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APPLICATION OF A CLASSIFICATION ALGORITHM TO THE EARLY-STAGE DAMAGE DETECTION OF A MASONRY ARCH

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Abstract. *The early-stage identification of structural damage still represents a relevant challenge in civil engineering. Localized damages if not readily detected can lead to disruption or even collapse, involving hazard to people and economical losses. Although the final goal of the identification is to localize and quantify the damage, a reliable discrimination between normal and abnormal states of the structure in the very early stage of the damage onset is not an easy task. In the field of Structural Health Monitoring (SHM) great attention has been paid to the development of damage detection methods based on continuous and automatic registration of the system response to unknown ambient inputs. The numerical algorithms exploited must be: (1) easy to implement and computationally inexpensive, eventually being embedded in the sensors; (2) as much independent on human decision as possible; (3) robust to the many sources of uncertainties affecting the monitoring; (4) able to detect small damage extents in order to provide an early warning; (5) suitable for the application in the case of few and sparse measurements collected only in the normal condition. The performance of a novel version of Negative Selection Algorithm, recently developed by the authors, is here analyzed with attention to these issues. The algorithm is tested against data collected on a segmental masonry arch built in the laboratory of the University of Minho and subject to progressive lateral displacement of one support.*

1 INTRODUCTION

In the context of Structural Health Monitoring (SHM), the Damage Identification (DI) and the early warning in case of damage onset are essential to support any engineered system management. Following the Rytter's hierarchy[1,2], the DI process can be summarized according to five main goals of increasing complexity: (1) Detection of existence; (2) Localization; (3) Classification of the type; (4) Quantification of the extent; (5) Prognosis. Such a hierarchical structure requires that all the lower levels are available before attempting a higher level of information. Thus, the detection of existence is the first basic step that a monitoring strategy must fulfil but, in many cases, it is a complex problem to address.

The SHM theory is based on the existence of a function f such that:

$$\boldsymbol{x} = f(\boldsymbol{y}, \boldsymbol{v}) \tag{1}$$

where $\boldsymbol{x} \in \boldsymbol{X}$ is a vector whose elements are all the features of the engineered system (e.g. a structure or infrastructure), $\boldsymbol{y}$ is a vector that describes the condition of this system and $\boldsymbol{v}$ is a vector which accounts for the environmental and operational variables that affect the system features. In damage detection, the state vector $\boldsymbol{y}$ is a binary variable, namely $\boldsymbol{y} \in \{Nonself, Self\}$ or $\boldsymbol{y} \in \{1,0\}$. The goal is the discrimination between a normal '0' and an abnormal '1', potentially damaged, state of the system. Each feature vector $\boldsymbol{x}$ is a point of a multidimensional domain called input space, namely the space of the domain of each single feature of the vector. The DI task aims at assessing the system state by analyzing the values assumed by the features. One of the main issues to tackle consists of the feature selection. Indeed, out of the potentially infinite features of the engineered system, whose domains might also be infinite, the detection is carried out on a scalar valued space called feature space $\boldsymbol{F} \subseteq \boldsymbol{X}$ [3]. Thus, the points $\tilde{\boldsymbol{x}} \in \boldsymbol{F}$ are the projection of the points $\boldsymbol{x} \in \boldsymbol{X}$, from the original input space to a space with reduced dimensionality. This process reduces the time requirement and the complexity of the problem, but also reduces the information content of the feature vector, including its sensitivity to damage. A proper selection should aim at identifying features such that:

$$\tilde{\boldsymbol{x}} = f(\boldsymbol{y}) \tag{2}$$

In other words, the selected features must have a high sensitivity to the system condition $\boldsymbol{y}$ and a negligible sensitivity to operational and environmental variables $\boldsymbol{v}$.

