

A Novel Approach for Automated Operational Modal Analysis Using Image Clustering

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ABSTRACT

The present paper deals with the novel approach for clustering using the image feature of stabilization diagram for automated operational modal analysis in parametric model which is stochastic subspace identification (SSI)-COV. The evolution of automated operational modal analysis (OMA) is not an easy task, since traditional methods of modal analysis require a large amount of intervention by an expert user. The stabilization diagram and clustering tools are introduced to autonomously distinguish physical poles from noise (spurious) poles which can neglect any user interaction. However, the existing clustering algorithms require at least one user-defined parameter, the maximum within-cluster distance between representations of the same physical mode from different system orders and the supplementary adaptive approaches have to be employed to optimize the selection of cluster validation criteria which will lead to high demanding computational effort. The developed

image clustering process is based on the input image of the stabilization diagram that has been generated and displayed separately into a certain interval frequency. and standardized image features in MATLAB was applied to extract the image features of each generated image of stabilisation diagrams. Then, the generated image feature extraction of stabilization diagrams was used to plot image clustering diagram and fixed defined threshold was set for the physical modes classification. The application of

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image clustering has proven to provide a reliable output results which can effectively identify physical modes in stabilization diagrams using image feature extraction even for closely spaced modes without the need of any calibration or user-defined parameter at start up and any supplementary adaptive approach for cluster validation criteria.

Keywords: Automated OMA (AOMA), automatization, clustering, operational modal analysis, stabilization diagram

INTRODUCTION

The advancement of automated operational modal analysis (OMA) has brought a recent trend in vibration-based monitoring and damage detection. Moreover, the mechanical and civil engineering appeal towards OMA is due to its ability to perform cost-effective and fast tests that depend solely on system responses.

The identification of modal parameters using nonparametric model involved direct estimation from frequency response or power spectral densities specifically peaks picking from the complex mode indicator function (CMIF) (Shih et al., 1988) or the averaged normalized power spectral density (Peeters, 2000), that are plotted as a function of frequency. The process to automate the peak selection have been recently introduced which heavily relied on the use MAC index and peak picking method (Brincker et al., 2007; Pioldi et al., 2017; Pioldi & Rizzi, 2017; Rainieri et al., 2007; Rainieri & Fabbrocino, 2010). In the frequency domain, the estimation of modal parameters is always overestimated particularly modal damping ratio due to the power of the signal 'leaking' out to neighboring frequencies, well known as spectral leakage and cause modal peaks of the spectral density functions will become wider (Brandt, 2011). Since simulation studies have confirmed that the identification modal parameters derived from the state space model of the parametric method are much more accurate than the non-parametric estimates (Peeters & De Roeck, 2001b; Reynders, 2009), most research effort has been spent in the automation of parametric techniques. Most research efforts have been heading towards automation engineering parametric techniques. Most research efforts have been directed towards parametric automation techniques.

In traditional modal identification using parametric method, the model order is often oversized in order to capture all physical modes in the frequency range of interest. Model oversizing is needed as models are often biased and do not include any noise modeling. The separation between physical and spurious modes involves a lot of interaction by a skilled analyst. Thus, a significant tool, such as a stabilization diagram, is needed to distinguish between physical and spurious modes. The selection of physical modes can be a complex task because it involved the setting of inconsistency thresholds for each modal parameter by the user (Piersol & Paez, 2010). The development of automated OMA procedures marked

a fundamental step toward the elimination of user intervention since traditional modal analysis requires a large amount of human intervention, particularly by an expert user.

Since a lot of human intervention is for monitoring purposes, early trials to automate modal identification focused on selection conditions and clustering tools to discriminate physical poles from others. The first attempts to automatically identify dynamic parameters were recorded during the last two decades based on the LSCF method performed using a number of deterministic and stochastic criteria and a fuzzy clustering approach. But it demanded high computational effort (Pappa et al., 1998; Peeters & De Roeck, 2001a; Vanlanduit et al., 2003). However, research efforts expanded after 2005, as demonstrated by the presence of numerous research papers over subsequent years. In recent years, research in automated OMA has become more systematic in term of analyses and arrangements (Andersen et al., 2007; Neu et al., 2017; Rainieri et al., 2011; Reynders et al., 2012).

A simple means for automated OMA was introduced by using the Stochastic Subspace Identification (SSI) technique and was utilized to perform structural health monitoring on the Z24 Bridge in Switzerland (Peeters & De Roeck, 2001a). This approach took advantage of the stabilization diagram on the choice of the poles that were at least five times stable and was able to trace the influences of varying environmental conditions on the modal parameters of Tamar bridge (Brownjohn & Carden, 2007). However, it had a drawback in terms of identifying physical poles. An enhancement of the SSI technique for automated OMA was introduced in subsequent years (Deraemaeker et al., 2008). Essentially, it was a tracking method because a number of modal parameters needed to be specified before beginning the procedure while using SSI and the stabilization diagram.

