IMPLEMENTATION OF OMA PROCEDURES USING LABVIEW: THEORY AND APPLICATION

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Abstract

During the last years, a number of techniques aimed at the experimental identification of the dynamic characteristics of structures has been developed. Their use has progressively extended to various fields, such as aerospace, automotive and civil structures. Besides the traditional techniques based on input knowledge, increasing interest is observed for techniques based on environmental vibrations that do not need any expensive excitation device.

Among the methods for the evaluation of the relevant dynamic parameters of structures under service conditions, some of them works in the time domain (Least Square Complex Exponential, Ibrahim Time Domain, etc.) and others in the frequency domain (Frequency Domain Decomposition, etc.).

In this paper some theoretical aspects of OMA methods are reviewed: in particular, attention is focused on frequency domain and time domain methods aimed at highlighting opportunities given by well-known tools like LabView Virtual Instruments. Some aspects related to the implementation of a OMA based software are therefore discussed. Furthermore, an application is briefly reported based on the data recorded on a real structure, the School of Engineering Tower in Naples and an evaluation of computational effort of different software architectures is presented.

1 Introduction

A very interesting engineering tool is now represented by the dynamic analysis of structures, since it allows the experimental identification of the modal parameters of a construction and the implementation of a reliable mathematical model, eventually optimised according to specific procedures [1]. Such a model can be used for various applications: analysis of the response of the structure under different dynamic loads (earthquake, wind, explosions), structural health monitoring purposes and early warning applications [2,3].

Besides the traditional Experimental Modal Analysis [4], based on externally applied input forces
measured together with the response of the structure, in recent years a lot of new techniques for identification of the modal parameters from output-only measurements has been developed. The main advantages associated with their use are related to the test execution, which is cheaper and faster since no artificial excitation is required and does not interfere with the use of the structure, and to the identification of its modal parameters in the actual operational conditions.

The most undemanding method for the modal parameters estimation from output-only data is the Basic Frequency Domain technique [5], also called the Peak-Picking method, since the identification of the eigenfrequencies is based on the identification of peaks of power spectrum plots. However, this method can lead to erroneous results if the basic assumption of low damping and well-separated frequencies are violated: in fact, the method identifies the operational deflection shapes which, for closely spaced modes, are the superposition of multiple modes. The singular value decomposition of the Power Spectral Density (PSD) matrix allowed to go over these shortcomings, leading to a method, the Frequency Domain Decomposition (FDD) [6], able to detect mode-multiplicity. However, they are both non-parametric methods, since the modal parameters are obtained without any fitting or estimation of parametric models.

Among parametric methods, more complex than the previous ones, Least Square Complex Exponential, Eigensystem Realization Algorithm, ARMAV models, stochastic subspace methods and the Maximum Likelihood frequency domain method can be mentioned [7]. Least Square Complex Exponential and Eigensystem Realization Algorithm are used, in the field of NE xt techniques, to extract modal parameters from auto and cross-correlations of the time signals. Dynamic system can be modelled also through ARMAV models [8]. In stochastic subspace identification a stochastic state space model is identified directly from measured output data or output correlations [9]. The frequency domain Maximum Likelihood approach, originally intended for application to frequency response functions, has been recently extended for the extraction of the modal parameters using the spectra obtained from output-only data [10].

The present paper tries to explore the opportunities given by well-known software environments like LabView (www.ni.com) for the output-only modal identification. A specific software implemented by the Authors and able to perform Operational Modal Analysis using the Frequency Domain Decomposition approach is described and a practical application, based on the data recorded by the Structural Health Monitoring system of the School of Engineering Tower in Naples, is presented. Moreover, an evaluation of the computational effort and of the efficiency of different architectures to implement the same algorithm is reported.

2 LabView environment overview

LabVIEW programs are called virtual instruments, or VIs, because their appearance and operation imitate physical instruments, such as oscilloscopes and multimeters. LabVIEW contains a comprehensive set of tools for acquiring, analyzing, displaying, and storing data, as well as tools for code troubleshooting [11].