Mathematically, the damage detection can be treated as a classification problem: given a point in the feature space related to a new acquisition of the monitoring system, assess whether the system continues in its normal state or shows an abnormal behavior. Thus, the goal is to define a classifier, namely an approximation of the inverse function:

$$\boldsymbol{y} = f^{-1}(\tilde{\boldsymbol{x}}) \tag{3}$$

This approximation is based on a set of known pairs $\langle \boldsymbol{x},\mathbf{y} \rangle$, i.e. a set of pre-measured samples. The nature of such pairs further complicates the damage detection problem as, normally, the only information available is for the system in normal condition, namely all the pairs are like $\langle \boldsymbol{x},0 \rangle$. This is a one-class classification problem which can be addressed only through few machine learning algorithms. The present study aims at discussing how a learning algorithm can be applied to real field testing data. A deterministic version of the Negative Selection Algorithm (NSA), developed by the authors of this work and preliminarily tested on other case studies with simulated data [4–6], is here employed making use of the vibration signals collected during a laboratory experimental campaign. The methodology is applied for the first time to a real case study under progressive damage scenarios. After describing the fundamentals of the algorithm in section 2, the structure object of investigation is presented in section 3.1. Then, the methodology to tailor the algorithm to the specific case study is discussed in section 3.2 followed by the description of the numerical tests used for the algorithm validation.

Based on the results, possible improvements to the methodology are provided in section 3.3. Finally, the main conclusions drawn from the work are summarized in section 4.

2 DETERMINISTICALLY GENERATED NEGATIVE SELECTION ALGORITHM

NSAs are a family of algorithms based on a minimal common framework, initially developed by Forrest et al. [7] and later improved with additional contributions [18,19]. The complete framework of the process underlying the NSAs is composed of several steps that are collected in three main consecutive stages: (1) Representation; (2) Censoring; (3) Monitoring.

The first stage is an overhead operation consisting in the definition of the feature space and the coding of the data set. In this stage, the *n* features are projected onto a unitary space $U=[0,1]^n$. To take into account the emergence of measurements that fall outside the range that is known during the training, such a range is increased by 20%. Future samples that fall outside this enlarged range are automatically labelled as damaged. It is also assumed that the unitary space is divided into two complementary subsets, Self and Nonself, such that:

$$Self \cup Nonself = U \qquad Self \cap Nonself = \emptyset \tag{4}$$

During the so-called censoring stage, the NSA analyses the training data set in the feature space to generate the detectors. The detector set is the tool used for anomaly detection, being a set of elements which covers and identifies the nonself portion of the space. Finally, in the monitoring stage, the new feature values, extracted from the system under analysis, are matched against the trained detectors, which bind to the ones that are likely to belong to an anomalous behavior of the system. The version of NSA used in the present study is called deterministically generated (DNSA), since the detectors are not randomly initialized before being matched against the training samples, but they are placed onto the unitary space according to a regular grid of given size. In order to reduce the time requirement and the complexity, the detection is carried out in a 2-dimensional feature space. Indeed, in Structural Health Monitoring for civil engineering systems, it is common to analyze the structural behavior in terms of correlation between pairs of variables (for instance temperature/first frequency, temperature/second frequency, etc.) [10,11].

3 APPLICATION AND VALIDATION THROUGH REAL VIBRATION DATA

3.1 A masonry arch as case study

The case study used to apply and validate the DNSA algorithm is a small-scale segmental masonry arch (Figure 1) built and tested in the structural laboratory of the Institute of Bio-Sustainability of the University of Minho (Guimarães, Portugal) in order to investigate the effects that support settlements may have on the dynamic behavior of masonry arch bridges. The specimen consists of four rows of 39 brick units (100x75x50 mm3) assembled with staggered lime mortar joints. It has a nominal span of 1900 mm, a springing angle of 40°, a nominal net rise of 430 mm and radial thickness of a 75 mm. Two lime bags of 25 kg each are symmetrically placed on the extrados to simulate the effect of backfill material [12,13].

The structure is supported by two concrete abutments. The left support is fixed to the floor, whereas the other one is allowed to move in horizontal direction through a simple sliding system. Progressive damage is induced by applying, in 5 steps, controlled and uniform increasing displacements to the movable support through a hydraulic jack. After each step, a dynamic identification test is carried out using the ambient noise as source of excitation. The vibration response of the arch is acquired through 8 accelerometers (model PCB 393B12, 0.15 to 1000 Hz frequency range, 10000 mV/g sensitivity, 8μg resolution) of which four are kept fixed and four are moved according to 12 consecutive set-ups, allowing to record the response of 26 measurement points in normal direction and 26 in tangential direction (Figure 2a). This provides a set of 96 acquisitions for each scenario: 48 from the moving accelerometers and 48 from the reference ones. The signals are sampled at 400 Hz for a minimum duration of 180 s, resulting in 72.000 data points per channel.

