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# A novel natural frequency-based technique to detect structural changes using computational intelligence

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**Abstract**

Structural changes are usually associated to damage occurrence, which can be caused by design flaws, constructive problems, unexpected loading, natural events or even natural aging. The structural degrading process affects the dynamic behavior, leading to modifications in modal characteristics. In general, natural frequencies are sensitive indicators of structural integrity and tend to become slightly smaller in the presence of damage. Despite this, it is very difficult to state the relationship between decreasing values of natural frequencies and structural damage, since the dynamic properties are also influenced by uncertainty on experimental data and temperature variation. In order to contribute to improving the quality of natural frequency-based methods used for damage identification, this paper presents a simple and efficient strategy to detect structural changes in a set of experimental tests from a real structure using a computational intelligence method. For a full time monitored structure, the evolution of natural frequencies and temperature are used as input data for a Support Vector Machine (SVM) algorithm. The technique consists on detecting structural changes and when they occur based on the structural dynamic behavior. The results obtained on a historic tower show the capacity of the proposed methodology for damage identification and structural health monitoring.


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*Keywords:* Damage detection; Structural dynamic; Computational intelligence; Structural health monitoring; Vibration monitoring

## 1. Introduction

Structural Health Monitoring (SHM) is concerned about safety and maintenance of structures. All structures are subject to changes in their environmental and operational conditions by means of natural or artificial factors, as earthquakes, winds, traffic loads, etc. The aforementioned situations can lead to alterations in structural behavior which can be associated to damage occurrence. This way, the main objective of the SHM is to track the changes of the structural behavior in order to prevent damages.

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The structural degrading process affects the dynamic behavior, leading to modifications in natural frequencies, mode shapes and damping ratios. Thus, the use of modal data to the assessment of structural integrity is a classical approach [1]. In the last years, many researches dedicated a considerable effort to this subject and several methods have been developed, such as those based on strain energy deviation [2,3], on changes in curvature [4], or even based on flexibility matrix analysis [5], among others.

In general, natural frequencies are sensitive features of structural integrity and tend to become slightly smaller in the presence of damage. Nevertheless, it is very difficult to state the relationship between decreasing values of natural frequencies and structural alterations, since they are also influenced by uncertainty on experimental data and temperature variation [6,7]. Considering this, the temperature measurements have to be taken into account to avoid false alarms, especially while employing natural frequency-based strategies.

Another approach to detect structural damage is based on machine learning methods. Computational intelligence methods such as Genetic Algorithm, Artificial Neural Network (ANN), Support Vector Machine (SVM), are considered useful tools for solving structural damage assessment problems [8,9]. In this context, the damage detection algorithms work as classifiers, which try to identify damage levels using, as input data, features extracted from dynamic responses.

According to Rytter [10], the detection methods are classified into four levels: Level #1 - determining whether damage occurs in the structure; Level #2 - identifying the geometric location of the damage; Level #3 - quantifying the severity of the damage; and Level #4 - predicting the remaining service life of the structure. Generally, levels #1 to #4 can be reached in works based on numerical simulations. Nevertheless, when dealing with actual structures, it is a hard task to determine the damage occurrence starting only from modal data. Therefore, robust methods that are able to achieve level #1 are still welcome. Once the structural damage is correctly detected (level #1), inspections can be provided to verify the localization and severity of the damage, achieving levels #2 to #4 in Rytter's classification. Thus, the development of a reliable method focused on detecting structural failures sometimes is enough to avoid safety problems.

In view of the foregoing paragraphs, a novel natural frequency-based technique to detect structural changes by using a computational intelligence method is presented in this paper. For a full time monitored structure, the evolution of natural frequencies and temperature are used as input data for a SVM algorithm. The technique consists in detecting structural changes and when they occur based on the structural dynamic behavior. The proposed methodology is validated by analyzing the continuous dynamic monitoring data collected on the historic Gabbia Tower in Mantua (Italy) that was subjected to an earthquake [11,12]. These first results demonstrate that the novel strategy can provide accurate detection results, demonstrating capacity for damage identification and structural health monitoring.

## 2. Support Vector Machine (SVM) - An overview

Computational learning methods are considered useful tools for solving structural damage assessment problems, once they can recognize similar observations in a database and separate them into groups that share similar characteristics [8,9]. A popular artificial intelligence technology for pattern recognition problem is the SVM, a statistical learning algorithm trained to determine the boundary between two classes of data in a space, where an optimal separating hyperplane is constructed in order to maximize the margin and minimize the misclassification [13]. The maximization of the margin is based on an optimization function to minimize the Euclidian norm of the vector that defines the direction of the separating hyperplane. The training data points located at the margins are called support vectors.