In LabVIEW, it is required to build a user interface, or front panel, with controls and indicators, which are the interactive input and output terminals of the VI, respectively. Controls are knobs, push buttons, dials, and other input mechanisms. Controls simulate instrument input mechanisms and supply data to the block diagram of the VI. Indicators are graphs, LEDs, and other output displays. Indicators simulate instrument output mechanisms and display data the block diagram acquires or generates. Types of controls and indicators include:

- numeric controls and indicators, such as slides and knobs, graphs, charts;
• Boolean controls and indicators, such as buttons and switches;
• strings, paths, arrays, clusters, listboxes, tree controls, tables, ring controls, enumerated type controls, containers, and so on.

Associated to the interface, the user adds related code using VIs and structures to get the control of the front panel objects. The block diagram contains this code. Objects on the block diagram include terminals and nodes. Block diagrams are built by connecting the objects with wires. The color and symbol of each terminal indicate the data type of the corresponding control or indicator. Constants are terminals on the block diagram that supply given data values to the block diagram.

LabVIEW can be used also to communicate with hardware such as data acquisition, vision, and motion control devices, as well as GPIB, PXI, VXI, RS232, and RS485 equipments.

LabVIEW adopts a dataflow model for running VIs. A block diagram node executes when it receives all required inputs. When a node executes, it produces output data and passes the data to the next node in the dataflow path. The movement of data through the nodes determines the execution order of the VIs and functions on the block diagram.

Visual Basic, C++, JAVA, and most other text-based programming languages follow a control flow model of program execution. In control flow, the sequential order of program elements determines the execution order of a program.

In LabVIEW, the flow of data rather than the sequential order of commands determines the execution order of block diagram elements. Therefore, it is possible to create block diagrams that have simultaneous operations.

Dataflow execution makes managing memory easier than the control flow model of execution. In LabVIEW, the user typically do not allocate memory for variables or assign values to them. Instead, a block diagram with wires that represent the transition of data is created. VIs and functions that generate data automatically allocate the memory for that data. When the VI or function no longer uses the data, LabVIEW deallocates the associated memory. When new data are added to an array or a string, LabVIEW allocates sufficient additional memory to manage the new data.

3 Parametric models vs. non-parametric methods

Non-parametric methods are traditionally based on the Discrete Fourier Transform. They are easier to use than the parametric models but they have some limits. A traditional non-parametric method for modal parameters estimation is the Basic Frequency Domain method [5], based on the computation of auto and cross power spectra.

VIs for the computation of auto and cross spectra are available in the signal processing palette of LabView but specific tools for vibration analysis exist, too. These tools allows, among the rest, the computation of the Power Spectral Density using the Periodogram method or the Welch method.

Parametric identification techniques extract modal parameters on the base of a parametric model fitted to the signal processed data. Parametric models are available both in time and frequency domain.

LabView Time Series Analysis Tools can be used to build models for univariate or multivariate time series. The relevance of the construction of mathematical models related to observed time series is due to the improvement of knowledge of the dynamic characteristics of the corresponding physical system which is important, for example, in monitoring applications. These LabView tools
Polynomial models: autoregressive, moving average, and autoregressive moving average models;

Modal parametric models: based on the following modal parameters: natural frequencies, damping factors, resonance magnitudes and resonance phases; i.e.: Least Square Complex Exponential method;

Stochastic state-space models.

