Condition Monitoring of Electric Motor with Convolutional Neural Network

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Abstract. Safe, efficient and uninterrupted operation of machine requires continuous monitoring of its health and modern autonomous smart factory demands a Condition Monitoring (CM) process without direct human involvement. Deep Learning (DL) algorithms have shown great success of learning directly from data in various real life applications and recently it become also popular in CM researches but still detail clarification of selecting the DL design and its relevance to learn the features from data are often missing. This paper shows a DL algorithm - Convolutional Neural Network (CNN) to CM of an Electric motor from its external vibration. The output of the deep layers of the learned model is analyzed to explain how the model extract features of raw vibration input and do the classification of different conditions.

Keywords: Condition Monitoring (CM) 1; Convolutional Neural Network (CNNs) 2; Feature Map 3;

1 Introduction

In the age of the fourth Industrial Revolution, application of Artificial Intelligence is not just a demand but a necessity. A smart factory involves numerous machines and sensors requiring machine to machine and machine to human communication without interruption. Condition monitoring and predictive maintenance of the machines to prevent failure in advance or detect any anomaly early enough before breakdown is one of the key trends of Industry 4.0.

Application of Machine Learning (ML) algorithms in the field of Condition Monitoring (CM) of Electric machines (EM) has been investigated and implemented in reality in various researches for the last several years, but this is still relatively new and has a lot of room for improvement. Vibration based CM of EM has been found very effective as the vibration frequency analysis can uncover several electrical, mechanical defaults and as well as running conditions of the machines. But for such analysis exact parameters of the machine and its drive is required and furthermore in real life impending fault signatures are not as ideal as theoretical fault signature. ML algorithms can learn from monitoring sensor data without prior knowledge of the EM and traditional ML based CM process involves extraction of useful information from raw data and use the extracted features as input of the ML and finally classify different faults. This feature extraction rules is often depend on the domain, so the same algorithm may not work for other domain or motor drive. Deep Learning (DL) algorithms which can directly learn the features from data have recently become very popular approach in many fields because of advancement of computation power, cloud computing, simpler tools or frameworks and also for easily accessible large database.

The presented paper is a continuation of previous work where novel convolutional neural network (CMCNN) architecture was shown to detect bearing faults using a public dataset [1]. In this work we used a newly generated vibration dataset for bearing faults to model the CMCNN architecture for multi-sensory input. Separately generated test data is used to evaluate the accuracy of the model and the learned model's deep layers are analyzed to understand the feature extraction process.

2 Related work:

The challenge of beginning researching ML and DL algorithms for CM or fault diagnosis is the access of dataset because creating a realistic mechanical fault dataset generating test-bench is complex and costly. For vibration based rolling bearing fault diagnosis the dataset produced by Case Western Reserve University (CWRU) is the most popular and easily accessible dataset that has been considered as standard reference in many publications [3]. Neupane and Seok reviewed a large number of publications regarding DL algorithms using CWRU dataset in their paper [3]. Smith and Randall have analyzed the entire dataset of CWRU to recommend benchmark for diagnostic technique [4]. CWRU dataset has mainly six classes of data: healthy, inner ring fault, rolling element fault and outer ring fault at three load zone [2]. The faults were implemented in sizes of 0.007 to 0.028 inch with Electric Discharge Machining and the monitoring bearings were either at Drive-side (DE) or Fan-side (FA) of the motor. All the vibrations are measured with three sensors located at DE, FE and at base plate and measurements were taken for four motor speeds.

