A Physics-based Deep Learning Approach for Fault Diagnosis of Rotating Machinery

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***Abstract*—During the recent few years, deep learning has been recognized as a useful tool in condition monitoring and fault detection of rotating machinery. Although existing deep learning approaches to fault diagnosis are able to intelligently detect and classify the faults in rotating machinery, most of these approaches rely exclusive on data and thus are purely data-driven, and do not incorporate physical knowledge into the learning and prediction processes. To address this challenge, this study proposes a novel approach, namely physics-based convolutional neural network (PCNN), for fault diagnosis of rotating machinery and targets fault detection of rolling-element bearings as a special application of PCNN. In the proposed approach, an exclusively data-driven deep learning approach, called convolutional neural network, is carefully modified to incorporate useful information from physical knowledge about bearings and their fault characteristics. The performance of the proposed PCNN approach in machinery fault diagnosis is compared with that of traditional machine learning- and deep learning-based approaches reported in the literature.**

***Index Terms*—convolutional neural network, deep learning, bearing fault detection, rotating machinery**

I. Introduction

The continuous monitoring of bearing health using sensor signals can contribute to avoiding unanticipated failures and improving the reliability and availability of rotating machinery [1].

For bearing fault diagnosis, signal processing techniques are often utilized to extract the desired diagnosis information from the raw sensor signals. Among the numerous existing signal processing techniques, spectral kurtosis (SK) analysis [2] and envelope analysis [3] have been recognized as among the most effective tools for improving the accuracy and robustness of machinery fault detection.

Traditionally, after extracting characteristic features of fault from the raw or pre-processed sensor signals acquired from an operating bearing, a machine learning technique such as support vector machine (SVM) and artificial neural network (ANN) [4] is often utilized to classify the health state of the bearing [2].

Over the recent years, a new branch of machine learning called deep learning has attracted increasing attention from researchers in the field of bearing fault diagnosis and has been recognized as a powerful tool for health monitoring of bearings. Unlike traditional machine learning techniques, deep learning techniques can directly learn the diagnosis information in sensor signals, without manually extracting features.

The unsupervised learning ability of deep learning has recently inspired many researchers to build deep learning models that mine the often large volumes of unlabeled sensor data to achieve high accuracy and robustness in fault diagnosis of machinery systems. Recently, Lu et al. [5] performed an empirical study on the use of stacked denoising autoencoders with multiple hidden layers to diagnose the faults of rotary machinery systems based on vibration signals. Convolutional neural network (CNN) has also attracted attention from researchers in the field of machinery fault diagnosis. Janssens et al. [6] used a shallow CNN structure with one convolutional layer consisting of wide kernels and a fully connected layer to assess bearing health condition. In their study, the discrete Fourier transform (DFT) was employed to process normalized vibration signals collected by two accelerometers placed perpendicularly to each other.

Although a number of deep learning-based techniques have recently been implemented and applied to monitor the health of machinery systems, little research effort has been devoted to examining how to incorporate physical knowledge into a data-driven deep learning model (e.g., deep belief network (DBN), deep neural network (DNN), and CNN), and more importantly, how to build the knowledge into the model's architecture, making the model physically meaningful. Without such an examination, the deep learning model is purely data-driven and may not be able to reveal and exploit useful information for fault diagnosis that is hidden in the sensor signals (e.g., vibration and acoustics) [7]. For instance, the above-mentioned deep learning approaches to fault diagnosis do not make use of the rotational speed or fault-characteristic frequencies when processing the sensor signals inside the deep learning models. However, it is well known that these physical parameters serve as part of the physical knowledge about rotating machinery and their fault characteristics, and can be useful and even essential to achieving accurate and robust fault diagnosis.

To solve the above-mentioned challenging problem, this study proposes a new deep learning approach called physics-based CNN (PCNN) for fault diagnosis of rotating

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machinery. The proposed PCNN approach has three unique characteristics: (i) three signal processing techniques, namely SK analysis, envelope analysis, and FFT analysis, are added to the front of the CNN architecture as new layers; (ii) the physics-based convolutional layer in the CNN architecture explicitly consider the rotational speed and fault-characteristic frequencies as the inputs in building the convolutional filters; and (iii) a recently proposed multi-channel CNN is adopted to make the PCNN model applicable when multiple sensors are used to monitor the health of machinery systems.

