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An iterated cubature unscented Kalman filter for large-DoF systems identification with noisy data

Esmaeil Ghorbani, PhD candidate [a], Young-Jin Cha, Assistant Professor [b, *]

[a] Department of Civil Engineering, University of Manitoba, Winnipeg, MB R3T 6B3, Canada
[b] Department of Civil Engineering, University of Manitoba, Winnipeg, MB R3T 5V6, Canada

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ABSTRACT

Structural and mechanical system identification under dynamic loading has been an important research topic over the last three or four decades. Many Kalman-filtering-based approaches have been developed for linear and nonlinear systems. For example, to predict nonlinear systems, an unscented Kalman filter was applied. However, from extensive literature reviews, the unscented Kalman filter still showed weak performance on systems with large degrees of freedom. In this research, a modified unscented Kalman filter is proposed by integration of a cubature Kalman filter to improve the system identification performance of systems with large degrees of freedom. The novelty of this work lies on conjugating the unscented transform with the cubature integration concept to find a more accurate output from the transformation of the state vector and its related covariance matrix. To evaluate the proposed method, three different numerical models (i.e., the single degree-of-freedom Bouc–Wen model, the linear 3-degrees-of-freedom system, and the 10-degrees-of-freedom system) are investigated. To evaluate the robustness of the proposed method, high levels of noise in the measured response data are considered. The results show that the proposed method is significantly superior to the traditional UKF for noisy measured data in systems with large degrees of freedom.

1. Introduction

Many aerospace, civil, and mechanical engineering systems are used despite their aging and the associated potential for damage accumulation. It is clear that degradation and the process of replacing infrastructure costs billions of dollars and has many other inevitable impacts. This presents a potential for research in this field to develop systems that detect damage in the initial stages. A linear Kalman filter was developed to track system states by compensating noisy data in the 1960s by Kalman and Kalman and Bucy [1]. It showed remarkable results in the identification of dynamic specifications when there is a linear assumption for a mathematical model, while the state vector dimension is limited.

The Kalman filter prediction accuracy decreases drastically when systems are assumed as linear by omitting their nonlinear nature. The extended Kalman filter (EKF) has been developed that works based on the first-order linearization of the mathematical model using the Taylor series [2–4]. There are other techniques, such as the Monte Carlo method, which can be used for nonlinear systems, but they often require a large amount of data and are therefore computationally expensive

* Corresponding author.
E-mail addresses: ghorbane@myumanitoba.ca (E. Ghorbani), young.cha@umanitoba.ca (Y.-J. Cha).

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[5]. The EKF as a standard local filter (using the standard linearization method) is a suitable technique that is used to identify mechanical systems [4,6–8]. However, it has two major problems that limit its applications in high nonlinear systems and systems with large degrees-of-freedom (DoF) systems and high loading [9,10]. The first problem is that the EKF uses Taylor expansion for first-order linearization. Therefore, the calculation of the Jacobian and Hessian matrix of the transition and measurement matrices is unavoidable, which is sometimes impossible or very complicated in some cases. Second, when the system has a high order of nonlinearity, the first-order linearization leads to divergence, and the accuracy of the predicted responses decreases significantly. To resolve these drawbacks, other kinds of filters are introduced that do not use the Tylor series expansion and are derivation free.

With the background knowledge of stochastic filtering, Bayesian statistics, and Monte Carlo techniques, the sequential Monte Carlo approach, also known as the particle filter (PF), is a useful techniques for system identification [11]. This technique handles both nonlinearity in the posterior distribution of states as well as systems with non-Gaussian noises. To deal with unknown input systems, the PF is used for joint parameter and state estimation, and many developments are achieved using the PF in structural health monitoring [12]. Refer to [13], although PF techniques are more robust than the UKF, in real-time simulation, the UKF is significantly faster and more efficient.

The unscented Kalman filter (UKF) is a local derivation-free filter that transforms the posterior error covariance matrix of states instead of the transition and measurement matrix [14]. It can be shown that when data have a Gaussian distribution, the UKF prediction is equal to the third order of the Taylor series. The UKF uses symmetric points around the mean, which are named sigma points and are propagated with the nonlinear transition and measurement matrix function. They capture the true mean and covariance up to the second order for any level of nonlinearity. If the prior (initial distribution) distribution is Gaussian distribution, the posterior mean and covariance are accurate to the third order for any nonlinearity [15]. Considering the robustness of the UKF, several studies have focused on system identification [16]. Some researchers have attempted to develop methods for worse cases (high order of nonlinearity, and severe loading) to improve their convergence rate [17], for the parameter identification of materials in finite element models [18], for the identification of noise adaptive models in a joint state and parameter estimation scheme [19], for damage detection purposes [20], and when the input is unknown [21–24]. Further, the most recent studies have integrated the UKF with the computer vision technique [25]. Extensive review of the published papers shows that no comprehensive studies have proposed the UKF for large-DoF systems with high levels of noisy measured data.

The main purpose of this study is to develop an UKF-based system identification method for large-DoF systems with noisy measured acceleration. The contents of this paper are divided as follows. The main concept of the UKF is explained briefly in Section 2.1, and a modified UKF is proposed in Section 2.2, which uses another sigma point calculation step during the recursive process. The main concept of the proposed method is a combination of cubature integration and unscented transform in the sigma point calculation process. Further, the propagation of new sigma points over the transition and measurement matrix is integrated with the iterated UKF to improve the accuracy of state prediction, as discussed in Section 2.3. Section 3 presents three different numerical models for evaluating the performance of the newly proposed methods with noisy data in contrast to the traditional UKF.

2. UKF-based system identification methods

In this section, first, a quick review of the UKF is presented with a flowchart of the algorithm given in Section 2.1. This flowchart is useful for comparison with the newly proposed method introduced in Section 2.2. The modified UKF is proposed by the integration of the UKF and cubature Kalman filter. It is also adapted with the iterated Kalman filter, leading to more accurate state prediction, as shown in Section 2.3.

2.1. Original UKF

The UKF was initially developed to overcome the limitation of the EKF in the linearization process of the mathematical model of a system using derivation-free local filters by an unscented transform (UT). The UT is found based on the fact that it is easier to approximate a probability distribution than an arbitrary nonlinear function or transformation [14]. A set of deterministically weighted points, which have an identical sample mean and sample covariance, named sigma points, are chosen so that their posterior mean and covariance are calculated over the propagated nonlinear transition and measurement functions. To determine the sigma points and related weights, Eqs. (1)–(3) must be solved, considering that the initial states mean is m and its covariance error matrix is P_0:

$$\sum_{i=0}^{2n} w_i = 1, \tag{1}$$

$$\sum_{i=0}^{2n} w_i \chi_i = m, \tag{2}$$