A New Strategy for Real-Time Structural Health Monitoring Based on Symbolic Data Objects

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Abstract. Many recent researches have been using Symbolic Data Objects (SDO) as the basis for Structural Health Monitoring (SHM). The advantage of using SDOs is that they have a very strong capacity to compress raw data, without losing the essence of the original information. This work presents a complete methodology to perform a real-time SHM, which was implemented in a software developed by the authors called TW-Parallel. A practical application was tested in a real structure: a historic tower in Mantua, Italy, called the *Gabbia* tower. The results showed that, after an adaptation period - when some false alarms occurred - the software was able to accurately detect a seismic event that occurred during the structure monitoring period.

Keywords: structural health monitoring, symbolic data object, real-time, experimental application.

1 Introduction

Structures such as tall buildings, bridges, viaducts and historic buildings have great economic, social and political importance, so they always need to maintain a good level of integrity, maintenance and security. The Structural Health Monitoring (SHM) emerged to assist in the task of keeping a structure safe and has been a great source of research in recent years. SHM consists of a set of equipment, hardware, software, and methodologies whose main objective is to notify if any novelty (or structural damage) occurs. With this prior alarm, the necessary actions can be taken to correct the problem quickly, before it evolves and can cause social, economic, and environmental losses.

It is possible to monitor a structure by constantly calculating its modal parameters, especially its natural vibration frequencies. However, this type of monitoring has a higher computational cost since a modal identification procedure is needed and may not be sensitive enough to detect small changes in the signal, or small structural damage.

More recent researches have pointed to the use of Symbolic Data Objects (SDO), whose intention is to represent a large amount of raw data (i.e., dynamic signals collected from the structure) through a few values, with minimal loss of information from the original data. There are several methodologies that use SDOs as a basis to detect structural novelties, with the advantage of not needing a post-processing procedure.

2 Methodology

The methodology used in this paper is based on the SDO and the novelty detection system presented in the paper by Cardoso, Cury and Barbosa [1], in which a new SDO was developed that encompasses signal information in both the time and frequency domains.

2.1 The Symbolic Data Object (SDO)

First, dynamic information is collected directly from the structure through sensors. The most common is to use accelerometers to collect acceleration data at strategic points on the structure. Once this is done, it is then possible to transform this signal into SDOs, which are extracted with a pre-defined length L, in seconds. From each channel, six values are collected per SDO, three corresponding to the three quartiles of the point density in the time domain, and three corresponding to the three quartiles of the signal spectrum in the frequency domain. For this last step it is necessary to first apply the Fast Fourier Transform (FFT) over the original signal. Figure 1 illustrates the procedure of extraction of an SDO of length L=10s, from a single channel.