Various DL algorithms like Deep Belief Networks (DBN), Autoencoder (AE), Generative Adversarial Networks (GAN), Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN) etc. are investigated to detect bearing faults using the CWRU dataset in the literatures. Stacks of AE based deep neural network (DNN) is applied to classify CWRU dataset among ten classes considering different fault sizes as different classes by Jia and et al, where they used the frequency spectrum of the raw data as the input [2]. Shao and et al. showed DBN based bearing fault classification using both simulated vibration data for inner and outer ring fault and the CWRU dataset dividing all the dataset into ten classes [6]. Jiang and et al proposed a deep recurrent network (DRNN) to automatically extract feature from input spectrum and diagnose rolling bearing fault in their work [7]. They consider frequency domain signal as input believing noisy vibration data may not be robust. The proposed DRNN has stack of recurrent hidden layers of long short-term memory (LSTM) units and classify the CWRU dataset into 12 conditions. GAN based fault diagnosis on CWRU dataset is studied by Jiang and et al [8]. Their idea of implementing GAN algorithm to differentiate faulty vibration from healthy vibration as anomaly detection, relating with real industrial scenario where faults appear in the bearings after millions of cycle hence data collection for faulty bearing is difficult. For Robust feature extraction and fault classification Shaheryar and et al proposed hybrid model (MCNN-SDAE) of two layers multi-channel CNN combined with three stacks of Denoising Autoencoder (DAE) using the CWRU dataset [9].

Gua and et al showed a hierarchical adaptive deep convolutional network (ADCNN) using CWRU data where the 1D vibration is converted to 2D matrix and they tested their model for both fault classification also fault size predictions [10].Wide first-layer kernels with deep CNN (WDCNN) model is proposed by Zhang and et al also using the CWRU data [11]. They used data argumentation technique which is basically dividing the long signal into segments to create bigger dataset in which the input width is 2048. Some sets of the training data were overlapped segments and some were not. Their five layer CNN was designed as the first layer has wide kernel size and following layers have very small kernel width and finally the model classified 10 labels. Other works of CNN based bearing fault diagnosis are presented in the literatures [12-15].

The investigated works in the literatures mostly used same dataset to test their model accuracy to test their domain adaptively for example the fan-end and drive-end vibration information should be clearly different and most cases it is not clear if they considered fault classes for both locations learn the domain robustly or not. Another most interesting note is many of the studies considered the faults sizes as separate classes, where the CWRU dataset fault sizes are clearly different (0.007 inch, 0.014 inch, 0.021 inch) which should be easily diagnosable. Among many DL based CM approaches, CNN has shown the most suitability of using raw data directly.

In our previous work we used the CWRU dataset to train CMCNN model and classified the classes considering both location of the bearing and fault sizes in same class. The aim of the current work is to introduce a new dataset to model the CNN model where same design approach is considered as CMCNN presented in previous work [1].

3 Dataset: IEEM - CMData

The dataset contains external vibrations of a motor having different types of faulty bearings at various speed and load combinations. External vibration means it should contain more noise or additional vibration from the rotating parts which is ideal for industrial applications. The bearing data generating test-bench is developed at the Institute of Energy Efficient Mobility (IEEM) of University of Applied Science and Technology Karlsruhe and supported by SEW-Eurodrive GmbH (SEW). In the Fig. 1 a view of the test-bench (left) and the CAD design (left) is shown.

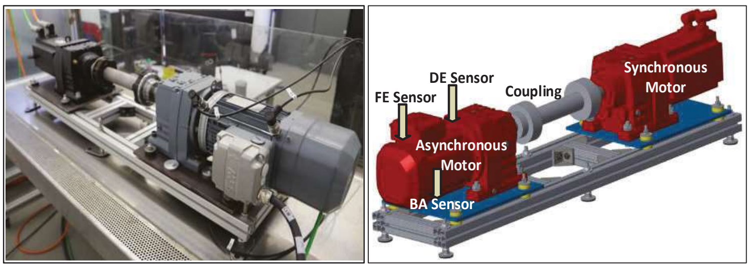

Fig. 1. IEEM-CMData test bench

The test-bench has test motor of power 0.75 kW and speed of 1440 RPM which is an asynchronous gear motor (R47 DRN80M4 by SEW) with 8.01 gear ratio connected thorough a highly flexible coupling with the load motor of output torque 144Nm, speed of 3000 RPM which is a synchronous gear motor (R47 CMP80M by SEW) with gear ratio 3.83. Artificial faults were implemented on different parts of the deep groove ball bearing (6304-2RSH by SKF). Three acceleration sensors (iCS80 by IDS Innomic GmbH) were installed near FE, DE and base plate (BA) to measure the vibrations. For training all types of data are generated for both bearings at Fan-End (FE) and Drive-end (DE) at two different sample rates. In this work the sample rate of all input data of the model is 12.8kS/s. National Instrument's cDAQ-9174 is used for data acquisition and data processing is done with MATLAB 2018a with additional package NI-DAQmx.