A fully automated OMA procedure by SSI was introduced in a similar period (Andersen et al., 2007). This multipatch subspace approach was applied to generate a clear stabilization diagram. Meanwhile, the selection for poles was implemented by the graph theory. It was a fast processing algorithm that was capable of being used as a monitoring routine, but additional enhancement was required to improve its robustness and reliability.

An improvised version of automated correlation-driven SSI, (COV-SSI) was accomplished several years later (Magalhaes et al., 2009). This algorithm was highly efficient in identifying closely spaced modes but was ineffective for weakly excited modes. The use of an advanced clustering algorithm permitted a reliable selection of physical modes with at least one user-defined parameter. However, several of these parameters needed to be specified at initial set up which could increase the time required for calibrations. A subsequent study proposed the use of an auto-generated parameter obtained from the real data using a fully automated with three-stage clustering approach. The three stages of the algorithm are related to the three stages in a manual analysis: setting stabilization thresholds for clearing out the diagram, detecting columns of stable modes, and selecting

a representative mode from each column (Reynders et al., 2012). However, this approach demands high computational time and effort.

An automated modal identification procedure using subspace identification techniques was proposed by tuning a few parameters and defining the clustering criterion for the random generation of the cluster seeds. This approach capable to deal with weakly excited and closely spaced modes (Ubertini et al., 2013). In 2015, a hybrid method for automated modal parameter identification (MPI) methods was introduced by combining analysis steps from different well-established OMA methods to simplify the interpretation of the stabilization diagrams, improving modal damping estimation and also neglecting the user-predefined parameter but demanded high computational efforts because the additional method like the standardized Euclidean distance and the single linkage method were used to compute the distance between pairs of poles and to construct hierarchical cluster tree respectively (Rainieri & Fabbrocino, 2015).

In subsequent year, an automated operational modal analysis was presented to reduce the number of user interactions to a single set of consistency thresholds by using agglomerative hierarchical clustering and a certain distance threshold. In this case, the sum of normalized pole distance and MAC were used to calculate inter-cluster distance between two nearest clusters (Neu et al., 2016). Then in the next year, automated operational modal analysis using parametric (SSI-COV) method with the construction of tri-dimensional stabilization diagrams and clustering (hierarchical clustering) tools able to efficiently obtain set of values for parametric method input parameters (Marrongelli et al., 2017). Then in the same year, a fully automated operational Modal analysis using parametric method (data-driven stochastic subspace identification (SSI) method) and multi-stage clustering was introduced to remove any user-provided thresholds and could be used for large system order ranges (Neu et al., 2017). The multi-stage clustering corresponds to hard validation criteria for remove certainly mathematical modes, k-means clustering to split modes into consistent and non-consistent sets, hierarchical clustering to divide the remaining modes into homogeneous sets and a threshold derived to remove mathematical modes. Additional steps were required in using hierarchical clustering. Besides that, Sun et al. (2017) introduced an automated operational modal analysis of a cable-stayed bridge by applying the proposed threshold for hierarchical clustering, two stages of k-means clustering were used to clear the stabilization diagram and identification of the final clusters and then density-based spatial clustering was applied to select the actual mode from each identified real cluster. In recent year, an automated procedure for covariance driven operational modal analysis (OMA) techniques was proposed to eliminate the need for a user interference for the selection of model order and size of the block-Hankel and block-Toeplitz matrices based on the reconstruction of the auto-correlation function from the cluster of complex poles (Bajrić et al., 2018). Then, the present study performed an

autonomous modal parameter estimation with three-dimensional space optimization by using non-iterative correlation-based method and fuzzy c-means for the clustering and bootstrap sampling (Yaghoubi et al., 2018). In the same year, an automated operational modal analysis methodology based on an eigensystem realization algorithm (ERA) and a two-stage clustering strategy was proposed (Yang et al., 2018). The proposed study using fuzzy C-means (FCM) clustering to separate stable modes from unstable ones. Also, in the presented study, the automated operational modal analysis (OMA) using stochastic subspace identification method and a three-stage clustering algorithm was proposed to automatically estimate the modal parameters (Marwitz et al., 2018). The most recent study introduced a novel multiscreening algorithm for the automated modal parameter identification based on the searching and averaging processes between clusters, and automatically identify the system poles on the basis of the numbers of their repetition in the spectral density via k-means clustering algorithms (Afshar & Khodaygan, 2019).

