Supervised learning algorithms for damage detection and long term bridge monitoring

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Supervised learning algorithms for damage detection and long term bridge monitoring

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ABSTRACT: In the past few years, numerous methods for damage assessment for structural health monitoring were proposed in the literature. Several problems are raised for making these approaches practical for the engineer. The first concern is to determine whether a structure presents an abnormal behavior or not. Statistical inference is concerned with the implementation of algorithms that analyze the distribution of extracted features in an effort to make decisions on damage diagnosis. Learning algorithms have extensively been applied to classification and pattern recognition problems in the past years and deserve to be used for structural health monitoring. In addition, data acquisition campaigns of civil engineering structures can last from several minutes to years. Dealing with large amounts of data is not an easy task and suitable tools are required to correctly extract important features from them: symbolic data analysis (SDA) is such an approach. In this paper, some supervised learning methods (Bayesian decision trees, neural networks and support vector machines) are introduced to discriminate structural features and are developed within the concept of symbolic data analysis in order to compress data without losing its inherent variability. To highlight the different features of these techniques for structural health monitoring, this paper focuses attention on the monitoring of a railway bridge belonging to the high speed track between Paris and Lyon. During the month of June 2003, a strengthening procedure was carried out in this bridge. In so doing, vibration measurements were recorded under three different structural conditions: before, during and strengthening. In the following years (2004, 2005 and 2006), new tests were performed to observe how the dynamic behavior of the bridge evolved, especially for the case of frequency changes. The objective was to verify whether the strengthening procedure was still effective or not, in order terms if the new data could be still assigned to the condition “after strengthening”. This paper reports the major results obtained and shows how the supervised learning techniques can be applied to cluster structural behaviors and classify new data. An original assignment approach is also presented: based on dissimilarity measures this approach shows that in fact the structural behavior of the bridge seems totally different of the initial behaviors used for training the supervised learning methods.

1 INTRODUCTION

Structural monitoring consists in observing, measuring and recording information. The development of high performance sensors, precision signal conditioning, Analog-to-Digital converters, optical or wireless networks, global positioning systems, etc have drastically changed the vision of structural monitoring giving to engineers a large amount of data, and consequently performance indicators. In connection with advanced software for structural analysis, significant developments can be expected regarding the detection of deterioration mechanisms. These developments open the way for a wide range of applications dedicated to efficient operation and maintenance of civil structures.

Vibration-based monitoring is such an approach since the acquisition of the structural dynamic response and its analysis are intended to give knowledge about the actual mechanical behaviour of a structure (LCPC 2009). Various reasons justify them, but among them, novelty detection (or diagnosis of abnormal behaviour) and structural characterization are of paramount importance for operating and maintaining structures. Detecting faults structural changes in a timely manner or understanding the mechanical behaviour are critical to ensure that the resulting disruption and the economical management issues are optimized. This explains why a lot of expectations have been placed in vibration-based monitoring.

The objective of this paper is to present a practical application of these two problems. The studied bridge is an embedded steel bridge (PK 075+317 bridge - Fig.1) located on the South-East high speed track in France. This bridge was built in the early eighties; the increase of the operating speed of high speed trains (TGV) has moved the excitation frequency of the trains close to the first natural frequency of the bridge. This risk of resonance was furthermore emphasized by the uncertainties in the mass of the ballast disposed on the bridge. To avoid this problem, the French railways SNCF set up a system of rods near the bearings tightened by torque wrench (Figs.1-2); this strengthening brings stiffness and increase natural frequencies. In 2003 a strengthening intervention was scheduled and led to a change in natural frequencies and mode shapes as given in Table 1 and Figure 3 (Cremona 2004).