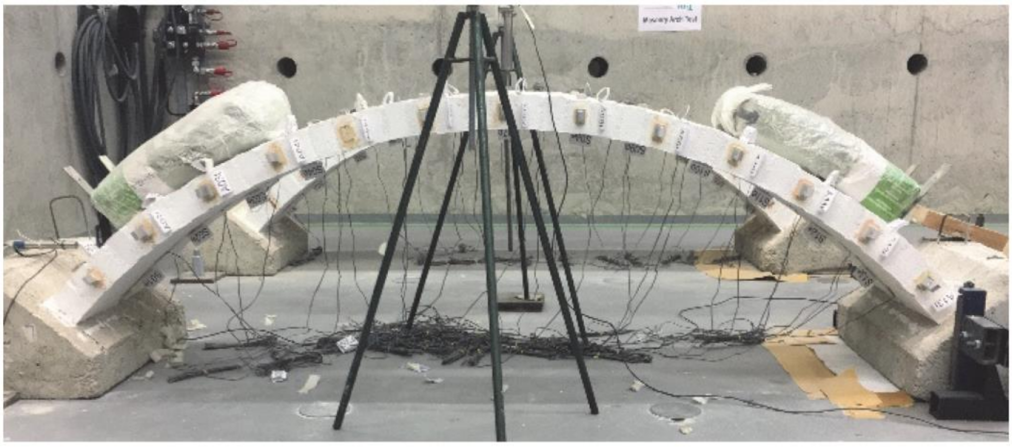
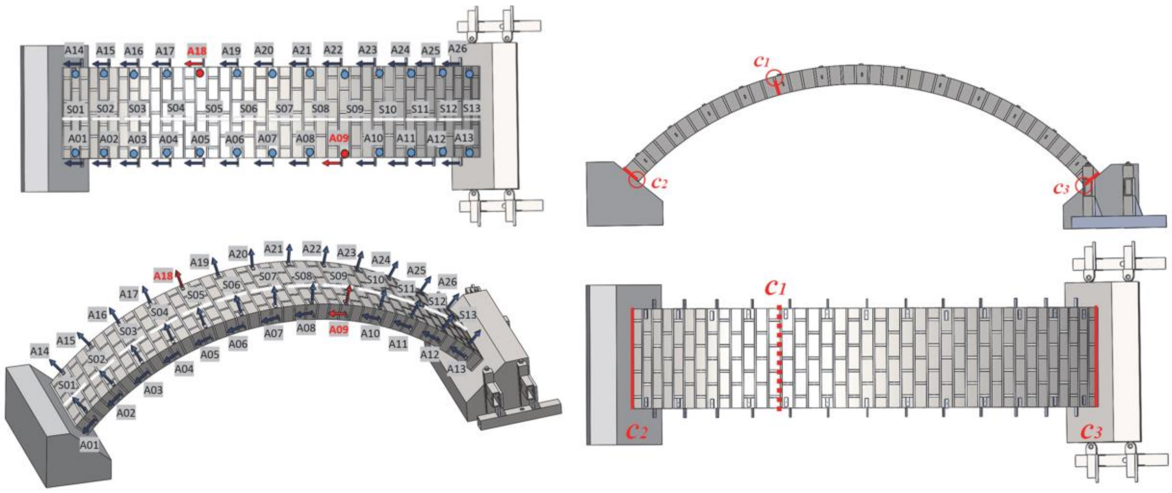


Figure 1: Configuration of the specimen.



(a) (b)

Figure 2: Test setup and crack pattern: (a) distribution of measurement points and accelerometers (A01 to A26); (b) location of settlement-induced cracks.

Aiming at detecting the damage in the very early stage, only the first two damage scenarios (corresponding to 0.4 and 0.5 mm of incremental displacement, respectively) are considered. After the first step, three cracks start to appear (Figure 2b): *c1* at the intrados, in the left region of the keystone; *c2* at the extrados of the left springing (fixed support) and *c3* at the extrados of the right springing (moving support). The outset of cracks induces a considerable drop of the structural stiffness which is clearly reflected by the downshift of the main natural frequencies of the arch (particularly for modes 1, 4 and 5).