The above-mentioned literature demonstrates the current clustering tools require at least one user-defined parameter, the maximum within-cluster distance between representations of the same physical mode from different system orders and the supplementary adaptive approaches have to be employed to optimize the selection of cluster validation criteria which will lead to high demanding computational effort (Neu et al., 2017; Rainieri & Fabbrocino, 2014; Reynders et al., 2012; Yaghoubi et al., 2018). Thus, this paper will focus on developing a new clustering algorithm using image feature extraction that effectively identifies physical modes and neglect any calibration or user-defined parameter at start up and the need of any supplementary adaptive approach for cluster validation criteria.

MATERIALS AND METHODS

This analysis concerning a set of data from real structure, the Heritage Court Tower (HCT) building for verifying the theoretical framework which is using automatic versions of SSI-COV with the actual characteristics of realistic civil engineering structures. The structural dynamic testing on 15 stories of the Heritage Court Tower (HCT) building was carried out by researchers from the University of British Columbia (Bricker & Venture, 2015).

This building generally is characterised by representations of the closely spaced modes for the first three modes with the expectations of torsional and lateral vibration mode couplings, especially in the east-west direction, and corrupted with “noise modes” or spurious modes that originated from drilling and human activities close to the sensors during data acquisition.

The input natural excitation was based on wind and human activity as the construction of the building was about to be completed. The measurements were captured over a long period of time in order to ensure the loading on the structure is stochastic enough and behave according to white noise excitation for all modes to be adequately excited. The adopted

parameters in the processing were: length of time series, t (327.7s); the adopted time step (0.025s); sampling frequency (40 Hz) and adopted frequency resolution (0.0031Hz). Then, the input data was decimated to a Nyquist frequency of 5Hz which only concerning the dominant modes with representations of the three closely spaced modes from 1.2 to 1.5 Hz.

Automated Stochastic Subspace Identification (SSI)-COV

Automated OMA using Stochastic Subspace Identification (SSI)-COV comprises the subsequent steps as shown in Figure 1.

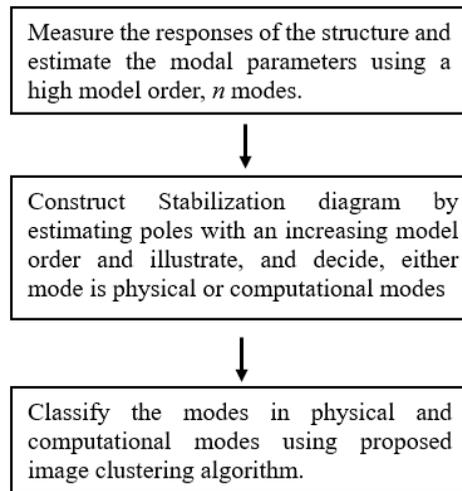


Figure 1. The following steps for automated OMA using parametric methods.

Stochastic Subspace Technique (SSI)

Stochastic Subspace Identification (SSI) has been a recognized approach since the previous decade, primarily because of its user-friendly execution (Bricker & Venture, 2015). This paper is only concerned with correlation-driven SSI (COV-SSI), one of SSI method. The COV-SSI analyze a stochastic state-space model from the response data of the structure (Rainieri & Fabbrocino, 2014) and working algorithm almost similar to Eigenvalue Realization Algorithm (ERA) (Peeters & De Roeck, 1999). The further details of its derivation are defined below.

The initial step was to compute the output correlations as shown in Equation (1). $[R_i]$ indicates the correlation matrix at time lag i based on discrete data as follows:

$$[R_i] = \frac{1}{N-i} [Y_{(1:N-i)}][Y_{(i:N)}]^T \quad (1)$$

Where $[Y_{(1:N-i)}]$ is the data matrix Y with the last block rows i removed and $[Y_{(i:N)}]^T$ is the transpose data matrix with the first block rows i removed. Hence each $[R_i]$ matrix got dimensions $l * l$. The computed correlations at different time lags were then stored in the

block Toeplitz matrix. The size of Toeplitz matrix became $n*n$ when estimating modal parameter with model order n . Thus, the subsequent Equation 3 should be correct for the number of block rows i :

$$li \geq n, i_{min} = x \frac{n_{max}}{l} \tag{2}$$

The magnitude, x and maximum system order, n were set as 2 and 50 modes respectively. The next step was to calculate the singular value decomposition (SVD) of the block Toeplitz that could provide the unitary matrices $[U]$ and $[V]$. The positive singular values were ranked in descendant order of the diagonal matrix $[\Sigma]$ as fin Equation 4 (Wall et al., 2003).

