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Structural Health Monitoring of Historic Masonry Towers: the Case of the Ghirlandina Tower, Modena

Donato Sabia¹, Giacomo Vincenzo Demarie² and Antonino Quattrone¹

¹Politecnico di Torino, Department of Structural, Geotechnical and Building Engineering, Corso Duca degli Abruzzi, 24, 10129, Torino, Italy

²Structural Engineer, Torino, Italy

ABSTRACT: Masonry towers are an important architectural heritage, whose conservation and maintenance requires a deep understanding of their structural behaviour. To this end, monitoring the dynamic response to ambient and service loads is a fundamental source of information. By repeating the data acquisition over the time, it is moreover possible to check for variations in the structure's response, whose entity may be correlated to the appearance or growth of a damage (e.g. following some exceptional event as an earthquake or as a consequence of materials and components ageing). The complexity of some existing structures and their interaction with the environment claim for a detailed monitoring plan, to support an evidence-based decision process. If the sensor network acquires data continuously over time, the evolution of the structural behaviour may be tracked continuously as well. This process needs the proper methods and algorithms to manage the large amount of available data and extract actionable information from it. This paper presents a methodology for the automatic structural long-term monitoring, which relies on existing methods from the Machine Learning and Data Mining fields. The results of its application to the real-world case of an ancient masonry bell tower, the Ghirlandina Tower (Modena, Italy) are also discussed.

1 INTRODUCTION

The main goal of the Structural Health Monitoring is to transform the experimental data into information for the assessment of the structural conditions (Farrar CR and Worden K, 2007). To this extent, two general approaches can be applied: physics-based and data-driven.

The physics-based approach involves building a model of the for analysis and prediction, starting from the “first principles” of Physics. In this case, the model formulation must be appropriate enough to characterize the actual structure.

In the data-driven approach no assumptions are made about the system generating the data, the model from the data only and has not any specific physical meaning. Such models are very general in their nature and well suited when large amount of data is available or the structural behaviour is too complex to be described from basing on physical principles (Ying EJ et al, 2013).

The purpose of long-term monitoring systems is generally to track over time the status of a structure and to answer questions about the safety and the serviceability after specific events, or as a consequence of the materials and components ageing (Cross EJ et al, 2013). In areas with

high levels of seismicity, for example, the assessment of the structural integrity can be paramount during the post-event activities.

The long-term monitoring produces a large amount of data and proper methods and algorithms are required to extract valuable and reliable information. In this context the methods and algorithms rooted in the Machine Learning and Data Mining fields have proven to be extremely effective (Farrar CR and Worden K, 2013; Worden K and Manson G, 2007).

The objective of this research is to define a method for the automatic identification of the vibration modes of a structure, so that they can be tracked continuously over a long period of time. The proposed approach unfolds into four steps: the model selection and validation, the system identification, the clustering and the classification steps. The natural frequencies, damping factors and mode shapes are automatically identified from the measured data and monitored over time to detect possible changes in the health state of a structure. Moreover, the observation of the environment parameters, such as the temperature, helps in classifying the stream of data and recognizing structural novelties.

The long-term monitoring of an ancient masonry bell tower, the Ghirlandina Tower (Modena, Italy), has been selected as a real-world case application for the proposed method. The structural characterization is performed by identifying the first modes of vibration, whose evolution over time has been tracked.

2 MACHINE LEARNING APPROACH

The methodology presented in this work aims to characterize the structural response, assuming the starting point in time as the normal condition with no damage and following its evolution over time. The time tracking is performed by detecting deviations from the normal condition (Demarie G and Sabia D, 2019).

The proposed method is implemented as a four-step process: Model selection and validation, System Identification, Clustering and Automatic Monitoring.