Autoregressive and autoregressive moving average models allows to predict the current value of a time series based on the past n values (with n order of the model) plus a prediction error. Both models can be used to describe a linear system: the ARMA models use poles and zeroes to describe a system, while AR models have only poles and no zeroes. A lot of linear systems can be accurately modelled by AR models. These models are particularly effective compared to ARMA models since they manage only linear regression equations and the resulting model is unique and stable. However, AR models cannot accurately describe linear systems which do not have an AR response. ARMA models, instead, can give a more accurate description, with respect to AR models, of the dynamic characteristics of a physical system which has an ARMA response. However, the moving average term introduces nonlinearities in the model estimation which require an iterative nonlinear optimization procedure to obtain the model coefficients: this procedure can erroneously give a sub-optimal solution instead of the optimal one. By the way, using AR or ARMA models to describe a system, the coefficients matrix is obtained from a multivariate time series: if dynamic characteristics of the system are of interest, this matrix has to be converted into a state transition matrix of a stochastic state-space model from which extract the modal parameters. The coefficients obtained from ARMA models can be used to estimate the Power Spectral Density of a time series with parametric methods, too.

Before estimating a model, a very important phase is related to the selection of an appropriate model order. It is quite obvious that the higher the model order, the better the model fits the time series, because a high-order model has more degrees of freedom. However, an overestimated order may introduce spurious spectral artefacts in the response. As a result it is important, when selecting the model order is selected, rely on the model-fitting error but also incorporate a penalty whenever the order increases. In LabView a set of model-selection criteria to estimate the model order is available (Akaike’s Information Criterion, Bayesian Information Criterion, Final Prediction Error Criterion, Minimal Description Length Criterion, Phi Criterion): they differ basically for the penalty evaluation.

The TSA Modal Parametric Modeling VI estimates the modal parametric model of an input univariate or multivariate time series. The modal parameters include magnitude, phase, damping factor, and natural frequency. Two methods to estimate the frequency components of the input time series:

- Prony: computes parameters of a modal parametric model by solving complex exponential equations in the least-square sense. This method is also called the Least-Square Complex Exponential method;
- Matrix Pencil: computes parameters of a modal parametric model by solving complex exponential equations in the least-square sense. This method is a modified
Prony method with noise disturbances considered.

When using these methods, noise and distortions in the recorded time series or inadequate model order specification can result in an estimated model containing spurious components. A valid component selection can be carried out using the stabilization diagram, that is a histogram for the estimated resonance components obtained specifying different model orders: in fact, the true resonance components of the dynamic system typically do not change with model orders.

Another opportunity is related to stochastic state space models. A stochastic state-space model describes an output-only dynamic system according to the following equations:

\[ x_{k+1} = Ax_k + w_k \]  
\[ y'_k = Cx_k + v_k \]

where the vector \( y_k \) is the output, \( x_k \) is the state vector with \( n \) state variables, \( n \) is the model order, \( A \) is the state transition matrix, \( C \) is the measurement matrix, or state observation matrix, and \( w_k \) and \( v_k \) are the process noise and the measurement noise (both with a mean value of zero) vector, respectively. The eigenvalues of the state transition matrix \( A \) characterize the dynamic behaviour of a physical system. By computing the state transition matrix \( A \) and measurement matrix \( C \), it is possible to obtain the modal parameters of the system.

Moreover, it is possible to implement any other algorithm thanks to a large family of VI s which allows computations in the fields of linear algebra (construction of Hankel matrix or Toeplitz matrix, Singular Value Decomposition, QR Decomposition, DOT product, and so on), probability and statistics, fitting, signal processing (FFT, Filters, Windows), Time-Frequency Analysis and Wavelet Analysis.