$$[T_{1|i}] = [U_1][\Sigma_1][V_1]^T = [O_i][T_i] \tag{3}$$

To extract the dynamic response, the state matrix $[A]$ needs to be obtained. This was done for each order from 1 to n_{max} . The observability matrix $[O_i]$ and the reversed controllability matrix $[T_i]$ were found by the factorization of $[T_{1|i}]$. The result of SVD of $[T_{1|i}]$ computed in Equation 4 could be used to find $[O_i]$ and $[T_i]$ by separating the SVD into two parts and using the identity matrix $[I]$ as in Equation 8 and 9:

$$[O_i] = [U_1][\Sigma_1]^{1/2}[I]^T \tag{4}$$

$$[T_i] = [I]^{-1}[\Sigma_1]^{1/2}[V_1]^T \tag{5}$$

Now that $[O_i]$ and $[T_i]$ had been obtained, the output influence matrix $[C]$ and the state-output covariance matrix $[G]$ could be computed. Matrix $[C]$ was attained from the first l rows of $[O_i]$. Meanwhile, $[G]$ was obtained from the last l columns of $[T_i]$. The normal Toeplitz matrix produces Equation 10:

$$[T_{2|i+1}] = [O_i][A][T_i] \tag{6}$$

Resolving the eigenvalue problem for $[A]$ produces the diagonal matrix $[M]$ and the eigenvectors $[\Psi]$ as in Equation 12:

$$[A] = [\Psi][M][\Psi]^{-1} \tag{7}$$

The mode shapes of the system $[\Phi]$ were attained from $[\Psi]$ and $[C]$ and the other modal parameters were attained from the eigenvalues μ_m , which were found in the diagonal matrix $[M]$. The values were in discrete time and need to be transformed to continuous time as in Equation 14:

$$\lambda_m = \ln[\mu_m] / (\Delta t) \tag{8}$$

the complex λ_m comprised the continuous time eigenvalues of each mode for the current order which used to estimate the natural frequencies (ω_n), damped modal frequencies

(ω_d) and modal damping ratio (ζ). The step of identifying the state matrix and the modal parameters were repeated for each order up until n_{max} before plotted in a stabilization diagram.

Stabilization Diagram

The stabilization diagram is a typical means to distinguish physical poles from noise (spurious) poles, and once the model parameters are obtained, it was achieved by identifying poles with an increasing model order. Since the system model was frequently oversized, the plot would comprise noise modes which arose from physical reasons. Theoretically, the stabilize physical modes can be identified by the vertical alignment of stable poles, while noise modes are scattered. This is based on the poles comparability with respect to the order of the given model with the obtained from a lower order model (Rainieri & Fabbrocino, 2014).

The natural frequencies and damping ratio of poles from two orders were compared using Equation 18 and 19 (Schanke, 2015):

$$\frac{|f(n-1)-f(n)|}{f(n-1)} < x \tag{9}$$

$$\frac{|\zeta(n-1)-\zeta(n)|}{\zeta(n-1)} < y \tag{10}$$

Only poles that satisfy a stabilization criterion set by the user (x and y) were considered as stable. The following thresholds were set for variation between models of following orders: natural frequency variation < 1% (Magalhães, 2010) and modal damping ratio variation < 5%. These thresholds allow the clear dissimilarity of vertical alignments of stable modes. The stabilization diagram constructed from the first data sets obtained from the structural dynamic testing of HCT can be seen in Figure 2 and Figure 3.

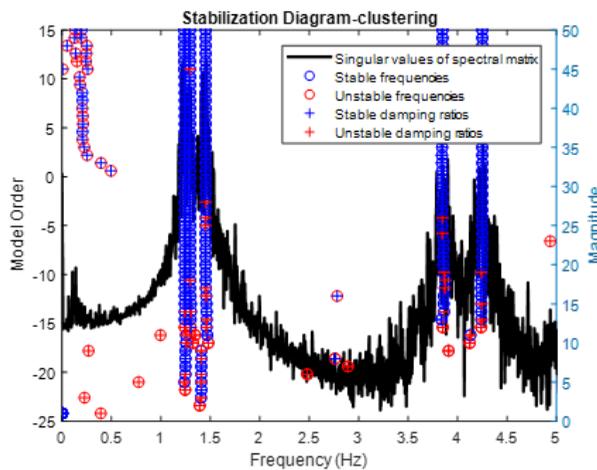


Figure 2. Singular values of the spectral matrix with stabilization diagram for first data sets of the HCT building.