2.1 Model Selection and Validation

A linear model is used to describe the relationship among the signals at different time instants. For the case of a single channel available, this assumption translates in the following equation:

$$y_t = w_0 + w_1 y_{t-1} + \dots + w_p y_{t-p} \quad (1)$$

For N different instants leads to the following system of linear equations:

$$\begin{cases} y_{t_1} = w_0 + w_1 y_{t_1-1} + \dots + w_p y_{t_1-p} \\ y_{t_2} = w_0 + w_1 y_{t_2-1} + \dots + w_p y_{t_2-p} \\ \dots \\ y_{t_N} = w_0 + w_1 y_{t_N-1} + \dots + w_p y_{t_N-p} \end{cases} \quad (2)$$

The system of equations 2 can be written in matrix form:

$$\{y\} = [Y]\{w\} \quad (3)$$

For the case where n_{ch} signals are acquired an expression similar to equation (1) holds. Specifically, the i -th signal at a certain time instant can be obtained as a linear function of itself and all the remaining signals at p previous instants.

$$y_{i,t} = w_{i,0} + w_{i,1}^{(1)} y_{1,t-1} + \dots + w_{i,n_{ch}}^{(1)} y_{n_{ch},t-1} + w_{i,1}^{(2)} y_{1,t-2} + \dots + w_{i,n_{ch}}^{(2)} y_{n_{ch},t-2} + \dots + w_{i,1}^{(p)} y_{1,t-p} + \dots + w_{i,n_{ch}}^{(p)} y_{n_{ch},t-p} \quad (4)$$

For N different instants of time we can write the following linear system:

$$[Y_{current}] = [Y_{past}][W] \quad (5)$$

The proper model order “ p ” and the signal length in samples “ N ” are estimated from a subset of the measured data.

2.2 System Identification

The linear model coefficients are repeatedly estimated from the measured signals by solving a sequence of linear regression problems.

The data produced by the monitoring system can be thought of as a continuous succession of blocks of data, each consisting of n_{ch} signals made of $N+p$ samples.

For each block of data the linear system of equations 5 can be set up and the matrix $[W]$ estimated from it. The process can be performed by applying it each time a new block of data is acquired. It results in a succession of matrices $[W]_1, [W]_2, \dots [W]_i, \dots$ which constitutes the basis for the long-term monitoring of the structure. The coefficients of the matrix $[W]$ can be re-organized in a way that allows for the eigenmodes of the structure to be evaluated. To this aim, Equation 4 can be re-stated in the following way:

$$\{y_t\}^T = \{w_0\} + [W^{(1)}]\{y_{t-1}\}^T + [W^{(2)}]\{y_{t-2}\}^T + \dots + [W^{(p)}]\{y_{t-p}\}^T \quad (6)$$

The system of equations 6 can be written in matrix form:

$$\{z_t\} = \{w_0\} + [A]\{z_{t-1}\} \quad (7)$$

The system is characterized by $n_{ch}p$ modes of vibration.

2.3 Clustering

The modes of vibration identified over a limited period are clustered based on the natural frequencies, damping values and the mode shapes. A decision is made on each cluster if it must be considered important and worth to be monitored. Such a decision is taken on top of a domain-specific knowledge and engineering judgement and it is intended to limit the monitoring only to the modes that are deemed as relevant for the practical case at hand.

2.4 Automatic Monitoring

A classifier is built on top of the clusters found as the outcome of the previous phase. Each new identified mode of vibration is automatically classified and, by repeating the process over time, the monitoring of the relevant modes is accomplished.

The first and third phases are performed at least once, but in general very few times, to properly define the model order and the clusters (that are the class types or relevant modes). The second and fourth steps, instead, are executed on every acquisition as soon as it is recorded or, alternatively, off-line.

The proposed method has been applied to the data provided by the monitoring system installed on the Ghirlandina Tower (Modena, Italy). The results obtained are discussed in detail in the Section 3.

3 LONG-TERM MONITORING OF THE GHIRLANDINA TOWER

The Ghirlandina is the bell tower of the Cathedral of Modena, Italy (Figure 1). The construction was started around the year 1160 and completed on 1184, following the initial five floors project. An additional sixth floor was built on 1261 and the gothic octagonal cusp closed the construction phase on 1319, reaching a final height of 89.3 m (Cadignani R and Lugli S, 2010; Cadignani R et al, 2017).

During the first half of 2012 an experimental modal analysis was carried out [so to](#) characterize the dynamics of the tower by measuring its response to the ambient excitation. The results obtained showed the interaction with the cathedral and the important contribution of the soil-structure interaction on the tower's modes of vibration (Lancellotta R and Sabia D, 2013; . Lancellotta R and Sabia D, 2014; Sabia D et al, 2015; Cosentini R et al, 2015).



