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Sparse structural system identification method for nonlinear dynamic systems with hysteresis/inelastic behavior

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ABSTRACT

A system identification technique suitable for single degree of freedom (SDOF) and multiple degree of freedom (MDOF) structural systems with either nonlinear elastic or inelastic/hysteretic behavior is proposed in this paper. The method is a parametric modeling technique based on sparse regularization. The proposed framework is capable of discovering the underlying governing equations of the system of interest from input-output data. We build on the work of Brunton et al. (2016) by including functions that allow the discovery of significant nonlinearities, and hystertic or inelastic behavior with permanent deformation. We also present model selection using sparse regularization and cross validation using Akaike criteria. We demonstrate through experimental validation that the technique presented in this paper is applicable to a significantly broader class of problems. The effectiveness of the proposed method is evaluated through numerical examples of a 2-story nonlinear or inelastic building with a adjustable stiffness device. We also present experimental validation using a unique nonlinear structural system that consists of a MDOF structural system and a nonlinear negative stiffness device (NSD) to illustrate the significant ability of the proposed framework. We successfully identify the following structural systems from experimental data: a SDOF yielding frame without NSD; a SDOF yielding frame with NSD; and a 3-DOF frame with NSD. The extracted sparse model also shows potential for generalization.

1. Introduction

Inverse modeling and system identification techniques in structural engineering provide researchers and engineers with ways to estimate the dynamic characteristics of real structural systems from input-output data. Forward mathematical modeling (e.g. Finite Element Methods) based on physics is useful to simulate both static and dynamic behaviors. Through mathematical modeling, one can estimate the output behavior of the system being modeled for different inputs [1,2]. On the other hand, inverse modeling and system identification techniques [3] are the process of developing a nonparametric or parametric model of a physical system from input-output data. It plays an important role since accurate forward modeling usually requires detailed knowledge of the system, which is often difficult as only partial information of the system is initially known. System identification can synthesize information from measurements and with prior assumptions can provide valuable insight into the physics of the actual system. System identification problems are often difficult due to the presence of

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nonlinearities and hysteresis/inelasticity. Factors such as the looseness of structural joints, amplitude dependent materials and boundary conditions with variable stiffness constraints, etc. make behavior of practical structures nonlinear [2] and complex.

Approaches typically used in the community of system identification fall into two categories [4,5]: (1) parametric methods; and (2) nonparametric methods. The first class of methods usually require a model structure and is parametrized by a finite set of parameters. With the real measured data from structures, one can minimize the prediction error to update the parameters. These methods are called prediction error methods (PEM). In PEM the final identified model structure is still in the same class as initial model structure, but with updated parameters [6–11]. Usually, for dealing with the nonlinear dynamic problems, initial model structure is assumed to be of a known structure — either bilinear or duffing or hysteretic. Thus, a critical requirement of parametric methods is that assumptions regarding initial structure are needed. Nonparametric methods are purely based on input-output data mapping, with no prior knowledge of model structure. Impulse response estimation in time domain or empirical transfer function estimate in the frequency domain are nonparametric methods. Subspace identification techniques [12–14] are projection based methods, that use state space structure, Hankel matrix, to estimate parameters. Statistical learning and sparse regression, using sparsity inducing regularization, are a class of methods that are more closer to the later then the former.

Another class of nonparametric identification methods, use measured input-output data, signal processing, statistical learning and data mining techniques to learn and extract the embedded patterns from data. For instance, blind source separation based modal identification [15–17] and artificial neural network based nonlinear system identification techniques [13,14] belong to this class of methods. The limitation of this methodology is that the extracted nonparametric model from data, which is a functional mapping between inputs and outputs, has no physical meaning. Unfortunately, these techniques rarely offer a straightforward physical insight into nonlinear dynamical systems.

Very recently, Brunton et al. [18] have proposed a new nonlinear identification method that discovers governing equation and corresponding parameters using sparse regression to address this shortcoming of traditional source separation methods. The newly proposed method seeks to extract the governing differential equations of the nonlinear dynamical system via sparse regression and a dictionary of possible functions. The only assumption is that nonlinear dynamics is governed by a few known functions, so the equations are sparse in the possible function space.

In this paper, we establish the framework of sparse identification for SDOF and MDOF nonlinear structural system with significant hysteresis and permanent deformation. We augment the work of Brunton et al. [18,19] to include functions that represent significant hysteresis or inelastic behavior. Thus we demonstrate that the augmented sparse technique presented in this paper has significantly broader class of nonlinear problems that it can address. We deal with (1) two different types of nonlinearity, which are commonly found in structural engineering: the first one is nonlinear elastic behavior and the second one is hysteretic or inelastic behavior in real-world structures; (2) sparse identification with training and cross validation using Akaike Information Criterion(AIC), which is implemented to optimize the choice of regularization parameters that scale the optimal basis functions. In finding the optimal regression model, trade-off between accuracy and model complexity is achieved; and (3) proposed framework is tested using real-world data from a unique system – a MDOF linear structures with a nonlinear NSD [20–24] or Adaptive Stiffness Device (ATSD). NSD or ATSD introduces adaptive stiffness to the linear elastic primary structure, such that the combined system of primary structure and NSD has nonlinear elastic behavior. Fig. 1 shows the conceptual force-displacement loops to illustrate the idea. We test the proposed framework in a SDOF yielding structures for the cases of either with or without NSD. A three degree-of-freedom (3-DOF) structural system installed with a NSD was tested under various seismic ground excitations [23]. These tests included inelastic behavior of the primary structure. With measured input-output data, the underlying governing differential equations and corresponding parameters are discovered and phyiscal interpreation along with inelastic/hysteretic force-displacement loops, are presented using the proposed method. We demonstrate by way of a number of numerical examples and experimental validation that sparse regularization discovers the model structure and parameters that characterize the dynamical behavior – i.e. extract a physics based parametric model.

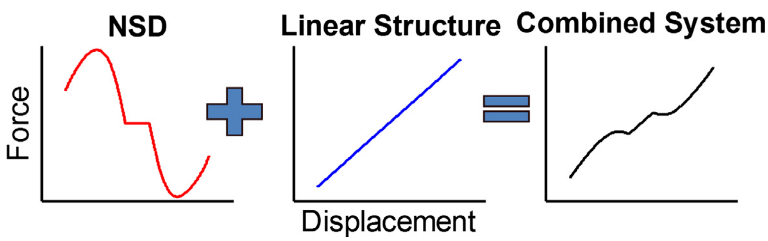

Fig. 1. Conceptual force-displacement behavior of a negative stiffness device (NSD) engaging into a linear system to generate a nonlinear elastic system.