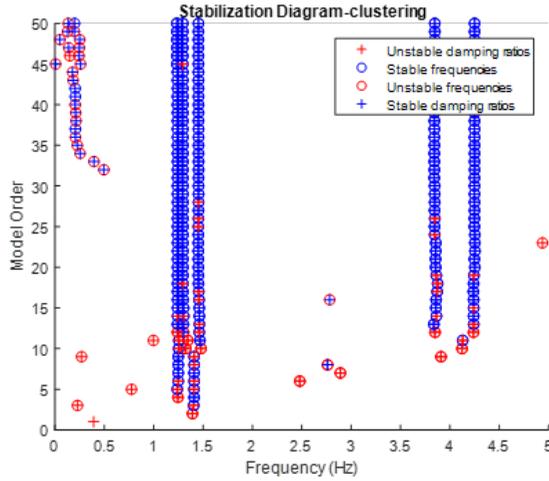


Figure 3. Stabilization diagram for first data sets of the HCT building.

Proposed Approach for Clustering. The procedure of using image clustering with respect to the similar physical pole of the stabilization diagrams is as follows:

Input Image

The process of image clustering requires the input image of the stabilization diagram that has been cut down into a certain interval frequency accordingly. In this case, the stabilization diagram was generated and displayed separately into every frequency according to 0.01 interval, (maximum frequency, 5Hz)/ 0.01 = 500 total images. Thus, every image represents the frequency of 0.01 Hz. The process of this procedure is shown in Figure 4 and Figure 5. In order to make image feature extraction more efficient, all axes and legend in the plot of these images had to be removed.

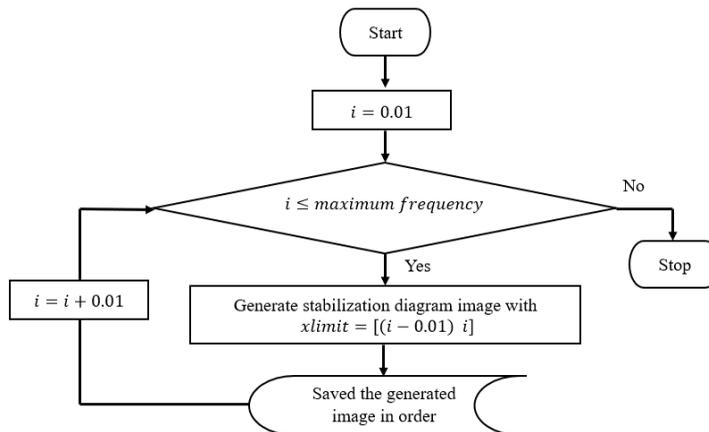


Figure 4. Flowchart process of generated input images from a stabilization diagram with a 0.1 Hz interval frequency

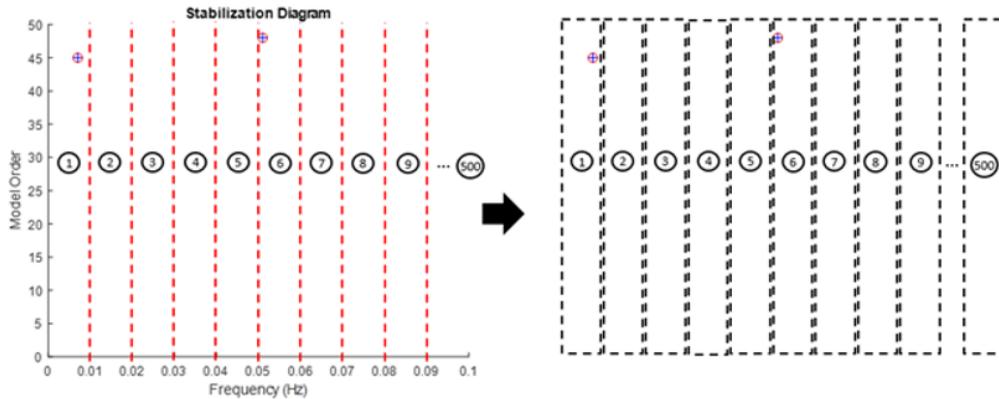


Figure 5. Illustration of generated input images from a stabilization diagram with a 0.1 Hz interval frequency for feature extraction

Image Feature Extraction

Then, the standardized image features from MATLAB was applied in this study to extract the image features of each image of stabilization diagrams that were previously generated. These features specifically represent the characteristics of each parameter (natural frequencies, damping ratios) for different conditions, either stable or unstable. Table 1 summarizes the features of the extracted images and their characteristic values. All the six standardized image features were used in this study in order to determine which image feature was the most appropriate to capture all the modes of interest particularly in term of computational mode appearance.