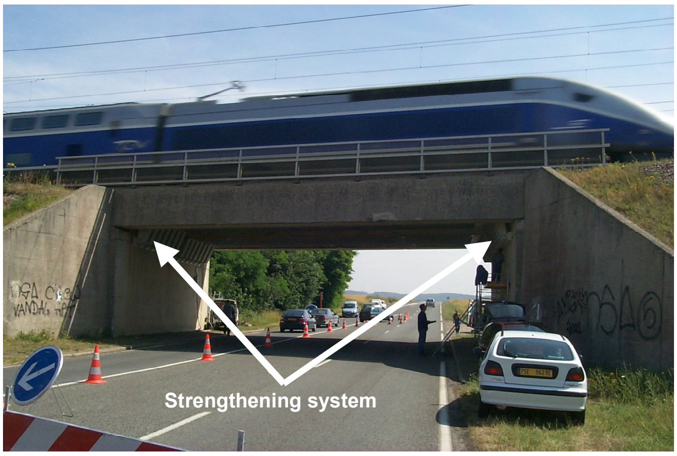


Figure 1. PK 075+317 bridge with its strengthening system

Figure 2. Close view of the strengthening system

Table 1. Natural frequencies before and after strengthening

Frequency	Before strengthening		After strengthening	
	Mean [Hz]	Standard deviation	Mean [Hz]	Standard deviation
1	5.848	0.242	6.461	0.267
2	8.507	0.322	8.592	0.415
3	13.017	0.305	13.078	0.296
4	16.850	0.502	17.142	0.507

A long term monitoring was later decided to appraise the efficiency of this strengthening over a non continuous 2 years period (December 2004 to March 2006). The arising problem is therefore to know if the bridge dynamic behaviour remained close to the behaviour after strengthening or if it had moved to the initial structural condition, or to a completely different behaviour. This problem is an assignment problem: assuming different clusters of data, is it possible to affect any new information to one of these clusters, or eventually to identify a new type of information that cannot be related to any of these clusters? In previous papers (Cury et al 2010, Cury & Cremona 2011), the authors introduced non supervised and supervised learning algorithms for bridge monitoring and novelty detection. The purpose of this paper is to apply supervised algorithms to evaluate how different is the data from 2004-2006 highlighting an eventual deterioration of the strengthening.

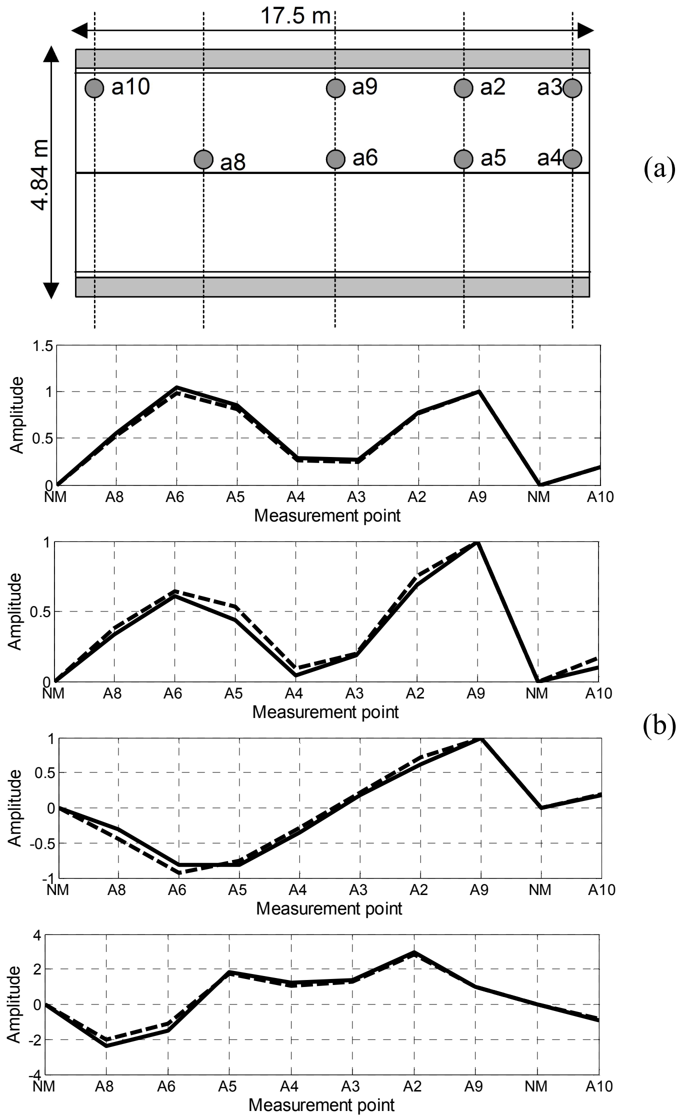


Figure 3. Instrumentation setup (a) and mode shapes (b)

