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On the usage of active learning for SHM

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Abstract

The key element of this work is to demonstrate a strategy for using pattern recognition algorithms to investigate correlations between feature variables for Structural Health Monitoring (SHM). The task will take advantage of data from a bridge. An informative chain of artificial intelligence tools will allow an active learning interaction between the unfolded shapes of the manifold of online data by characterising the physical shape between variables. In many data mining and machine learning applications, there is a significant supply of unlabelled data but an important undersupply of labelled data. Semi-supervised active learning, which combines both labelled and unlabelled data can offer serious access to useful information and may be the crucial element in successful decision making, regarding the health of structures.

1 Introduction and problem statement

The central idea behind active learning is that a pattern recognition algorithm can obtain computational and performance accuracy efficiency by utilising fewer training labels if it is allowed to find the most informative data from which it learns. In many SHM applications, there is a significant supply of unlabelled data but an important undersupply of labelled data which are usually difficult, time-consuming or expensive to extract. In this case an active learner will arise queries, in the form of unlabeled data to be labelled by a predictor.

To make it clear to the reader why active learning is a novel element to SHM and a useful tools in modern novelty detection and structural integrity evaluation, the example of the Z24 bridge will be utilised (the Z24 is fully labelled and it is a very good example to understand active learning as it is one of the first times introduced in SHM). This semi-supervised learning tool will use only very few data points from the Z24 data as labelled data and will try to classify all the rest incoming data with no prior knowledge exchange. And because the engineering knowledge is very informative regarding the bridge labelled data one can check accurately if the active learning technique performs as good as it should by clustering correctly the unlabelled data to the labelled clusters coming from very few measured observations.

The current study is a further continuation and discussion of a recent paper [1, 2] that investigates the nonlinear manifold unfolding for SHM in terms of the influential effects of environmental variations before choosing and using a reliable feature. Different methods and algorithms have been used in order to investigate the influence of external variations such as principal component analysis, auto-associative neural networks [3] or more recently cointegration [4–11] and robust regression and robust multivariate statistics as a means of characterising and distinguishing the influence of environmental and operational conditions on the structural response [12, 13]. The effect of temperature on structural response affects the dynamic response of the structure, due to its influence on the stiffness of structural parameters and on the boundary conditions of the structure [4, 14–17]. As a result feature extraction is a critical step in order to derive useful insight from the measured data that can further be post-processed via signal processing techniques. The methods for feature extraction serve two purposes; a reduction in the dimensionality by mapping the data from high-dimensional spaces to lower-dimensional spaces and a revealing of hidden aspects of the data by learning the structure between the variables of interest.

The layout of this paper is as follows. The discussion begins with active learning approach. In Section 3, the strategy that will be followed in this paper is presented and gives some background regarding the description of the Z24 bridge with a little analysis. The study concludes with the presentation of some key results.

2 Active learning

Active learning (commonly called "query learning") is a machine learning approach with one purpose to learn with less data. When supervised learning is utilised especially in an SHM context then often a large number of labelled observations is needed. Active learning tools seek to bypass the labelling curse by generating queries for unlabelled data points that have to be labelled online and automatically by a learner. In turn, the active learner is trying to achieve optimal results by using as few labelled observations as possible. In SHM where labelled data is minimal and very expensive to obtain (how many aircrafts, bridges or wind turbines can be damaged?) active learning is a vital ally as a machine learning tool to address classification problems [18–25, 25–27].

In this work the active learning tool that is used comes from the "art" of text classification (as can be seen in all modern on-line searching machines). Generally talking, in order one to train a certain classifier that continuously and automatically categorises texts into different libraries, then one needs a large number of labelled examples. But on the other hand, a difficult problem arises within the active learning remit of identifying which unlabelled data points carry more information during training [18–25, 25–27].

In a nutshell, the active learning method seeks to find data which contains the most informative points and as result to identify these data points that will give the trained classifier the best performance in terms of reduced labelled observations. Some popular methods in the machine learning community are active support vector machines, probabilistic decision boundary algorithms, query-by-committee or error reduction methods [18].