Table 1 reports the dynamic identification results provided by the SSI-UPCX estimator [14] in terms of averaged frequency values for all meaningful vibration modes. In order to test the algorithm in unfavorable conditions, the classification is performed by analyzing the values of the second and third natural frequencies, whose variation between scenarios is the smallest. The test is carried out under constant environmental conditions. For each frequency, the dataset is composed of 96 values extracted through peak-picking directly from the power spectral density of each acquisition. It is worth noting that the ambient vibrations are weak, and the response signals have a low signal to noise ratio, making the second frequency peak not clearly distinguishable. Nevertheless, it is interesting and reasonable to test the damage detection strategy against a dataset affected by such ordinary sources of uncertainties.

Scenario	**Frequencies [Hz]**				
	Mode 1	**Mode 2**	**Mode 3**	**Mode 4**	**Mode 5**
Reference (D0)	30.06	50.95	59.44	95.23	120.62
Damage 1 (D1)	26.31	50.28	59.04	80.47	113.16
Damage 2 (D2)	23.4	48.86	58.14	75.75	111.44

Table 1: Arch eigenfrequencies variation over progressive damage scenarios.

3.2 Training, validation and monitoring

The classifier design and application are divided into three stages: (1) training; (2) validation; (3) monitoring. The latter step is the actual assessment of the system through the analysis of new measurements. The first two steps, instead, are offline preliminary tasks necessary to generate the classifier and tailor it to the specific case study. The training requires a set of samples that are fed to the DNSA to generate the detectors. As mentioned before, in one-class classification problems, the samples belong only to one class (e.g. the self space or normal state). In order to keep some of the collected self data for the validation and the monitoring, out of the 96 records, 50 points are randomly selected to form the training set.

Each algorithm version requires the definition of a set of inner parameters, the so-called parameter setting. Once these parameters' value is fixed, a specific algorithm instance is determined. Different settings lead to different detectors sets and different performances. Thus, the parameter setting consists in comparing different algorithm instances. The parameters are analyzed as controllable variables which assume in their domains different values called levels [15]. The comparison must be cast into a statistical design of the experiment (DOE) and analyzed in terms of a reliable performance metric. Considering the possible outputs of the detection, only two families of errors are possible: false positive (FP), namely normal samples classified as abnormal; and false negative (FN), namely abnormal samples classified as normal. Experience demonstrated that the trend of FPs and FNs for different parameter settings is inverse. Thus, it is not possible to reduce one family of errors without increasing the other and the performance metric should take both into account. When dealing with one-class classification problems, this issue is quite complex because only one type of samples is known, thus the only possible inference is on the number of FPs. In [6] the authors developed a methodology based on the artificial generation of outliers of the normal samples' distribution. The same methodology is here applied, so the classifier can be validated against known self samples and artificial nonself samples, referred as outliers. Three are the main parameters that affect the DNSA performance: (1) number of divisions of the side of the unitary space, which is directly related to the detector radius, r_{det}; (2) self radius, r_{self}; (3) censoring distance, *Cens.dist*. The latter is a qualitative parameter that depends on the values of the other two. Thus, a three-level two-factor full factorial design (3^2 FFD) is used for the experiment, considering the two quantitative parameters (detector and self radii), repeated for three possible formulations of the censoring distance. The validating self set is composed of 23 samples out of the remaining 46 (e.g. 96 minus the 50 used for the training). The validating nonself set is composed of 133 artificial outliers. Figure 3 displays the samples used for both training (D0-T) and validation (D0-V, Outliers) in the unitary feature space.

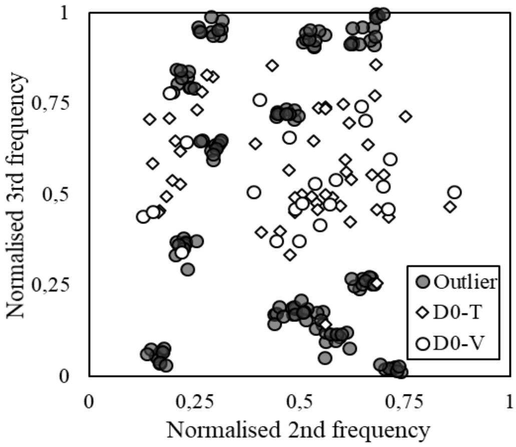


Figure 3: Normalized samples belonging to the training and validating sets.