2 SYMBOLIC DATA ANALYSIS OVERVIEW

In general, data acquisition campaigns in civil engineering structures gather thousands of accelerations values measured by several sensors. As a consequence, analyzing all of these data (classical data) directly may usually be time-consuming or even prohibitive. In this sense, transforming this massive quantity of data into a compact but also rich descriptive type of data (symbolic data) becomes an attractive approach (Billard & Diday 2006). Let us consider, for instance, a signal X (which is part of a dynamic test) containing *n* acceleration values measured by one single sensor. There are several ways to transform classical data into symbolic data. This signal can be represented by:

- a k-category histogram: X={$a_1(n_1)$, $a_2(n_2)$, $a_3(n_3)$, …, $a_k(n_k)$};
- an interquartile interval: X = [$a_{25\%}$; $a_{75\%}$];
- a min/max interval: X = [$a_{\min}$; $a_{\max}$];

The same representation can be applied to modal parameters, i.e. natural frequencies and mode shapes. In other words, both of these quantities can be represented by intervals or histograms. Transforming classical data to symbolic data is carried out almost instantly which does not prohibit or make difficult the use of this methodology for a large ensemble of dynamic tests.

3 PRINCIPLES OF SUPERVISED LEARNING

Any classification method uses a set of features or parameters to characterize each object. Supervised classification means that an expert both has already determined into what classes an object may be categorized and also has provided a set of sample objects with known classes. This set of known objects is called the training set because it is used by the classification programs to learn how to classify objects. There are two phases to constructing a classifier. In the training phase, the training set is used to decide how the parameters ought to be weighted and combined in order to separate the various classes of objects. In the application phase, the weights determined in the training set are applied to a set of objects that do not have known classes in order to determine what their classes are likely to be. Two supervised algorithms have been introduced in this paper: the neural networks and the support vector machines.

Supervised learning is a machine learning technique for deducing mapping functions from a training dataset consisted of input-output pairs. The goal is to predict output values of the mapping function for any valid input after having seen a number of training examples (i.e. pairs of inputs and target outputs). To achieve this, the network has to generalize from the training data to unseen situations in a "reasonable" way. For neural networks (NN), mapping functions are obtained through an optimization scheme based on the evaluation of the mean-squared error. This scheme tries to minimize the average squared error between the network's output and the target value over all the training dataset pairs. In this paper, a feed-forward multilayer perceptron neural network is used for classifying dynamic tests. Multilayer networks use a variety of learning techniques, the most popular being back-propagation. In this case, the output values are compared with the correct answer to compute the value of some predefined error-function and the error is then fed back through the network. Using this information, the algorithm adjusts the weights of each connection to reduce the value of the error function by some small amount. After repeating this process for a sufficiently large number of training cycles, the network will usually converge to some state where the error of the calculations is negligible. At this point, it is said that the network is “trained” (Cury & Cremona 2011).

Support Vector Machines (SVM) are also useful techniques for data classification problems. As previously, the objective is to separate two different classes by a function which is induced from available examples (training dataset). This technique came up from statistical learning theory and is based on the structural risk minimization principle. Commonly, SVMs are used for two-groups classification problems but can easily be extended to multi-groups classification problems (Cury & Cremona 2011).

Bayesian Decision Trees (BDT) form a decision procedure which is able to solve classification problems. The general idea of this method is to classify a particular object into one of the classes (groups) previously defined in a training set. The steps of this symbolic discrimination procedure are to represent a given partition in the form of a BDT and create a rule that is able to assign a new test to one class of a prior partition (Cury & Cremona 2011).

4 CLASSIFICATION OF NEW TESTS

For the supervised methods, once the mapping functions are determined then new data is placed as input and the mapping function returns an assignment value to one of the classes.

An alternative approach, that does not require mapping functions, has been recently introduced by the authors (Cury & Cremona 2012). As for supervised learning methods, let us assume an a priori set of clusters with the help of the training dataset. For a given cluster, a within-cluster variation is calculated thanks to a dissimilarity measure. In a common sense, small dissimilarity values must represent similar objects since they are gathered in the same cluster. Conversely, the objects allocated into different clusters have larger dissimilarity values. Dissimilarity measures can take a variety of forms and some applications might require specific ones. In the present study, the Hausdorff distance has been introduced, since it is faster to evaluate and it shows a better performance when compared to the other data distances presented in the literature (Malerba et al 2001).