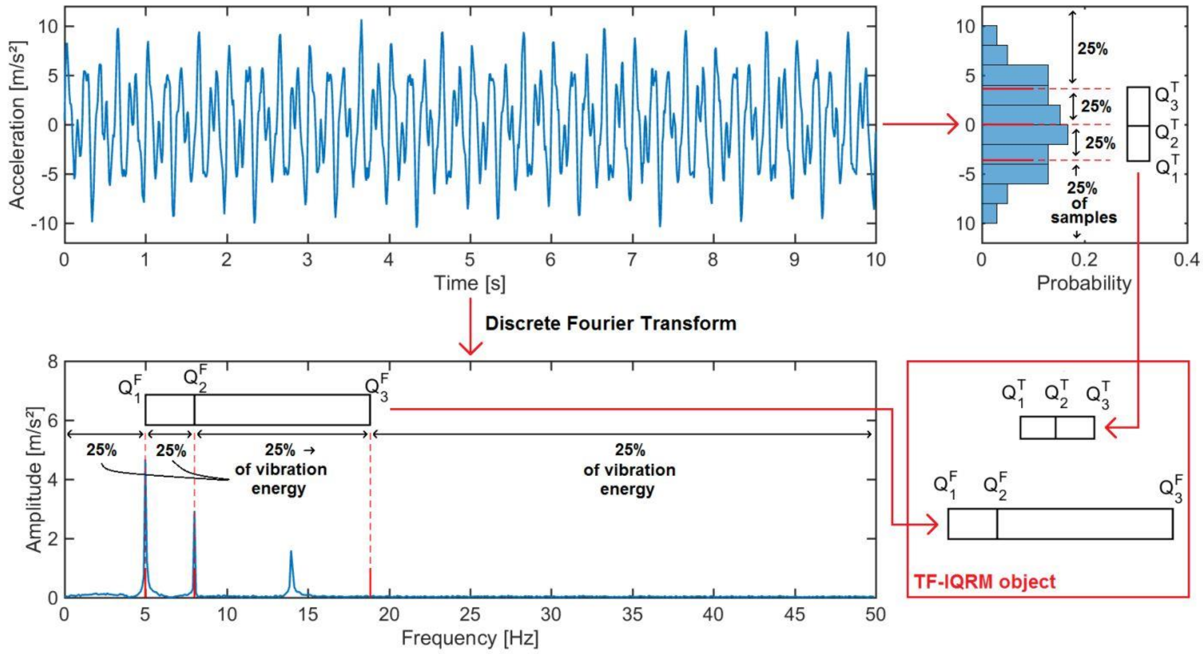

Figure 1. Extraction of a Symbolic Data Object (Cardoso, Cury and Barbosa [1])

The SDO is named *TF-IQRM*, where *IQR* refers to the interquartile range, *M* refers to the median (second quartile) and *TF* shows that aspects were considered in both time and frequency domains.

Usually, more than one channel is used to monitor a structure. In this case, an SDO index i can be written through six vectors. Equations (1) and (2) present the time domain (superscript T) and frequency domain (superscript F) vectors, respectively.

$$\boldsymbol{L}_i^T = \begin{bmatrix} Q_{1,1}^T \\ Q_{1,2}^T \\ Q_{1,3}^T \\ \vdots \\ Q_{1,p}^T \end{bmatrix}, \boldsymbol{M}_i^T = \begin{bmatrix} Q_{2,1}^T \\ Q_{2,2}^T \\ Q_{2,3}^T \\ \vdots \\ Q_{2,p}^T \end{bmatrix}, \boldsymbol{U}_i^T = \begin{bmatrix} Q_{3,1}^T \\ Q_{3,2}^T \\ Q_{3,3}^T \\ \vdots \\ Q_{3,p}^T \end{bmatrix}, \tag{1}$$

$$\boldsymbol{L}_i^F = \begin{bmatrix} Q_{1,1}^F \\ Q_{1,2}^F \\ Q_{1,3}^F \\ \vdots \\ Q_{1,p}^F \end{bmatrix}, \boldsymbol{M}_i^F = \begin{bmatrix} Q_{2,1}^F \\ Q_{2,2}^F \\ Q_{2,3}^F \\ \vdots \\ Q_{2,p}^F \end{bmatrix}, \boldsymbol{U}_i^F = \begin{bmatrix} Q_{3,1}^F \\ Q_{3,2}^F \\ Q_{3,3}^F \\ \vdots \\ Q_{3,p}^F \end{bmatrix}, \tag{2}$$

where $Q_{k,r}$ is the quartile number k, of channel r = 1, 2, 3, ..., p; Vectors $\boldsymbol{L}$, $\boldsymbol{M}$ and $\boldsymbol{U}$ contain the first, second and third quartiles, respectively. The quartiles shown in eq. (1) have units according to the configuration of the sensor used, and those shown by eq. (2) are the indices of the FFT coefficients.