Table 2 reports the results of the parameter setting together with the performance metric. In the present work, the area under the Reception Operating Characteristic (ROC) curve, called AUC, is used for this purpose. The ROC curve plots, for each classifier, the False Positive Rate (FPR) and the True Positive Rate (TPR). The best combination of parameter levels corresponds to the highest value of the AUC which, for this case study, is: small r_{det}, medium r_{self} and censoring distance equal to $r_{det} + r_{self}$.

Cens.dist=r_{det}			*Cens.dist=0.5*($r_{det}+r_{self}$)			*Cens.dist*=($r_{det}+r_{self}$)		
divisions	r_{self}	**AUC**	*divisions*	r_{self}	**AUC**	*divisions*	r_{self}	**AUC**
70	0.01	0.518	70	0.01	0.518	70	0.01	0.576
70	0.035	0.518	70	0.035	0.576	70	0.035	**0.776**
70	0.07	0.518	70	0.07	0.701	70	0.07	0.747
20	0.01	0.626	20	0.01	0.579	20	0.01	0.662
20	0.035	0.626	20	0.035	0.626	20	0.035	0.763
20	0.07	0.626	20	0.07	0.726	20	0.07	0.690
10	0.01	0.678	10	0.01	0.537	10	0.01	0.684
10	0.035	0.678	10	0.035	0.638	10	0.035	0.698
10	0.07	0.678	10	0.07	0.678	10	0.07	0.667
	Avg.	0.607		Avg.	0.620		Avg.	0.696
	Dev.st.	0.071		Dev.st.	0.073		Dev.st.	0.062

Table 2: Results of the parameter setting. In bold the best combination of parameter levels.

The optimized classifier is used to simulate the monitoring of the arch. This means testing the classifier against the samples that it has not met before. The testing self set is composed of the remaining 23 samples, whereas the testing nonself set is composed of just 39 D1 samples and 16 D2 samples, since the others fall outside the unitary space and are automatically classified as damaged. The classifier shows a good performance against the damaged samples with a success rate of 82% for D1 samples and of 94% for D2 samples in terms of correct labelling. However, 48% of the new health samples are wrongly classified.