Fig. 2. Example of engraved spall in the inner-ring (left) and example of reduced amount of lubrication for measurement (right)

Artificial faults are implemented on different parts of the bearing to achieve different types of faults and one third of the recommended lubrication is used during measurements. Fig. 2 shows an example of a prepared bearing having a small inner-ring spall created by electric engraver (left) and the amount of lubrication used for the measurement (right). Table 1 contains the description of different types data created for the dataset with short names and labels of classes for the model. Among all prepared bearings, ten bearings (Training Bearings) are used to create training data for the CMCNN model and three bearings (Test Bearings) are kept for testing the model. Four speeds (Speed-1 to 4) and five loads (Load-0 to 4) were pre-selected for the measurements, which are called Known Speed-Load data used for training the model and some data are collected at randomly selected Speed and Load combinations which are called Unknown Speed-Load data used for testing the model accuracy.

Table 1. Fault description and short naming of the data types with labels for the model

Fault Description	**Short Name**			**Class Labels**			
	Fault	**DE**	**FE**	**4 class**		**8 class**	
Healthy(NO)	NoFault	DEOK	FEOK	0	0	20	10
Inner ring ((IR) spall of 2mm(S1)	IRSpall	DEIRS1	FEIRS1	1	1	21	11
Inner ring (IR) spall of 3.5mm(S2)	IRSpall	DEIRS2	FEIRS2	1	1	21	11
Outer ring (OR) spall of 2mm (S1)	ORSpall	DEORS1	FEORS1	2	2	22	12
Outer ring (OR) spall of 3.5mm (S2)	IRSpall	DEORS2	FEORS2	2	2	22	12
Rough rolling surface (RR)	RRSurface	DERR	FERR	3	3	23	13

4 IEEM-CMCNN Architecture for Bearing Fault Classification

The model is named as IEEM-CMCNN; has input of three channels 1D data, six convolution layers, three Fully-connected layers and four or eight output classes. The detail architecture of the IEEM-CMCNN is described in the Fig. 3.

The input is a three-channel 1D vibration data considering three sensors at three positions. The first channel contains the main-sensor data, second channel belongs to the opposite-sensor data and third channel for the base-sensor data. Main-sensor for the FE bearing is the sensor at FE and sensor at DE is the opposite-sensor; for DE bearing this is reversed accordingly. During training the input of IEEM-CMCNN is a fixed-size: 1 x 1000 x 3 vibration data. The one dimensional vibration input length is considered as approximately one revolution of the motor shaft as described in previous paper [1]. No pre-processing is done on the training dataset.