2.2 The distance metric

As the proposal is to detect structural novelties, it is necessary to adopt some measure of dissimilarity between the SDOs. In the present paper, the symbolic metric created by Cardoso, Cury and Barbosa [1] will be used, which calculates the distance d between two SDOs i and j according to eq. (3):

$$d_{i,j} = \frac{\left\|\Delta_{i,j}^{T}\right\|}{\max\left(\overline{\mathrm{RMS}}_i, \overline{\mathrm{RMS}}_j\right)} + \frac{\left\|\Delta_{i,j}^{F}\right\|}{N/2}, \tag{3}$$

where $\overline{\mathrm{RMS}}_i$ is the mean of the Root Mean Square values of the p channels of SDO i; N is the number of points in the frequency spectrum (number of FFT points); ||•|| is the Euclidean norm of the vector •; $\Delta_{i,j}^{T}$ and $\Delta_{i,j}^{F}$ are distance vectors, defined by the eqs. (4) and (5):

$$\Delta_{i,j}^{T} = \begin{bmatrix} \left\|\boldsymbol{L}_j^T - \boldsymbol{L}_i^T\right\| \\ \left\|\boldsymbol{M}_j^T - \boldsymbol{M}_i^T\right\| \\ \left\|\boldsymbol{U}_j^T - \boldsymbol{U}_i^T\right\| \end{bmatrix}, \tag{4}$$

$$\Delta_{i,j}^{F} = \begin{bmatrix} \left\|\boldsymbol{L}_j^F - \boldsymbol{L}_i^F\right\| \\ \left\|\boldsymbol{M}_j^F - \boldsymbol{M}_i^F\right\| \\ \left\|\boldsymbol{U}_j^F - \boldsymbol{U}_i^F\right\| \end{bmatrix}. \tag{5}$$

Note that the metric shown in eq. (3) always results in a dimensionless value, composed of two plots expressing dissimilarities, one in time domain and the other in the frequency domain.

2.3 Detection Parameters

The methodology is based on the concept of a window that moves through time (TW – Time-Window). This window consists of S SDOs, each with size L, in seconds. The k-medoids clustering is applied to each new window, aiming to group objects by similarity, generating k clusters, where $k \in [2, S\text{-}1]$. Each cluster is represented by a prototype SDO (Kaufman and Rousseeuw [2]), which is chosen as having the smallest sum of distances between the other SDOs belonging to the same cluster. In other words, it is the cluster's medoid SDO.

After choosing the prototypes, the novelty index (NI) is calculated by means of eq. (6):

$$NI = \max\left(d_{i,j}\right) \mid \mathrm{i, j} = \mathrm{t}_1, \mathrm{t}_2, \ldots, \mathrm{t}_k \;, \tag{6}$$

where NI is given as the maximum distance between all possible pairs of SDO prototypes; the distance $d_{i\,j}$ is calculated by eq. (3); t_1, t_2, ..., t_k are the indices of the prototypes.

To estimate whether any structural novelty was detected, it is necessary to compare the value of NI with some confidence boundary (CB). Here, the CB proposed by Cardoso, Cury and Barbosa [1] is used, and is calculated as shown in eq. (7):

$$CB_{TW} = \overbrace{\underset{i}{med}\left(NI_i\right)}^{Expected\ Value} + t_{[S-1,\ 99.9\ \%]} \times \overbrace{\frac{1.1926\,\underset{i}{med}\left\{\underset{j}{med}\left|NI_i - NI_j\right|\right\}}{\sqrt{S}}}^{Variability};\; i, j = TW - S + 1, \ldots, TW\,, \tag{7}$$

where CB_{TW} is the confidence boundary established in a window with an index TW; med (•) is the median of •; $t_{[S\text{-}1,\ 99.9\%]}$ is the 99.9 percentile of a t-Student distribution with S-1 degrees of freedom (it is used a t-Student type distribution because the sample population is small); The factor 1.1926 present in the variability is defined by Rousseeuw and Croux [3] to make this estimator consistent with Gaussian populations.

