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Remaining useful life estimation based on discriminating shapelet extraction

Simon Malinowski*, Brigitte Chebel-Morello, Noureddine Zerhouni

FEMTO-ST, ENSMM, Besançon, France

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ABSTRACT

In the Prognostics and Health Management domain, estimating the remaining useful life (RUL) of critical machinery is a challenging task. Various research topics including data acquisition, fusion, diagnostics and prognostics are involved in this domain. This paper presents an approach, based on shapelet extraction, to estimate the RUL of equipment. This approach extracts, in an offline step, discriminative rul-shapelets from an history of run-to-failure data. These rul-shapelets are patterns that are selected for their correlation with the remaining useful life of the equipment. In other words, every selected rul-shapelet conveys its own information about the RUL of the equipment. In an online step, these rul-shapelets are compared to testing units and the ones that match these units are used to estimate their RULs. Therefore, RUL estimation is based on patterns that have been selected for their high correlation with the RUL. This approach is different from classical similarity-based approaches that attempt to match complete testing units (or only late instants of testing units) with training ones to estimate the RUL. The performance of our approach is evaluated on a case study on the remaining useful life estimation of turbofan engines and performance is compared with other similarity-based approaches.

1. Introduction

Remaining Useful Life estimation is one of the main tasks in the Prognostics and Health Management domain. The aim of any RUL estimation technique is to provide, as early as possible, accurate prediction of the time after which an equipment will not be able to meet its operating requirements. RUL estimation is hence very important for industrial purposes as it can help in planning maintenance strategies, maximizing the useful operational life of equipment, reducing maintenance costs and avoiding breakdowns that might have critical impacts.

RUL estimation techniques are separated into three families : model-based, data-driven and hybrid approaches. Model-based approaches rely on building a physical model describing the degradation behavior of the equipment. For instance, stochastic filtering [1], particle filtering [2] have been used to model degradation in the case of fatigue crack growth. This kind of approaches is very accurate but requires the knowledge of the physical degradation of the system, which is not always the case. In most of the cases, the equipment is composed of many components for which a different model needs to be defined. Furthermore, model-based approaches are closely related to the considered application. They hence lack genericity. Data-driven approaches make use of available run-to-failure data to extract relevant information based on a learning process. These approaches do not attempt to derive an analytical model from the data, but attempt to capture the relationship between sensory data and the degradation level of an equipment, in order to estimate its RUL. These approaches are usually easier to obtain and implement, and are mainly used when a physical model of the degradation cannot be derived. They hence can be applied to a huge variety of applications provided that an history of run-to-failure data is available. Most of the data-driven approaches in the literature are based on machine learning, probabilistic or statistical tools. A good survey of machine learning and statistical techniques for prognostics can be found in [3]. Neural Networks have been widely considered to estimate the RUL [4–11]. Other machine learning tools have also been applied for RUL estimation, for instance support vector regression in [12], functional regression in [13], and fuzzy decision trees in [14]. Probabilistic and statistical tools have also widely been used for prognostics applications. Bayesian learning techniques [15,16], Wiener processes [17,18], copulas [19,20], ensemble approaches [21], Hidden Markov models [22,23], and Support Vector Machines combined with particle swarm optimization in [24] and autoregressive-moving-average

* Corresponding author.
E-mail addresses: simon.malinowski@femto-st.fr (S. Malinowski), brigitte.morello@femto-st.fr (B. Chebel-Morello), noureddine.zerhouni@femto-st.fr (N. Zerhouni).

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models [25,26] have been considered in the literature. Hybrid approaches, for instance in [27–30], combine model-based and data-driven approaches. Similar to model-based approaches, knowledge about the physical degradation of components is required for hybrid-ones, which lowers the applicability of such approaches.