4 Operational Modal Analysis in Frequency Domain: Theory of FDD methods

The modal parameters identification in the frequency domain can be performed by the Frequency Domain Decomposition technique [6]: it is an extension of the Basic Frequency Domain technique, often called the Peak-picking technique. In fact, it is known that the relationship between the input \( x(t) \) and the output \( y(t) \) can be written in the form [13]:

\[ [G_{yy}(\omega)] = [H(\omega)]^T [G_{xx}(\omega)] [H(\omega)]^T \]

where \( G_{xx} \) is the Power Spectral Density (PSD) matrix of the input, \( G_{yy} \) is the PSD matrix of the output, \( H \) is the Frequency Response Function (FRF) matrix, and \( ^* \) and \( ^T \) denote complex conjugate and transpose respectively. Making use of the Heaviside partial fraction theorem and under the assumption that the input is random both in time and space and has a zero mean white noise distribution so that its PSD is a constant matrix, after some mathematical manipulations the output PSD can be reduced to a pole/residue form as follows:

\[ [G_{yy}(\omega)] = \sum_{k=1}^{m} \left( \frac{[4]}{j\omega - \lambda_k} + \frac{[4]^*}{j\omega - \lambda_k^*} + \frac{[R]}{-j\omega - \lambda_k} + \frac{[R]^*}{-j\omega - \lambda_k^*} \right) \]

where \( A_k \) is the k-th residue matrix of the output PSD. Considering a lightly damped system and that the contribution of the modes at a particular frequency is limited to a finite number (usually
one or two), then the response spectral density matrix can be written in the following final form:

\[
\begin{bmatrix}
G_{yy}(\omega) = \sum_{k \in \text{Sub}(\omega)} \left( \frac{d_k \psi_k \psi_k^T}{j \omega - \lambda_k} + \frac{d_k^* \psi_k^* \psi_k^{*T}}{j \omega - \lambda_k^*} \right)
\end{bmatrix}
\]

(5)

where \(d_k\) is a scalar constant and \(\psi_k\) is the \(k\)-th mode shape vector. Thus, performing the singular value decomposition of the output PSD matrix known at discrete frequencies \(\omega = \omega_i\) one obtains:

\[
\hat{G}_{yy}(j \omega_i) = U_i S_i U_i^H
\]

(6)

where the matrix \(U_i\) is a unitary matrix holding the singular vector \(u_{ij}\) and \(S_i\) is a diagonal matrix holding the scalar singular values \(s_{ij}\); the superscript \(^H\) denotes complex conjugate and transpose. Near a peak corresponding to the \(k\)-th mode in the spectrum, only the \(k\)-th mode is dominant, and the PSD matrix approximates to a rank one matrix as:

\[
\hat{G}_{yy}(j \omega_i) = s_i u_{i1} u_{i1}^H \quad \omega_i \rightarrow \omega_k
\]

(7)

The first singular vector at the \(r\)-th resonance is an estimate of the \(r\)-th mode shape:

\[
\hat{\phi}_r = u_{r1}
\]

(8)

In case of repeated modes, the PSD matrix rank is equal to the number of multiplicity of the modes. Modal frequencies can be identified via the peaks of the singular values plots, while the corresponding singular vectors give the mode shapes. It is worth noting that not only natural frequencies and mode shapes can be estimated using such a method, since the Enhanced Frequency Domain Decomposition technique allows also the estimation of damping ratios. Here, the singular values near the peak with corresponding singular vector having MAC higher than a MAC rejection level are transferred back to time domain through inverse FFT, resulting in an approximated correlation function of the equivalent SDOF system. According to the free decay function of the SDOF system, the damping ratio can be calculated by the logarithmic decrement technique.

Compared to the conventional Frequency Domain Decomposition, the Enhanced FDD can compute a natural frequency not affected by the frequency resolution of the spectrum, since it is obtained from the approximated correlation function of the equivalent SDOF system by determining the number of zero crossing as a function of time. Moreover, starting from the identified SDOF Bell function, an improved estimate of the mode shape is obtained by using a weighted sum of the singular vectors with the corresponding singular values whereby random noise is efficiently averaged out.