Now the so-called Detection Index (DI) can be simply defined as shown in eq. (8):

$$DI_{TW} = NI_{TW} - CB_{TW}\,. \tag{8}$$

Thus, when DI presents a positive value, it means that some novelty was detected in the signal. Figure 2 illustrates a good overview of the methodology presented until this point.

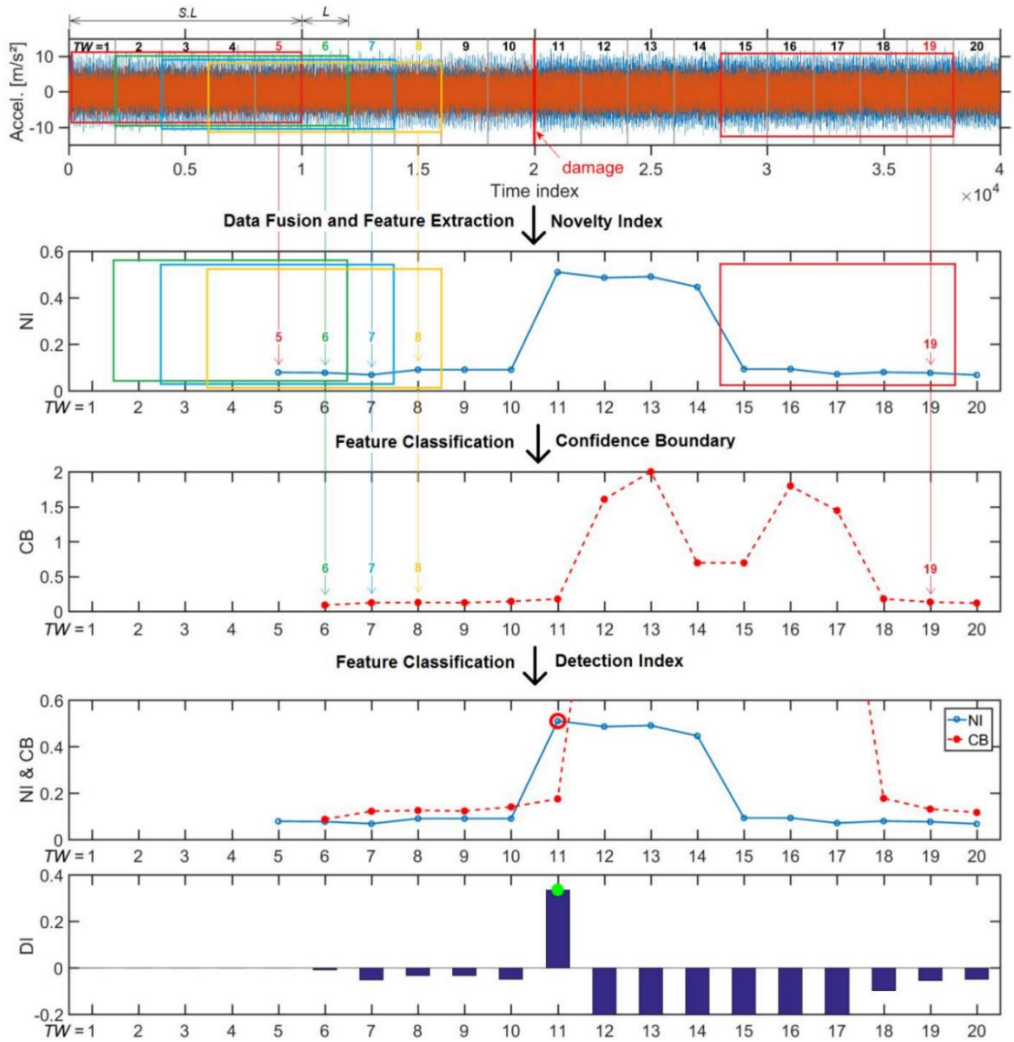

Figure 2. Overview of the methodology (Cardoso, Cury and Barbosa [1])

As shown in Fig. 2, a structural damage has been inserted in the signal from halfway forward. The damage was correctly detected, because the NI value exceeded the CB value, resulting in a positive DI value. After the TW containing S=5 SDOs have gone through the novelty in the signal, the NI values returned to normal levels, meaning that this SHM adapts to new structural states.