In this paper, we focus on similarity-based approaches which are particular cases of data-driven ones. Fig. 1 depicts the general framework of such approaches. Sensory data (often multidimensional) is first processed : noise filtering, feature extraction, data fusion, and so on. Note that the kind of processing depends on the type of data. After these steps, data is sometimes transformed into an 1-dimensional indicator, denoted *health indicator* (HI), that models the degradation of an equipment by a time-series (or trajectory). If the original sensory data already captures the health status evolution of the equipment, data can also be kept multi-dimensional. In Fig. 1, this step is depicted by the data processing box. After this step, data is formalized into instances. The kind of instances depends on the method : instances can represent complete HI trajectories or blocks of HI trajectories for instance. Hence, in an offline phase, a library of instances is constructed from the training sensory data. In an online phase, the same processing and formalization operations are applied to testing sensory data (whose RUL is to be predicted) in order to obtain a new instance. This instance is then compared to the library of instances in the retrieval step and the most similar ones are selected in order to predict the RUL of the testing instance (RUL estimation box in Fig. 1). The authors of [31] have won the 2008 PHM challenge with a similarity-based approach where instances were the HI's obtained after fusion of different sensor measurements and that relied on Euclidean distance between training and testing HI's to select most similar instances. In this method, the whole testing trajectory is used to be matched to the library of training units. Another approach, in [32], aims at matching only last points of testing HI's with training ones (as last parts are more likely to be correlated with the degradation level). More recently, other similarity-based approaches have been proposed, as for instance in [33–35]. The approach proposed in this paper differs from classical similarity-based approaches in the instance formalization, retrieval and RUL estimation steps (gray boxes in Fig. 1). It is based on the extraction, from the run-to-failure data, of discriminative shapelets that are used in a second step to estimate the RUL of new testing units.

Shapelets have been introduced in [36–39] for classification and early classification of time series. We extend here this notion and define a new kind of shapelets called rul-shapelets, that correspond to patterns correlated to the remaining useful life of an equipment. In this paper, in the formalization step, discriminative rul-shapelets are first extracted from a training set of trajectories representing run-to-failure data of equipment. This step produces a library of rul-shapelets that will be used for RUL estimation of testing units. In the online phase, the testing instance is created and rul-shapelets from the library are searched in this testing instance. The rul-shapelets that are found in the testing instance provide an estimation about the RUL. Hence, the RUL estimation relies here on finding similar behaviors between subsequences of the testing time series and rul-shapelets that have been extracted for their correlation with the remaining useful life. Hence, a major difference with other traditional approaches is that the RUL estimation is based on some parts of the testing units (and not the whole testing unit or last instants), these parts being chosen because of their high correlation with the RUL.

This approach is compatible with any applications satisfying the following assumptions:

- Run-to-failure data is available.
- Trajectories capturing the health status evolution can be obtained from sensory data.
- Testing components are assumed to go through the same degradation process as training ones.

The rest of this paper is organized as follows. Section 2 gives an overview of related work on similarity-based RUL estimation techniques and positions our proposed approach within this context. Section 3 describes how discriminative shapelets are extracted from a set of time series representing run-to-failure data. Section 4 explains how these shapelets are used to perform RUL estimation of testing units, and Section 5 evaluates the performance of the proposed approach on a case study.

2. Related work

In this section, related work about similarity-based approaches for RUL prediction is presented. We focus on explaining in details how the formalization, retrieval and RUL prediction steps are performed in the literature. Similarity-based approaches are relatively new for prognostics applications. Wang et al. [31] proposed an approach that was amongst the best three in the 2008 PHM challenge. Instances are represented as 1-dimensional health indicator trajectories obtained by linear regression of the sensory data. In the online step, for a given training trajectory, the Euclidean distance between a testing trajectory and every sub-trajectories (shifted by different number of cycles) of the training one is computed and the minimum distance is retained together with the optimal shift. This procedure is repeated for every training trajectories. The most similar trajectories are selected according to the similarity measure, up to a given threshold. RUL is estimated as a weighted average of the RULs of the selected trajectories. Xue et al. [40] proposed a fuzzy-instance-based approach for RUL prediction. A Local fuzzy model is built for a testing engine. The fuzzy model defines a cluster of peers in which each of these peers is a similar instance to the given testing engine with comparable operational characteristics. The final RUL

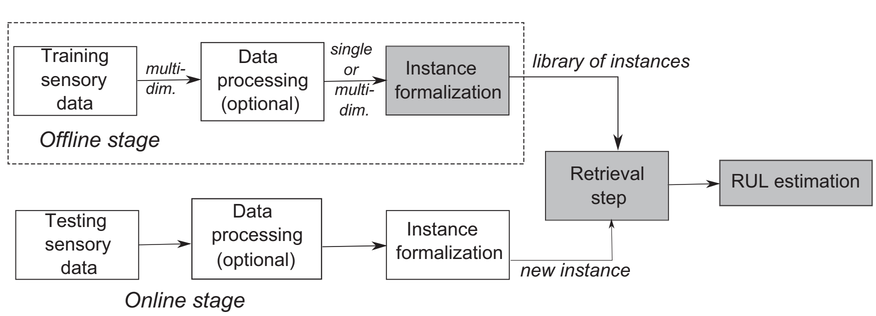

Fig. 1. General framework of similarity-based RUL estimation schemes.