Thus, let us assume that the clusters are *perfectly* known; the following methodology is proposed:

1. For each cluster C_i, evaluate its prototype P_i. The prototype is the test in the cluster that minimizes the total sum of the distances between this later one and all the other tests in the cluster. The prototype will represent the cluster;

2 Evaluate a vector of distances between the set of tests and the prototype;
3 Fit a probability distribution of the calculated distances;
4 Determine a threshold distance value $d_{th,i}$ having a probability α to be exceeded (generally 5 %). This procedure is highlighted on Figure 4;
5 Calculate the distance between the *new* test and the different prototypes P_k. Assign the new test to the cluster C_k giving the smallest dissimilarity distance If this distance is smaller than the threshold distance $d_{th,k}$, then the new test is definitively assigned to cluster C_k. If not, a new structural behaviour C is identified.

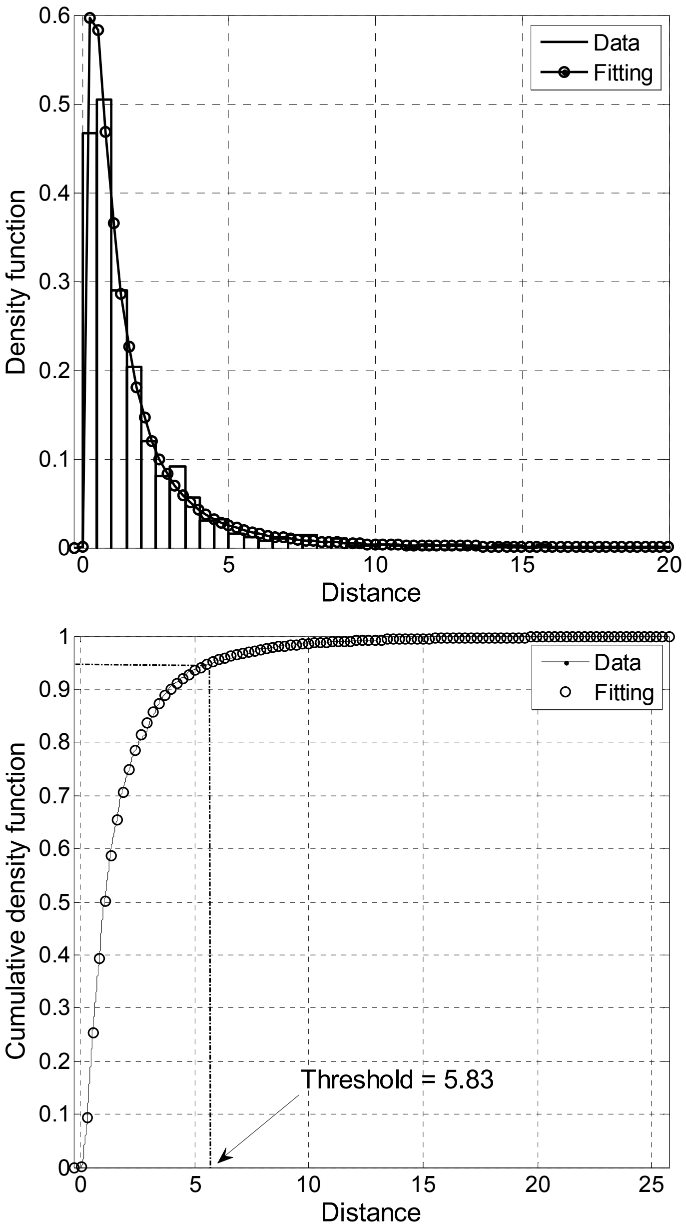


Figure 4. Example of lognormal distribution fitting and determination of a threshold value.

To fit a probabilistic distribution (step 3), some functions present in the literature are considered and evaluated using the Kolmogorov-Smirnov goodness of fit test. This test is used to decide if a sample comes from a hypothetical continuous distribution relatively to the empirical cumulative distribution function. If the test is not rejected, the *p*-value is calculated based on the test statistics and denotes the threshold value of the significance level. The optimal distribution is the one whose *p*-value is minimal. In this paper, four distributions were considered: normal, lognormal, logistic, log-logistic and Weibull.

