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Identification of Size and Location of Bearing Damage via Deep Learning

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Abstract

Rotating machine is one of the most important machines used in various sectors. The most important unit is the rotating part and the shaft held by bearings. Most of the maintenance and repair cost of these machines is related to the replacement and service of bearings. Therefore, it is very important to identify the damaged bearings and determine the location of the damage. Different methods have been developed to monitor their condition, including recording and analyzing the vibration signals of bearings. So far, vibration-based methods have often been used to analyze them. Recently, the use of machine learning and deep learning techniques have been considered. Therefore, in this paper, a convolutional neural network is developed that directly receives the raw information recorded by vibration sensors as input and after analysis, a healthy bearing is detected from a defective one, the location and size of the damage are determined. In this research, the data set of Case Western Reserve University is used to validate the model and the results show that the proposed model has very high accuracy for analysis of samples.

Key Words: Rotary Machine, Bearing, Fault Detection, Reliability, Deep learning, Convolutional Neural Network

Introduction

Rotary machines such as electrical motors, turbines, compressors and pumps are the main components in the most industries, which use a rotating shaft or shaft to do their function. For example, in a milling machine, the movement of the machine tool and axes is due to the rotation of an electrical motor, or in a gas turbine, the shaft and blades connected to it and connected to a generator are rotated. All of these machines use bearings as supporter and axle supporter. Failure of these bearings is one of the most important factors for stopping or reducing their efficiency. Bearings have deferent shapes and sizes. Due to their wide application in industry, design principles and classic formula related to their design and initial estimation of their life can be found in mechanical component design books and bearings catalogs. However, due to their vital importance in some industries, as well as uncertainty in their life, as well as the variety of damage models and failure locations in a bearing, research on them, especially their life expectancy, has always been considered and today the use of modern monitoring methods and advanced computational methods are also of serious interest. Therefore, in this article, the issue of bearings and estimating the location and size of damages using deep learning techniques based on data recorded by the American University of RCWU is examined.

Bearings and damage types

Bearings are a sensitive component of rotary machines that are used as sliding, rolling or combination.

Due to the working conditions and the way of using bearings, their consumption is very high and in our country, over one hundred million bearings are annually used in various industries. This volume of consumption indicates the importance and extent of damage that can be noticed. Factors which in impress the failure and damage of bearings are various, but the most important factors are:

- The amount of the load applied more than expected value
- Lubrication is incomplete or unsuitable
- Improper installation
- Ineffective sealing and penetration of external items such as moisture and abrasive particles
- Impact load and suddenly shock

Due to the variety of destructive factors, various damages occur in a bearing, for example: a failure is appeared due to fatigue, cracking, wear, locking,heating and corrosion processes. The most of these factors increasethe temperature during operation and the bearing to heat up, and also the most of them lead to vibration in the bearing components and even in a critical condition lead to the production of undesirable sounds. Therefore, the use of methods based on vibration and acoustic analysis in health assessment and prediction of failures has received much attention. In the next section, some research in this area will be reviewed.

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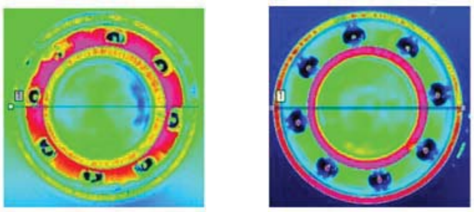
A review of previous research

The subject of bearings and damage detection in them has always been the focus of researchers and industrial users. So that various methods have been used for this purpose. The most common methods are oil analysis, thermography, vibration analysis and sound propagation. In the oil analysis method, the particles in the oil used for lubrication or cooling, are analyzed. The amount (number) and type of particles in the oil are the most important factors in this analysis. This method was very popular in the past when the condition monitoring equipment was not very developed, and today it is less used, but it is more used to monitor the condition of gearboxes. For example, Peng et al. Tried to determine the cause of wear in roll bearings by online analysis of abrasive particles in oil and examining their shape [1]. The use of thermographic tools and bearing temperature analysis during operation is one of the useful methods for examining and analyzing rotating machines because during operation of machines due to friction between moving parts, a section of the energy is converted to heat and causes the temperature of parts to be increased. In the process of designing and manufacturing different types of bearings, efforts are made to minimize the amount of friction, but during operation and especially when a damage occurs in it, the amount of heat produced and the temperature of bearing components are increased.Thus increasing the temperature and temperature distribution map in bearings can be considered as an indicator. The following figure shows an example of the recorded changes for an industrial bearing at 3000 rpm [2]. Morales et al. Also used this method to diagnose bearing failure of an induction electric motor [3].