The algorithm that will be used here is called the Manifold Adaptive Experimental Design Algorithm or (MAED). For the purposes of this paper a sort description of the main steps is given and for more details the reader is referred to [18] as this is a mathematically not trivial-intensive algorithm and out of the scope of this specific paper. MAED is a combination of Optimal Experimental Design (OED), Transductive Experimental Design (TED) and Manifold Adaptive Kernel (MAC) methods [18–25, 25–27]. In simple terms for each data point x_i, one should find its k nearest neighbours $N(x_i)$ and put "border" between x_i and its neighbours.

The basic tasks the active learning algorithm has to perform so that the readers can easily follow the concept behind active learning tools are (see Fig.1):

- Find an initial clustering of the data.
- Sample a few chosen points in each cluster that contain the most information.
- Assign each cluster a label (of course based on engineering knowledge the step 2 can be enhanced by assigning more labelled points).
- One can use this labelled data set to build a classifier (the nature of classifier at this points is not critical as the main job was performed by the active learning clustering. So, one can use support vector machines, neural networks, radial basis networks or Gaussian processes).

The MAED algorithm is not any different to the previous philosophy. It follows similar steps (as all active learning query asking machine learning tools) in order to find the best labels on the given training set via automatic unsupervised learning and then one can assign a supervised classification tools to assign new labels

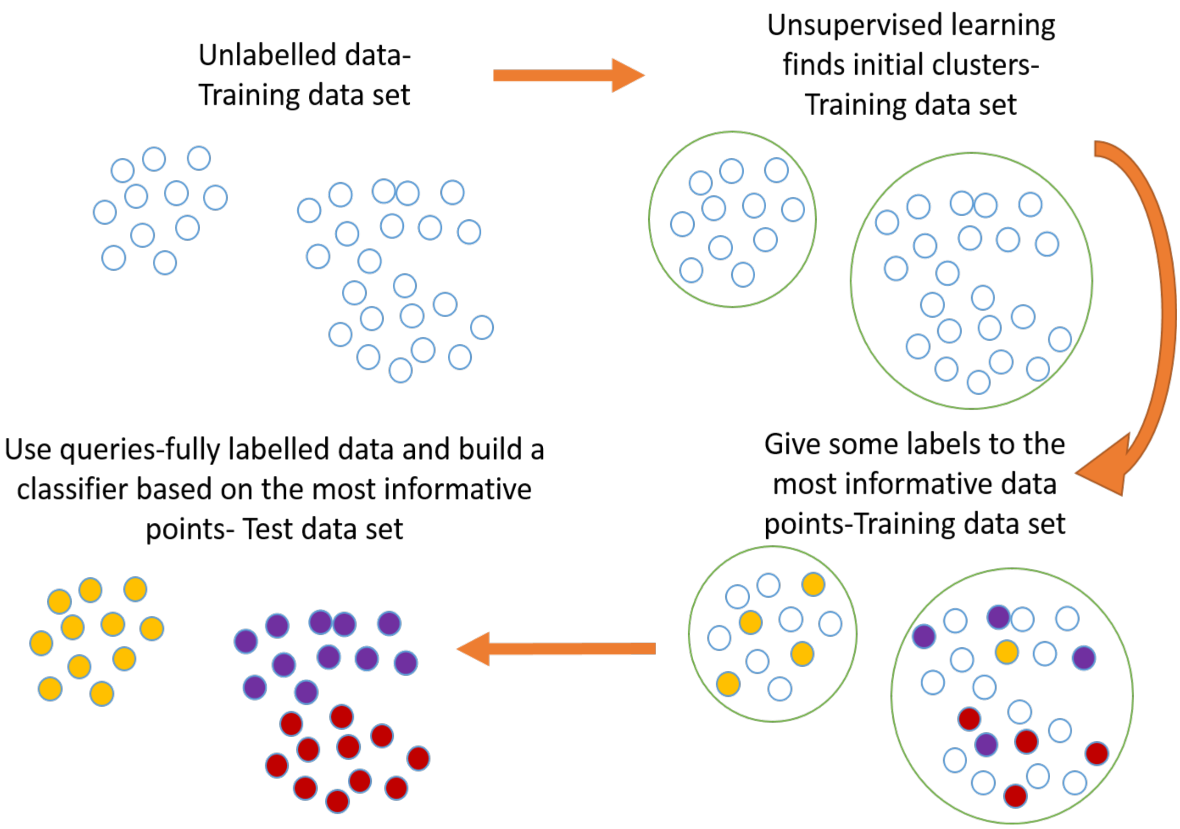

Figure 1: Active learning graphical steps.