5 APPLICATION TO BRIDGE MONITORING

There are many ways by which one can organize a discussion of bridge health monitoring. The authors have chosen to follow the one described by Farrar and Worden (2007) that defines the process in terms of a four-steps statistical pattern recognition paradigm:

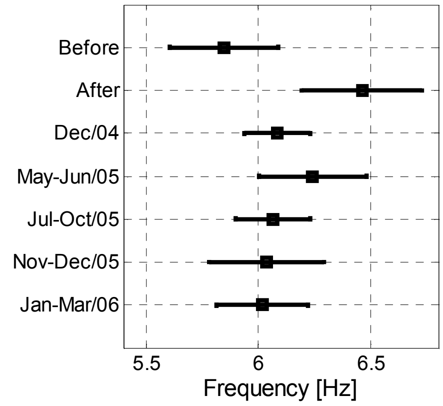
1 operational evaluation,
2 data acquisition, normalization and cleansing,
3 feature selection and information condensation, and
4 statistical model development for feature discrimination.

Operational evaluation sets the limitations on what will be monitored and how the monitoring will be accomplished. In the present study, operational evaluation is performed by dynamic tests with sensors spread over the structure in order to detect and locate damage. In addition, temperature sensors are added to correlate structural behavior with environmental effects. Data acquisition, normalization and cleansing involve selecting the excitation methods, the sensor types, number and locations, and the data acquisition/storage/transmittal hardware. Ambient vibration is used to excite the bridge (train crossing), and capacitive accelerometers (1V/g) with sampling frequency 500 Hz have been applied. During monitoring, the numbers and locations of sensors have been kept identical to those introduced during the strengthening process. Environmental variability is an issue: changes in modal properties are not always based on modifications in the physical properties. Environmental changes (such as temperature) can affect the modal properties and it may be necessary to account for this. The first issue is therefore to define a baseline temperature for defining a correction law. A correction law is intended to make frequencies insensitive to temperature. This consists in fixing a reference temperature and correcting each frequency (or mode shape) identified for a specific temperature T as if measured at the reference temperature. In the case of the PK 075+317 bridge, neural networks were applied by the authors [13] to fit a non linear model for data normalization. The fitting was performed on the 2003 strengthening campaign; such a fitting presented a major drawback since it was over-conditioned by a training sample at the same range of temperatures (ranging from 20°C to 27°C). The data normalization for low temperatures (winter) can be biased compared to the summer period. Furthermore since the bridge monitoring is not continuous, winter conditions are under-represented in the data (197 tests over 558 tests). It has therefore been noticed that data normalization from temperature effects does not modify significantly the clustering results (Cury 2010). At last, this data normalization cannot be applied to the signals themselves. Since a comparison between rough data (signals) and processed data (mode shapes, frequencies) is sought, the influence of environmental variability is not included in this paper. Operational variability is also not considered since the excitation (high speed train) is stable over time.

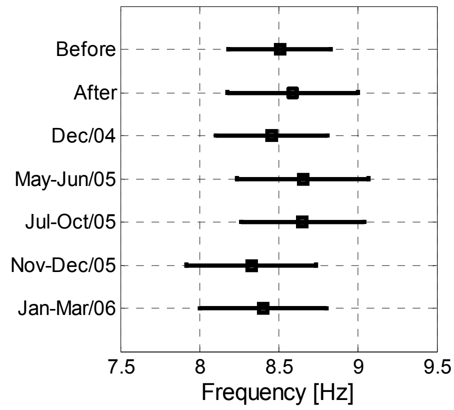
Feature extraction has been performed by the random decrement technique associated with the Ibrahim time domain method for identifying modal parameters. Information condensation is then made by a symbolic data analysis process and expressed in terms of histograms to get the features' variability. The statistical model for discrimination is based on supervised/unsupervised learning methods to qualify change in the structure's mechanical behavior. These techniques are used as outlier or novelty detection and are only applied to detect damage (level 1 of the Rytter's scale – Rytter 1993).

The instrumentation of the bridge comprises 8 vertical accelerometers under the bridge deck (Fig.3). The sampling frequency was fixed at 4096Hz during the strengthening phase, then to 500 Hz during the long term monitoring phase. The signal analysis due to high speed train crossings highlights a good repeatability (Cremona 2004), mainly because the operating conditions are mostly constant over time. In the following analyses, only acceleration measurements are used for classification. Modal parameters are extracted from the response measurements by the random decrement technique in connection with the Ibrahim Time Domain for modal parameters extraction (Alvandi & Cremona, 2006). This method requires fixing the model size (i.e. the number of modes present in the response). This disadvantage can be turned into an advantage by noting that automatically varying the model size can lead to get an evaluation of the stability of the modal parameters and therefore to assess the good quality of the modal identification by generating histograms.