II. Convolutional Neural Network (CNN)

As a multi-stage neural network, CNN starts with multiple convolutional layers, batch normalization (BN) layers, activation layers, and pooling layers, and ends with a classification layer [8].

The convolutional layer convolves the inputs with a set of unknown filters called kernels and then the activation layer generates the output features from the convolved inputs.

The BN layer is designed to reduce the shift of internal covariance and accelerate the training process of CNN. This layer is usually added between the convolutioanl layer and the activation layer.

The activation layer enhances the ability of the network in representing the non-linearity of the input signal [8]. In recent years, a number of activation functions have been developed by researchers in the machine learning community. In this study, we implement Rectified Linear Unit (ReLU) since it can accelerate the convergence when training the CNN model.

Similar to a down sampling operation, the pooling layer can be added after the activation layer to reduce the number of hyperparameters of the network. In this study, we use max-pooling which performs the local max operation over the input features. The CNN architecture ends with a classification layer that is similar to those used in ANNs.

III. Physics-based Convolutional Neural Network (PCNN)

As shown in Fig. 1, the proposed PCNN architecture contains multiple layers, among which some in the front are built based on the physical knowledge about bearings and their faults and the others are purely data-driven. The first layer implements SK analysis to denoise the input signal using the optimum frequency/frequency resolution that maximizes the kurtosis of the subsignal [10]. At the second layer, the denoised signal is demodulated to remove the carrier frequencies while only keeping the diagnosis information.

The next layer, which serves as the most unique part of PCNN, is a convolutional layer that functions based on the similarity between the input signals (data) and the fault-characteristic signals (physics). The kernels in this physics-based convolutional layer are generated based the rotational speed and fault-characteristic frequencies of a bearing. Therefore, no hyperparameters are involved in generating the physics-based kernels. This feature makes it possible to have

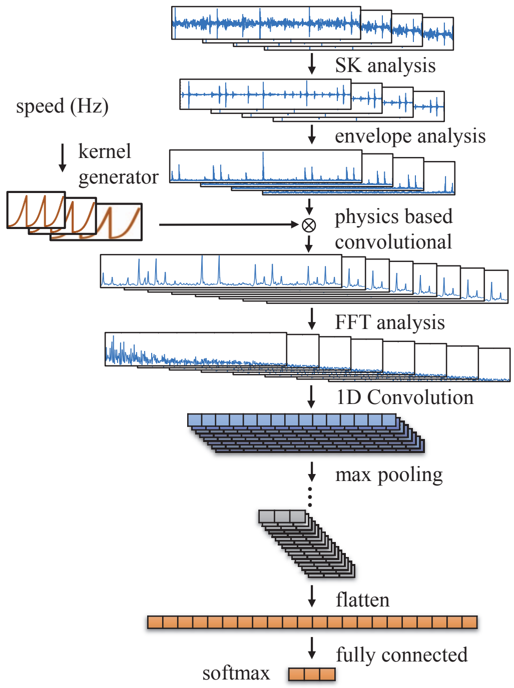

Fig. 1. The architecture of the proposed PCNN.

wide kernels without introducing additional hyperparameters to the PCNN model (see Subsection III-A for more details).

The outputs of the first three layers are in time-domain. However, due to the use of multiple sensor signals as the network inputs and the presence of unknown time delays among these signals, it is essential to convert the signals from the time domain to the frequency domain (see the fourth layer in Fig. 1).

The remaining layers in Fig. 1 (from the second convolutional layer to the last classification layer) are similar to those explained in Section II. Since the first four layers are predetermined based on the physics of bearings and their faults, these layers do not add any new hyperparameters to the set of hyperparameters that need to be learned during the training process. This can help reduce the risk of overfitting, which is a common issue in deep learning models with high-dimensional inputs.