as the the new data flows continuously. In simple terms for each data point x_i, one should find its k nearest neighbours $N(x_i)$ and put "border" between x_i and its neighbours.

3 Is active learning working? The Z24 bridge example

The Z24 Bridge (see Fig.2) was a concrete highway structure in Switzerland connecting Koppigen and Utzenstorf, and in the late 1990s, before its demolishment procedure, it was used for SHM purposes under the "SIMCES" project [4, 28]. During a whole year of monitoring of the bridge, a series of sensor systems captured modal parameter measurements, as well as a family of environmental measurements such as air temperature, soil temperature, humidity, wind speed etc. The critical point in this benchmark project was the introduction of different types of real progressive damage scenarios towards the end of the monitoring year.

For the purposes of this study, the four natural frequencies that were extracted over a period of year, including the period of structural failure of the bridge are used. Fig.3 shows the four natural frequencies with values between 0-12 Hz (vertical $y - axis$ is the natural frequencies in Hz). The beginning of the introduced failure occurs at observation 3476.

Figure 2: The Z24 bridge.

It was found that the Z24 bridge has a highly nonlinear behaviour. As it can be seen there are some visible fluctuations between observations 1200-1500 (below -5 Celsius degrees). The critical fluctuations are highly related to periods of very cold temperatures much under zero degrees Celsius and there is a direct connection with increased stiffness based on the freezing of the asphalt layer of the bridge deck. In turn, these large temperature fluctuations are suitable candidates to introduce nonlinear characteristics. This is the reason that advanced machine learning techniques are utilised as a means of revealing the hidden characteristics of the structural modal data.

First the Z24 natural frequency data is projected into 2-D manifold space using LLE.

Locally linear embedding (LLE) [29, 30] is also utilised here as continuation of [1, 2] as an effective method of nonlinear manifold learning. An extensive overview of the algorithm can be found in [29, 30].

The LLE method is based on simple geometric intuition. If the observations consist of N real-valued vectors $\{x_i\}$ with dimensions D and they are sampled from a smooth underlying nonlinear manifold, then each data point and its neighbours is expected to lie on or close to a locally formed patch of the manifold. The local geometries can be characterised by finding linear coefficients that can reconstruct each data point with respect to each set of neighbours.

If one establishes K nearest neighbours per data point then the reconstruction error is given by the cost function:

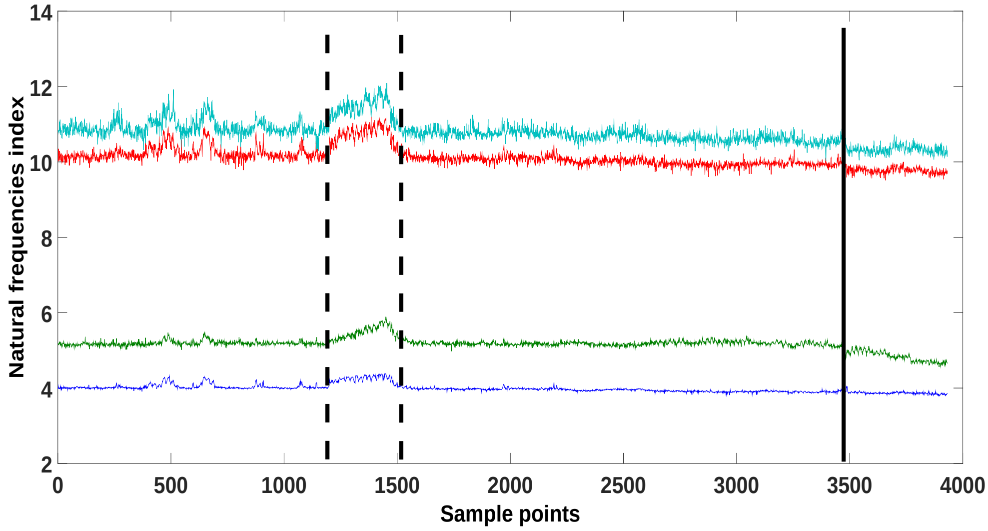

Figure 3: Time history of natural frequencies of the Z24 Bridge (The dotted lines represent the very cold temperatures fluctuation and the black solid line the introduction of damage).