For non-linear binary classification, the inputs are mapped into a high-dimensional feature space through a kernel function. The kernel Gaussian function is used in this paper, which is also called Radial Basis Function (RBF). In this case, the SVM has two free parameters that need to be specified: $\sigma$ from the RBF kernel function; and C, a regularization parameter from the formulation of the margin maximization, used to avoid data overfitting. These parameters are estimated by training the SVM for multiple values of C and $\sigma$. Then, the pair that minimizes the generalization error is chosen.

## 3. A new strategy to detect structural alterations

The interest in the investigation of the influence of ambient effects on the structural behavior has led to the development of dynamic monitoring programs with the purpose of detecting and evaluating possible abnormalities. Nowadays, continuous structural monitoring has been more frequently used, specially for large structures. Millau viaduct [14] and Tsing Ma bridge [15] are some examples. In all of these cases, time histories are recorded, being structural accelerations under ambient loading and temperature commonly registered.

Hence, considering a full time structural monitoring, which includes time histories of accelerations and temperatures, the main steps of the present method may be established:

1. Being T the overall time of the analysis, one must define the discretization parameter N, such that

$$\Delta t = \frac{T}{N} \tag{1}$$

where the length of each discretized time history is $\Delta t$:

$$\sum_{i=1}^{N} \Delta t_i = T \tag{2}$$

Fig. 1 shows the time discretization scheme.

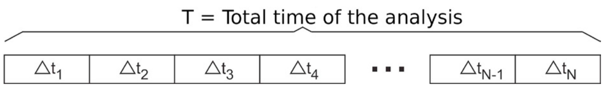


Fig. 1. Time discretization.

2. The modal identification is perfomed for each interval time $\Delta t_i$. Afterward, the frequencies identified during $\Delta t_i$ are assigned to matrix $\mathbf{F}$ with elements $F_{i,j}$ , where rows $i$ are attached to respective $\Delta t_i$ and $j$ columns are related to the $j^{th}$ natural frequency. The mean temperature at the period $\Delta t_i$ is defined as $\Gamma_i$ and all mean temperatures are grouped in vector $\mathbf{\Gamma}$.

3. The next step is to define the frequency submatrices $\mathbf{f}_{und}$, $\mathbf{f}_{dam}$ and temperature subvectors $\gamma_{und}$, $\gamma_{dam}$:

$$\mathbf{f}_{und} = \mathbf{F}_{(u...u+n-1),(1...j)} \tag{3}$$

$$\mathbf{f}_{dam} = \mathbf{F}_{(d...d+n-1),(1...j)} \tag{4}$$

$$\gamma_{und} = \mathbf{\Gamma}_{(u...u+n-1)} \tag{5}$$

$$\gamma_{dam} = \mathbf{\Gamma}_{(d...d+n-1)} \tag{6}$$

where $n$ is the number of lines of submatrices $\mathbf{f}_{und}$ and $\mathbf{f}_{dam}$ and $d = u + n$. The adopted nomenclature is $\mathbf{M}_{(l_i...l_f),(c_i...c_f)}$: submatrix of matrix $\mathbf{M}$ including lines from $l_i$ to $l_f$ and columns $c_i$ to $c_f$.

4. Now, it is assumed that matrix $\mathbf{f}_{und}$ and vector $\gamma_{und}$ were obtained with the structure without damage and, on the other hand, $\mathbf{f}_{dam}$ and $\gamma_{dam}$ were achieved with the damaged structure.

5. Using a SVM based classifier applied to the two assumed classes of data it is expected that the SVM algorithm is able to correctly distinguish damaged and undamaged classes. If the algorithm fails to differentiate both classes, it represents that all data came from the same kind of classes. Thus, admitting structural integrity at the beginning of the application of the proposed methodology, it means that no damage is detected. Otherwise, if the algorithm successfully detect two classes, it means that damage occurred.

For a two classes problem, failures in SMV predictions are taken into account if around 50% of the testing data were wrongly predicted. Therefore, no distinction can be done between the two assumed classes and, consequently, no alteration is detected. This way, here one admits that damage is only considered if the accuracy of SVM is above 90%.

In the present study, for each SVM classification, 2/3 of data was used to train and 1/3 for testing. A SVM with Radial Based Function implemented by Matlab® was applied. The input matrices and vectors are calculated as follow:

**for** $u = 1$ **to** $R$ ($R$ is the number of analysis)
$\mathbf{f}_{und} = \mathbf{F}_{(u...u+n-1),(1...j)}$
$\mathbf{f}_{dam} = \mathbf{F}_{(d...d+n-1),(1...j)}$, being $d = u+n$
$\gamma_{und} = \mathbf{\Gamma}_{(u...u+n-1)}$
$\gamma_{dam} = \mathbf{\Gamma}_{(d...d+n-1)}$
$SVM_{struct}(\mathbf{f}_{und}, \mathbf{f}_{dam}, \gamma_{und}, \gamma_{dam})$
**end**

This algorithm allows to verify if a instant damage occurs. Fig. 2 shows a graphical representation of the used data for $R = 4$ and $n = 3$.