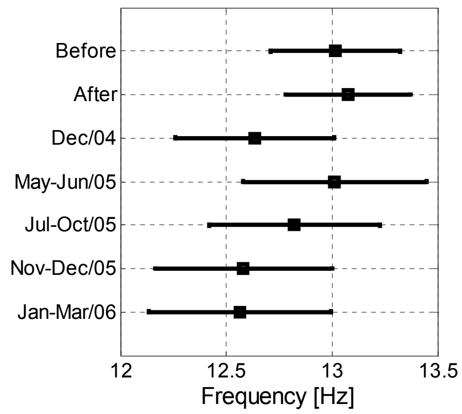
In 2003, three sets of dynamic tests were performed: 15 before strengthening (represented by the letter "*A*"), 13 during strengthening (represented by the letter "*D*") and 13 after strengthening (represented by the letter "*B*"). The idea is to apply supervised/non supervised learning methods in connection with symbolic data analysis to discriminate the three different stages *A, D* and *B*. The objective is to breakdown the whole set of 41 tests into three specific groups (before, during and after). Measured data (signals), natural frequencies and mode shapes of the bridge were employed.



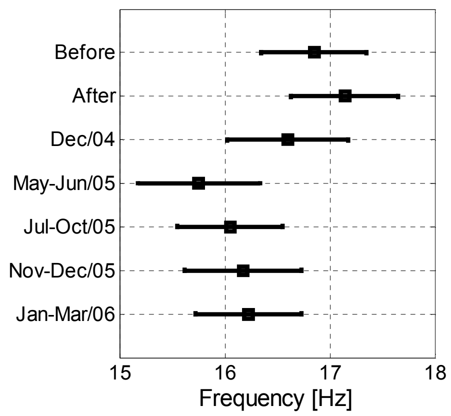
First frequency



Second frequency



Third frequency



Fourth frequency

Figure 5. Confidence intervals for the identified frequencies

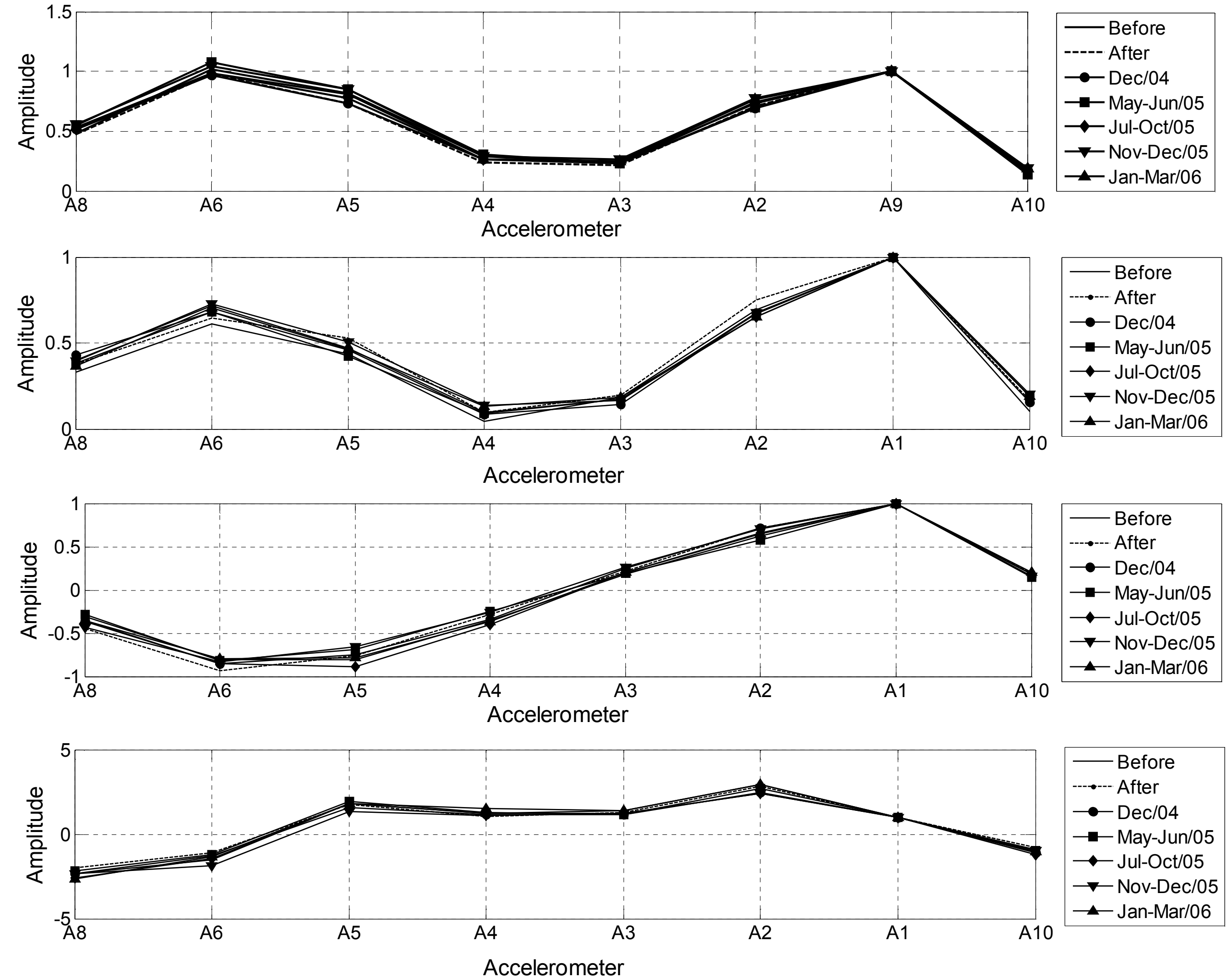


Figure 6. Comparison of the averaged mode shapes over the different measurement periods

5.1 *Preliminary analysis*

A long term monitoring was later on decided to appraise the efficiency of this strengthening over a non continuous 2 years period (December 2004 to March 2006). Figure 5 gives the confidence intervals of the identified natural frequencies (±1.96 standard deviation) for the different measurement periods compared to the frequencies before and just after strengthening. It can be noticed that, for all frequencies, but most notably for the first one, the mean values have a shift to the right characterising a sensitive frequency increase after the strengthening procedure. For the subsequent campaigns (especially those in 2005), there is a slight frequency decrease tendency showing a possible efficiency loss of the strengthening procedure. However, the confidence intervals are always superposed.

Figure 6 compares the different mode shapes. It is particularly obvious that it is hardly difficult to distinguish them over the measurement period. The MAC values between “after strengthening” and the different measurement sequences vary from 97% to 99%. Let us note that several more advanced methods exist for detecting structural changes (flexibility curvature methods, strain energy method, mode shape curvatures…). These methods provide damage indicators that have been successfully used for the PK 075+317 bridge (Alvandi & Cremona 2006) but introduce a second layer of uncertainties due to the calculation of curvatures in particular. This is why the present analysis is only based on vibrational responses and modal data only.

