Development of Deep Learning Based Prognostics for Rotating Components

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ABSTRACT

Rotating components such bearings and gears are one of the most critical components in many industrial machines. Predicting the remaining useful life (RUL) of these components has been an important task for condition-based maintenance of industrial machines. One critical challenge for performing such task in the age of Internet of Things and Industrial 4.0 is to automatically process massive data and accurately predicting RUL of these components. The limitations of current methods rely quite heavily on user expertise in signal processing and explicit model equations such as the state transition model. The objective of this research is to addresses the limitations of traditional data driven prognostics by presenting new methods based on deep learning for RUL prediction of rotating components. Real data collected from both gear test rig and bearing run-to-failure tests are used to test and validate the methods to be developed. The preliminary results have shown the promising RUL prediction performance of the deep learning based approaches.

1. PROBLEM STATEMENT

In the age of Internet of Things and Industrial 4.0, the prognostic and health management (PHM) systems are used to collect massive real-time data from mechanical equipment. Mechanical big data has the characteristics of large-volume, diversity, and high-velocity. Remaining useful life (RUL) has been used as an important parameter for condition-based maintenance decision making (Huynh *et al*. 2014). Effectively mining features from such data and accurately predicting RUL of the rotating components of the equipment in use with new advanced methods become issues in PHM. Traditionally, data driven prognostics is largely dependent on signal processing and feature extraction techniques. Over the past years, many prognostic methods that require explicit model equations have been developed (Vachtsevanos *et al*. 2006). This critical process of establishing explicit model equations requires much prior knowledge about signal processing techniques and prognostic expertise.

Since the introduction of a deep belief network by Hinton *et al*. (2006), deep belief networks and other deep learning methods have become a popular approach for big data processing and analysis. Deep learning has the ability to yield useful and important features from data that can ultimately be useful for improving predictive power (Bengio *et al*. 2013). It has also the capability of processing big data and mining hidden information due to its multiple layer structure. There have been great successes in building deep neural network architectures in various domains such as image recognition, automatic speech recognition, natural language processing (LeCun *et al.* 2015), and many more. It has also recently shown promising results for machine fault diagnostics on extraction of raw vibration signals (Chen *et al*. 2016) as well as time-domain features (Shao *et al*. 2015). Although much success in deep learning has been focused on classification problems, deep learning has also proven to be successful in solving prediction problems. There are many types of deep learning algorithms present including auto-encoders, restricted Boltzman machines, deep belief networks, convolutional neural networks, and more that can also be used for prediction problems. Deep learning represents an attractive option to process mechanical big data for RUL prediction as deep learning has the ability to automatically learn features that otherwise require much skill, time, and experience. This research will develop deep learning based prognostic methods for rotating components and validate the developed methods using real bearing and gear run to failure test data.

2. EXPECTED CONTRIBUTIONS

The potential contributions of this research include:

(1) New deep learning based prognostic methods developed using vibration, acoustic emission, and other sensor signals.
(2) New deep learning based approach for prognostic feature extraction, state transition modeling, and for a completely data driven particle filter.
(3) Validation of the developed deep learning based prognostic methods using real bearing and gear run-to-failure test data.

3. RESEARCH PLAN

3.1 Development of Deep Learning based Methods for Prognostics

The tasks include: (1) Continue to survey and study the deep learning methods in literature such as: denoising auto-encoders, deep auto-encoders, and mixture density networks

(Bishop 1994); (2) Experiment with different deep learning structures for RUL prediction; (3) Compare the performance of the deep learning based methods with existing PHM methods to determine the best prognostic methods with big data.

3.2 Real Gear and Bearing Run to Failure Test Data

To validate the developed deep learning based RUL prediction methods, vibration, acoustic emission, and other sensor data collected at the NASA Glenn Spiral Bevel Gear Test Facility and from bearing run-to-failure tests in the laboratory as shown in Figure 1 and Figure 2 will be used.

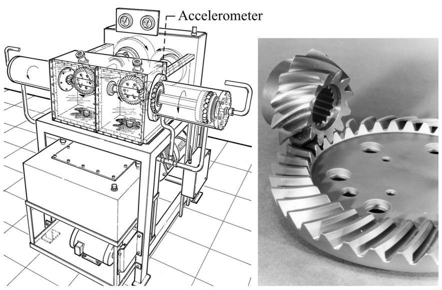

Figure 1. The bevel gear test rig and bevel gears (Dempsey *et al*. 2002)

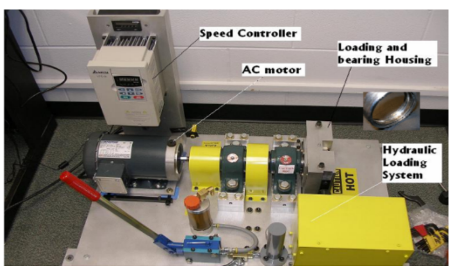

Figure 2. The bearing run-to-failure test rig

3.3 Validation of the Developed Deep Learning Based Fault Prognostic Methods

The developed deep learning based prognostic methods will be validated with big data collected from both the gear and bearing test rigs. The performance of the developed methods will be compared to determine the best method for both gear and bearing RUL predictions.

3.4 Work Performed

Preliminary research has been conducted and shown promising results using deep learning based methods for modeling the RUL at various L steps ahead in the future.

