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Rolling element bearing remaining useful life estimation based on a convolutional long-short-term memory network

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Abstract

The rolling element bearing is the leading cause of failures in rotating machinery; on that account, the accurate prediction of its remaining useful life (RUL) using sensor data is an important challenge to improve the reliability and decrease the maintenance costs. Classical data-driven approaches rely on manually extracted features from raw sensor data followed by an estimation of a health indicator, the degradation states and the prediction of RUL using a failure threshold.

Based on the recent success of deep neural networks in various artificial intelligence domains, we propose an end-to-end deep framework for RUL estimation based on convolutional and long-short-term memory (LSTM) recurrent units. First the neural network extracts the local features directly from sensor data using the convolutional layer, then an LSTM layer is introduced to capture the degradation process, finally the RUL is estimated using the LSTM outputs and the prediction time value. Experiments are conducted on the ball bearing data provided by FEMTO-ST Institute. The results demonstrate the efficiency of our approach.

Keywords: Rolling element bearing;Condition-based maintenance;Prognostics;Convolutional neural network;Long-short-term memory network

1. Introduction

In the increasingly complex and automated modern industry, the economic cost of a failure became increasingly high; faulty components can affect the reliability of other associated assets in the system; consequently, adopting effective maintenance strategies is crucial for the enhancement of the overall reliability and profitability.

Recently, the development of modern sensor technology and condition monitoring systems led to the adoption of condition-based maintenance (CBM) [1]. CBM is conducted by recommending maintenance actions in real time based

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on the collected sensor data. The most challenging CBM activity is prognostics [2] defined as the prediction of future conditions and the residual life of the system.

There are mainly three paradigms for prognostics: model-based approaches [3], data-driven approaches [4] and hybrid approaches [5]. The application of general model-based or hybrid prognostic approaches relies on the understanding of the system's physics-of-failure which is difficult in a complex engineered systems. The data-driven approaches are mainly based on sensor data with less requirement on knowing the inherent system failure mechanisms. This led to a large increase in their popularity in recent years.

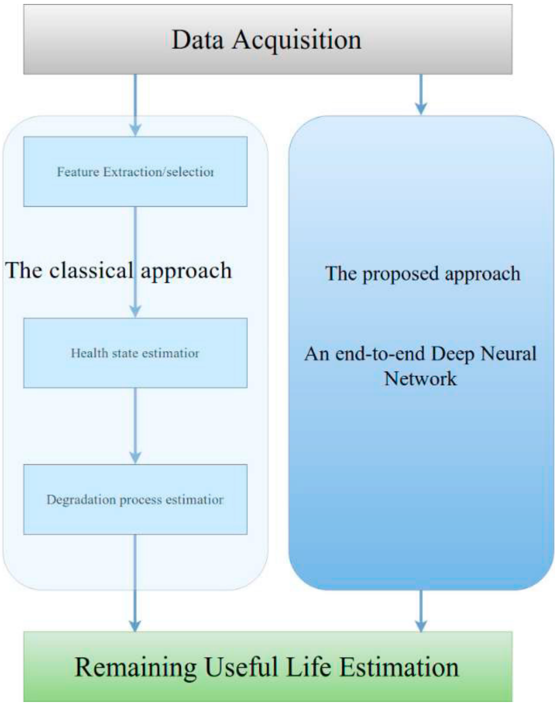

Fig. 1. The RUL estimation pipeline

The rolling element bearing is the most common component in rotating machinery; it accounts for 45–55% of these equipment failures [6], The corresponding vibration signals can be collected in real time at a relatively low cost. As a result, a wide range of studies on data-driven methods for rolling element bearing prognostics exists in the literature ([7], [8], [9], [10], [11], [12], [13], [14], [15]).

Most of these methods are composed of three steps (figure 1):

- A feature extraction and selection step from the raw vibration data;
- A health state estimation step typically done by combining the extracted features into a health indicator;
- A degradation process estimation step generally realized by extrapolating the health indicator until it reaches a failure threshold.

This classical pipeline present drawbacks which are required to be solved:

- The identification of the suitable features for prognostics requires considerable domain expertise and a great deal of human labor. These features can exhibit different degradation signatures at different stages of the degradation process. Some features don't change their values until the bearing is very close to the end of its useful life; others are not monotonic or very sensitive to the measurement noise;