5.2 *Classification with non supervised techniques*

The non supervised techniques require using a training data set (28 tests randomly chosen from 41 dynamic tests) and a validation data set (13 tests). The testing data set in the present case is composed of the 575 dynamic tests measured between 2004 and 2006. The classification may include some errors since all the data of the validation set may be not assigned to the right initial clusters. As the probabilities of correct classification do not reach 100%, it implies that a new test assigned to a cluster with a supervised method can only be stated with a confidence probability that is the probability of correct classification.

Table 2 provides the average probabilities of correct classification for the supervised learning methods. This table highlights that the NN technique is the most efficient technique followed by the BDT method. The SVM technique presents poor results when using modal parameters.

Table 2. Average probabilities of correct classification for the Bayesian decision tree (BDT), the neural network (NN) and the support vector machine (SVM) methods (data transformed into histograms)

Signals			Frequencies			Mode shapes		
BDT	NN	SVM	BDT	NN	SVM	BDT	NN	SVM
64%	93%	85%	75%	95%	54%	63%	90%	57%

5.3 *Assignment of new tests*

In December 2004, further dynamic investigations were scheduled to analyse the dynamic properties of the bridge. In this measurement campaign 21 tests were recorded. During the year of 2005, three extra campaigns were also performed. The first one, during May-June, 107 tests were recorded. For the second one, during July-October, 254 tests were made. The third campaign, during November-December, comprised 52 tests. Finally, the last monitoring took place between the months of January-Mars 2006, with a total of 141 tests. With the distance method, new data can be assigned to the three initial clusters or to a totally new one based on the threshold value estimated from the normalized histograms of dissimilarity measures. For the supervised learning methods, this extra-assignment is not possible and assignments can only be made to one of the three groups. Tables 4-6 give the probabilities of assignment for each method over the different dynamic investigation periods. It come from the supervised learning methods that the structural behaviour of the bridge after two years can be mostly assigned to the states "before" or "during" highlighting a loss of the strengthening effect.

