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Remaining useful life prediction of aircraft engine based on degradation pattern learning

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ABSTRACT

Prognostics, which usually means the prediction of the field reliability or the Remaining Useful Life (RUL), is the basis of Prognostic and Health Management (PHM). Research in this paper focuses on remaining useful life prediction of aircraft engine in the same gradual degradation mode. As the gradual degradation with same failure mechanism has some regularity in macro, there would be certain relation between an arbitrary point of the degradation process and the correspondent RUL. This paper tries to learn this certain relation via neural network and the learned network, which reflects the relation, can be partly perceived as degradation pattern. The main prognostic idea of degradation pattern learning is firstly proposed and illustrated. And then an improved back propagation neural network is designed and analyzed as the implementation technique, in whose loss function an adjacent difference item is added. Next details of implementation via adjacent difference neural network are elaborated. Finally, the proposed approach is validated by two experiments respectively using different aircraft engine degradation datasets. Results of the experiments show a relatively good prediction accuracy, which verifies the correctness, effectiveness and practicability of the idea.

1. Introduction

As conventional maintenance strategies like scheduled preventive maintenance and breakdown corrective maintenance [1–3] are becoming decreasingly able to meet the higher demand of reliability, safety and efficiency in many technical areas, the idea of Prognostic and Health Management (PHM), which is also called with other terms such as Condition-Based Maintenance (CBM) and Predictive Maintenance (PdM) [2], has received increasing attention, especially for safety related critical component or system with costly downtime and failure like aerospace devices, nuclear equipment and large industrial machines [4,5]. Prognostic and Health Management is designed to conduct maintenance before system/facility failures take place, via assessing system condition including operating environments and estimating the risk or Remaining Useful Life (RUL) in a real-time way, based on the history trajectory data [2]. Through this predictive maintenance policy, PHM is not only able to protect the system from faulty casualty loss, but also able to avoid unnecessary maintenance activities and resource wasting. Thus the system reliability, safety and efficiency is improved as well as the maintenance cost is reduced.

Prognostics, defined as the analysis of the symptoms of faults to predict future condition and residual life within design parameters by the international standard organization [6], is the key process and basis of Prognostic and Health Management [7]. Considering the differences of expertise, generality, practicability and feasibility between condition estimation and RUL prediction, the research of the latter is more attractive.

As the heart of the increasingly complex aircraft system, the engine is expected to maintain high reliability for long while working at quite harsh environment. Therefore, it is of paramount significance to ensure the steadiness and reliability of the aircraft engine. Fortunately, this can be achieved by PHM through conducting suitable maintenance actions based on RUL.

In general, approaches dealing with RUL prediction problem fall into three categories: model-based, data-driven and hybrid approach. Interesting reviews related with prognostics are given in [5,8–15]. For model-based methods, the damage model needs to be selected or constructed according to the degradation characteristics of the object before prediction. After that, one-step prediction is iteratively progressed via the model until the estimated damage state reaches a threshold or interval as the failure state. However, it is difficult to make a model for increasingly complex systems. Common model-based

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Nomenclature

CBM	Condition Based Maintenance
EKF	Extended Kalman Filter
HMM	Hidden Markov Model
NASA	National Aeronautics and Space Administration
NN	Neural Network
PdM	Predictive Maintenance
PHM	Prognostic and Health Management
RUL	Remaining Useful Life
RVM/SVM	Relevance/Support vector machine
ν	the scope coefficient, representing the initial health level
$HI(t)$	the Health Index ranging from 0 to ν
D	the degradation pattern
g	the function relation between the Health Index (HI) and the time (t)
g^{-1}	the inverse function of g
h	the transfer function, being related with the global degradation pattern D
ω	the time coefficient which controls the degradation speed
t_0	the time translation constant, meaning the different degrees of initial wear
t_k	any fixed time in different trajectories
t_f	the failure time
$X_t^{(l)}$	the state of unit l at time t
X_{t_f}	the failure state
$HI^{(l)}$	the lth degradation trajectory
S_t	the structured data at time t, containing the necessary state information
f	the function relationship between local parameters and the structured data of certain unit trajectory
p_0	an intermediate mathematical relationship, simplifying the derivation
p	the function relation between $HI_{t-t_s+1}^{(l)}, HI_{t-t_s+2}^{(l)}, \ldots, HI_t^{(l)}$ and $RUL^{(l)}$.
W	the weights of the network.
$w_{i,j}$	the weight associated with the connection between unit j in the front layer, and unit i in the posterior layer.
n	the number of units in the front layer.
b	the bias(the intercept term)
J	the loss function
λ	the weight decay parameter
γ	the coefficient of the adjacent difference term