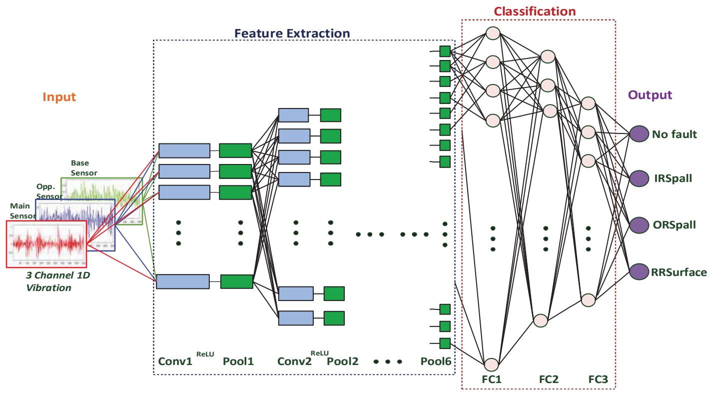

Fig. 3. IEEM-CMCNN architecture for four fault classes

The three sensor vibration input is than passed through stack of six convolution (Conv) layers. At the first layer the filters have very large receptive field i.e. 1×50 and gradually reduced sized filters towards higher level thus at final layer filter size become 1×2. The convolution stride is fixed to 1×1 and padding varies from lower layers i.e. 24×24 to higher layers i.e. 2×2 (where the stride and padding size is to capture left/right centre). The last Conv Layer padding is 0×0. The convolution stride and padding in layers are calculated in way to preserve the most of length of the input of each layer. After first Conv layer one batch normalization layer is kept. Each convolution layers are followed Rectified-Linear unit Layer (ReLu) to remove the negative value, those followed by Max-Pooling layers (Pool) of window size 1x2 with stride 2 and zero-padding.

The stack of Conv layers is then followed by three fully connected (FC) layers: first FC layer has 1024 channels with a ReLu layer, second FC layer has 1000 channels also with one ReLu layer and third has same number of channel as number of class. The final layer is soft-max layer. We compared different architecture of different number of filters after analysing the filter activities at each Conv layer: in this work the developed architecture has similar number of filters as VGG16 [16].

The training was stopped when accuracy is not improving after 3 epochs.

5 Model Accuracy Analysis

As discussed in Section-2, most of the literatures considered to classify all data types where FE and DE data should be easily detectable. In this work we compare two models: 1) training the model for four classes (Model: 4-Class) where location of bearing (DE and FE) is not known to the model and 2) training the model for eight classes (Model: 8-Class) where two bearing locations belonged to different classes.

The accuracy of the models are also evaluated by testing Unknown speed-load data from training bearings and test bearings as well as Known Speed-Load data from test bearing. This way, the test data can be divided into three groups: 1) Unknown Speed-Load data from Training Bearings (UnSpLd_TrBr), 2) Known Speed-Load data from Test Bearings (KnSpLd_TsBr) and 3) Unknown Speed-Load data from Test Bearings (UnSpLd_TsBr).

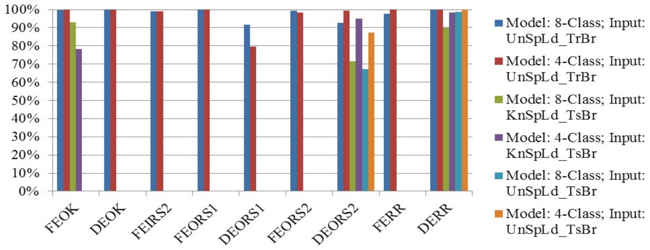

Fig. 4. Test accuracy comparison for 4 Class Model Vs 8 Class Model

Model: 4-Class and Model: 8-Class both has average training accuracy above 99% and to evaluate the performance accuracies are checked per class labels. In Fig. 4 the performance of two models are compared for fault sizes and location of the bearings. The labeling of the classes is given in Table 1.

6 Feature Map Analysis

DL based CM of electric machine has been successfully applied in many researches but in general it is still not clear why the fault detections were made with high accuracy and how the network is learning the features from vibration. In a previous work [1], we analyse the first Conv layer output by converting them to frequency domain and showed that a significant range of frequencies were learned by each filters for each classes. In the paper [11] the authors also focused feature visualization with FFT and showed feature distribution for each layer and each 10 classes using Stochastic Neighbour Embedding (t-SNE). In this work, we focused on understanding the how in all convolution layers features are learned and thus the classes are separated.

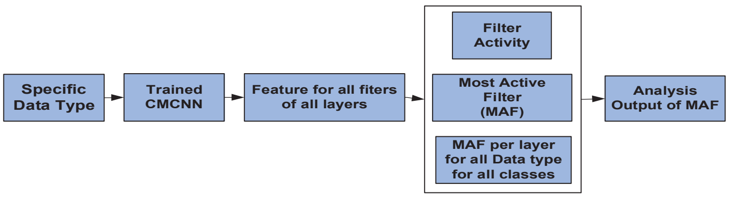

Fig. 5. Tasks involed for analysis the feature map of trained IEEM-CMCNN

One feature visualizing technique in computer vision is to feed the network with large amount of dataset and keep track of which images highly activate some neurons, which is shown by Girscick et al [17]. We followed similar approach, aiming to understand among number of filters in the convolution layers if certain filters are contributing to learn the features comparing other filters of the same layers.