Figure 1. The Cathedral of Modena and the Ghirlandina Tower.

During the same year a sensor network made of 12 capacitive accelerometers and 3 thermocouples was permanently installed on the tower, in order to implement a monitoring system acquiring data continuously over a long period of time (Figure 2). Since the end 2012 the network has been measuring the accelerations at the rate of 100 Hz.

The whole database of acquisitions from August 2012 to August 2013 has been considered and each phase of the 4-step process is addressed and detailed.

3.1 Model Selection and Validation

The correlation structure between the signals at the current instant and their past values is expressed through the linear system in Equation 4, whose dimensions depend from the system order p and the length in samples N .

A set of 50 couples of 1 hour long acquisitions have been randomly chosen from the entire August 2012 – August 2013 database. The selected signals have been used for the estimating the

linear regression coefficients “ w ”. The parameters p and N has been determined by averaging across the values obtained from each couple of signals in the set considered for the model selection and validation.

The optimal value of the system order “ p ”, as defined above, turned out to be equal to 9 and the minimum signal length to be considered for the identification step has been found equal to 24 minutes.

Figure 2 compares the experimental signal acquired by the channels 10 and 12 respectively with the corresponding linear regression model fit. The good level of approximation given by the model fit prove that the dynamics of the Ghirlandina Tower has been well captured.

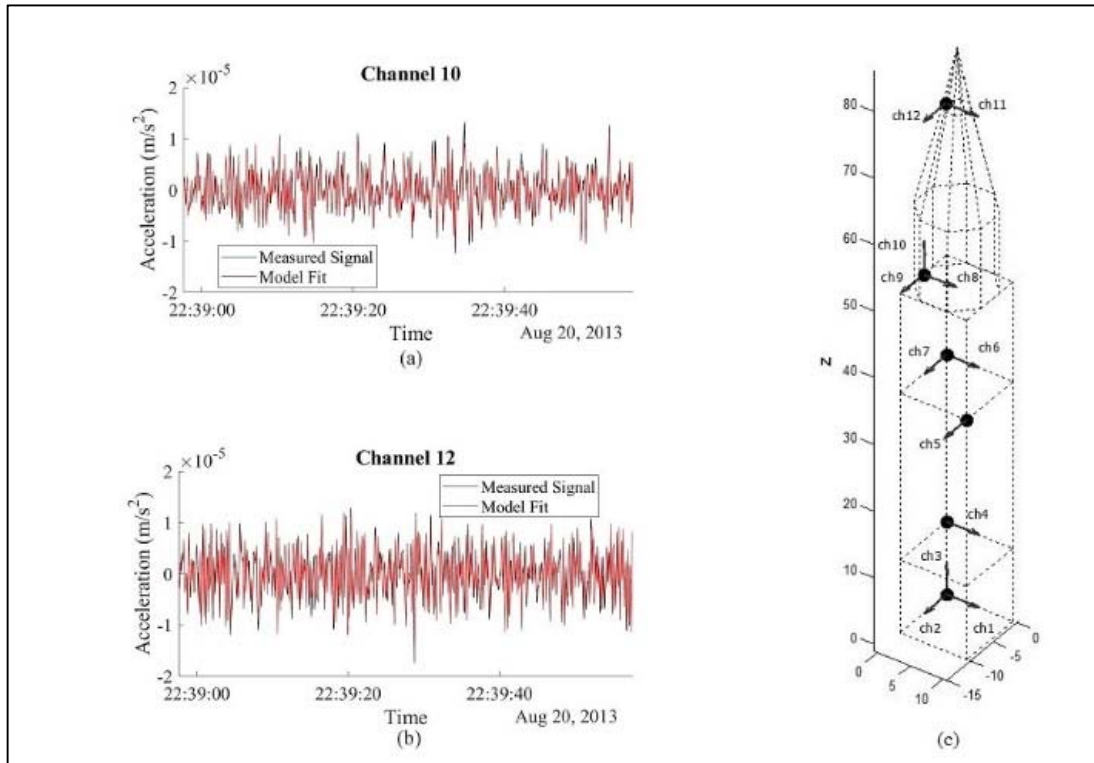


Figure 2. (a) Linear regression accuracy channel 10, (b) Linear regression accuracy channel 12, (c) Sensor positions and channel names (Modified, source: Demarie G and Sabia D, 2019).