Table 1

Image features and their characteristic values

No	Feature	Characteristic value
1	Features from FAST	Corner Points
2	Minimum Eigenvalues	Corner Points
3	Harris Stephens	Corner Points
4	Speeded-Up Robust Features	Blob
5	Binary Robust Invariant Scalable Keypoints	Multiscale Corner
6	Maximally Stable External Regions	Regions

Generally, the image feature will provide a certain value based on its image characteristic. If the image is blank, the value will become zero, otherwise if the pole appears, the value will increase. The increasing value of image feature extraction depends on the number of poles appeared in that particular image. It works well with stabilization diagram because the stabilize physical modes consists of the vertical alignment of stable poles, while noise

modes are scattered. By generating the image of stabilization diagram according to 0.01 interval frequency (cut down vertically), the poles can be clustered accordingly. Therefore, the generated input image based on interval frequency of stabilization diagram play a key role for the performance of the image feature extraction. Details explanation about the process of this procedure was shown in Figure 6.

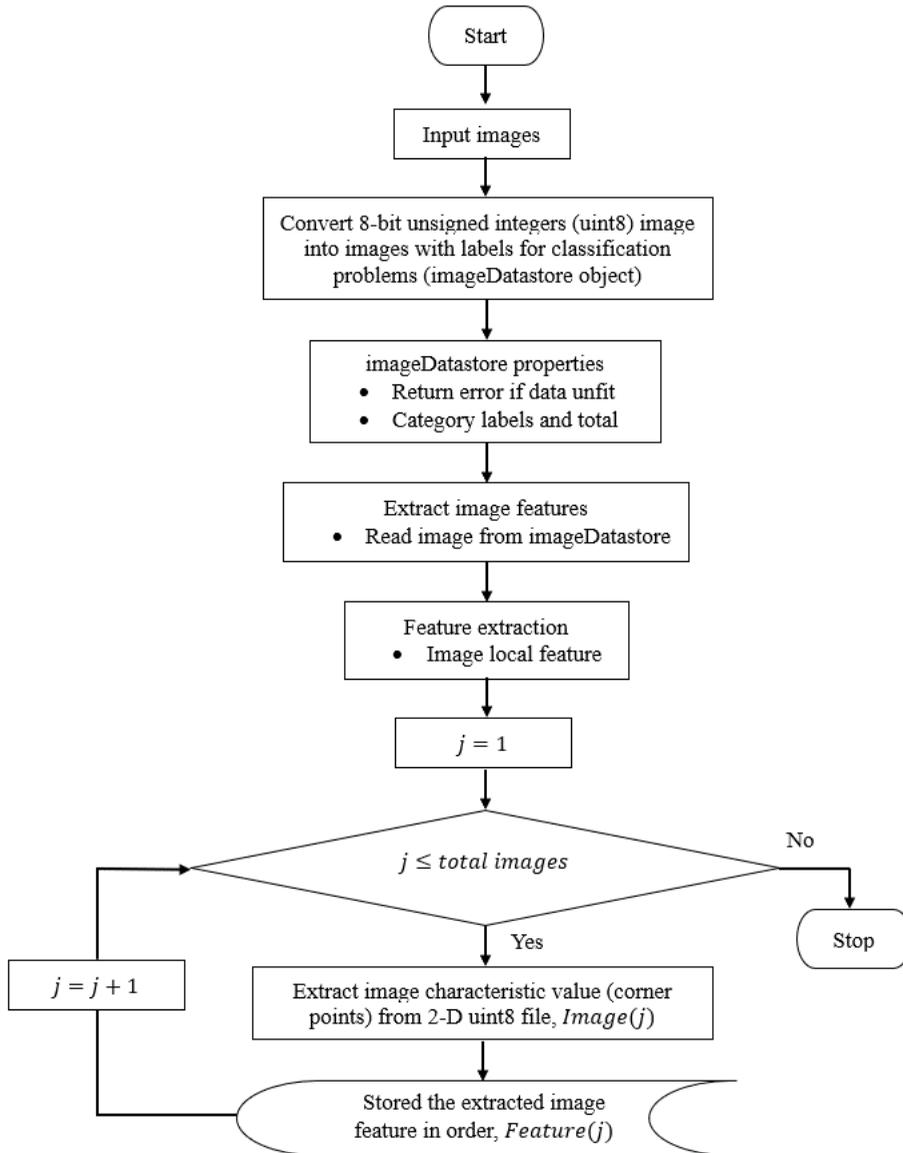


Figure 6. Flowchart process of image feature extraction

Selection of Physical Modes

The selection of the physical modes of the system that was autonomously implemented involved the MATLAB command – *find* – and the threshold in order to discriminate the unwanted mode and the actual modes. The threshold is determined by the half of the maximum peak in the image clustering plot. The selection of peaks in the image clustering plot are determine by using MATLAB command – *find* –. The value of image features extraction below than this threshold in image clustering plot represents the unwanted or computational mode, otherwise consider as dominant mode or physical mode.