2.4 A parallel monitoring

One of the greatest difficulties in directly applying the methodology described so far is the ideal choice of the SDO length. Cardoso, Cury and Barbosa [1] have performed a sensitivity analysis, in which some lengths of SDOs were chosen and the adequacy of the method to detect structural alterations was verified. Their conclusion was: the smaller the length of the object (smaller value of L, in seconds), the greater the chance of detecting structural novelties. However, there was also greater probability of appearing false alarms. In addition, the choice of the SDO's length is made difficult by other variables, such as sampling frequency, variety of structures, sensors installation points, the magnitude of the damages to be detected, etc. Therefore, it is not possible to select a unique value of L that will fit to all structures.

To overcome this limitation, this paper presents a new proposal. A software called TW-Parallel was developed, which monitors the signal through 11 TWs working in parallel, in real time. The initial size of the SDOs is defined through the vector $\boldsymbol{V}$, shown in eq. (9):

$$\boldsymbol{V} = \frac{500}{sf}\{1.0,\ 1.2,\ 1.4,\ 1.6,\ 1.8,\ 2.0,\ 2.2,\ 2.4,\ 2.6,\ 2.8,\ 3.0\}\ , \tag{9}$$

where *sf* is the sampling frequency of the signal. Equation (9) was conceived through several tests performed with different structures, and it was found that this is a good starting point for the lengths of the SDOs.

Thus, a novelty detection happens if more than 50% of the parallel TWs present at least one positive DI value during the same test. As the lengths of SDOs are initially small, there is a high probability of sounding false alarms early on. Therefore, when a novelty is detected, a message appears asking if the structure is still intact, if it does, the program multiplies the length of all objects (vector $\boldsymbol{V}$) by 1.5 and continues with the monitoring. This procedure is repeated until the length of the SDOs reaches a value compatible with the target structure and the common forms of dynamic excitation present. After this period of self-adaptation, which is usually short, the system stops sounding false alarms and only detects if some higher intensity novelty is found in the signal.

The number of SDOs per TW is fixed as S=5, which is a reasonable quantity.

3 Application

The proposed methodology was applied to a continuous SHM of a historical masonry tower, called the *Gabbia* tower, consisting of massive bricks and located in Mantua, Italy. The tower is the tallest in the region, measuring 54 meters high, and its construction was completed in the year 1227, according to recent researches (Saisi, Guidobaldi and Gentile [4]). Figure 3 shows the dimensions (in meters) of the tower in a longitudinal section and three cross sections, as well as a recent photograph of it.