3.2 System Identification and Clustering

The database of signals acquired by the sensor network from August 1st 2012 to August 28th 2013 has been processed and the matrix $[W]$ of the linear regression coefficients has been repeatedly estimated according to the values of p and N determined in the previous section, for a total of 16944 times. Each time the matrix $[A]$ of the first order difference representation has been formed from $[W]$ and the eigenmodes of the systems evaluated. Provided that $p = 9$ and the number of channels is 12, a database of 1829952 identified modes has been built.

Before clustering the data, a significant portion of the modes have been excluded based on the engineering criteria. A correlation coefficient higher than 0.975 has been assumed as the threshold for considering a modal shape as “almost” real. Furthermore, a threshold in the damping factor equal to 25% has been adopted, this leading to the exclusion of all the modes characterized by higher damping. At the end of the preliminary selection based on the engineering criteria 56537 modes of vibration have been retained.

The clustering process is essential to detect the modes that are worth to be tracked over time. To this end, the complete set of modes identified in the interval August – September 2012 has been clustered. Figure 3 summarizes some of the outcomes obtained from the identification of the signals in the August – September 2012 interval. The charts (a) and (b) also suggest the existence of six clusters. The figures 4 show some of the principal mode shapes identified.

The type of the mode along with the frequency and damping values are summarized in Table 1.

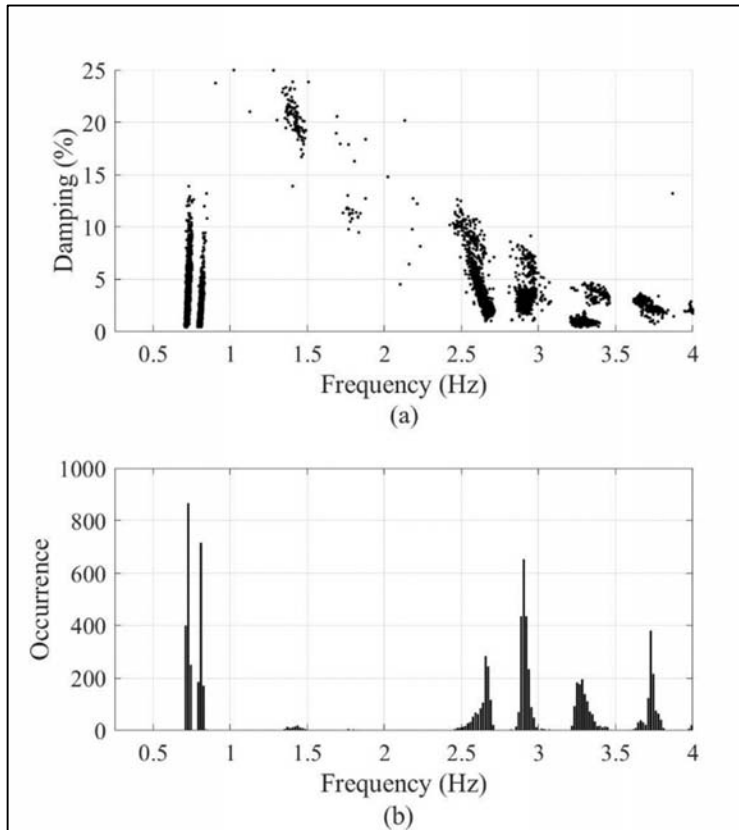


Figure 3. Identified mode (August – September 2012) (Modified, source: Demarie G and Sabia D, 2019).

Table 1. Correspondence between clusters and mode types (Modified, source: Demarie G and Sabia D, 2019).