Normal condition **Lubrication weakness**

Figure 1. Temperature variation in a damaged bearing

Sound propagation or acoustic emission is one of the advanced methods used to check and control the quality of parts. This method is used to investigate the creation and growth of defects such as cracks. Sound propagation refers to the production of elastic (mechanical) waves caused by a sudden change in stress level in a component. When an external factor such as force or heat or pressure is applied to the body, the concentrated sources of energy in the material begin to release elastic waves, which propagate to the surface of the part and are detected by a sensor. By data collection and analysis, useful information can be discovered about the cause of breakdown and damage in the bearing. This method has been used by many researchers. Liu et al. Used sound propagation to detect a wind turbine bearing failure [4].

Using vibration analysis is probably the most widely used method of the condition monitoring of rotating machines. In this method, the vibration waves generated by the components of the machine are collected and analyzed. Generally, the frequency of the waves is recorded in the range of zero to 15000 Hz and the damaged part is identified by performing mathematical analyzes. In this method, the following three techniques are usually used for measurement and analysis: time domain, frequency domain, and time-frequency domain. Recorded vibration is a complex signal and a combination of several waves with different frequencies that must be processed and interpreted. In these techniques, the goal is to analyze the values recorded by the sensors and calculate frequencies that are generated due to a fault or more. In this method, the type of defect is determined by examining the recorded frequency and rotational speed. BakhtiariNejad et al. presented a suitable theory model for determining the vibrations of bearings after failure and their model have been evaluated by performing a practical test [5]. In the last decade, the use of neural networks along with common methods such as vibration analysis has led to the expansion of these techniques and their performance in assessing the health of the rotarymachine and increase their accuracy. The use of these techniques in online monitoring has also been considered. Some of these researches are described below.

Paul Everett et al. proposed an inexpensive method for establishing a roll bearing monitoring and troubleshooting system of a neural network-based induction motor [6]. Johar bin Ali et al. tried to troubleshoot bearings using an experimental relationship, a neural network and analysis of recorded vibrations. They also provided a health indicator for this [7]. Farsi and Hosseini also used a multilayer neural network to estimate the remaining useful life of a bearing. They filtered the values recorded by the vibration sensors using statistical distributions and removed the noise. Then, by the utilization of a multilayer neural network, they estimated the amount of bearing damage and calculated the time remaining to achieve a critical value of failures, for bearing replacement process [8]. Although the use of stochastic and probability-based methods along with the methods of expression in the previous sections have been developed, but in recent years with the development of machine learning knowledge and especially deep learning techniques, their application in this field have been considered by several researchers. This topic will be explained in the next section.

Machine Learning

Today, condition monitoring equipment and methods have been developed, and a variety of sensors and data collection techniques have been improved. The collected data plays a very important role in analysis, decision making, and maintenance planning. This data is generally largely called big data and may change over time or under the influence of other influential factors. Therefore, one of the horizons ahead is the increasing use of computer engineering knowledge, or in other words, artificial intelligence utilization, from the processing and analysis of collected data from the monitoring of the situation, especially continuous data collection. Artificial intelligence-based methods, especially deep learning, can process large amounts of data with appropriate accuracy and speed. Also, they can be used somewhat independently of the type of data (data from thermographic images or vibrational data, etc.). In recent years, the use of these techniques has grown very rapidly [8-11]. The use of these methods is recommended for higher efficiency (Figure below).