5 Operational Modal Analysis in Frequency Domain: Implementation of FDD methods in LabView

A specific module of the structural monitoring system has been implemented in order to identify relevant dynamic parameters of the School of Engineering at the University of Naples Federico II. Further details about the above mentioned building are reported in the following section that gives an overview of the applicative results of the present work. The main features of the software module can be summarised as follows:
- Overlapping and averaging;
- Windowing (Hanning, etc.), used to reduce leakage problems in frequency analysis;
- Decimation;
- Auto and cross-power spectra and coherence functions for couples of channels (modal identification by classical Peak-Picking method);
- Identification of the modal parameters by the Enhanced Frequency Domain Decomposition procedure;
- Computation of the MAC matrix, if an appropriate file containing the FE model mode shapes is loaded;
- Computation of the AutoMAC matrix among the experimental mode shapes for validation purposes;
- Report of the results of identification in terms of natural frequencies, damping and mode shapes;
- Mode shapes, 3D histograms of MAC and AutoMAC matrices, and Complexity Plots visualization.

Moreover, a specific module for data pre-processing (mean and trend removal, data classification and validation, identification of spurious harmonics through Short Time Fourier Transform of the responses shown in a contour plot, filtering) has been implemented.

The software has been validated using numerically simulated data obtained from numerical models before using field records [14].

The user interface has a main windows holding various buttons (Figure 2); each button opens the related main SubVI:

- Insert Data: includes controls related to overlapping, averaging mode, decimation, windowing;
- Show Waveforms: allows a visual inspection of the response time series;
- Spectral Plot: auto and cross spectra (amplitude and phase) and coherence functions for couples of channel are reported; a cursor allows the selection of a peak on the amplitude plot of the spectrum and some indicators show the corresponding values of frequency, amplitude, phase and coherence; saving on a spreadsheet .txt file is possible;
- Peak Selection: allows the selection of the peaks on the singular values plots through cursors which can be added or removed depending on the needs;

Figure 2 Software interface
- Mode Shapes: includes a 3D animation of the experimental mode shapes, 3D histograms for MAC and AutoMAC matrices visualization, Complexity Plots;
- Damping Ratio: allows an interactive selection of the MAC Rejection Level by inspecting the resulting SDOF Bell function and shows its IDFT and the logarithmic envelope of the correlation function to help in the damping ratio estimate;
- Show Report: shows the results of identification in terms of natural frequencies, damping and mode shapes and allows saving a report on a .txt file.

Two different architectures have been tested in the implementation of the software, sequential programming and event structure (Figure 3), to compare performances.

Figure 3 Final structure (event structure) of the software

In both cases, a modular application has been developed decomposing the algorithm in SubVIs hierarchically organized (Figure 4). The final number of the employed SubVIs is 35. The interactive interface of the main SubVIs is obtained by means of While Loop structures and taking advantage of the properties and methods of the objects in LabView: for example, the properties of the plots have been used for peaks selection. The modular structure of the application assures the possibility to quickly manage the code and its integration in a wider system with little
modifications: for example, the software can be interfaced to a data acquisition system just by adding a SubVI to manage the data acquisition hardware and changing a part of the code in the Insert Data SubVI so that data are received from the hardware and not from a file.

To compare performances of the two different structures tested during implementation of the software two parameters have been considered: total memory usage and total size on disk. The following table (Table 1) shows their values for the VI of both structures and for the main subVIs when event structure has been used.

<table>
<thead>
<tr>
<th>VIs (italic) and SubVIs</th>
<th>Total Memory Usage [Kb]</th>
<th>Total Size on Disk [Kb]</th>
</tr>
</thead>
<tbody>
<tr>
<td>EFDD (event structure)</td>
<td>246.2</td>
<td>75.2</td>
</tr>
<tr>
<td>Insert Data</td>
<td>100.0</td>
<td>43.9</td>
</tr>
<tr>
<td>Show Waveforms</td>
<td>146.6</td>
<td>43.1</td>
</tr>
<tr>
<td>Spectral Plots</td>
<td>178.5</td>
<td>51.9</td>
</tr>
<tr>
<td>Peak Selection</td>
<td>113.3</td>
<td>60.5</td>
</tr>
<tr>
<td>Mode Shapes</td>
<td>674.0</td>
<td>214.0</td>
</tr>
<tr>
<td>Damping Ratio</td>
<td>250.5</td>
<td>88.9</td>
</tr>
<tr>
<td>Show Report</td>
<td>68.0</td>
<td>28.4</td>
</tr>
<tr>
<td>EFDD (sequence structure)</td>
<td>1869.5</td>
<td>685.3</td>
</tr>
</tbody>
</table>