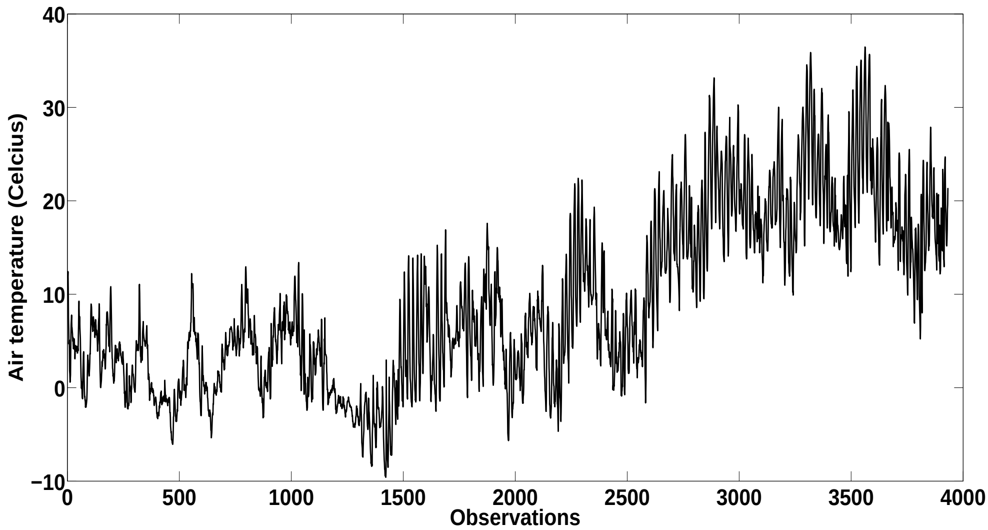

Figure 4: Time history of deck temperature.

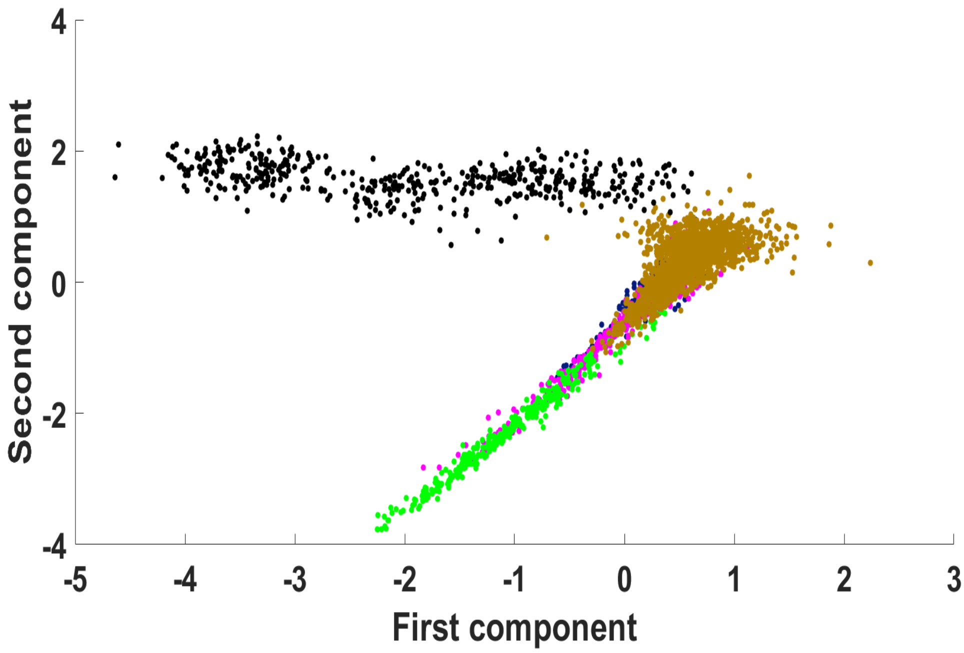

Figure 5: LLE 2-D manifold projection.