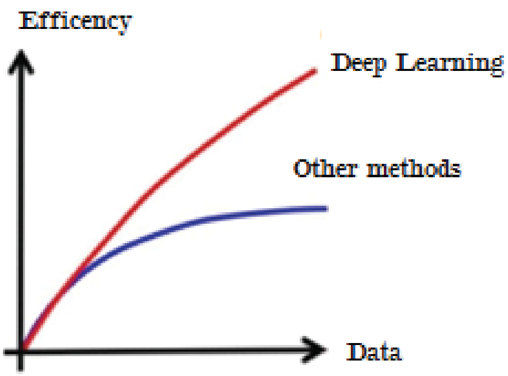


Figure 2. Comparison among traditional learning methods and Deep learning

Various algorithms such as convolutional networks [12], backup vectors [13], and self-cryptography [14] have received more attention. Also, to promote research in this field, various databases have been created based on the results of practical experiments. The most famous of them are as follows:
Case Western Reserve University Database (CWRU)
PRONOSTIA Database [15]
Paderborn University Database [16]
The Case Western Reservation (CWRU) data is applied to develop a convolution neural network for bearing failures, which is described in the rest of the paper.

Data used

The Case Western Reserve University dataset is a big data collected from a ring test asFigure 3. In this rig test and data collection equipment, an electric motor with a power of one or 2 Hp (left) and a dynamo motor with a power of 3 Hp (right) and a torque converter / encoder (middle of the image) are used. Data collection is performed by two accelerometers connected to the drive and the fan connected to it at 12KHz and 48KHz. This data is now available on web and has been used in many researches in the field of machine learning as well as deep learning [17].

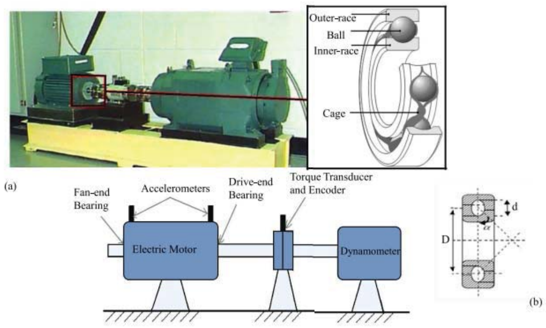


Figure 3. Laboratory equipment for bearing data collection

In this database, a type of damage and failure has been created on each bearing by using spark machining (electrical discharge) process. SKF bearings were used in these tests, so that the failures as holes were implied on different parts of them. The dimensions of this hole are also different. In this paper, thedata is used that it has been collected from a test rig that includes the electrical motor with 1 Hppower and 1775 RPM speed.Three sizes of the hole in this study are 0.1778, 0.3556 and 0.7112 mmwhich they were created on the inner and outer rings and oneball. In this study, the data recorded from damaged bearings and an undamaged sample of the same bearing has been used. Because the purpose is to evaluate the ability of the proposed network to identify the damaged part and determine the location and size of a damage. The data recorded by this collection process for healthy and defective bearings are presented in Figure 4. These data collected show when a bearing is damaged, the vibration domain is increased and we can use this variation for fault detection.

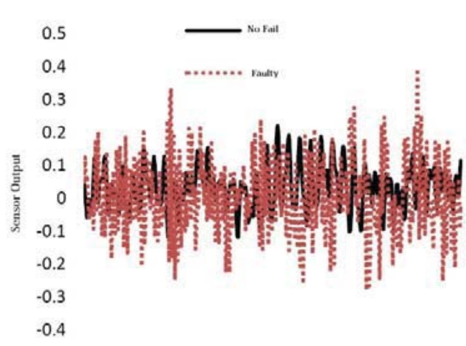


Figure 4. Vibration sample recorded for healthy and defective assembly

Convolutional Neural Networks

Convolutional neural network (CNN) is a new type of neural network that has been proposed in the last decade as a pioneer of deep learning methods and it commonly is applied in machine vision, especially classification problems. This method is now used by large companies such as Google, Facebook, Amazon, etc. For instance, Google uses this technique in its image search engine. The most application of this method so far has been in the separation and identification of images.