Using the event structure, the EFDD VI is always loaded while the main SubVIs are loaded in turn and then closed: this assures a lower memory usage. Using the sequence structure, instead, all SubVIs are loaded in memory; moreover, this structure is extremely rigid with respect to the previous and does not allow parallelism.
6 Operational Modal Analysis in Frequency Domain: Application

Recently, the School of Engineering Tower in Naples (Figure 5), a thirteen stories reinforced concrete building, has been equipped with a monitoring system combining seismological, geotechnical and structural models. It is an open system, since it can be expanded using different and complementary data acquisition and transmission systems [15]. The architecture of the monitoring system has been designed so that it is able to transmit data also in critical conditions, such as during an earthquake. The third floor, the seventh and the roof have been instrumented by uniaxial accelerometers FBA EpiSensors ES-U2; geotechnical parameters are monitored, too. The sensors on the structure are placed in couples at two opposite corners of each instrumented floor. The data coming from the sensors are stored into a MySQL Database: using specific drivers, the software can link directly to the Database for data retrieval.

The modal parameters identification has been performed through the LabView software developed by the Authors on the base of six different records of variable length (twenty minutes to about an hour) and relative to different days and different hours. Each record is made up by twelve measurement channels. In Figure 6 an acceleration record relative to a channel located on the roof of the building is shown. A sampling frequency of 100 Hz has been adopted. Analyses have been performed applying a Hanning window to reduce leakage, with 66% overlap. In Figure 7 the Singular Value plots obtained from one of these data sets performing the Singular Value Decomposition of the Power Spectral Density matrix is reported. In Table 2 the main results of this identification, which can be considered as a preliminary evaluation in view of the comparison with the results of more refined techniques and of the finite element model of the structure, are reported; the values of natural frequencies and damping are mean values computed using the above...
mentioned six data sets.

<table>
<thead>
<tr>
<th>Mode number</th>
<th>Type</th>
<th>Frequency [Hz]</th>
<th>Damping Ratio [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Prev. translational (long side)</td>
<td>0.93</td>
<td>≈ 3</td>
</tr>
<tr>
<td>2</td>
<td>Prev. translational (short side)</td>
<td>0.99</td>
<td>≈ 3</td>
</tr>
<tr>
<td>3</td>
<td>Prev. torsional</td>
<td>1.30</td>
<td>≈ 2</td>
</tr>
</tbody>
</table>

Table 2 Results of identification

It is worth noting the only three modes are reported, since only a preliminary analysis is available at the present stage. For validation purposes, the AutoMAC matrix has been computed (Figure 7), which shows values of 1 on the main diagonal, and close to zero in the rest of the matrix.

Figure 7 Singular Values plots and AutoMAC matrix

7 Conclusions

In this paper the opportunities given by well-known tools like LabView Virtual Instruments for the output-only modal identification have been explored. A specific software module of a SHM system has been implemented. It is able to perform Operational Modal Analysis using the Frequency Domain Decomposition approach. An application, based on data recorded by the Structural Health Monitoring system of the School of Engineering Tower in Naples, has been briefly discussed. Moreover, an evaluation of the computational effort and efficiency depending on the software architecture has been reported. Since multi-channel measurement systems are relatively inexpensive today, any user can optimize his measurement system, with advanced analysis functionalities and ensure a high level of versatility. A careful design of the software however is required to maintain and upgrade easily performances and introduce additional features.

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9 References