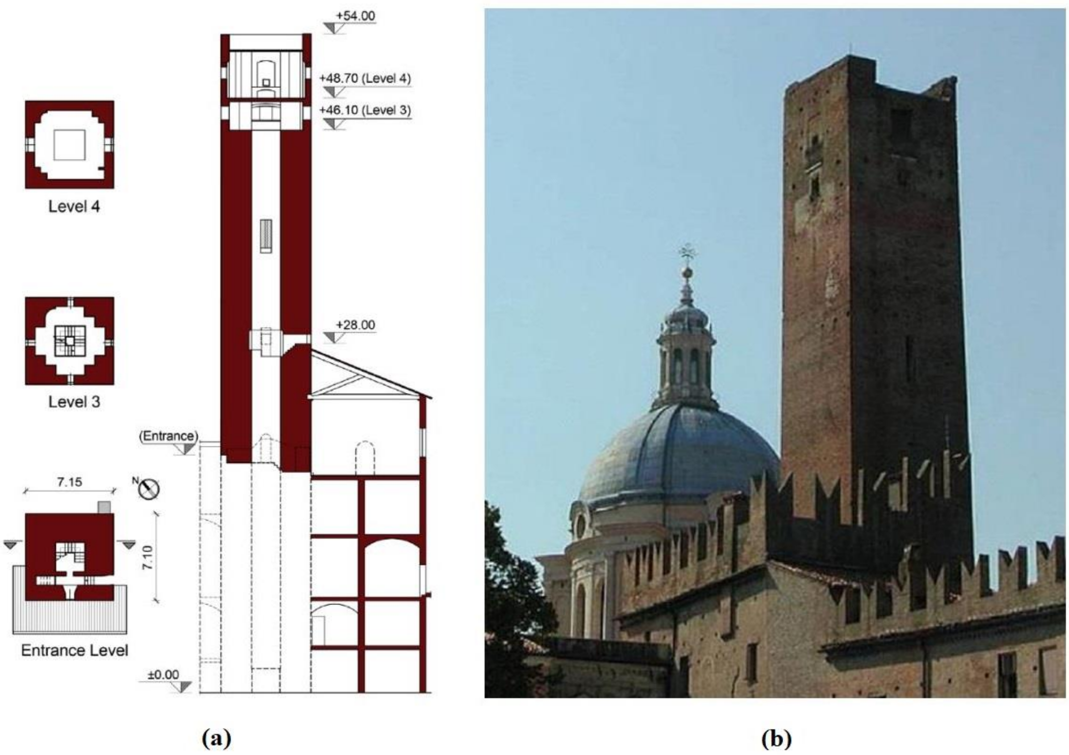

Figure 3. *Gabbia* tower: (a) Schematic drawing; (b) Photography (Saisi, Gentile and Guidobaldi [5])

The *Gabbia* tower was monitored through a continuous monitoring system, consisting of the installation of three piezoelectric accelerometers in its top section. Every hour, a new signal is filed, over which a 20 Hz low-pass filter is applied and decimated five times, which takes the sampling frequency from 200 Hz to 40 Hz (Saisi, Gentile and Guidobaldi [5]). Each file consists of a matrix of dimensions 143200 x 3, which corresponds to the acquisition of 3580s for each one of the three channels.

An earthquake occurred during the tower monitoring period, on June 21, 2013, between 12:00 and 13:00

hours. Thus, the intention of the present work is to detect this seismic event through the presented SHM methodology. For this purpose, signals from June 17th to 25th in 2013 were used. Figure 4 shows the final result of the monitoring carried out by the software TW-Parallel (only the positive DI values were plotted).

