Mechanical Systems and Signal Processing ∎ (∎∎∎∎) ∎∎∎–∎∎∎

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

journal homepage: www.elsevier.com/locate/ymssp

Particle filter-based prognostics: Review, discussion and perspectives

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ARTICLE INFO

Article history:
Received 17 September 2015
Received in revised form
27 October 2015
Accepted 3 November 2015

Keywords:
Prognostics
Particle filters
Implementation
Issues
Challenges

ABSTRACT

Particle filters are of great concern in a large variety of engineering fields such as robotics, statistics or automatics. Recently, it has developed among Prognostics and Health Management (PHM) applications for diagnostics and prognostics. According to some authors, it has ever become a state-of-the-art technique for prognostics. Nowadays, around 50 papers dealing with prognostics based on particle filters can be found in the literature. However, no comprehensive review has been proposed on the subject until now. This paper aims at analyzing the way particle filters are used in that context. The development of the tool in the prognostics' field is discussed before entering the details of its practical use and implementation. Current issues are identified, analyzed and some solutions or work trails are proposed. All this aims at highlighting future perspectives as well as helping new users to start with particle filters in the goal of prognostics.

1. Introduction

Prognostics and Health Management (PHM) is an enabling discipline that aims at utilizing real monitoring data to facilitate relevant indicators and trends that depict the health of a system. Seven modules ranging from data acquisition to decision making are combined to help preserving the integrity of a system [31]. A key activity in PHM is prognostics. Indeed, it enables predicting the remaining useful life (RUL) of the system and helps anticipating and avoiding failure. A great variety of techniques are available to perform prognostics [70] depending on the knowledge and data available.

Among these techniques, particle filters are more and more employed. It has been developing this last decade in the prognostics' field even becoming considered as a state of the art technique. However, no comprehensive review is available to discuss the issues coming with this tool, or to compare the different existing points of view on the subject. It can be interesting to notice, and also to show, that most of works dealing with particle filters in the prognostics field are just using existing approaches and applying it to prognostics. Most of them lack of real adaptation to prognostics requirements. Moreover, with no synthesis of the existing literature, it is quite difficult to start with particle filters to perform prognostics with only basic notions.

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http://dx.doi.org/10.1016/j.ymssp.2015.11.008
0888-3270/

To provide answers to these comments, or at least to start addressing them, the main contributions of this paper are the following: (1) the background and a short review about particle filters in a general context, (2) an analysis of particle filters in prognostics applications addressing all the issues from the filter selection to the uncertainty management, and (3) the highlighting of remaining issues and challenges as well as the proposal of solutions or work trails. For this purpose, this paper is organized in two main parts.

In a first part, the theory of particle filter and its basic functioning are presented. A short state of the art is also drawn to show the existing types of implementation and some of the general challenges. Then, in the second part, the use of particle filter in the prognostics' field is studied. A comprehensive analysis of the different techniques available for each step of the implementation is proposed. To do so, first the perception of the tool in the PHM community, the requirements for prognostics as well as its advantages and drawbacks are discussed. Then, the model adaptation needed to have the state and measurement models are discussed and the different types of filters most commonly encountered for prognostics are discussed. Section 2.5 deals with the implementation of particle filters while Section 2.6 discusses how to use it to perform prognostics. Finally, the existing metrics to evaluate the results based on particle filters are summarized before discussing how to deal with uncertainty with such a tool.

Part I: Particle filters – theory and generalities

Particle filers are used in many fields: robotics, statistics, automatics, etc. and more recently in diagnostics and prognostics. However, the bases always remain the same.

1. Nonlinear Bayesian tracking

1.1. Problem statement

A Bayesian tracking problem is defined by two elements [3]:

1. a state vector that contains all the relevant information required to describe the system under investigation;
2. a measurement vector representing the noisy observations that are related to the state vector. It is generally of dimension equal to or lower than the state vector.

The signal is modeled as Markovian, nonlinear, non-stationary and may be non-Gaussian [19]. We remind that a Markov process is a stochastic process with the Markov property, i.e. the conditional probability distribution of future states only depends from the current state and not the past states. Nonlinear refers both to the classical definition of a nonlinear system, i.e. a system for which the output is not directly proportional to the input, and its mathematical representation, i.e. a nonlinear state equation.

The knowledge of this information is translated into at least two models in order to analyze and make inference about the dynamic system [3,19]:

1. *the state model* (or system model): describes the evolution of the state with time $\{x_t, t \in \mathbb{N}\}$, $x_t \in$ X is modeled as a Markov process of initial distribution $p(x_0)$ and a transition equation $p(x_t|x_{t-1})$. Note that this state can be unobserved (hidden states).
2. *the measurement model* (or observation model): relates the noisy measurements to the state. The observations are written $\{y_t, t \in \mathbb{N}^*\}$, $y_t \in$ Y are assumed to be conditionally independent given the process $\{x_t, t \in \mathbb{N}\}$ and of marginal distribution $p(y_t|x_t)$.

According to [3], an important assumption is that these models are available in a probabilistic form. However, to be used in a filtering framework, the models are more commonly found in the following forms [38]:

$$x_t = f(x_{t-1}, u_t, \omega_t) \leftrightarrow p(x_t|x_{t-1}) \tag{1}$$

$$y_t = h(x_t, v_t) \leftrightarrow p(y_t|x_t) \tag{2}$$

where u_t is the command input of the system and ω_t and v_t are white noises, non-necessarily Gaussian. Some examples of non-Gaussian white noises can be found in [24]. The probabilistic state-space formulation and the updating of information based on new measurements are ideal for the Bayesian approaches [3].

1.2. Bayesian approach

The Bayesian approach consists in constructing the posterior probability density function (pdf) of the state based on all available information, such as the knowledge of the system or sets of measurements. In principle, an optimal (with respect to any criterion) estimate of the state may be obtained [3].

The state is estimated recursively via a filtering approach. According to [3], it means that received data can be processed sequentially rather than as a batch so that it is not necessary to store the complete data set nor to reprocess existing data if a

Please cite this article as: M. Jouin, et al., Particle filter-based prognostics: Review, discussion and perspectives, Mech. Syst. Signal Process. (2015), http://dx.doi.org/10.1016/j.ymssp.2015.11.008