RESULTS AND DISCUSSION

Image-based vibration measurement has brought a great attention to civil engineering communities and is increasingly being used in the area of structural dynamics, particularly for modal analysis and damage identification (Javh et al., 2018; Olaszek, 1999; Park et al., 2018; Peters & Ranson, 1982; Sarrafi et al., 2019). Optically-acquired data, usually from digital image correlation as an alternative method was introduced to reduce labor-intensive tasks during dynamic testing involving multiple number of accelerometers and handling the wiring and the connections (Chang et al., 2019; Sarrafi et al., 2019). Numerous image-processing techniques are being used to identify the displacements from image sequences. Among the most commonly used technique are: Gradient-Based Optical Flow (Horn & Schunck, 1981; Javh et al., 2017; Lucas & Kanade, 1981), Gradient-Based Digital Image Correlation (DIC) (Peters & Ranson, 1982), in fact the Lucas-Kanade method from (Lucas & Kanade, 1981) is the general form of DIC (Schreier et al., 2009), Point Tracking (Olaszek, 1999) and Phase-Based method (Fleet & Jepson, 1990; Sarrafi et al., 2019). Existing image-based applications are mostly used to detect movement of target objects and act as virtual sensors, but in contrast to this study the use of image-based applications involves image feature extraction as a new tool for clustering of actual modes and unwanted modes in the stabilization diagram.

The image clustering results plotted using image features extraction were displayed in Figure 7 with all the poles of the stabilization diagram that are presented in Figure 3. Moreover, the results of the estimated natural frequency using automated SSI- COV with image clustering in identification of physical modes are characterized in Table 2.

Based on the results of image clustering using six standardized image features in Figure 7, they show that all standardized image featured except for speeded-up robust features which was using blob as characteristic value capable to provide the clear illustration of image clustering plot with the appearance of all modes of interest particularly for computational or unwanted mode. A clear appearance of noise or unwanted mode was at a frequency of 0.21 Hz. Knowing the frequency that represents noise mode is essential because it can be used for the next step for removing the unwanted mode from original