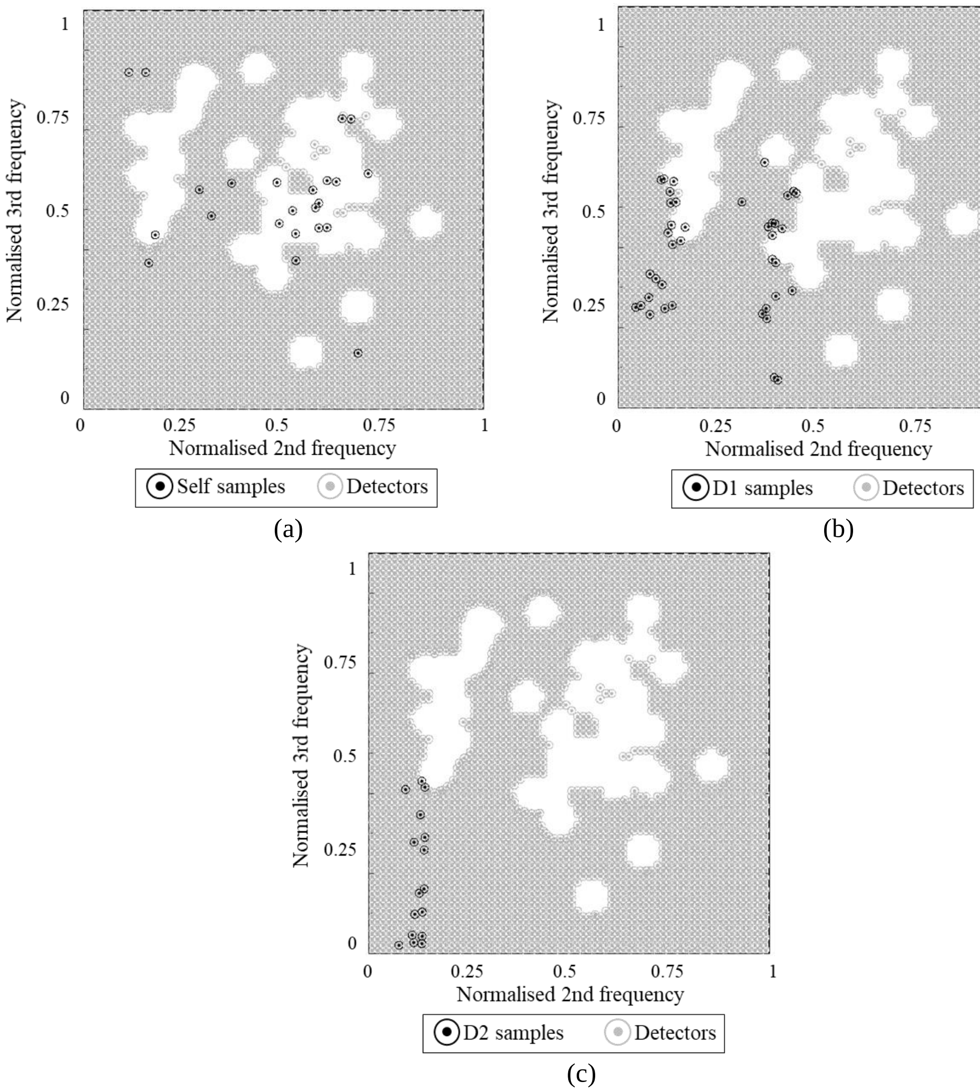


Figure 4: Comparison of the optimized detector set against the testing sets: (a) self samples; (b) D1 samples and (c) D2 samples.

3.3 Improved training

Based on the detector set distribution, the quite “aggressive” behavior highlighted in Figure 4a is likely due to the sparsity of the self samples used for the training. These were mainly distributed in two regions. However, experience supports the idea that frequency values, in conditions similar to the one of the case-study, are continuously distributed over a single region. Thus, new emerging samples are expected to fall in between the two identified areas. Based on this assumption the classifier is improved by artificially generating self points according to a bivariate normal distribution. The mean and the covariance matrices of the 50 training samples are used to define the distribution. Before repeating the training, the new points which fall outside the area within the boundary that envelopes the prior training samples are rejected, assuming that this boundary delimits the known self region. Figure 5 shows the prior and the new training sets. The improved classifier is thus generated keeping the same parameter setting and tested against the same sets. Figure 6 shows the new detector set, compared to the testing sets and Table 3 reports the confusion matrix for the two classifiers. The improved version outperforms the prior one.

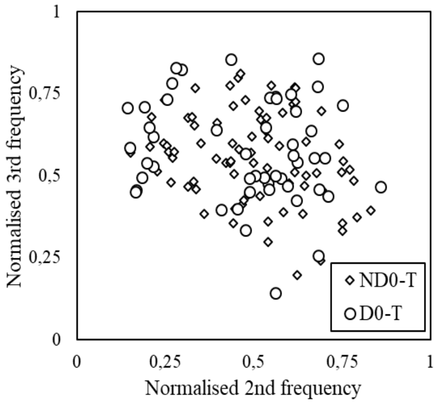


Figure 5: New normalized training samples (ND0-T) compare to the original training set (D0-T).

	TN	FP	Tot. D0 samples	TP1	FN1	Tot. D1 samples	TP2	FN2	Tot. D2 samples
Prior classifier	12	11	23	32	7	39	15	1	16
New classifier	17	6	23	30	9	39	16	0	16

Table 3: Confusion matrix of the prior and the improved classifier over the same testing sets.