A. Physics-based convolution

Convolutional operator in CNN aims to extract the features from an input signal by quantifying the local similarities between the convolutional kernels and input signal. For instance, if the object is to extract the vertical lines in a two-dimensional (2D) image, the kernels with different vertical lines convolve the input image to find their similarities (vertical lines). In our task of bearing fault diagnosis, a desirable feature should reflect the likelihood that the signal has a modulating frequency close to a bearing fault-characteristic frequency. Therefore, the kernels should simulate the signals produced by faulty bearings. As such, the kernels can be pre-defined based

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on sample fault-characteristic signals. Suppose a bearing has M critical failure models (or fault types). For the m^{th} fault type ($m = 1, 2, , M$), the fault characteristic to be mapped into a PCNN is represented as a hand-constructed kernel that emulates the sensor signal from the bearing in the presence of the m^{th} fault type. These M kernels, once generated, become the reference fault-characteristic signals that capture physical knowledge about bearing faults. A reference signal can be generated by using a simulation model developed in earlier studies on bearing fault physics [2], [9] and takes the following form

$$\phi(k) = a_0 \sum_{s=0}^{n} \left[H(k - s/f_0) \cdot e^{-\xi(k - s/f_0)} \right] \tag{1}$$

where k is the time index ($k = 1, 2, ..., K_w$ with K_w being the kernel width), a_0 is a constant amplitude that accounts for the radial load and fault severity, $H(k)$ is the unit step function and simulates fault-induced impulses that switch on at time $k = 0$, f_0 is the fault-characteristic frequency of the defective bearing, and ξ is the damping coefficient. After generating the reference kernels, an input signal x can be convolved using the following formula

$$(x \otimes \phi)[k] = \sum_{v=0}^{K_w} x(k - v) \cdot \phi(v) \tag{2}$$

where $(x \otimes \phi)[k]$ denotes the convolution of x and ϕ. Fig. 2 shows a sample convolution at the first convolutional layer of the proposed PCNN architecture. The input signal, which has been already filtered and demodulated, contains the fault-relevant information at a characteristic frequency of f_0. This signal is convolved using three physics-based kernels that are generated using (1) with the frequencies less than f_0, equal to f_0, and larger than f_0. By comparing the corresponding convolved signals, it can be clearly seen that the second convolved signal has the highest magnitude. Thus, it can be concluded that convolving an input signal by a kernel generated based on the characteristic frequency of a fault can help reveal the information relevant to the fault that is carried by the signal.

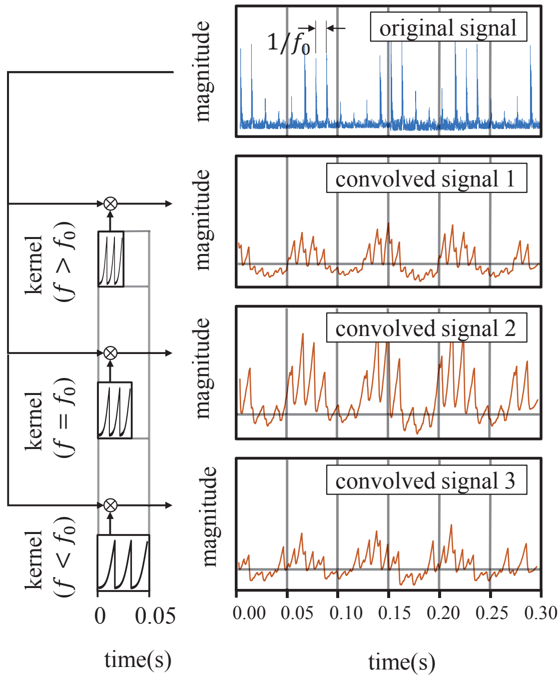

Fig. 2. Convolutional operation on a sample preprocessed vibration signal of a defective bearing. The first plot from the top shows the sample vibration signal of a defective bearing with a fault-characteristic frequency of f_0. The second, third, and fourth plots from the top show the convolved signals using three physics-based kernels generated with the frequencies less than f_0, equal to f_0, and higher than f_0, respectively.

