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Non-parametric identification of multivariable systems: A local rational modeling approach with application to a vibration isolation benchmark

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A B S T R A C T

Frequency response function (FRF) identification is often used as a basis for control systems design and as a starting point for subsequent parametric system identification. The aim of this paper is to develop a multiple-input multiple-output (MIMO) local parametric modeling approach for FRF identification of lightly damped mechanical systems with improved speed and accuracy. The proposed method is based on local rational models, which can efficiently handle the lightly-damped resonant dynamics. A key aspect herein is the freedom in the multivariable rational model parametrizations. Several choices for such multivariable rational model parametrizations are proposed and investigated. For systems with many inputs and outputs the required number of model parameters can rapidly increase, adversely affecting the performance of the local modeling approach. Therefore, low-order model structures are investigated. The structure of these low-order parametrizations leads to an undesired directionality in the identification problem. To address this, an iterative local rational modeling algorithm is proposed. As a special case recently developed SISO algorithms are recovered. The proposed approach is successfully demonstrated on simulations and on an active vibration isolation system benchmark, confirming good performance of the method using significantly less parameters compared with alternative approaches.

1. Introduction

Accurate and fast identification of multivariable frequency response functions (FRFs) is essential in many applications, including the analysis of mechanical structures, see, e.g., [1–3]. Furthermore, the FRF is often used for controller design and validation [4], and as an intermediate step towards the identification of a parametric system model [5,6]. Recent developments in the design and control of mechanical precision systems have led to an increased relevance of the lightly damped resonant dynamics of such systems [7], as well as an increase in the number of sensors and actuators used to control them [8]. Efficient FRF identification is a crucial step in enabling the use of such advanced design and control methods. In this paper, this problem of efficient FRF identification for lightly damped multivariable systems is considered.

The quality of an FRF estimate depends on the identification method used to obtain it. Key aspects include the applied excitation signal, noise mitigation through averaging, and the suppression of transient contributions. In early literature on time series- and spectral analysis, the methods have been developed for transfer function estimation based on

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measurements using random time series excitations, see, e.g., [9–11]. These methodologies have been further developed in, e.g., [12]. Subsequently, the advantages of periodic excitations have been advocated, see, e.g., [6,13], including the analysis of nonlinear distortions [14]. In recent years, more advanced non-parametric identification methods have been proposed to further improve the transfer function estimate, e.g., [15–17]. One of these methods is the local polynomial method (LPM) [17–19], which uses least squares estimation in a small local frequency band to obtain improved estimates. A key mechanism through which this improvement is achieved is the explicit estimation and suppression of transient contributions. In [20], this method is further extended towards the use of rational models, known as the local rational method (LRM). In [20], the LRM is formulated for single-input single-output (SISO) systems and uses a linear cost criterion, in the sense of [21], to estimate the local rational models. The use of these local rational models instead of polynomials has been shown to lead to significant improvements in the estimation quality for systems containing lightly damped resonances, [22–24]. For a recent overview of FRF identification methods applied to a lightly-damped mechanical positioning system, see, e.g., [24].

Although FRF identification has been significantly developed, the application of these advanced methods to multivariable systems, especially those with a large number of inputs and outputs, leads to several aspects that are presently unclear and which are essential for efficient FRF identification. In particular, the LPM can suffer from large interpolation errors around the lightly damped resonances [22,23]. The LRM, on the other hand, has been successfully applied for lightly damped SISO systems [20,22], but, as will be shown in the present paper, the multivariable extension allows substantial design freedom in the model parametrization.

The main contribution of this paper is a framework for local rational modeling of multivariable systems with high input-output dimensionality and lightly-damped complex dynamics. The focus herein lies on the extension of the existing LRM to a multi-input multi-output (MIMO) approach and the involved parametrization issues. One of the main parametrization issues for such a MIMO LRM approach is the number of parameters that are used. It is important to use a low number of parameters since this leads to a smaller minimal windows size, which in general leads to a smaller interpolation bias [6, Section 7.2.2.3]. Therefore, parsimonious parametrizations are investigated. Of particular interest herein are the directionality aspects associated with such multivariable system parametrizations. Iterative algorithms are proposed to mitigate the possible negative effects of this directionality. Finally, the advantages of the considered methods are demonstrated on relevant simulation examples as well as experimental data from a recently proposed benchmark system.

The outline of this paper is as follows. In Section 2, the local parametric modeling approach is introduced and the advantages of this approach for the identification of mechanical systems are explained. In Section 3, the problem of finding a suitable parametrization for the MIMO LRM is considered and a number of parametrizations are proposed and analyzed. In Section 4, iterative methods for solving the output error LRM problem are considered. In Section 5, the results of the simulation study are shown. In Section 6, the results based on experimental data from a recent system identification benchmark system are presented. In Section 7, the conclusions of this paper are presented as well as an outlook on ongoing research.

2. Problem formulation

In this section, the considered problem of local rational modeling for multivariable systems is formulated. First, the core idea of local parametric modeling for FRF identification is introduced. Second, a practically relevant example is presented showcasing the superior transient suppression properties of the local parametric modeling approach. Third, an example is presented which shows the advantage of rational parametrizations for the identification of lightly damped systems. Fourth, the bias and variance aspects of the LRM estimator are discussed. Last, the challenges concerning multivariable local rational parametrizations are explained, which are addressed in the remaining sections of this paper.

2.1. Local parametric modeling for FRF identification

Consider the discrete time signal $u(n),\ n = 0, \dots, N-1$. The discrete Fourier transform of $u(n)$ is defined as

$$U(k) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} u(n) e^{-j2\pi nk/N}. \tag{1}$$

When the signal $u(n)$ is applied as input to a linear time invariant system G_0 with additive output noise $v(n)$, as in Fig. 1, the resulting output in the frequency domain equals

$$Y(k) = G_0(\Omega_k)U(k) + T(\Omega_k) + V(k), \tag{2}$$

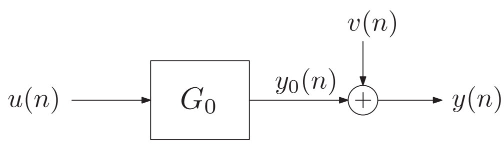

Fig. 1. LTI discrete time system in an output error setup.