In a CNN, an image or system mode is considered as input; this datais imported in a complex network with several convolutional and nonlinear layers. In each of these layers, operations are performed on it to extract the final output. For example, in one layer, the edges of the image are identified, and at the end, in the output layer, a class or the percentage of occurrence of several different classes is displayed. The main and important part of this network is the middle layers, and how they work?

The first layer in a CNN is always a convolutional layer which input is an array of numbers. In general, the inner layers are responsible for maintaining dimensions and nonlinear affairs. Several and different layers can be used as inner layers. When the number of these layers is increased, usually, the capability of the network is increased and learning is deeper. In the last layer, the output of the other layers is received as input. The output of the last layer is a vector with N items. N is the number of predefined classes. For example, if your network detects numbers and handwriting, the number of classes is tens; Because we have ten numbers that should be classified. In the final vector, each component represents the probability of similarity of an input to a class, so thatthe higher probability demonstrates the more similarity. The following figure shows an example of the structure of a CNN.

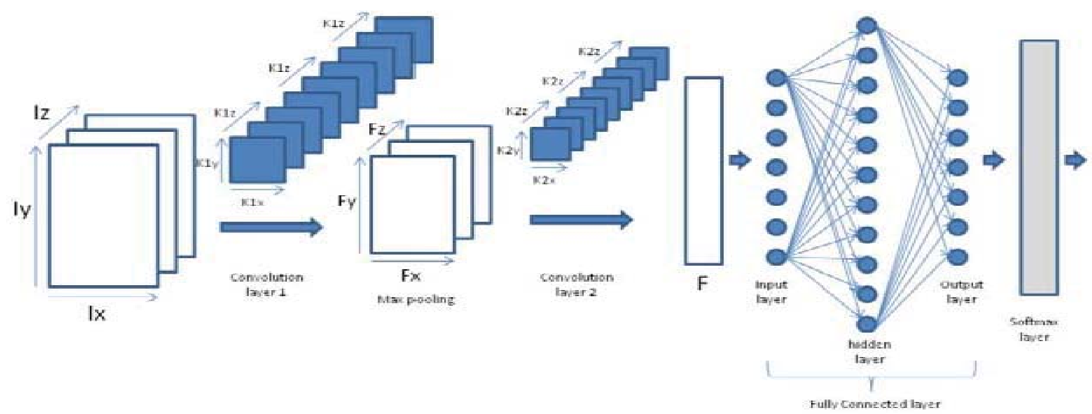


Figure 5. Structure of a convulsive neural network [18]

Network training and evaluation

Almost all deep learning methods require a training process, so some of the available data is used for training and some for evaluation and testing. In this paper, data samples presented by the WCRU database were used to identify defective bearings from healthy bearings, as well as to determine the location and size of the damages. For this purpose, a convolutional network is be developed to analyze the raw values (data) collected by sensors. This network processes input data and produce an output in the form of a seven-dimensional vector that indicates a defective bearing, also the location of the damage (on the inner, outer ring, or ball), and the amount of damage (three artificial grooves of different sizes) are determined. The main point of this article is to use the raw data in the database and not to do any pre-processing and filtering or changing of them. It should be noted that most methods require noise filtering and removing, also sometimes initial frequency analysis should be conducted. This advantage reduces processing time and increases the possibility of online analysis to monitor bearing status.

To analyze the recorded vibrations, a CNN with the structure shown in Figure 6 is created and implemented using the Python programming language.

In this network, 33 sets of nets were used to train and evaluate the network. In other words, each time the loop is repeated, the values consist of the 33 time-series sets (including 400 data recorded by the sensor), which generally include all modes (their order is randomly selected). This data is used for the optimization of network parameters and determining the final coefficients are performed using the ADAM optimizer.

According to the trial and error, the best result is obtained for 200 repetitions, the changes are made and the reduction of the error process in each repetition is shown in Figure 7.