IV. Experimental validation

An experiment was carried out on a machinery fault simulator to evaluate the performance of the proposed PCNN approach in detecting artificially seeded faults of bearings. Two test bearings were mounted on the simulator (see Fig. 3). Eight sensors including four vibrations sensors, two acoustic emission sensors and two consumer microphones were used to monitor the health of the bearings.

Four different types of defect including inner race defect, outer race defect, ball defect, and combination of all defects were introduced to the test bearings. Table I presents the fault-characteristic frequencies of the bearings mounted on the simulator.

The shaft was run under varying rotation speeds from 10 Hz to 30 Hz. To simulate the true behavior of the machinery systems in real applications, the rotor unbalance and shaft misalignment were also considered in the test plan. Table II summarizes the design of experiments used in this case study. In total the simulator was run under 2,340 different testing conditions.

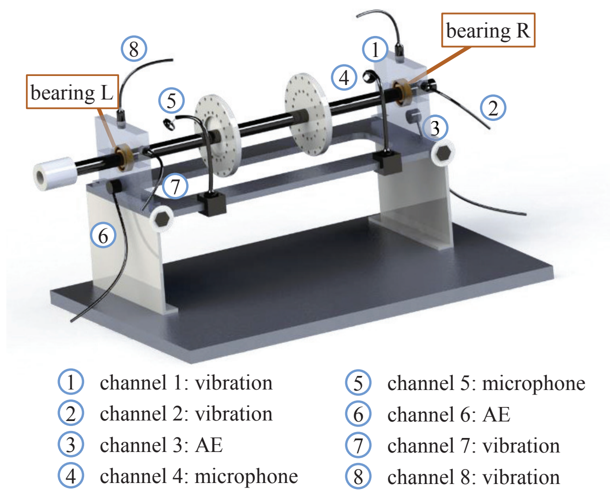

Fig. 3. Machinery fault simulator.

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TABLE I
FAULT-CHARACTERISTIC FREQUENCIES OF THE SIMULATOR BEARINGS

ball pass frequency of outer race f_o	$3.048 \times f_R$
ball pass frequency of inner race f_i	$4.950 \times f_R$
ball spin frequency f_{bc}	$1.992 \times f_R$
fundamental train frequency f_{tr}	$0.378 \times f_R$

A. Parameter of PCNN

Table III shows the architecture of the PCNN model used in this case study. At the first two layers, the input data with eight signals, each of which has 30,000 by 1 elements, are filtered using SK and envelope analysis.

At the third layer, based on the shaft rotating speed and the fault-characteristic frequencies, three reference kernels were generated to simulate the vibration signals of bearings with inner race defect, outer race defect, and ball defect. The size of a kernel depends on the fault-characteristic frequency, the speed of the shaft, and n in (1). In this case study, n was set to 3. At the fourth layer, the convolved time-domain signals are transformed into frequency-domain signals and the first 500 elements are kept as the input to the 5th layer.

At the fifth layer, the wide kernels of the length 48 convolves the input signal with the stride size of 8. The remaining layers followed the traditional CNN architecture explained in Section II.

B. Results

The performance of the proposed PCNN approach was evaluated via the use of two classification scenarios. The first scenario was used to evaluate the ability of PCNN in detecting bearing faults in the simulator and the second scenario to assess the ability of PCNN to identify the locations of these fault (i.e. which bearing(s) are faulty).

The experiment was preformed in 9 different speeds from 10 Hz to 30 Hz. To estimate the accuracy of the proposed PCNN, one set of data corresponding to one speed was left out, as the testing data, and the remaining data was first shuffled and then 30% of that was used for the model validation and the rest for training the PCNN model. This process was performed for each of 9 speeds (at each time one speed was considered as the testing speed). Fig. 4 shows the accuracy of the proposed PCNN in fault detection and fault localization when the testing speed was varied from 10 Hz to 30 Hz. The results suggest that in all speed, the proposed PCNN is able to detect and localize the fault with high accuracy under the noisy environment and the presence of other source of malfunction including rotor unbalance and shaft misalignment.