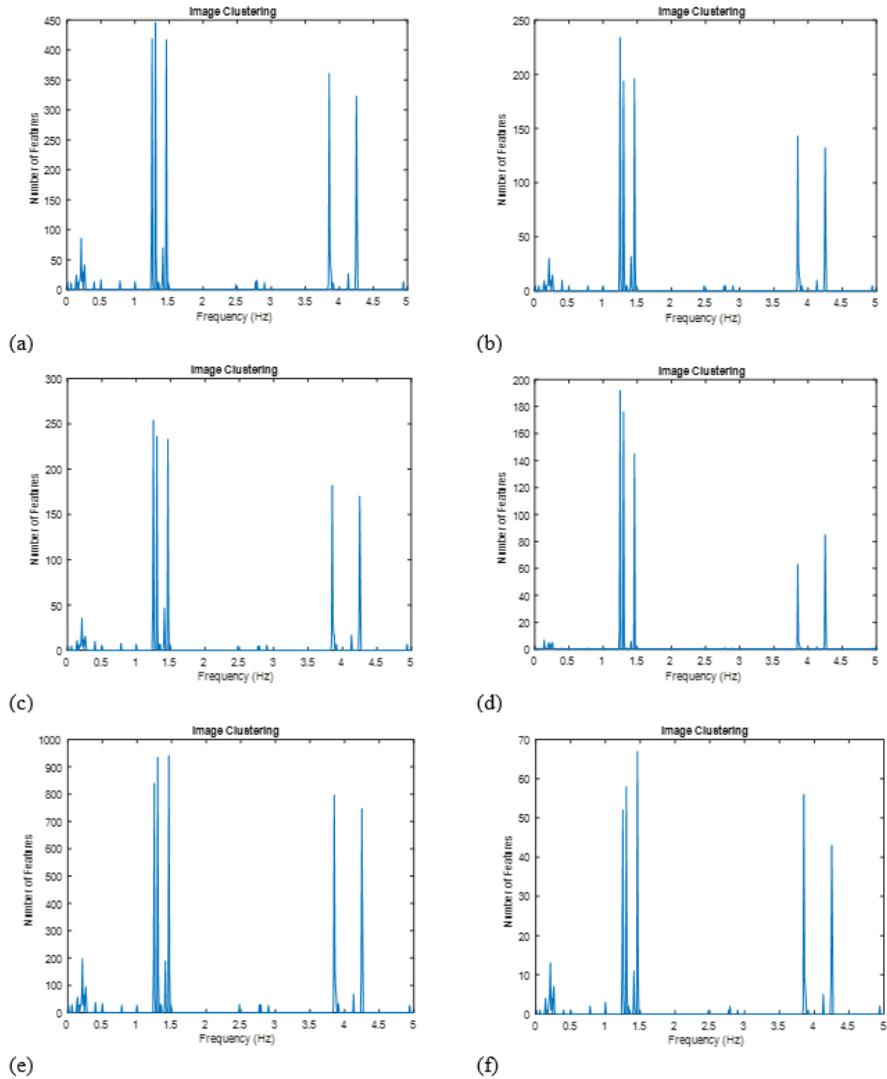


Figure 7. Image clustering plot by using image features extraction from (a) FAST, (b) Minimum Eigenvalues, (c) Harris Stephens, (d) Speeded-Up Robust Features, (e) Binary Robust Invariant Scalable Keypoints and (f) Maximally Stable External Regions respectively

Table 2

Identification results using image clustering on the stabilization diagram for the first data sets of the HCT building case. Modes determined to be physical are shown here

Mode	Feature	Frequency value
1	419	1.2500
2	446	1.3000
3	417	1.4600

Table 2 (Continued)

Mode	Feature	Frequency value
4	361	3.8500
5	323	4.2500

signal and reconstructed back to become a clean input time series signal. Moreover, this approach is also highly efficient in identifying and clearly separating closely spaced modes as seen in Figure 7 for the first three closely spaced modes of HCT from 1.2 to 1.5 Hz.

The outcomes of this study show that image clustering for the physical modes identification of stabilization diagrams is an effective method to identify modes without the need of any calibration or user-defined parameter at start up and any supplementary adaptive approach for cluster validation criteria that are summarized in Table 3 below. The comparative study with existing clustering is also well described in that table. Using standardized image features in MATLAB, image clustering provided a clear distinction of stable modes that signify structural modes. These standardized image features play a vital role in identifying which image represents the vertical alignment of stable modes.

In summary of Table 3 above, some common deficiencies have compromised the existing automated OMA methods (Hasan et al., 2019):

- The estimation of actual structural modes requires several predefined set parameters
- A time-demanding setting procedure for each analysis of the data set is compulsory at start-up
- The values for thresholds and parameters are inconsistent due to natural variations in modal properties of structures that come from damage or environmental influences.
- The existing clustering algorithms need supplementary adaptive approach for cluster validation criteria.

Table 3

Comparison of the proposed approach with existing clustering algorithms

	Proposed approach (image clustering)	Hierarchical	Non-hierarchical
Advantages	Effective identification of modes without the need of any supplementary adaptive approach for cluster validation criteria Does not require any parameters setup. Easy to implement and does not requires any expert user.	The more informative structure that allowing a good choice of the last number of clusters, depending on the previous construction of hierarchical tree.	Computationally faster than Hierarchical clustering for many variables. May produce tighter clusters than hierarchical clustering

Table 3 (Continued)

	Proposed approach (image clustering)	Hierarchical	Non-hierarchical
Disadvantages	Require plenty of images for reliable identification of structural modes.	Computationally demanding due the existence of many individuals, and the similarity of each individual must be calculated. Data order has an impact on the results. Highly sensitive to outliers.	The number of clusters must be specified, and cluster seeds need to be chosen. Seeds are chosen randomly which can cause inconsistent results.

CONCLUSIONS

This research demonstrates that the use of image clustering approach permits reliable identification of structural modes and unwanted modes without the need of any calibration or user-defined parameter at start up and any supplementary adaptive approach for cluster validation criteria. This prove by a clear appearance of noise or unwanted mode is at a frequency of 0.21 Hz. This approach is also user-friendly and does not require any expertise to conduct. Moreover, this approach is highly efficient in identifying and clearly separating closely spaced modes as seen in Figure 7 for the first three closely spaced modes of HCT from 1.2 to 1.5 Hz.

This research will be the basis for future research to improve automation technique as a modal information engine in vibration-based monitoring and damage detection by reducing some of the general shortcomings of the automated OMA methods.

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