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Seismic-induced damage detection through parallel force and parameter estimation using an improved interacting Particle-Kalman filter

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A B S T R A C T

Standard filtering techniques for structural parameter estimation assume that the input force is either known or can be replicated using a known white Gaussian model. Unfortunately for structures subjected to seismic excitation, the input time history is unknown and also no previously known representative model is available. This invalidates the aforementioned idealization. To identify seismic induced damage in such structures using filtering techniques, force must therefore also be estimated. In this paper, the input force is considered to be an additional state that is estimated in parallel to the structural parameters. Two concurrent filters are employed for parameters and force respectively. For the parameters, an interacting Particle-Kalman filter is used to target systems with correlated noise. Alongside this, a second filter is used to estimate the seismic force acting on the structure. In the proposed algorithm, the parameters and the inputs are estimated as being conditional on each other, thus ensuring stability in the estimation. The proposed algorithm is numerically validated on a sixteen degrees-of-freedom mass-spring-damper system and a five-story building structure. The stability of the proposed filter is also tested by subjecting it to a sufficiently long measurement time history. The estimation results confirm the applicability of the proposed algorithm.

1. Introduction

Stochastic parameter estimation problems are characteristically categorized as nonlinear stochastic inverse problems. The related forward problem nonlinearly maps a set of model parameters to the corresponding measurements. Among the existing methods for inversely estimating the parameters, methods defined using a state space formulation are found to be popular [1–7] due to the relative ease in the estimation. Within this scope, filtering based recursive online system estimation techniques [8–10] are shown to be more efficient in using available measurements.

Filtering-based inverse estimation recursively employs (i) the Bayesian belief propagation technique (i.e. Chapman-Kolmogorov equation) to model the current estimate evolving over time and (ii) subsequent minimum mean square error (MMSE) based correction of the current estimate using the available measurements.

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To execute the Chapman-Kolmogorov equation in discrete time, a state space model is needed to replicate the system dynamics in discrete time. For filtering-based parameter estimation algorithms, the system is usually defined using a state-space formulation of the dynamic model with parameters additionally appended to the unobserved state vector and collectively observed through the response measurements. Due to the nonlinear relationship of the unobserved parameters (as augmented states) to their respective observation (i.e. measurements), parameter estimation problems are inherently nonlinear. Over the years, Particle Filter (PF) [11–13] has been established as a better estimator than several other nonlinear variants of Kalman filter (KF) (e.g. Extended [8] or Unscented [14,15] KF) for nonlinear problems [16–18]. However, the relatively high computational cost of PF is sometimes the major concern [19].

In most of the filtering-based parameter estimation algorithms, the system states and parameters are usually estimated jointly as an extended state vector [16,20–22]. Being model based, these filters optimally estimate the parameters of a quasi-steady model of the real dynamic system. Nonetheless, any time variance in the system dynamics may cause the estimation to completely diverge yielding a false or infeasible solution. By decoupling the estimation of states and parameters (also called Rao-Blackwellisation [23–25]) and applying separate but interacting filtering strategies that attempt conditional estimation of states based on parameters and vice versa, time varying system model parameters can be optimally estimated. The benefit of such dual estimation over joint estimation strategies is discussed in [26]. Along similar lines, an interacting filtering strategy has been employed in [27] for damage detection in a flexible plate, where a particle filter is employed on a reduced order numerical model followed by an update of the particle positions through an Extended Kalman Filter (EKF).

Techniques for dual estimation of states and parameters by coupling two concurrent EKFs were proposed in [28,29], whereas a dual estimation technique with two parallel PFs was used in [30,31]. This approach not only ensures greater stability in the estimation, but also helps to keep the system dimension within limits. However, while the EKF based algorithms are reported to be not efficient with highly nonlinear systems [32], implementation of PF based dual estimation raises concerns regarding computational expense [19]. It should be noted that, while the parameter estimation is a nonlinear problem, the state estimation focuses on a linear process model. One can thus exploit this by engaging different filter types for state and parameters, such as Interacting Particle-Kalman filters (IPKF) [33] which make a clever use of costly PF for parameter estimation while standard KF handles the linear state estimation problem. Such techniques have a definite computational cost, which can be handled by integrating them in parallel computing methods (GPGPU) as in [34]. The major advantage of IPKF is that, with the strategy of decoupling the estimation of states and parameters, the state dimension can always be maintained at a reasonable size.

Ultimately, the optimal convergence of any filtering based parameter estimation algorithm depends on the information on the system input. Traditionally, while the time series of the system input is usually unknown, a stationary white Gaussian noise (WGN) model of it is however assumed to be available. Nevertheless, for systems subjected to non-stationary unknown input, traditional approaches fail to provide an optimal solution. A typical example would be the problem of monitoring structural health with seismic force as input which cannot be modeled as a stationary WGN. A breakthrough can however be achieved by recursively updating the information about the seismic force and then supplying this information to the damage detection filter to achieve optimal structural health estimation.

In order to estimate the system input parallel to state, an unbiased minimum-variance linear state estimation filter without any a priori assumption on the input was pioneered in [35]. A practical method improving the filter used in [35] was later proposed in [36]. Other relevant works on joint state and input estimation involve the development of unbiased minimum variance optimal filters with no direct transmission term in the system formulation [37]. A modification is then proposed in [38] that relates a system to its direct transmission term. In [39], similar filters targeting issues related to numerical instability in the estimation, especially when the systems are redundantly instrumented, were proposed. An augmented KF (AKF) approach for input estimation was developed in [40]. However, he concluded that with AKF, the unobservability of the system may lead to instability in the estimation.

As mentioned above, estimating the force acting on a time invariant system using a dual PF approach was attempted in [31]. In a more recent study [41], joint input-parameter estimation was discussed for a time-varying system subjected to seismic excitation using the UKF technique. Their proposal is based on an AKF approach that augments the parameters and system inputs together in a very large state vector. Additionally, the system under consideration is time invariant with no sudden change in parameters in the course of estimation.

Naets et al. [42] discussed an EKF-based joint input-state-parameter estimation which handles all three components in an extended state vector. When implemented with particle filtering, this strategy may become intractable since a large dimensional state space has to be explored with particles that might be computationally impractical. Eftekhar Azam et al. [43] proposed a coupled DKF-UKF algorithm in which the DKF (Dual KF) algorithm estimates the input required for an UKF filter that estimates the state and parameters. Again, no sudden change in parameters (and therefore in the system) is addressed in this approach.

It is evident from the above discussion that, while there exists sufficient research on joint state and input identification for time invariant linear systems, similar research for time varying systems is scarce. Force estimation for a time varying system is however crucial, especially for typical SHM problems, since the anomalies in structural systems are mostly due to some rare events involving high magnitude forces for which no prior prediction can be made. Thus, in order to develop a robust SHM algorithm, these uncertain forces need to be estimated alongside and communicated to the core SHM algorithm for greater precision. In this paper, we develop a novel technique to detect damage in the presence of non-stationary input. A two-stage filtering strategy has been adopted, in which the first filter detects damage in the system while the second