Cluster #	Frequency (Hz)	Damping (%)	Type
1	0.73	3.6	1 st bending (y-direction)
2	0.81	2.4	1 st bending (x-direction)
3	2.65	2.7	2 nd bending (y-direction)
4	2.91	2.9	2 nd bending (x-direction)
5	3.28	0.8	1 st torsional

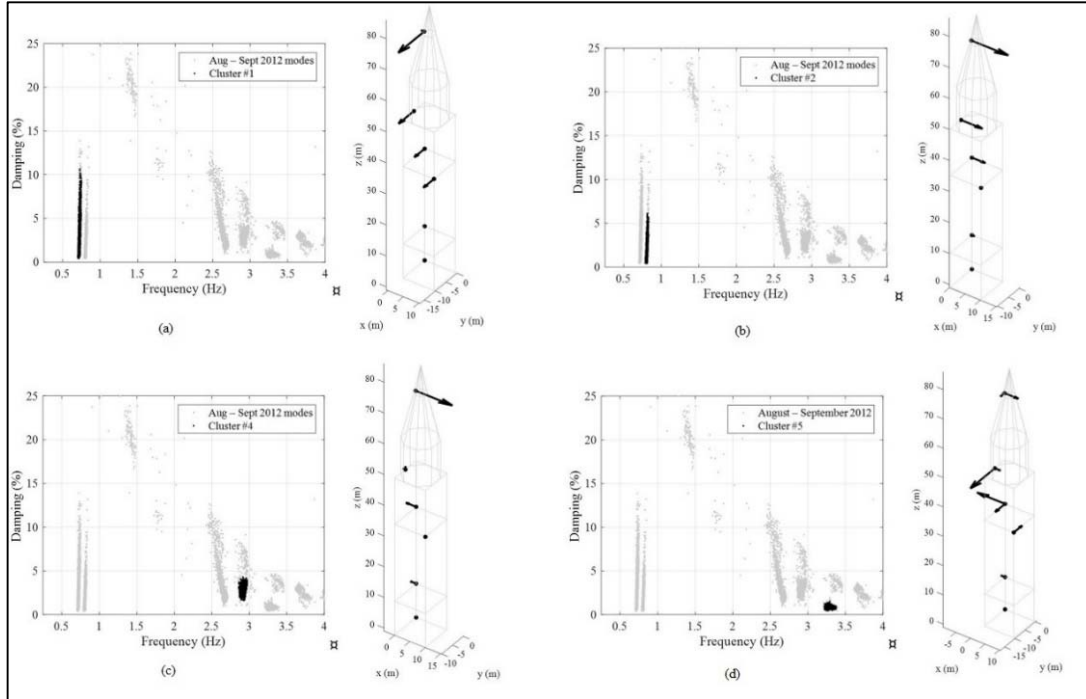


Figure 4. Clusters and mode shapes identified: (a) 1st bending mode (y-direction), (b) 1st bending mode (x-direction), (c) 2nd bending mode (x-direction), (d) 1st torsional mode (Modified, source: Demarie G and Sabia D, 2019).

3.3 Monitoring

The last step of the process implements the continuous time monitoring by making automatic the classification of the identified modes. To this end, a rule is needed so that each time a mode is identified it is possible to decide which mode it is, that is, which is the class it belongs to. This is implemented through a classification algorithm drawn from the Machine Learning literature, which for the case at hand is the k -nearest neighbor (k NN) classification (Gareth J et al, 2013).

The time evolution of the modal frequencies for four structural modes over the entire monitoring period is represented in Figures 5.

The modal frequencies, particularly those related to the bending modes along the x-direction and the torsional mode, clearly show a trend. The frequency values tend to increase from October to December 2012, remain stable on the average until April 2013 and then reduce to the initial values from July 2013 on. Such a variation is smooth for the bending modes, while it shows **up** abrupt for the torsional mode. The Figure 6 proposes once again the torsional modal frequency along with the time evolution of the temperature overlapped, showing the correlation between the quantities: the lower the temperature is, the higher the modal frequency are. Figure 7 shows the seasonal movements of the tower detected by a pendulum, and the trend of the temperature over the years (Lancellotta R and Sabia D, 2013). The cause of such trends is likely to be found in the movement of tower towards the Cathedral when the temperature decreases, which is likely to affect the interaction between the two structures.

During the period considered for the monitoring a few relevant earthquakes happened, but no evidence of causing a change in the structural behaviour has been found in the identified modes.

