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Chi-squared smoothed adaptive particle-filtering based prognosis☆, ☆☆

Christopher P. Ley [a,b,*], Marcos E. Orchard [a,c]

[a] Department of Electrical Engineering, Universidad de Chile, Santiago 837-0451, Chile
[b] Commonwealth Science and Industrial Research Organisation (CSIRO) Chile, Avda. Tupper 2007, Santiago 837-0451, Chile
[c] Advanced Mining Technology Center (AMTC), Universidad de Chile, Santiago 837-0451, Chile

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ABSTRACT

This paper presents a novel form of selecting the likelihood function of the standard sequential importance sampling/re-sampling particle filter (SIR-PF) with a combination of sliding window smoothing and chi-square statistic weighting, so as to: (a) increase the rate of convergence of a flexible state model with artificial evolution for online parameter learning (b) improve the performance of a particle-filter based prognosis algorithm. This is applied and tested with real data from oil total base number (TBN) measurements from three haul trucks. The oil data has high measurement uncertainty and an unknown phenomenological state model. Performance of the proposed algorithm is benchmarked against the standard form of SIR-PF estimation which utilises the Normal (Gaussian) likelihood function. Both implementations utilise the same particle filter based prognosis algorithm so as to provide a common comparison. A sensitivity analysis is also performed to further explore the effects of the combination of sliding window smoothing and chi-square statistic weighting to the SIR-PF.

1. Introduction

Condition Based Maintenance [1] (CBM) is a relative new paradigm that, using a prediction of the degrading system, optimises the maintenance process. In this regard, CBM relies heavily on the concept of prognosis. “Prognosis is the science of predicting the health condition of a system and/or its components based upon knowledge of past usage, current state, and future conditions” [2]. As such, prognosis encapsulates both state estimation and prediction. Recursive Bayesian algorithms are well suited to real-time estimation and prediction since they incorporate process data into prior state estimates by considering the likelihood of measured values [3]. The underlying uncertainty can then be projected for n steps into the future using state models, thus providing a realisation of the future uncertainty of the state [4].

Particle Filters (PFs) or Sequential Monte Carlo (SMC) are a form of recursive Bayesian algorithms that provide a solid and consistent theoretical framework to handle model non-linearities or non-Gaussian process/observation noise. PFs are based on the concept of sequential importance sampling (SIS) and Bayesian Theory, which have been proven in literature to be a

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* Corresponding author.
E-mail addresses: christopher.ley@csiro.au (C.P. Ley), morchard@ing.uchile.cl (M.E. Orchard).

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highly effective method of online estimation. PFs do not use the assumption of Normally distributed process noise, as in the case of the Kalman Filter, thus allowing a more accurate representation of the true state evolution in non-Gaussian stochastic processes [5–9,4,10,11,2]. The PF framework has also been utilised in literature as a tool for prognosis [6,4,10,11], as the particle population can be projected by the state models. The resulting projection can then be used as a representation of the uncertainty of future state evolution. This is particularly useful in cases where an analytical solution to the future uncertainty probability density function (pdf) is difficult or impossible to calculate.

In general, prognosis algorithms are sensitive to the uncertainty associated with the current state estimate. Prognosis routines utilise a stochastic state model to propagate state estimates into the future, and thus all state predictions can only be more uncertain. In fact, the increase in future uncertainty follows the rules of information *entropy* [12,13] (Shannon entropy), which indicates that if the system includes a stochastic component then *entropy* will only increase. Particle Filtering based Prognosis (PFP) algorithms are no different to any other prognosis routine: uncertainty associated with current estimates can only increase when projected into the future. However, as PFP algorithms project the current likelihood into the future by utilising the state process model, errors in that model exacerbate problems related to prediction uncertainty by introducing additional biases. With this in mind, it is natural to aim at improving the accuracy of PF-based prognostic results by reducing the uncertainty associated with the state estimates that we use as initial condition for prediction algorithms; ensuring that the state transition model accurately reflects the system evolution in time.

A suggested solution to the problem of a biased process model is to introduce an additional parameter that adapts to the observed state evolution, this is often referred to as an Artificial Evolution (AE) [9]. The introduced parameter is shaped by a process resembling simulated annealing [14]. The resulting process model accurately reflects the observed state evolution, but introduces additional hurdles for PFP algorithms. Due to the time associated with the convergence of unknown system parameters, AE naturally incorporates a time delay that constraints the moment in which prognosis can be accurately performed. The convergence of AE can also be a problem given situations of high measurement uncertainty.

The Chi-squared likelihood weighting and smoothing window introduced in this paper serves to alleviate the shortcomings associated with the introduction of the AE parameter, effectively improving the precision of prognosis results. The results are demonstrated with total base number (TBN) oil degradation data in comparison with the traditional PF algorithm with a Normally weighted likelihood function so as to create a benchmark for performance. A sensitivity analysis is also performed to explore the effects of AE in the chi-squared algorithm. The TBN measurements exhibit many of the characteristics that are undesirable in estimation applications, namely high measurement uncertainty and an unknown phenomenological model. A novel performance index is also presented to demonstrate a statistical improvement in the precision of obtained results.

This paper is divided as follows:

- Section 2, which provides the background and previous work in literature utilised as the basis of the Particle Filtering based Prognosis
- Section 3, introduces the case study utilised in this paper as well as the motivation for using this data. This data is haul truck total base number measurements from oil.
- Section 4, introduces the Chi-squared Smoothed Adaptive Particle-Filtering based Prognosis.
- Section 5 analyses the effects of the Chi-squared kernel on various aspects of the algorithm, as well as delivering insight into the effects of selecting certain parameters in the Chi-squared Smoothed Adaptive Particle-Filtering based Prognosis algorithm.
- Section 6 presents the application of the Chi-squared Smoothed Adaptive Particle-Filtering based Prognosis to the TBN case study as well as the Normalised Integral of Precision Index for validating the results.
- Section 7 offers Conclusions

2. Particle-filtering based prognosis

"*Particle Filters* (PF) or *Sequential Monte Carlo* (SMC) methods are a set of simulation-based methods which provide an attractive approach to computing the posterior distributions" [3]. PF are very flexible, parallelisable and applicable to any non-linear or linear system. The advent of cheap and formidable computational power in conjunction with the recent proliferation of scientific papers on PF & SMC have led to their wide spread application to many fields, particularly in the area of control and observation. Several closely related algorithms, under the names of *bootstrap filters, condensation, Monte Carlo filters, interacting particle approximations, Sequential Importance sampling filter* and *survival of the fittest* have appeared in several research fields [3]. This paper focuses on an implementation of a derivative of PF called *Sequential Importance Sampling and Re-sampling filter* (SIR).

We first introduce the general continuous PF to demonstrate the underlying concept and to highlight the flexibility when selecting the transition kernel and the likelihood function that can be applied without changing the underlying assumptions (and the convergence characteristics). This flexibility in the likelihood function selection will be a key aspect exploited later in this paper (Section 4.1)

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