



Real-time moving horizon estimation for a vibrating active cantilever



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ABSTRACT

Vibrating structures may be subject to changes throughout their operating lifetime due to a range of environmental and technical factors. These variations can be considered as parameter changes in the dynamic model of the structure, while their online estimates can be utilized in adaptive control strategies, or in structural health monitoring. This paper implements the moving horizon estimation (MHE) algorithm on a low-cost embedded computing device that is jointly observing the dynamic states and parameter variations of an active cantilever beam in real time. The practical behavior of this algorithm has been investigated in various experimental scenarios. It has been found, that for the given field of application, moving horizon estimation converges faster than the extended Kalman filter; moreover, it handles atypical measurement noise, sensor errors or other extreme changes, reliably. Despite its improved performance, the experiments demonstrate that the disadvantage of solving the nonlinear optimization problem in MHE is that it naturally leads to an increase in computational effort.

1. Introduction

Slender shapes are often used in current machines and structures to advocate savings in material costs, while increasing speeds and decreasing operation cycle times help to keep up with customer demand. Unfortunately, accomplishing these features results in the increase of undesirable vibration levels as well. The active control of mechanical structures has therefore attracted attention in recent years [1,2]. Vibrating mechanical structures may also change the character of their dynamic response, which is due to several factors; such as environmental effects, faults in sensors or actuators, cracks, fatigue, etc. Structural changes manifest themselves as parameter variations in the mathematical representation of the vibrating system. These may be identified in real-time using joint state and parameter estimation; then used to create adaptive control algorithms, adaptive energy harvesting devices or even structural health monitoring schemes.

Fault and damage detection methods have been extensively studied for vibrating systems, specifically for cantilever beams. Fuzzy-genetic algorithms [3] particle swarm optimization [4], wavelet transform [5] and artificial neural networks [6] are just a few methods for this purpose. Most of these approaches have excellent fault detection properties, however, are not applicable for real-time implementation in practical hardware due to their enormous computational requirements.

The extended Kalman filter (EKF) is a model-based recursive predictor-corrector algorithm for observing unmeasured states of nonlinear models. It is based on the well-known Kalman filter and, as the name implies, is an extension for nonlinear models using first order linearization. In addition to observing inherently nonlinear systems, it may also be used to estimate unknown model

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parameters. The extended Kalman filter can be considered as the industry standard for nonlinear estimation [7]. It is readily accepted for various applications, it is computationally efficient and is proved to be convergent for the neighborhood of the linearized model [8].

The moving horizon estimation (MHE) strategy is built on a similar concept as model predictive control (MPC) in its algorithmic design. A moving window of predicted states is used in MPC to formulate a cost function that is minimized to compute the optimal sequence of control inputs. The same strategy is used in reverse for moving horizon estimation: a window of measurement data is trailed behind the current sample. This horizon of measurements is then used to formulate a weighted and constrained least-squares optimization problem, that is solved to observe unknown model states and parameters.

There are several situations in which the performance of the EKF deteriorates in comparison to MHE. Even without a model mismatch and constraints, EKF can fail to converge if the model and measurements are defined in a way that several solutions exist for the steady state measurement and also, if the estimation procedure is being provided with a poor initial guess [9]. MHE may behave more robustly to a poor initial guess, due to the incorporation of constraints and optimizing over a window of measurements, unlike a single measurement based estimator, e.g. the EKF for the case studies presented in [9]. For our application, state and parameter constraints—such as damping being only positive—can be built in the formulation itself. It has been shown that the receding horizon strategy also plays a significant role in improving convergence properties and estimation precision. Izadi et al. employed MHE and the unscented Kalman filter (UKF) for parameter estimation in a simulation study, to provide a fault tolerant framework for MPC [10]. Based on their comparison, MHE showed much faster convergence response and better estimation performance than the UKF [10]. In [9] Haseltine and Rawlings provided several examples for chemical processes, where EKF is unsuccessful to converge compared to MHE, even though no constraints are assumed active. Due to the smoothing effect of taking a window of measurements into account along with the update used for the arrival cost, MHE usually shows a better performance than EKF. They came to the conclusion that “the benefits in MHE arise, because it incorporates physical state constraints into an optimization, accurately uses the nonlinear model, and optimizes over a trajectory of states and measurements”. The same conclusion can be deduced from [11] comparing the results for the application of MHE and EKF on thermally coupled distillation columns. Ibrahim et al. [12] and Grover and Xiong [13] used the same analogy for their comparison study on toxicant concentration estimation for water supply and on a chemical process. On the other hand, Busch et al. showed that EKF and MHE have a comparable performance which only means that in some examples it might not worth solving a nonlinear optimization problem, if a recursive based approach has the same performance [14]. Moving horizon algorithms for control and estimation are often considered in fault tolerant applications [15–17], since the receding horizon formulation may behave more robustly in atypical control and estimation scenarios.

Constraint handling, fast convergence response, explicit incorporation of nonlinearities, robustness to unexpected measurement noise and faults are among the known benefits of MHE over EKF which will be investigated in this paper for the estimation of vibration dynamics. The main advantages of EKF are computational efficiency—that also implies low cost of hardware—software design simplicity and acceptance. The extended Kalman filter is used in numerous control engineering applications, however, the incorporation of this algorithm for vibrating systems is rare. It has been used for structural health monitoring [18,19] and as a tool to observe the parameters for an adaptive vibration control system [20]. A structural health detection approach was also developed by Shao and Mechefske [21] using EKF as a gearbox vibration monitoring system. A simulation study using EKF estimation on a vibrating micro-cantilever beam is presented in [22]. On the other hand, the moving horizon estimation method is seldom used in structural vibration applications. A simulation study was performed for a nano-positioner in [23], while a pseudo real-time experimental evaluation of MHE was presented in [24]. Based on the literature research and the knowledge of authors, there is no previous work presenting an embedded real-time experimental implementation of the moving horizon estimation method for a vibrating mechanical system.

This paper introduces the moving horizon estimation method for a vibrating active cantilever in real-time. An aluminum cantilever equipped with piezoceramic actuators is supplied with pseudo-random noise; while the displacement of the free end of the beam is measured by a laser triangulation system. This setup is modeled by a linear single degree of freedom actuated point-mass system, with unknown and potentially changing set of parameters. The aim of the online estimation method is to jointly compute the unmeasured states and the unknown parameters. A low-cost computing platform is utilized to implement the parameter estimation method, in order to demonstrate its feasibility on simple and relatively cheap hardware. The MHE method is contrasted to EKF in various experimental scenarios. These include a change in the structure that is emulated by modifying the dynamic weight of the cantilever beam, artificially introduced sensor faults and noise distribution and amplitude that is not encompassed by the original formulation.

The main goal of this paper is the real-time implementation of MHE on a low cost computationally efficient platform while, investigating the performance of MHE over EKF. The aim is not a comprehensive comparison of MHE and EKF as it has been covered previously in [9], hence, the evaluation of convergence rate and robustness to the disturbances are only valid for our case study. Furthermore, it is important to note that this work does not discuss the further use of the estimated parameters, that is, the details of possible structural monitoring or adaptive control schemes; we only focus on implementing the estimation methods and the comparison is being performed only to evaluate the properties of these estimation methods for vibrating systems.

This paper is organized as follows: in Section 2 the system model and the state augmented by parameters is described. Next, Section 3 briefly introduces the theoretical fundamentals of the two estimation methods considered in this paper. The hardware description and algorithm implementation is presented in Section 4. The experimental results are presented and discussed in Section 5, which is followed by a conclusion given in Section 6.

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