approaches include state space algorithms, such as the extended Kalman filter (EKF) and the particle filter [16–18], and classical deterioration methods such as Weibull distribution [19] and Eyring model [7,20,21]. For data-driven approaches, the available information is usually limited to the complete historical observation data of as much units to learn and the current condition monitoring data of units to predict. As data-driven approaches do not concern the special things of the object except data, they are much easier to be generalized, which leads to their flourishing of research. Classical data-driven approaches include various neural networks (NN) [22–29], hidden Markov models (HMM) [1,30,31], Gaussian process regression [32], relevance/support vector machine (RVM/SVM) [33,34], etc. [35–38]. For hybrid methods, it is usually the combination of the two above-mentioned methods that are applied to the prognostics research as details can be seen in [18,19,39]. I think the hybrid method is promising as not only the data information but also the data structure information which may reflect the potential relationship in data is used.

For the problem of aircraft engine RUL prediction, there are several main ideas in large part of public literatures. The first is the similarity based idea, in which the training units are processed into a model library and they conduct the prediction through the similarity of the current monitoring data with the models in the library, as can be seen in literatures [36,37,40]. The second is mapping based idea, in which the key is to construct a kind of mapping from the current monitoring data to the RUL and the difficulty is to ensure the reliability of the mapping, as can be seen in literatures [25,27]. Mapping here means mathematical relationships including one-to-one, one-to-many, many-to-one and many-to-many relationships, while the reliable mappings refer to relationships of one-to-one and many-to-one, namely function relationship. The third is statistical parameter estimation and iterated prediction idea, in which the model parameters are estimated by statistical methods and then the degradation state is carried forward iteratively by one step prediction until the threshold, as can be seen in literatures [16,21].

Approach proposed in this paper belongs to hybrid method as degradation pattern learning is implemented through an improved neural network and the main idea is to construct a robust mapping. The approach is verified on the first set of Turbofan Engine Degradation Simulation Data Sets (containing four datasets) and the PHM08 Challenge Data Set, both provided by NASA Ames Prognostics Data Repository. There are four reasons choosing them. The first is the authority. Datasets provided by NASA are believable. The second is the typicality. These signals in the datasets are representative that they degraded gradually mixed with invalid signals and noise in one fault degradation mode. That means the RUL can be predictable while it's challenging. The third is the expansibility. We can focus on the basic dataset just as the first dataset and then expand the proposed approach to those more complex datasets just as the second. The fourth is comparability. There are many studies focusing on these datasets so it is easier to do comparison.

These datasets cannot be used for learning directly. We need to turn the data into samples and this is the process of data preprocessing, which mainly contains performance assessment, data form reconstruction and sample distribution reset. The samples then can be trained to get the prediction net by tools of neural network. After that, the learned network can give the predicted RULs of testing units based on their input information. At last, a series of indicators are designed to evaluate the prediction result.

The following parts of the paper mainly include three sections. In Section 2, the main idea of degradation pattern learning in this paper and corresponding adjacent difference neural network design are illustrated. The idea in Section 2.1 is the guiding thought and basis of the proposed methodology. The design in Section 2.2 is the most important innovative point of the approach or tool used for realizing the main idea. In Section 3, the entire procedures of the basic and expanding experiments taken to complete RUL prediction are elaborated. In Section 4, conclusions as well as future work on this approach are discussed.

2. Idea of degradation pattern learning and design of adjacent difference neural network

2.1. Mapping idea of degradation pattern learning

Idea in this paper is to consider the mapping as a set of degradation patterns obeying a certain distribution and the close connection between them will be identified in this subsection. After that we can obtain the mapping through degradation pattern learning.

The main bases of RUL prediction idea are the consistency of the degradation pattern and the Markov property of degradation process. And the global degradation pattern and local parameters also need to be paid close attention.