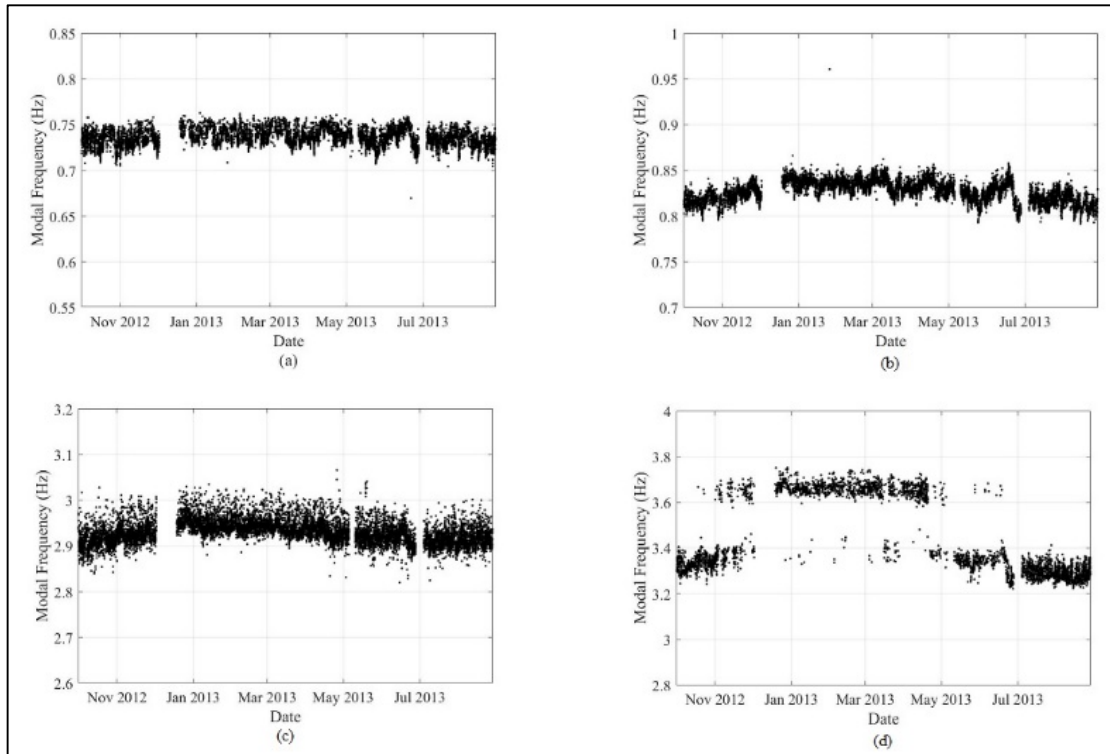


Figure 5. Modal frequency evolution: (a) 1st bending mode (y-direction), (b) 1st bending mode (x-direction), (c) 2nd bending mode (x-direction), (d) 1st torsional mode (Modified, source: Demarie G and Sabia D, 2019).

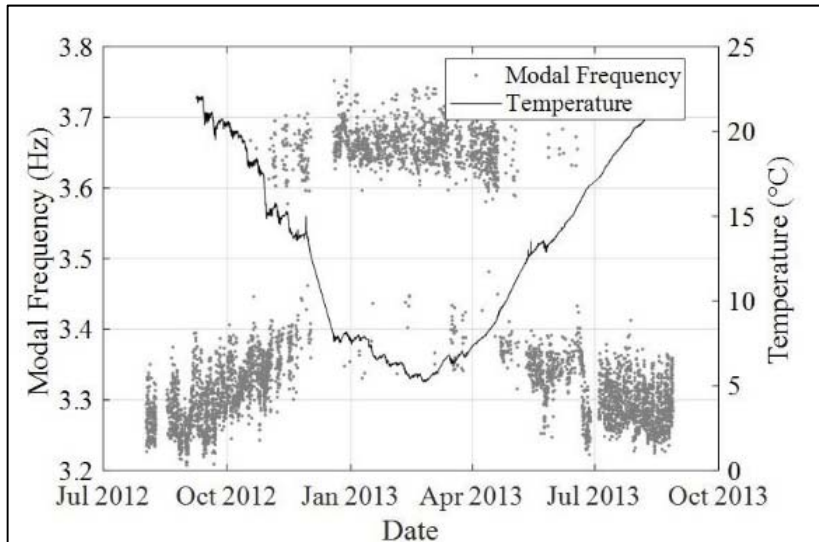


Figure 6. 1st torsional modal frequency and temperature time evolution (Modified, source: Demarie G and Sabia D, 2019).