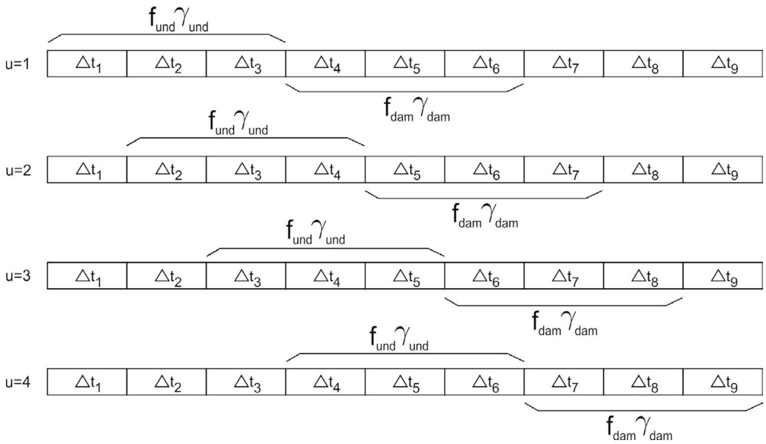


Fig. 2. Illustration of the adopted strategy to identify structural changes.

## 4. Experimental tests - Monitoring data of a historic tower

The presented methodology is evaluated by using monitoring data of Gabbia Tower in Mantua, Italy. Built in the XII century, the investigate structure is 54 m high and it is a symbol of Mantua's cultural heritage. Due to the seismic sequence of May 2012 in Italy, an extensive research program was carried out to assess the structural condition of the tower [11,12]. In this work, experimental data extracted from 44 days (1056 hours) of continuous instrumentation were used, starting from June $1^{st}$, 2013. The instrumentation installed in the tower consists of a 4-channel data acquisition board, 3 piezoelectric accelerometers with sensitivity of 10 V/g and 1 temperature sensor. A binary file, containing 3 acceleration time series (sampling frequency of 200 Hz) and the temperature, is created every hour, stored in an industrial PC on site and transmitted to Politecnico di Milano for being processed. At June $21^{th}$ 2013, this structure was subjected to an intense seismic event, corresponding to the earthquake registered in the Garfagnana region in Tuscany. After this event, a structural damage was detected, which was characterized by a slight natural frequency decrease of the fundamental modes [12].

In the proposed technique, data were organized using $N = 1056$, making $\Delta t = 1$ hour. Time samples from $\Delta t_1$ to $\Delta t_{492}$ are attached to measures made before the earthquake. For sample $\Delta t_{493}$, it is possible to detect the occurrence of the earthquake. The other samples, from $\Delta t_{494}$ to $\Delta t_{1056}$, are associated to the time after the earthquake. In order to mount the matrix $\mathbf{F}$, the natural frequencies were extracted from each $\Delta t_i$ using an automated procedure [16] based on the covariance-driven Stochastic Subspace Identification (SSI-Cov) algorithm [17]. Vector $\mathbf{\Gamma}$ was calculated with the mean temperatures at each analyzed hour. Five principal natural frequencies were detected between around 1 to 10 Hz. However, they are not necessarily found in all time samples ($\Delta t_i$), leading to differences between the number of each identified frequency. For example, the first natural frequency appeared in 975 time samples; the second in 836; the third in 347; the fourth in 722 and the fifth in 854. Due to reduced quantity of data, the third natural frequency was not considered. In that way, the proposed method was applied by frequency $j$, resulting in four analysis respectively associated to each natural frequency. For all analyzed cases, it was adopted $n$ = 200. The obtained results are shown in Fig. 3. In order to facilitate the reader comprehension, the key time associated to $u$+$n$-1 (end of the assumed undamaged data) and $u$+$n$ (beginning of the assumed damage data) was placed in the horizontal axis, making clear the earthquake moment. It is possible to verify that the results associated to natural frequencies #1, #2, #4 and #5