The tasks involved to analyse the feature map of IEEM-CMCNN can be described by Fig 5. As the trained dataset has different motor operating conditions and two bearing locations in first step we define the Data type, so one specific class (i.e. IRSpall) has 4 Speeds times 5 Loads in total 20 types of data type for both bearing location. Each type of data is feed through the trained model and all the feature maps of all the filters of all layers are saved for later analysis. Filter activity is measured by calculating the area under the curve of the Pool output. In Fig. 6 the Conv output or the feature map of all six layers (left) for one input for DE bearing at Speed-4, Load-4 and the filter activity pointing the most active filter in red star at all layers for the same input (right) is shown. It is seen that at each layer one filter is highest active than others; for example at layer-1, filter-3 is most active among the 16 filters and at layer-6 filter-338 is the most active among 512 filters.

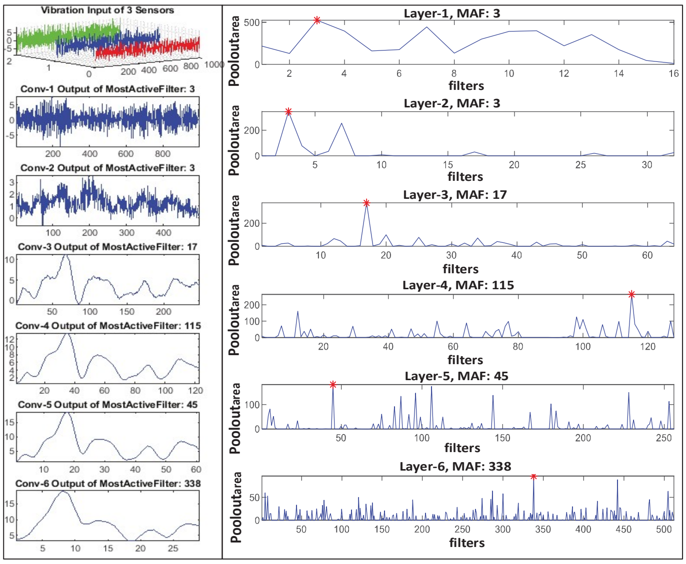

Fig. 6. Convolution output or Feature Map of all layers (left) and filter activity for the same input at all layers (right)

In the next step for all data type Filter Activity is checked thus the most active filter (MAF) of all data type is known. MAF means for all 128 inputs of a specific data type most of the time (i.e. 90% times) one particular filter is always highest active. In Fig.7 MAF for all 20 data of for both bearings are shown for four layers. In the similar figure MAF for one test data (TsKnLd) is also plotted and it is shown that almost all time MAF for test data and training data are same. In this way it can be concluded that for one trained model some certain filters are contributing to learn the class features and now these features of MAFs can be examined to know if the features are more differentiable for classes and thus fault classification is highly accurate. In Fig. 8 extracted feature or Conv output of MAFs for four classes is plotted over each other over for 1^{st}, 2^{nd} 4^{th} and 6^{th} layers and it is observed that from to higher layers the classes are becoming more distinguishable and thus easily diagnosable as different class.