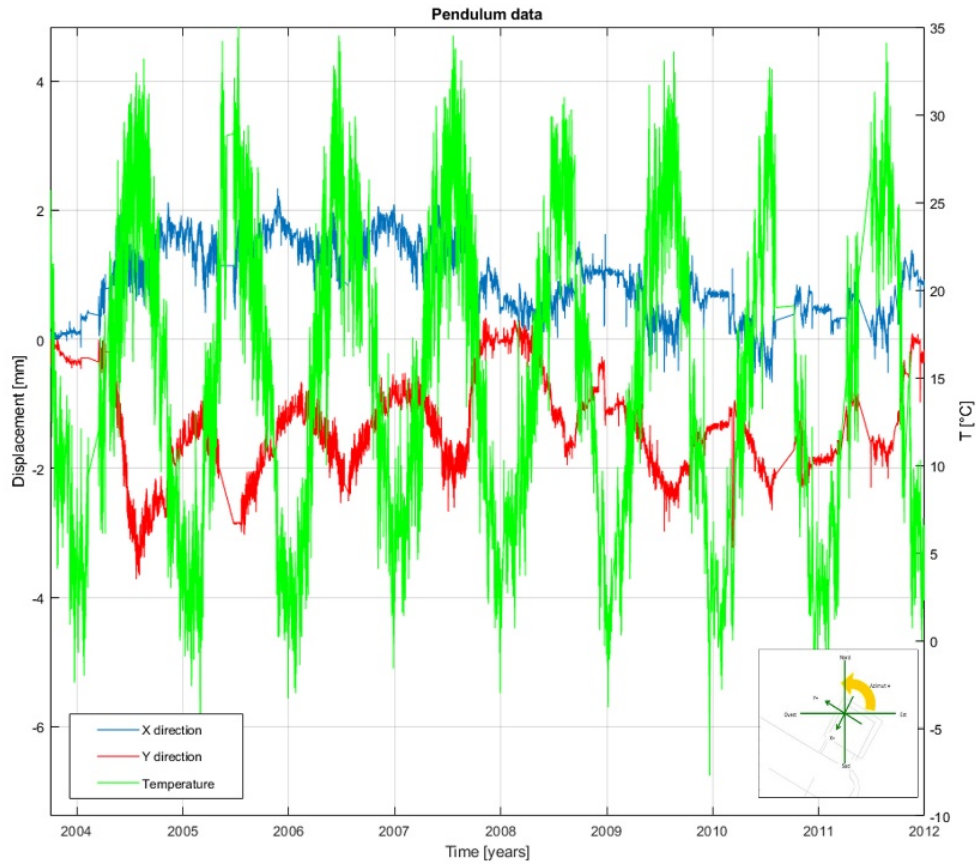


Figure 7. Seasonal movements of Ghirlandina tower and the trend of temperature

3.3.1 The impact of temperature

The hypothesis of correlation between the frequency variation of the tower, its seasonal movements recorded by the pendulum and the trend of the temperature over the year has been verified implementing a novelty detection algorithm able to recognize the deviations from a “normal” condition of data, i.e. the modal parameters.

The robustness of the procedure has been tested processing the data recorded in 2016. The evolution of the modal frequencies in this period resembles that observed in 2013. The algorithm classifies as an anomaly the variation of the 5th mode from 3.7 Hz to 3.35 Hz with respect of a training period of two month of data streaming. The Figure 7a shows the trend of the torsional mode in 2016, highlighting in red the detected novelties. Two distinct distributions of the variable frequency are clearly observable in Figure 7b.

Under the hypothesis of a correlation between the frequency variations and the temperature, the novelty detection algorithm has been finally trained using a one-year series of frequencies and temperature data, adopting a bivariate normal distribution and a 95% confidence interval as a rejection criterion. Introducing the temperature variable, the novelties are only detected when a mode shows a high frequency at warmer temperature and vice versa (Figure 8, red dots). The results confirm the interaction between the Ghirlandina tower and the Cathedral is highly influenced by the seasonal variation of temperature.

