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Convolutional Neural Network Based Fault Detection for Rotating Machinery

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ABSTRACT

Vibration analysis is a well-established technique for condition monitoring of rotating machines as the vibration patterns differ depending on the fault or machine condition. Currently, mainly manually-engineered features, such as the ball pass frequencies of the raceway, RMS, kurtosis an crest, are used for automatic fault detection. Unfortunately, engineering and interpreting such features requires a significant level of human expertise. To enable non-experts in vibration analysis to perform condition monitoring, the overhead of feature engineering for specific faults needs to be reduced as much as possible. Therefore, in this article we propose a feature learning model for condition monitoring based on convolutional neural networks. The goal of this approach is to autonomously learn useful features for bearing fault detection from the data itself. Several types of bearing faults such as outer-raceway faults and lubrication degradation are considered, but also healthy bearings and rotor imbalance are included. For each condition, several bearings are tested to ensure generalization of the fault-detection system. Furthermore, the feature-learning based approach is compared to a feature-engineering based approach using the same data to objectively quantify their performance. The results indicate that the feature-learning system, based on convolutional neural networks, significantly outperforms the classical feature-engineering based approach which uses manually engineered features and a random forest classifier. The former achieves an accuracy of 93.61 percent and the latter an accuracy of 87.25 percent.

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1. Introduction

To reduce operational costs, prolong machines their lifetime and enhance operational uptime, condition monitoring (CM) is required. CM is used to inspect the state of the machine and to detect faulty components. Components that are often the main source of failure in rotating machines, such as wind turbines, are rolling-element bearings [1]. To monitor the condition of machine components, such as rotors, shafts, couplings, gears and also bearings, vibrations are often used. The presence of the rolling elements in the bearings induce vibrations that are inherent to the system. The position of the rolling

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elements change continuously with respect to the load, causing a behaviour that depends upon the rotation speed. Furthermore, geometrical imperfections or surface roughness also cause vibrations. Not only are vibrations generated in normal operational conditions, but also due to faults, such as outer-raceway faults, inner-raceway faults, rolling-element faults, cage faults, imbalance and misalignment.

To detect if a fault is present, a frequency spectrum analysis is often done [2]. This technique requires the frequency spectrum to be calculated together with the fundamental frequencies of the bearings. The amplitude at these frequencies can then be monitored for anomalies. However, such a technique has many disadvantages. First, the frequency calculations have the assumption that there is no sliding, i.e., the rolling elements only roll on the raceways. Nevertheless, this is seldom the case. Often, a bearing undergoes a combination of rolling and sliding. As a consequence, the calculated frequencies may differ slightly, i.e. 1–2 percent, compared to the actual frequencies [3]. Second, if multiple faults occur simultaneously, the frequencies generated can add and subtract, obfuscating important frequencies [2]. Third, there is also the possibility that interference is induced due to additional sources of vibration, i.e. bearing looseness, hence obscuring useful features. Lastly, some faults, such as lubrication related faults, do not even manifest themselves as a new cyclic frequency [4], which makes them very hard to detect via traditional vibration analysis techniques. Because of these various challenges, manually-engineered features based on vibration signals can be difficult to interpret, especially in a real-time manner, other than by an experienced vibration analyst [2].

Opposed to feature engineering, recently there has been a considerable effort in machine learning on the development of end-to-end learning methods [5]. Instead of manually devising features that preserve the discriminative characteristics of the data, the goal of end-to-end learning is to learn the discriminative feature representation directly from input data. The latter approach does not require human expertise or prior knowledge of the problem, and is advantageous in tasks where it is challenging to develop characterizing features. Therefore, in this paper we develop a feature learning method to autonomously detect different faults in rotating machinery using vibration data. For comparison reasons, we also develop a more classical method using engineered features for fault detection. The chosen features are determined based on a literature review discussed in the next section. We test both approaches on experimental data generated by different bearing conditions and evaluate the capability of the methods in distinguishing between several fault classes.

The remainder of this article is as follows. In the next section a literature review is given. Subsequently, the data capturing procedure and the data set are discussed. Then, the feature-engineering based approach is presented. Consequently, the feature-learning based approach is discussed. Next, the results of both systems are evaluated and compared. Finally, the conclusions are presented together with possible future work for the presented research.

2. Related literature

To automatically detect faulty components, machine learning algorithms can be used. Machine learning algorithms use data to construct a model that can detect different conditions. Data used to train models are features which are constructed and extracted by an expert from raw data. Raw data, such as vibrations, can be obtained by attaching accelerometers to the machine that has to be monitored.

2.1. Feature engineering

Vibration patterns depend on the machine's condition, and are therefore very suitable to detect specific conditions. For example, imbalance, which is caused due to the shift between the principal axis of inertia and the axis of rotation, results in a high amplitude at the rotation frequency of the machine in the frequency spectrum [6]. Other faults which can be detected in a similar manner are damaged raceways, since these faults generate a peak at a specific fundamental frequency [7]. Besides indicative frequency features, it has also been shown that certain time based statistical features, such as kurtosis and crest factor, are useful in identifying a defect bearing [8]. Furthermore, it was shown that the root-mean-square (RMS), another time-based feature of the vibration signal, is indicative of the amount of separation between the rolling elements and the raceways due to lubrication in a linear bearing [9].

To summarize, several different features with a specific goal can be extracted from vibration data. However, a human expert is still required to interpret the features to identify different machine conditions or anomalies. Hence, machine learning is required to automate this interpretation process.

2.2. Machine learning

Machine learning for machine fault detection focuses on two major topics, i.e.: anomaly detection and fault/condition classification. Anomaly detection is the process of identifying measurements that do not conform to the other patterns of the data set [10]. The assumption here is that these anomalous measurements indicate that the condition of the machine has changed, e.g. a fault has occurred. Anomaly detection does not require samples from the different possible conditions, but only samples taken during normal operational conditions. Hence, anomaly detection is straight-forward to apply. Often, features, as discussed in the previous sub-section, are used by algorithms such as one-class support vector machines (SVM), Gaussian distribution fitting, clustering in combination with principal component analysis, hidden markov models and neural networks [10–13].

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