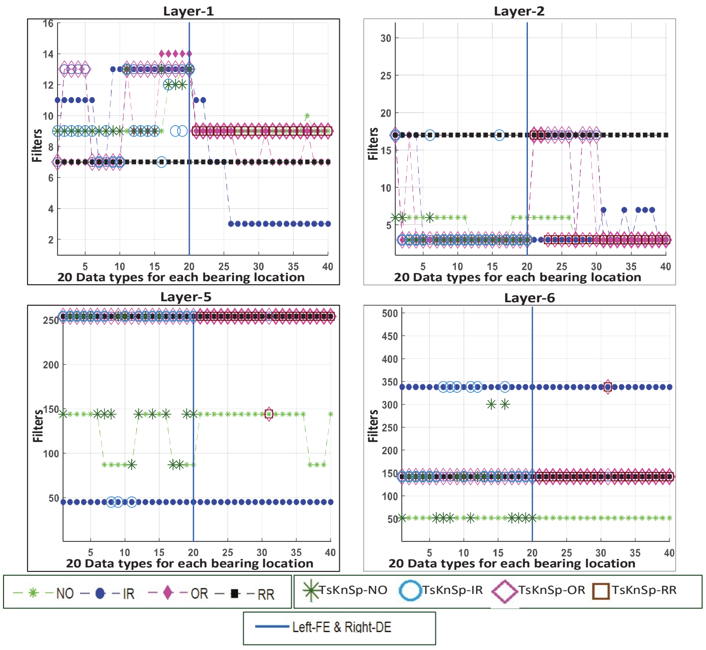

Fig. 7. MAF for all data type for four layers (1st, 2nd, 5th and 6th) of trained IEEM-CMCNN for 4 classes

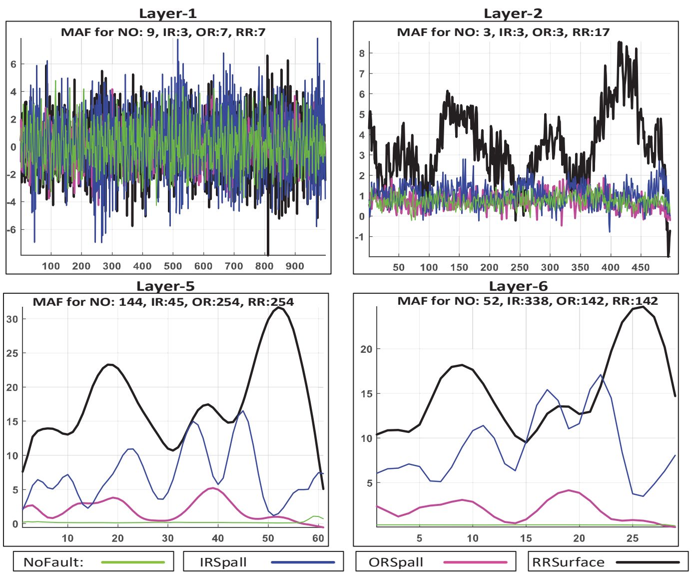

Fig. 8. Extracted features or Conv output by the MAF relevant to the classes at four layers (1st, 2nd, 5th and 6th) of trained IEEM-CMCNN for 4 classes

The plotted Conv outputs of all classes are of same Speed-Load, that means all the inputs has same noise or vibration infused in their data and the different fault classes should have different significant pattern after de-noising. In Fig. 8 we can see that the infused noise in this case the healthy or NOFault (in bright green colour) is becoming less and less visible in higher layers and the patterns of the fault classes are becoming more visible in higher layers.

7 Conclusion

This work shows that the design criteria for the CNN architecture in previous work can be adapted for different test-bench data. The accuracy comparison in section-5 (Fig. 4) reveals that both models can detect fault classes with high accuracy for both Training Bearings and Test Bearings. The feature analysis explains how in deep layers the model learns the features for different classes.

This work shows the approach of designing the input size for vibration based bearing fault detection applied for CWRU dataset also adaptable for IEEM-CMData. The multi-channel input design can be considered in other applications where multiple sensors are involved. Feature analysis shows that how features are learned from noisy data similar like computer vision where it is known that lower layers detect the low-level features like edges, dark spots and high-level features like shape, object are learnt in the higher layers. It shows in vibration based detection the lower layers are de-noising the data and in higher layers the pattern of the vibration curve which is becoming trainable for the classifier or final layer with high accuracy. This analysis approach can be implemented in different vibration based problems and number and thus sizes or numbers of filters in each layer can be analyzed to optimize the model architecture.

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