Two deep learning approaches were used for estimating the RUL. The first method was based on using a deep belief network (DBN) to directly estimate the RUL. Vibration signals were processed using fast Fourier transform (FFT) to obtain condition indicators/features. These features were then embedded as inputs to the network using a technique known as the sliding window approach (Frank *et al*. 2001). The DBN was then trained using the embedded FFT features in a completely unsupervised learning phase. Once training was complete, a supervised fine tuning layer was added on top of the last layer of the DBN, where it is fully connected to the (last) hidden layer of the DBN which serves as a weight initializing for the feedforward neural network This process has been shown to to add robustness to deep architectures and decrease the probability of obtaining a poor local minima (Erhan *et al*. 2010).

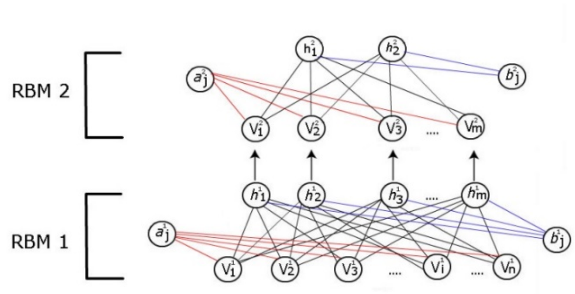

Figure 3. A deep belief network with two hidden layers

The results from this approach indicate promising results that are fairly competitive with the particle filter approach as shown in Table 1 and Table 2.

Table 1. DBN based approach vs. Particle Filter (gear data)

Deep learning based approach		
L	RMSE	MAPE
1	2.54	6.70%
10	3.35	10.04%
Particle filter based approach		
L	RMSE	MAPE
1	2.62	7.14%
10	3.48	10.87%

Table 2. RMSE and MAPE results for bearing data

Deep learning based approach		
L	RMSE	MAPE
1	2.64	8.40%
10	3.71	9.31%
Particle filter based approach		
L	RMSE	MAPE
1	2.53	7.47%
10	3.65	8.73%

The second approach combines a DBN with a particle filter to create an integrated approach. Typically, the traditional particle filter requires the knowledge of a state transition model and a probability density function (PDF) between the measurement and the state Using the sequential importance resampling (SIR) algorithm (Gordon *et al.* 1993), we set the proposal distribution to the state transition function, which generates samples/particle and we then sample these particles based on a series of weights:

$$x_t^i \sim p(x_t|x_{t-1}^i) \tag{1}$$

$$w_t^i = \frac{p(z_t|x_t^i)}{\sum_{i=1}^{N} p(z_t|x_t^i)} \tag{2}$$

Preliminary results have shown promising results from modeling (1) by creating i number of bootstrap samples of training set $([z_t, z_{t-1}, \ldots, z_{t-d+1}], x_{t+L}\ )$, $t = d-1, \ldots, \mathrm{N} - L - 1$, where d is the embedding dimension, t is the time, and L is the time horizon. The proposal distribution in (1) is then generated by the following Gaussian distribution:

$$\mathrm{N}\left(ST_{avg}(z), \hat{\sigma}_{ST}^2(z)\right) \tag{3}$$

where $ST_{avg}(z), \hat{\sigma}_{ST}^2(z)$ are the mean and variances of the i bootstrap sample predictions With respect to (Baraldi *et al.* 2013), the PDF between the measurement and the state can be generated by the following Gaussian distribution:

$$p(z_t|x_t) \approx \mathrm{N}\left(\varphi_{avg}(x), \hat{\sigma}_m^2(x) + \hat{\alpha}_t^2(x)\right) \tag{4}$$

where $\varphi_{avg}(x)$ is the mean of the bootstrap samples $(x_t, z_t)_{t=1}^{N_{training}}$ and the variances $(\hat{\sigma}_m^2(x) + \hat{\alpha}_t^2(x))$, can then be derived using the same dataset. Equations (3) and (4) can be developed by using a DBN and then combined using the weighted sampling scheme in the SIR algorithm. .

The results in Table 3 show better performance on the bearing data using the integrated approach against the traditional particle filter.

Table 3. Integrated approach vs. Particle filter

Combined DBN and particle filter approach		
L	RMSE	MAPE
1	1.62	7.06%
10	3.33	8.52%
Particle filter based approach		
L	RMSE	MAPE
1	2.53	7.47%
10	3.65	8.73%

3.5 Remaining Work

In the next stage of the research, other deep learning methods such as deep auto-encoders with sparse coding and deep denoising auto-encoders will be investigated. The DBN combined particle filter approach will also be tested on the gear data to further validate this method. Mixture density networks will be investigated and experimented with in order to obtain the PDF between the state and the measurement and possibly to model the state transition models.

4. CONCLUSIONS

Predicting remaining useful life of rotating components has been an important task for condition-based maintenance of industrial machines. One critical challenge for performing such task in the age of Internet of Things and Industrial 4.0 is to automatically process massive data and to accurately predict the RUL of these components. The objective of this research is to develop new deep learning based prognostic methods and tools for rotating components using various sensor signals. Our preliminary research results have shown the promising performance of deep learning based prognostic methods for bearing and gears. This research will explore the optimal design and combination of deep learning structures for the best prognostic performance with big data. The developed methods will be validated with real bearing and gear run-to-failure test data.

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