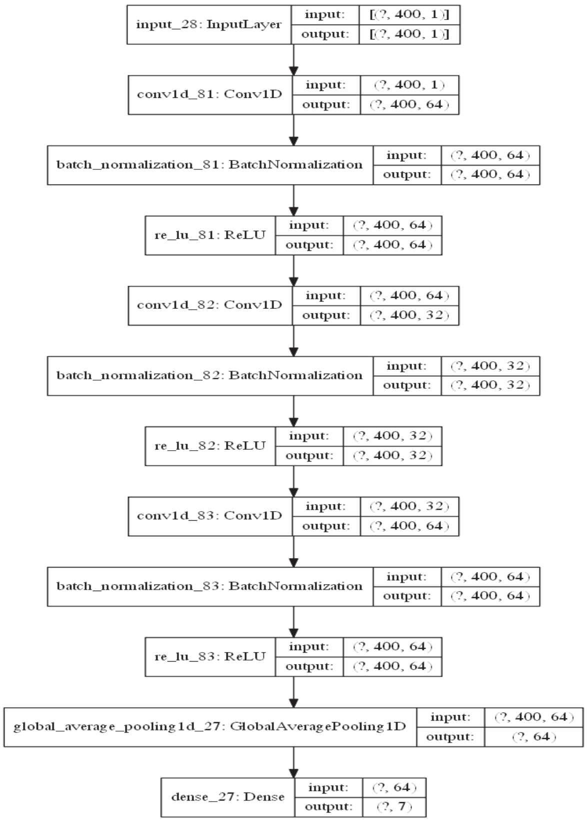


Figure 6. The proposed CNN structure

As shown in this figure, the convergence rate was very high for the training samples but slower for the test and evaluation samples, but this convergence has occurred over time. It should be noted that in this research, 1400 samples and data series were used for training and 140 data sets for evaluation and testing, and none of the network evaluation samples were used during the training. In total, the number of recorded data used in this analysis is 616,000 data, this matter indicates that a special method is required to analyze this large volume of data.

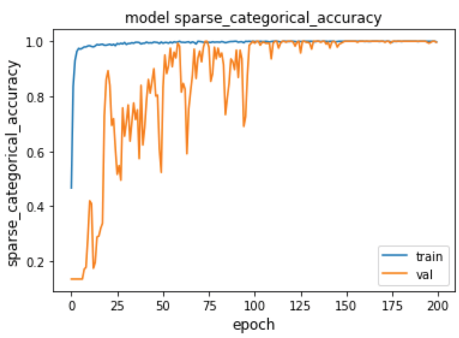


Figure 7. Model convergence and reduction of model error

In this particular case, the accuracy of the network used is 99.64% and it can be said that the proposed network was able to accurately identify all the samples after training and while separating the pattern of a healthy set from other sets, the pattern created by each damage (according to the location and size of the damage). This expresses the high capability of convolutional networks to distinguish defective and damaged parts from healthy parts. The important point is not to use preprocessing or post-processing in this issue, and this indicates the lack of need for knowledge of vibration analysis, while in most methods there is a need for preprocessing and the use of a conversion function such as Fourier to process signals.

Conclusion

Always damage detection and the effect of damage on the performance of systems and components have been of interest to researchers. Bearings have always been the focus of attention due to their widespread use in industry as well as their high failure rate and impact on the cost of operating and maintaining rotating machines. Monitoring the status and recording data from the operation of bearings such as their vibrations is a common solution in the industry.Vibration physics analysis methods are frequently used to identify the damaged part. The use of machine learning methods has received much attention from scientists in the last decade. Therefore, in this paper, while reviewing the available methods, a convolutional neural network is developed that based on the raw data recorded by the vibration sensor, firstly can detecta defective bearing from a healthy and perfect bearing, and then determine the location and size of the damage. For this purpose, the data of the Bearing Research Center of the Western Reserve University have been used. The results of the analysis show that the proposed model can perform this task well and with very high accuracy (99.66%) for collected samples. To continue this research, the authors will consider other models of damages and other modern methods, such as the Bayesian Learning Network, for online bearing monitoring, damage identification, and estimation of their remained useful life.

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