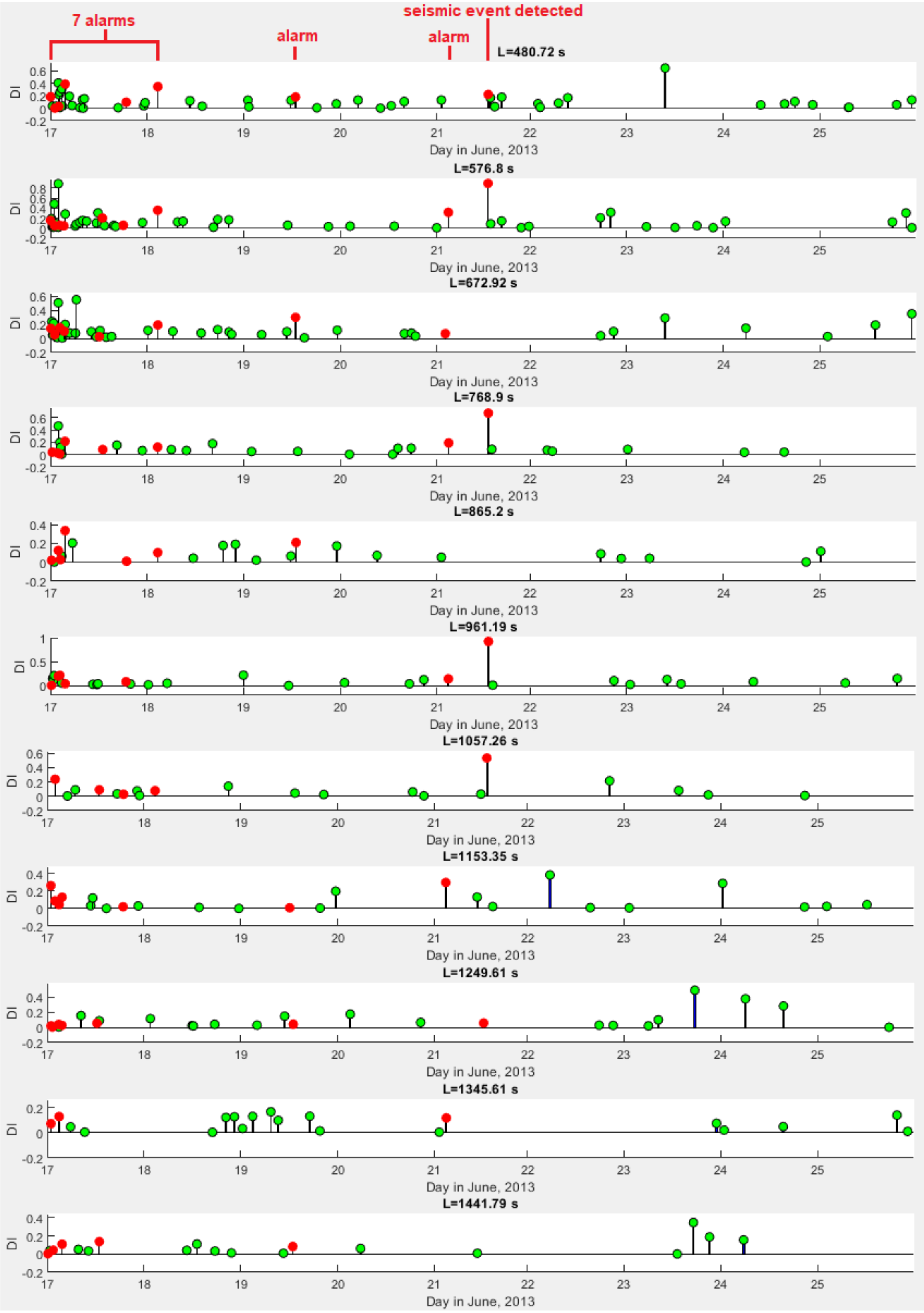

Figure 4. Result of the SHM performed by the software TW-Parallel

Figure 4 illustrates the process of adaptation of the proposed methodology through the arrangement of the alarms. The positive DI values that were counted for the alarms were marked with red circles. Remembering that an alarm only occurs when more than 50% of the 11 parallel monitoring show a positive DI value during the same test, which in this case is every hour. Note that most of the alarms occurred at the beginning of the monitoring (7 alarms). After that, two false alarms were detected: one in June 19th and another on 21st.

The SDOs started with lengths $\boldsymbol{V}$ (calculated according to eq. (9)) and stabilized with lengths $(1.5)^9\boldsymbol{V}$, as there were 9 detections until stabilization, before the seismic event. Thereby, the SDOs reached ideal lengths (shown in Fig. 4) to accurately detect the seismic event and not trigger any false alarms during the following days.

4 Conclusions

With the practical application presented in section 3 of this paper, it was clear the adaptive nature of the proposed SHM methodology, which works through the TW-Parallel software. After 9 novelty detections, the software was calibrated to detect only novelties of greater intensity in the signal, this was confirmed by the accurate detection of a seismic event that hit the *Gabbia* tower in Italy on June 21st, 2013. After this detection, no false alarms were detected during the following days.

The software provided a solution to the problem of the difficulty of selecting suitable lengths for SDOs, with the condition of having human inspections each time a novelty is detected, in other words, it is a supervised process.

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