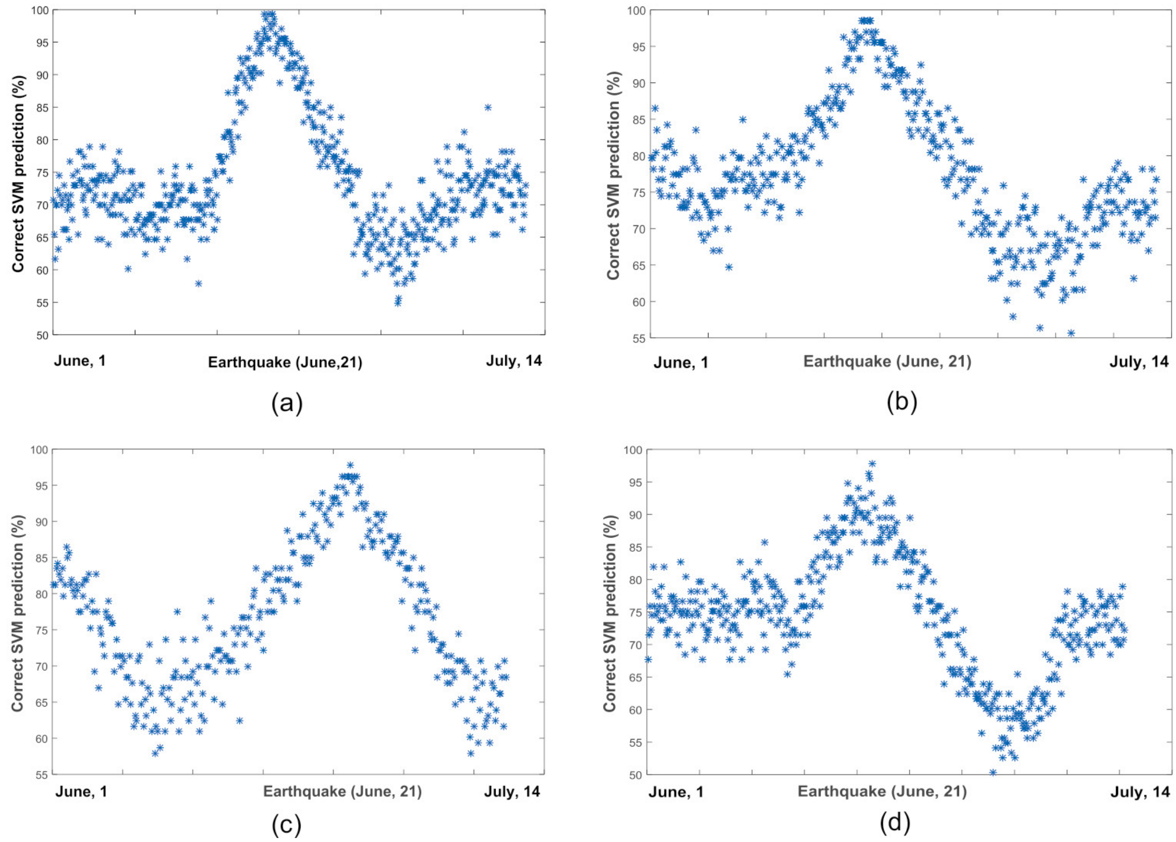


Fig. 3. Accuracy of SVM using the proposed strategy. (a) First natural frequency - $R$ = 576; (b) Second natural frequency - $R$ = 437; (c) Fourth natural frequency - $R$ = 323; (d) Fifth natural frequency - $R$ = 455.

present the same behavior, divided into three distinct parts:

- *Predictions between around 50% to 80%.* One can observe that at the beginning and at the end of the time, SVM fails to distinguish the two assumed classes, indicating that there was no alteration in the integrity state of the structure for these two time regions.
- *Predictions between around 80% to 90%.* It is also possible to see these transient time regions where indicating possible changes in the integrity of the structure.
- *Predictions higher than 90%.* In this case, SVM classifications indicate alterations in the structural behavior, it means that damage occurs in this time region. It is easy to see this last referred time region match the earthquake moment.

## 5. Conclusions

This paper presented a technique to identify structural changes based on modal analysis and Support Vector Machine (SVM) classifications. In order to verify the proposed methodology, experimental results from Gabbia Tower, in Italy, were applied. This data contains the record of the structural behavior before, during and after a seismic event. The natural frequencies and temperature measurements of the structure were used as input for the SVM computational method. Two classes are assumed over time, damaged structure and undamaged structure. If the algorithm fails to distinguish both classes, it means that data came from the same kind of classes and, consequently, there is no structural damage. Otherwise, if the algorithm successfully detect two classes, it means that damage occurred.

By analyzing the graphics of the Gabbia Tower application, it was observed that the present natural frequency-based technique was efficient in detect structural changes, once the results were considered in agreement with actual situation of the tower since damages caused by an earthquake were clearly identified.

The obtained results encourage the development of computational tools for structural damage assessment. Nevertheless, more investigation is required to validate this damage identification strategy, such as checking the algorithm for other structures and excitations and include more parameters besides natural frequencies and temperature, or even using all identified natural frequencies together as input of the SVM computational method, focusing on the best performance of the damage detection technique.

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