$$error(W) = \sum_i \left| \{x_i\} - \sum_j [W_{ij}]\{x_j\} \right|^2 \tag{1}$$

where $[W_{ij}]$ is the weight contribution of the j^{th} data point to the i^{th} reconstruction. In order to compute these weights the cost function has to be minimised under the following constraints. The reconstruction errors that are subject to the constrained weights should be invariant to rotations and rescaling. In turn, in order that the LLE algorithm preserves this invariant manifold idea as a final step of the method, each measurement $\{x_i\}$ should be mapped to a lower dimensional vector $\{Y_i\}$ that minimises the cost function:

$$error(Y) = \sum_i \left| \{Y_i\} - \sum_j [W_{ij}]\{Y_j\} \right|^2 \tag{2}$$

The main difference with the previous cost function is that here the weights are fixed but the $\{Y_i\}$ co-ordinates are optimised.

In the Table.1 a description of the different data sets in relation to temperature is given as they appear in Fig.5.

Observation	**Condition**	**Colour**
1-400	undamaged	blue
401-1200	undamaged (with some cold temperature variations)	pink
1201-1500	undamaged (very cold temperature)	green
1501-3475	undamaged (with hot temperature variations)	brown
3476-3932	damaged	black

Table 1: Description of data sets as they appear in the Figs.6-9.

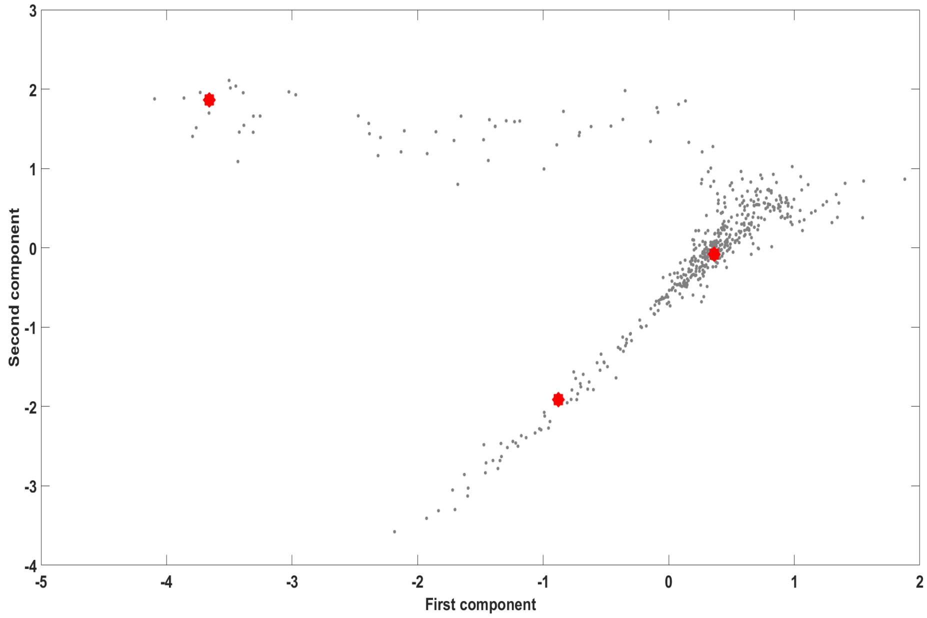

Figure 6: Data selection by active learning algorithm MAED during training of randomly selected 500 points. The selected data points are marked as red stars and in this example the number of labelled samples to select is 3.