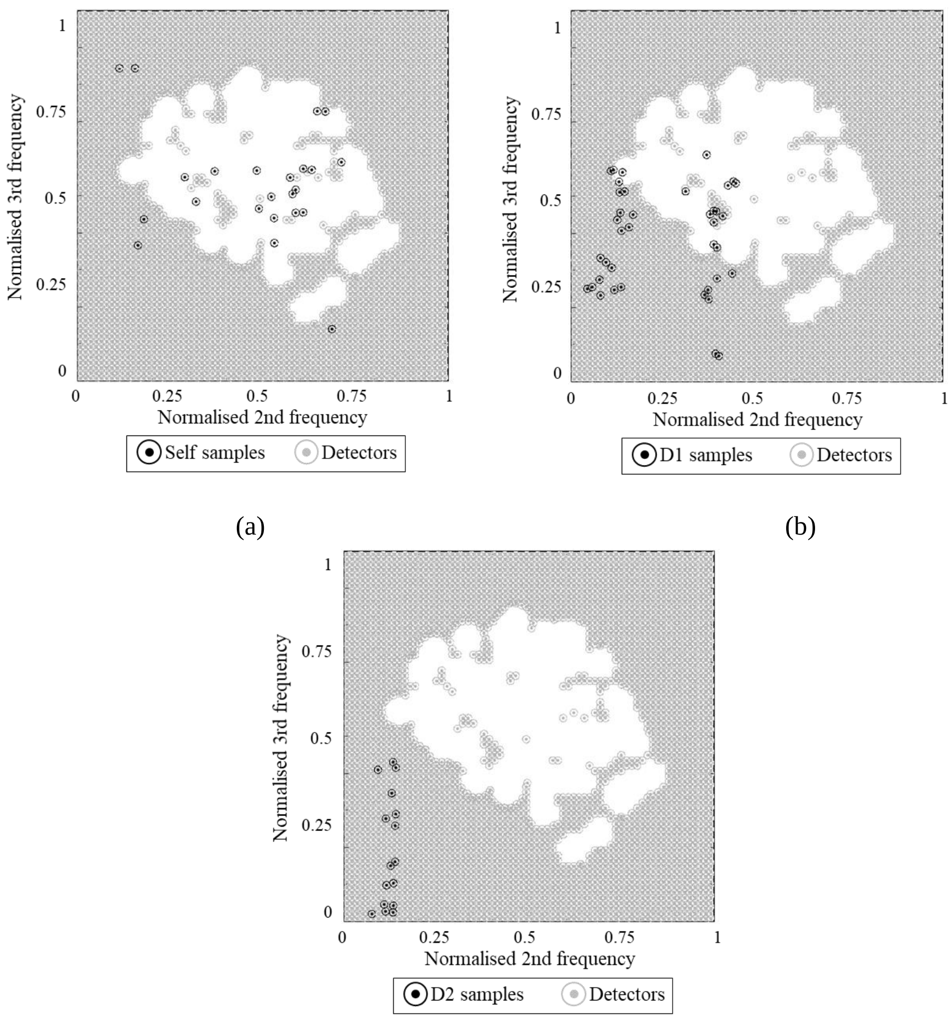


Figure 6: Comparison of the new detector set against the testing sets.

4 CONCLUSIONS AND FUTURE SCOPE

The simple discrimination between the normal and the abnormal behavior of an engineered system is a complex task in many real-world applications. The lack of knowledge regarding possible abnormal conditions and the limited knowledge about the normal behavior itself reduce the number of non-model-based numerical methods suitable for damage detection purposes (e.g. one-class classification). In the present work a combination of real and artificial data is proposed to improve the design of a tailored damage detection strategy for real-world applications. The analyzed case study consists of a segmental masonry arch built and tested in the laboratory of the University of Minho and the applied damage detection algorithm is a customized version of the NSA, developed by the authors in a previous work. Hitherto, the following preliminary conclusions can be drawn:

- the performance is robust against the sources of uncertainties, as the noise in the signals or the modal feature extraction through a simplified peak-picking strategy;
- the classification is successful for small damage extent – indeed the frequency downshift estimated for modes 2 and 3 was on the average 1.6% and 0.9% for the first damage scenario (D1), and 1.9% and 2.3% for the second damage scenario (D2);
- the artificial generation of new self and nonself samples, according to the training data distribution, improved the performance facing the reduced and sparse information available;
- the methodology might be suitable for sensor embedment, since the features are extracted from a single sensor acquisition.

To realize the full potential of the algorithm, more research is needed. Indeed, although the cracks after the first displacement stage are barely visible in the arch, the drop in the first frequency value might suggest that the damage is not as small as required for a proper assessment of the algorithm sensitivity. Moreover, the strategy for artificial data generation should be tested on a larger dataset and the analysis should be cast in a statistical framework to infer the behavior of the final classifier in different conditions.

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