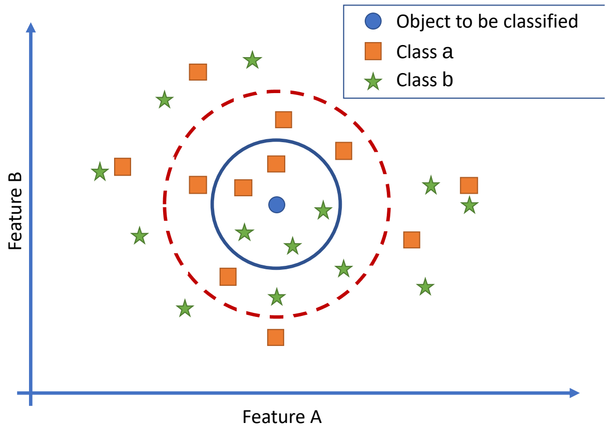

Fig. 2. KNN algorithm Classification representation respect two features (A,B). Round object is the object to be classified, the square objects represent the object of class α, the star objects represent the objects of class β.

IV. EXPERIMENTAL RESULTS

For the experimental results an acquisition system composed by a AE sensor, DAQ board and multi-triggered generator system [11, 22] is considered. The AE sensors used in the experiment are the R15α characterized by a resonant frequency 150 kHz and peak sensitivity 69V/(m/s). the sensors are connected to the input channel of the acquisition system. The acquisition system used is the National Instrument NI6110 DAQ board with four channels, a sampling frequency equal to 5 MHz and an amplitude resolution of 12-bit. The multi-triggered generator system is connected to the sensors to generate the trigger signal to start the acquisition of an acoustic event. In order to the test the method in controlled conditions a sample with known characteristic is considered. In particular, a concrete cube is used as samples. Instead the material is obtained accorded to EN12390-3 [33].

In order to fix the sensors to the sample a silicone adhesive bonding agent was used. The sensors are fixed on the center of the longitudinal face of the sample (Fig.3) [1, 33].

In the experimental setup is necessary to stress the samples in order to generate an AE. With this aims the samples are placed in a hydraulic press. This press stresses the samples with a controlled uniaxial compression, permitting to obtain load-displacement and the load-time diagrams. Both the controlled hydraulic press and the acquisition system are connected and managed by a PC with a proper software developed in Matlab environment.

Following the standard EN 12390-3 [33] it is considered that for a stress lower than 40% of its maximum resistance of compression, the macroscopic behavior of the specimen is linear and elastic, and there are no important cracks

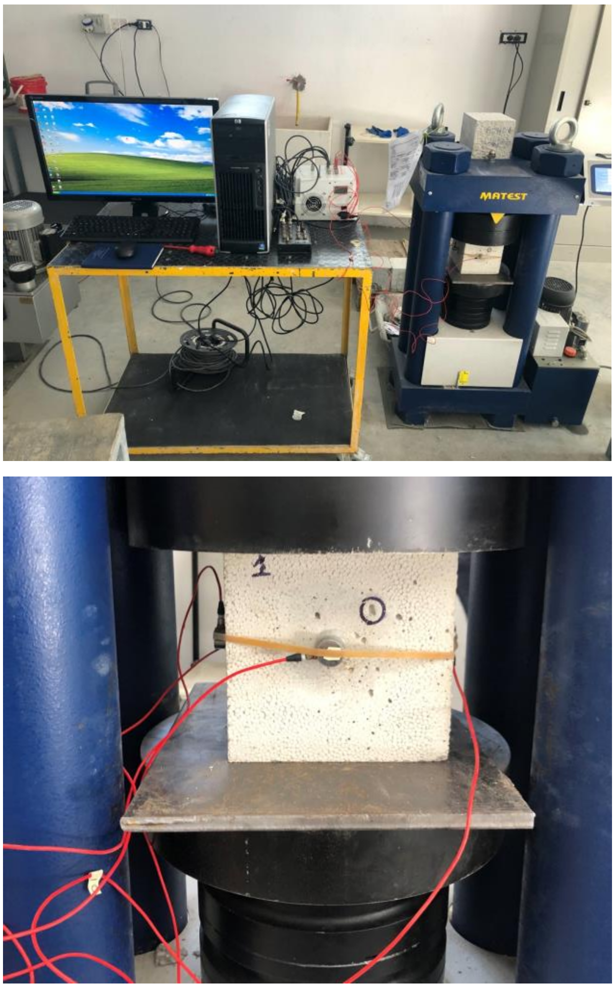

Fig. 3. Experimental setup

because they are not inside the specimen. In the case under consideration this value is equal to 10 MPa. Instead, for stress in the range [40, 85] % of maximum resistance of compression, the macroscopic behavior of the specimen is not linear and the micro-cracks develop with the increasing of the stress. By considering this, the AE signals detected during the first 600 s, corresponding to the compression of 1 mm of specimen, are discarded.

A. Analysis of the samples

Preliminary data are acquired and used to train the KNN. With this aim the AE acquired are classified as and the classification of the critical/non-critical events are provided by the information arising from the hydraulic press and the analysis of the operator. The features memorized for the training and the comparison with the non-classified samples are the a-value and A_{dm}, evaluated an all the four channels of the acquisition system.

In the training 2500 AE events are considered 50% of them are critical events and the other 50 % are non-critical events. The KNN classifier is preliminary trained with this supervised learning data and then used with blind acquisition of different sample. In particular, other 3000 AE events are considered. Also in this case the 50 % represent non critical events and the other 50 % critical events, respectively.

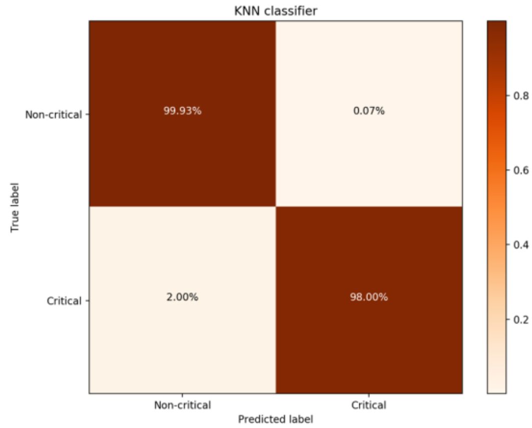

Fig. 4. KNN classification algorithm results.

The confusion matrix representing the results are shown in Fig.4. The analysis of the confusion matrix highlights as the classifier have a misclassification equal to 2 % for critical events, and lower then 0.1 % for the non-critical events.

V. CONCLUSION

In the paper, in order to monitor historical heritage building or structure a Structural monitoring system that automatically detect critical events is proposed. The monitoring system acquire and analyze the acoustic emission generated in the structure by the stress to which the buildings are subjected. the analysis of the acoustic emission is performed by using the modification of the Guttemberg-Richter law. Instead, the automatic detection of the critical events is performed by using a machine learning technique. The machine learning technique used is k Nearest Neighbor Classifier (KNN) because it provides faster classification results and then it is suitable for the online monitoring of the historical heritage. The proposed architecture is experimentally tested on concrete cube samples. The results show that the KNN has good classification accuracy and low misclassification.

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