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COMPREHENSIVE IDENTIFICATION OF NONLINEAR STRUCTURAL SYSTEMS WITH THE LOW NUMBER AND NON-HOMOGENEOUS SENSING USING MODERN BAYESIAN METHODS

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In this paper, a general framework is presented to estimate the unknown parameters of structures. The unknown parameters can consist of a vast range of variables, such as the dynamical parameters of structure, the motivation inputs, the responses of other degree of freedoms (DOFs) except un-sensed ones, etc.

Engineering problems can be widely classified into four general areas:

1. **Direct problem:** The system matrices, the initial conditions, and the external forces are the inputs of problem and the output variables should be calculated.
2. **Inverse problem:** The system matrices as well as some measurements related to the DOFs are the inputs of problem and the external forces and initial conditions should be determined.
3. **System identification problems:** The external forces and initial conditions together with some measurements related to the DOFs are the inputs of problem and the system matrices or some components of them should be determined.
4. **Research problems:** Some measurements related to the DOFs are taken as the inputs of problem and the system matrices, external forces, initial conditions, and remaining DOFs are the outputs.

Apparently, the last case is the most difficult as compared with other ones, which the attentions are focused on this case in this study. For this purpose, two general approaches, including off-line and on-line methods, are available in the technical literature.

In the off-line methods, identification process can be initiated just after completing the sensing operation. In the other words, in these methods, all sensed data are necessary for the analysis. The most popular off-line method is Tikhonov regularization that includes the dynamic programming and L-curve techniques in its structure. The dynamic programming is a technique used to determine the optimal solution that consists of backward and forward processes. For tuning the parameters of these processes, some smoothness methods, such as L-curve technique, should be employed. In the recent years, many researchers and engineers have used the off-line methods in different engineering applications and the results are almost satisfying. However, these methods have some drawbacks. First, these methods are acutely weak to handle the problems with large number of variables. In fact, off-line methods use the optimization basics in their solving process, in which, the complexity of problem is drastically increased with increasing the number of variables. The second weakness of these methods is the difficulty to handle the nonlinear problems. Although, some new tricks are used in recent years, but all of them solve a part of the model nonlinearity, while the observation processes of them are different.

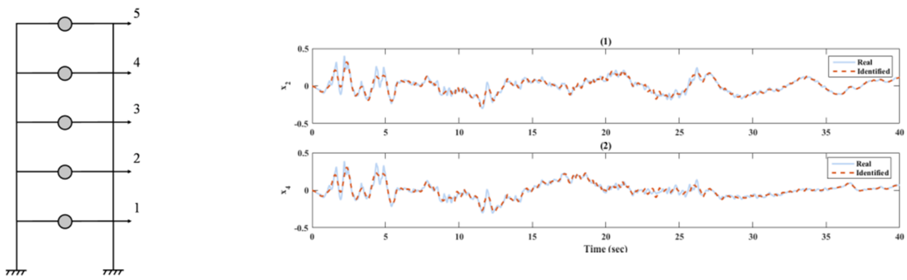
Unlike the off-line methods, the online methods can find the unknown parameters in each step interactively without considering the whole observations. These methods are originally based on Bayesian theorem that itself works with conditional probability. Two main stages of Bayesian algorithms are prediction and updating. In the prediction stage, k^{th} variables, including states, external forces, etc., are constructed from $(k\text{-}1)^{th}$ variables. After that, the results are updated by combining the observations with them by a suitable gain. In fact, at this stage, the prior probability is updated to the posterior one. This process continues to the end.

The most popular method of Bayesian-based algorithms is Kalman filter. However, this filter can work only for linear and Gaussian systems. For nonlinear systems, extended Kalman filter is introduced. Nonetheless, this filter gives fatal errors when the system has high nonlinearity or it is non-Gaussian.

At these problems, using sophisticated Bayesian algorithms is inevitable. Unscented Kalman filter (UKF) is one of the solutions. This filter works with sigma-points. Another approach is particle filter (PF). Particle filters make a set of solutions at each step. After that, by constructing the probability density functions (pdfs) for both considered variables and related observation, the solution is estimated by using conditional probability formula. In fact, particle filter is a population-based approach.

In recent years, many successful implementations of unscented Kalman filter and particle filter on different complex problems are reported by the researchers.

In order to validate the presented algorithm, three examples are presented in this study. In first example, a 5-story building is affected by base-induced force. For this purpose, two forces, including the El Centro earthquake and the combined sinusoidal-impulse forces, are selected. Some of results are shown in Figure 1. In second example, vehicle-bridge interaction (VBI) system is considered. Estimation of axle-forces as well as remaining states via accelerometers attached to the top of each axle is the goal of this problem. Finally, for last case, a 3-story building with a nonlinear hysteretic component is studied.



(a) (b)

Figure 1. 5-story building motivated under El Centro earthquake: (a) a schematic side of building; (b) Identified displacements time history of 2nd and 4th stories acquired PF.

The results show a good accordance between identified variables with real values. To survey the capability of methods, the observation signals are polluted to some noises. However, the results are slightly affected in the presence of high percent of noises.

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