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Particle-filtering-based failure prognosis via sigma-points: Application to Lithium-Ion battery State-of-Charge monitoring

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ABSTRACT

This paper presents a novel prognostic method that allows a proper characterization of the uncertainty associated with the evolution in time of nonlinear dynamical systems. The method assumes a state-space representation of the system, as well as the availability of particle-filtering-based estimates of the state posterior density at the moment in which the prognostic algorithm is executed. Our proposal significantly improves all particle-filtering-based prognosis frameworks currently available in two main aspects. First, it provides a correction for the expression that is used for the computation of the Time-of-Failure (ToF) probability mass function in the context of online monitoring schemes. Secondly, it presents a method for improved characterization of the tails of the ToF probability mass function via sequential propagation of sigma-points and the computation of Gaussian Mixture Models (GMMs). The proposed algorithm is tested and validated using experimental data related to the problem of Lithium-Ion battery State-of-Charge prognosis.

1. Introduction

One of the most critical aspects to consider in the elaboration of decision-making processes is the manner in which uncertainty and risk are quantified. The latter, due to the impact that these uncertainty sources may have on the final cost associated with all available choices; costs that in some cases are related to the operational continuity of industrial systems. In this regard, several techniques intend to address the problem of uncertainty characterization from different points of view. Some methods follow possibility-based approaches, fuzzy logic, or evidence theory [1–4]. Nevertheless, most of researchers have preferred probability-based methods for the implementation of online failure prognostic algorithms [5], because these approaches allow including the notion of uncertainty under a well-known and accepted mathematical formalization.

In the context of probability theory, Bayesian approaches [6] arise as a suitable option for most online learning systems. Bayesian schemes allow the implementation of filtering algorithms (also known as Bayesian processors) for uncertainty characterization in nonlinear dynamic processes [7–9]. This task is performed via the computation of posterior estimates of the state vector, where both prior information (provided by the system model) and measurements (acquired in real-time) are efficiently used. In failure prognosis, these states typically correspond to critical variables whose future evolution in time might significantly affect the system health, thus yielding into a failure condition. However, except for a reduced number of

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cases, it is not possible to obtain an analytic solution for the filtering problem. A well-known solution for linear Gaussian systems is the Kalman filter (KF) [10,11], which provides an optimal estimate in the mean-square error sense. Although some nonlinear systems may be approximated by linearized versions within bounded regions of the state space, KF implementations will generally offer a suboptimal solution. Moreover, underlying uncertainties may distribute differently from a Gaussian Probability Density Function (PDF). In this regard, Sequential Monte Carlo (SMC) methods, a.k.a. Particle Filters (PFs) [6], provide an interesting solution for the filtering problem in the context of nonlinear non-Gaussian systems. PFs approximate the underlying PDF by a set of weighted samples, recursively updated, yielding an empirical distribution from where statistical inference is performed.

Although PFs allow characterizing uncertainty associated with the state vector in filtering problems, our interest in prognosis is really focused on describing the future evolution of uncertainty [12]; all to take preventive measures and avoid failures that may lead to catastrophic events [13] that could affect system interoperability. Monte Carlo (MC) simulation [14] offers a solution to this problem. However, the computational cost associated with MC simulation complicates the implementation of real-time MC-based prognostic schemes. In this regard, the Prognostic and Health Management (PHM) community has chosen particle-filtering-based algorithms [15] as the state-of-the-art in this matter, since those algorithms offer an efficient alternative to Monte Carlo simulation in the implementation of real-time prognosis approaches.

Our research focuses on two aspects that help to significantly improve all particle-filtering-based prognosis frameworks currently available in literature. Firstly, it provides a correction for the expression that is typically used for the computation of the Time-of-Failure (ToF) Probability Mass Function (PMF) in the context of online monitoring schemes; providing a better understanding of the risk associated with future operation and extending the ToF PMF definition to general nonlinear systems that may present regenerative behavior. Secondly, it presents a novel method for improved characterization of the tails of the ToF PMF via sequential propagation of sigma-points [16–18] (a set of deterministically defined weighted points that preserve the first two moments of a PDF) and the computation of Gaussian Mixture Models (GMMs). The proposed algorithm is tested and validated using experimental data related to the problem of battery State-of-Charge prognosis.

The structure of the paper is as follows. Section 2 presents theoretical background on SMC methods and sigma-points. Section 3 presents a modification to the expression that is used to compute the ToF PMF. Section 4 shows a general description of the proposed prognostic algorithm and, subsequently, Section 5 shows a validation case study on Lithium-Ion battery State-of-Charge prognosis, a.k.a. End-of-Discharge prognosis. Section 6 shows conclusions and future work.

2. Theoretical background

This section aims at providing a proper theoretical framework on some of the concepts that are included in the design of our proposed prognostic algorithm, as well as motivating the intuition of the reader.

2.1. Particle filters

Particle Filters are computational methods designed for recursively estimating the evolving posterior distribution of a nonlinear, non-Gaussian, dynamic system, given a set of sequentially acquired measurements (problem also known as *optimal filtering*).

Let $X=\{X_k,\ k\in\mathbb{N}\}$ be a first order Markov process denoting a n_x-dimensional system state vector with initial distribution $p(x_0)$ and transition probability $p(x_k|x_{k-1})$. Also, let $Y=\{Y_k,\ k\in\mathbb{N}\setminus\{0\}\}$ denote n_y-dimensional conditionally independent noisy observations. PFs assume a state-space representation of the dynamic nonlinear system:

$$x_k = f(x_{k-1},\ \omega_{k-1}) \tag{1}$$

$$y_k = g(x_k,\ v_k), \tag{2}$$

where ω_k and v_k denote independent non-Gaussian random variables. The objective is to estimate the posterior distribution $p(x_k|y_{1:k})$. As this is a difficult task to achieve, estimators require the implementation of structures based on Bayes' rule where, under Markovian assumptions, the filtering posterior distribution can be written as

$$p(x_k|y_{1:k}) = \frac{p(y_k|x_k)p(x_k|y_{1:k-1})}{p(y_k|y_{1:k-1})}. \tag{3}$$

Sequential Monte Carlo methods (SMC), a.k.a. PFs, efficiently simulate complex stochastic systems to approximate the posterior PDF (3) by a collection of N_p weighted samples or *particles* $\{x_k^{(i)},\ W_k^{(i)}\}_{i=1}^{N_p}$, $\sum_{i=1}^{N_p} W_k^{(i)} = 1$, such that:

$$\hat{p}(x_k|y_{1:k}) \approx \sum_{i=1}^{N_p} W_k^{(i)}\delta_{x_k^{(i)}}(x_k). \tag{4}$$

The weighting process is performed by applying *sequential importance resampling* (SIR) algorithms in two stages: Sequential Importance Sampling and Resampling.