The next step is to use active learning in order to predict the manifold classes. The active learning method is given a number k of training examples and is let free to find these labelled points that carry the most information. As can be seen from Fig.6 the active learning algorithm selected data points that carry the most information by utilising only 500 points from the 3932 points of the total observation without giving any a priori knowledge of the exact labels (this follows the schematic of Fig.1). In reality, engineering judgement can be utilised and a certain number of training data points can be used on top of the active learning job. Then one can use any sort of classifier (support vector machines, neural networks, radial basis networks or Gaussian processes) that is trained on these active learning points with their labels. The trained classifier can then be used in order to predict the class labels of the unlabelled remaining observations. As can be seen from Figs.6-9 the classification accuracy will definitely increase with more training examples as more labelled points are automatically selected. It is very encouraging that the learning method performs noticeably good even when there is limited number of training data points. In reality of course, when only a limited number of data points are selected, then it would be possible that some categories are not represented at all and this could lead to misclassification of certain categories. Therefore, labelling resources during active learning can critically affect the performance in terms of classification results.

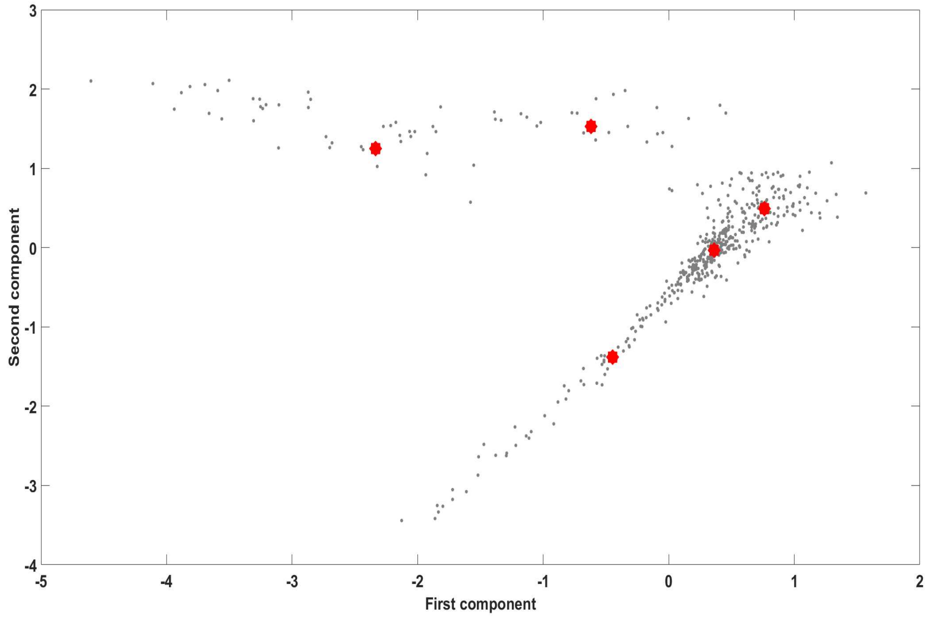

Figure 7: Data selection by active learning algorithm MAED during training of randomly selected 500 points. The selected data points are marked as red stars and in this example the number of labelled samples to select is 5.