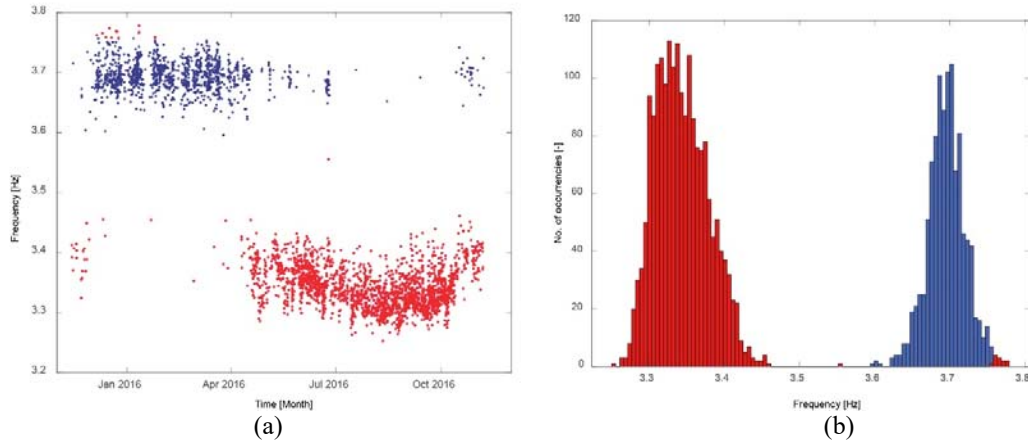


Figure 7. (a) 1st torsional modal frequency time evolution during the year 2016 and (b) statistical distribution.

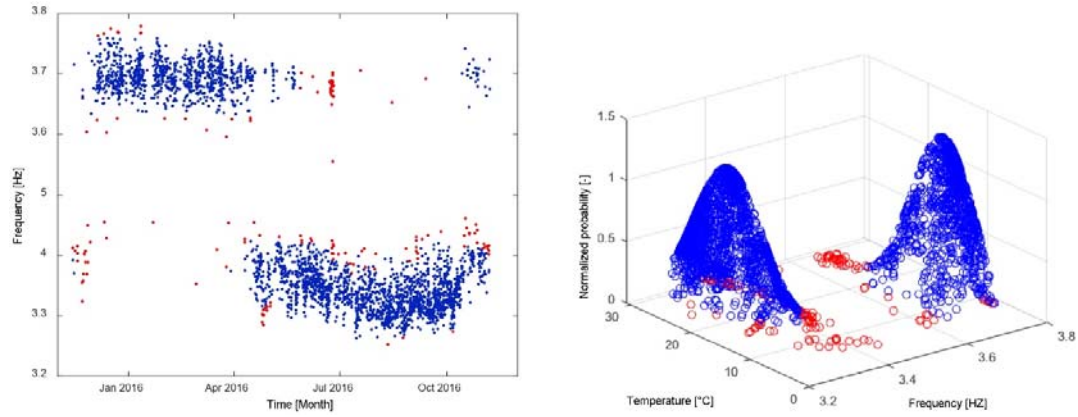


Figure 8: 1st torsional modal frequency evolution during the year 2016 with temperature correlation.

4 CONCLUSIONS

This paper introduces a novel method for the automatic identification of the vibration modes of a structure and implements a concrete approach for the long-term continuous structural health monitoring. The method belongs to the data-driven framework, it relies on some existing algorithms in the Machine Learning and Data Mining fields.

The long-term monitoring of an ancient masonry bell tower, the Ghirlandina Tower (Modena, Italy), has been selected as a real-world case application.

The obtained results prove the capability of the method not only to automatically identify the relevant structural modes with a very limited classification error, but also to highlight some long-term trends which have shown up during the August 2012 – August 2013 and January – December 2016 periods. In particular, the consistency between the seasonal trends of the modal frequencies, the movements of the tower and the temperature suggests the latter as affecting the structural interaction between the Tower and the Cathedral.

A novelty detection algorithm, based on a bivariate distribution which integrates the modal data and the temperature, has been implemented. The algorithm correctly classified the seasonal trends, recognizing the variation in frequencies correlated to the temperature.

As a final remark, even if the method has been applied off-line to a large database of measurement, it naturally allows for the extension to the on-line monitoring and classification of stream of data.

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