Table 3. Probabilities (%) of assignments with the BDT method

	Date	Dec/04	May-Jun/05	Jul-Oct/05	Nov-Dec/05	Jan-Mar/06
Signals	*A*	37	39	45	22	33
	D	**44**	**43**	**22**	**56**	**47**
	B	19	18	33	22	20
	C					
Frequencies	*A*	15	28	26	38	45
	D	**37**	**44**	**39**	**32**	**30**
	B	48	28	35	30	25
	C					
Mode shapes	*A*	20	25	12	17	29
	D	**39**	**44**	**57**	**51**	**44**
	B	41	31	31	32	27
	C					

The results with the distance method are more conclusive due to the possibility to assign tests to a new cluster *C*. It seems that the structural behavior cannot be compared to the three initial states. In any case, it appears clearly that the state "after" is no longer selected; this tends to prove that the efficiency of the strengthening is no longer valid.

Table 4. Probabilities (%) of assignments with the NN method

	Date	Dec/04	May-Jun/05	Jul-Oct/05	Nov-Dec/05	Jan-Mar/06
Signals	*A*	18	5	12	29	24
	D	**80**	**79**	**70**	**56**	**61**
	B	2	16	18	15	15
	C					
Frequencies	*A*	0	0	0	0	0
	D	**100**	**100**	**100**	**100**	**100**
	B	0	0	0	0	0
	C					
Mode shapes	*A*	0	0	0	0	0
	D	**100**	**100**	**100**	**100**	**100**
	B	0	0	0	0	0
	C					

Table 5. Probabilities (%) of assignments with the SVM method

	Date	Dec/04	May-Jun/05	Jul-Oct/05	Nov-Dec/05	Jan-Mar/06
Signals	*A*	0	0	0	0	0
	D	**100**	**100**	**100**	**100**	**100**
	B	0	0	0	0	0
	C					
Frequencies	*A*	0	0	0	0	0
	D	**100**	**100**	**100**	**100**	**100**
	B	0	0	0	0	0
	C					
Mode shapes	*A*	8	28	22	15	12
	D	**45**	**67**	**75**	**81**	**88**
	B	47	15	3	4	0
	C					

Table 6. Probabilities (%) of assignments with the distance method

	Date	Dec/04	May-Jun/05	Jul-Oct/05	Nov-Dec/05	Jan-Mar/06
Signals	*A*	0	0	0	0	0
	D	0	0	0	0	0
	B	0	0	0	0	0
	C	**100**	**100**	**100**	**100**	**100**
Frequencies	*A*	25	23	37	43	37
	D	**35**	**33**	**40**	**25**	**37**
	B	18	15	18	16	6
	C	22	29	5	16	20
Mode shapes	*A*	0	0	0	0	0
	D	0	0	0	0	0
	B	0	0	0	0	0
	C	**100**	**100**	**100**	**100**	**100**

6 CONCLUSIONS

In this paper a novelty detection method based on supervised learning methods (Bayesian decision tree, neural networks, support vector machines) has been introduced to classify different structural behaviours. For this purpose, raw information (acceleration measurements) and processed information (modal data) are used for feature extraction. The approach has been applied to the monitoring of a railway bridge located in France. In June 2003, this bridge has been strengthened in order to avoid any resonance effects from high speed train crossing. Dynamic measurements before and after strengthening were performed in order to compare the structural changes induced by the repair process. The first objective of this paper was to use the clustering methods and the symbolic data analysis to discriminate these two different conditions. The results obtained showed that the methods are efficient to classify and to discriminate structural modifications either considering vibrational data or modal parameters.

During the years of 2004 to 2006, 575 new measurements were recorded to attest the efficiency of the reinforcement works over time. Preliminary analyses considering natural frequencies or mode shapes demonstrated to be insufficient to classify new tests (Alvandi & Cremona, 2006). As second objective, pattern recognition methods were introduced to assign these tests to the previously identified clusters, or eventually to a totally different structural behaviour. Results obtained showed that new tests were rarely classified into the cluster representing the state "after" strengthening. Overall, natural frequencies seem to be the more sensitive features compared with signals and mode shapes.

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