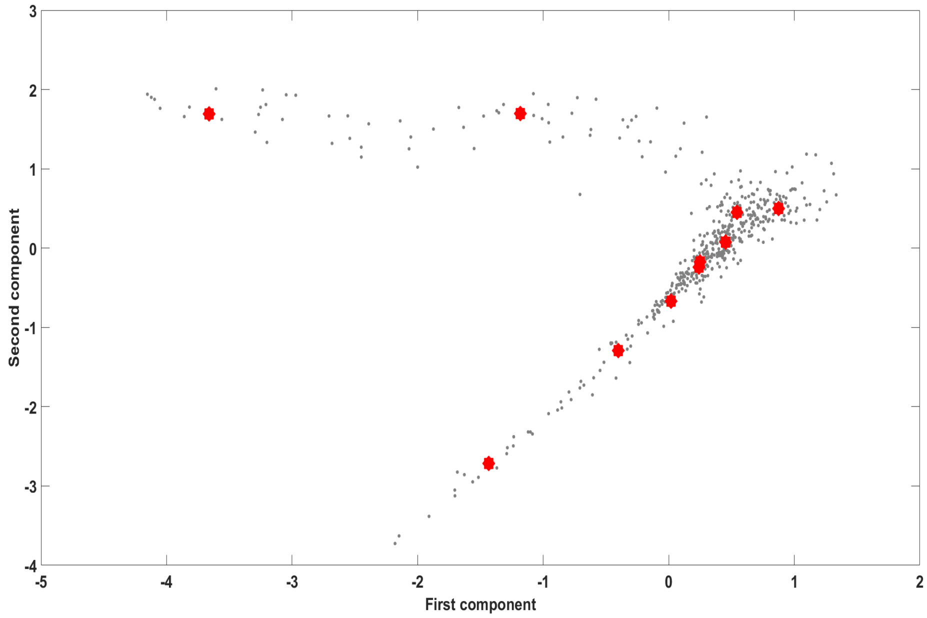

Figure 8: Data selection by active learning algorithm MAED during training of randomly selected 500 points. The selected data points are marked as red stars and in this example the number of labelled samples to select is 10.

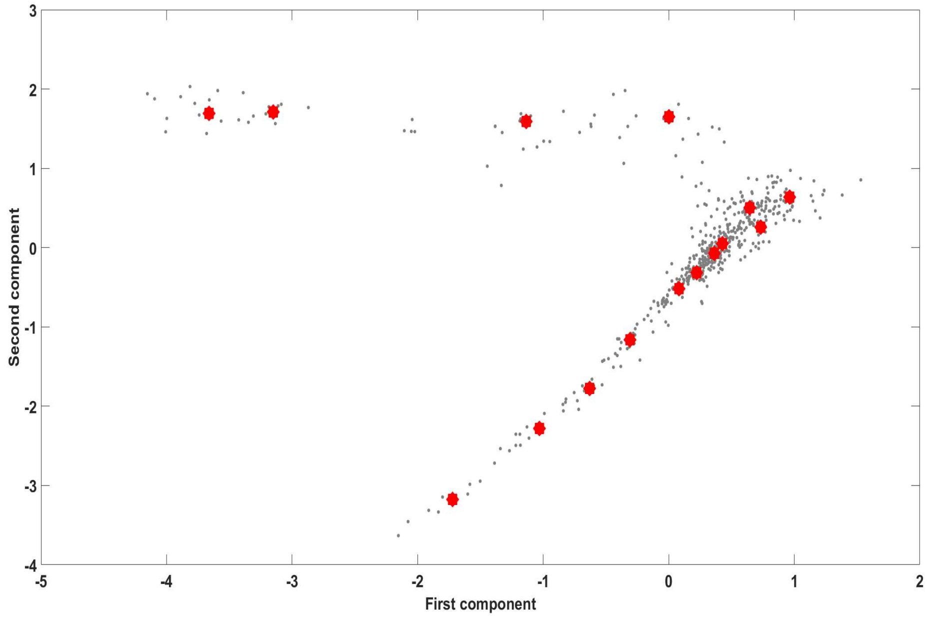

Figure 9: Data selection by active learning algorithm MAED during training of randomly selected 500 points. The selected data points are marked as red stars and in this example the number of labelled samples to select is 15.

4 Conclusion

The purpose of this paper is to highlight the key utility of some specific machine learning methods, as a method of investigating the uncertainty of the space where data clusters are lying. The main benefit of the active learning approach taken here is that gives more robust determination regarding clustering. Active learning is a geometrically growing area of interest in machine learning and computer science. The authors believe in terms of SHM and system identification the concept of active learning can be a key player, especially when big data bases are extracted and considered. There is no doubt that SHM interest can be fuelled by the cruel reality that data is easy and a lot of times inexpensive to extract from a given structure but very difficult or expensive to label for training (supervised learning damage localisation and classification). The vital understanding which queries are selected from the machine learner perspective for both damage assessment or progression or system identification (Gaussian processes for example are very expensive to run) can give evidence that the number of labelled examples necessary to train accurate models can be effectively reduced as was seen in the Z24 bridge where the active learner needs just a few points to understand the clusters of the manifold and assign sensible labels.

Acknowledgments

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