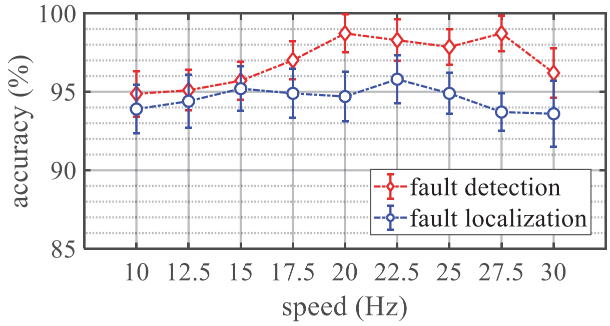

Fig. 4. The accuracy of the proposed PCNN in fault detection and localization under the varying testing speed.

In Fig. 5, the performance of the proposed PCNN approach is compared with the multi-channel CNN and two well-known machine learning-based approaches. It can be seen that for both classification scenarios, the proposed PCNN outperforms the existing approaches. A comparison of the classification accuracy between multi-channel CNN and PCNN suggests that incorporating physical knowledge directly into the architecture of a deep learning model has the potential to significantly improve the performance of the model.

TABLE II
DESIGN VARIABLES

parameter	value
shaft speed (Hz)	10, 12.5, ..., 30
misalignment level (in)	0, 0.01
rotor unbalance (gr)	0, 5
bearing 1 condition	no defect, inner race defect, outer race defect, ball defect, combination of defects
bearing 2 condition	no defect, inner race defect, outer race defect, ball defect, combination of defects
trials	1, 2, ..., 10

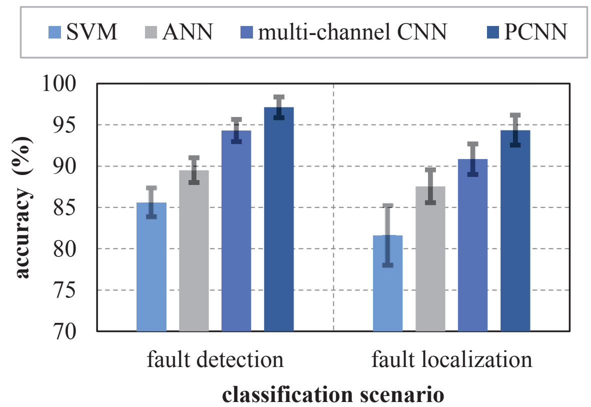

Fig. 5. Accuracy of different methods in fault detection and localization.

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TABLE III
THE ARCHITECTURE OF THE PROPOSED PCNN

no.	layer (type)	kernel size	number of kernels	kernel stride	output shape (width, depth)	padding
1	SK	-	-	-	30000, 8	false
2	envelope	-	-	-	30000, 8	false
3	convolution 1	[6100-10640]	3	1	30000, 24	false
4	FFT	-	-	-	500, 24	false
5	convolution 2	48	8	3	151, 24	true
6	max pooling 1	2	8	2	75, 24	false
7	convolution 3	9	16	3	20, 48	true
8	max pooling 2	2	16	2	10, 48	false
9	convolution 4	3	32	1	8, 96	true
11	max pooling 3	2	32	2	4, 96	false
12	convolution 5	3	32	1	2, 96	true
13	global max pooling	2	32	2	192	false
14	fully connecter	100	1	1	100	true
15	softmax	2	1	-	2-4	-

V. CONCLUSION

In this study, a novel approach named physics-based convolutional neural network (PCNN) is proposed for fault diagnosis of rotating machinery, with a special application to fault detection of rolling-element bearings. In PCNN, the conventional CNN is modified to incorporate useful information from physical knowledge about bearings and their fault characteristics. Based on the bearing fault-characteristic frequencies and the shaft speed, new physics-based kernels are generated for use in the first convolutional layer of the proposed PCNN model.

An experiment is carried out on a machinery fault simulator to examine the performance of the proposed PCNN approach in monitoring the health of multiple bearings. Compared to the conventional machine learning- and CNN-based approaches, PCNN is able to detect and localize the faults with higher accuracy.

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