Machine Fault Detection using Vibration Signal in Smart Factory

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Machine maintenance is important in the smart factory, that decides the efficiency of its operation. Nowadays, predictive maintenance is improving due to the improvement of IoT network and real-time analysis. The vibration can be collected, analyze with high accuracy and efficiency, make the fault detection easy to implement, and reduce the cost. In our study, we use the Spectra Quest's Gearbox Prognostics Simulator data to analysis. The AI algorithms are Artificial Neural Network, Linear Regression, and Support Vector Machine. The highest accuracy reached is 100%.

Keywords—Machine Learning, ANN, LR, SVN, Vibration Signal.

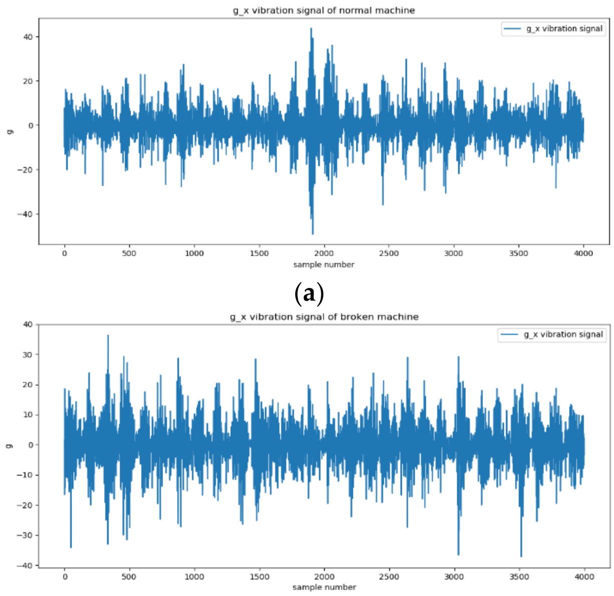
I. INTRODUCTION

Machine maintenance is a critical field in the manufacturing industry, that decides the normal operation of a smart factory. Recently, predictive maintenance has been a significant acceptance in manufacturing due to accessibility and handling the manufacturing process data in real-time, inexpensive sensors and software that is capable of handling big data and performing real-time data analytics. Today, predictive maintenance involves collecting machine data, performing signal processing, early fault detection, fault diagnosis, time to failure prediction, maintenance resource optimization, and scheduling by using concepts from statistics, machine learning, and data mining [1]. Based on the following components, various architectures and processing models have been proposed over the years, and most of the architectures use supervised learning. The vibration signal is the main data resource for the fault detection application with high accuracy and low cost. In this paper, we propose a machine fault detection method using vibration signal. The Machine Learning algorithms applied are Artificial Neural Network (ANN) [2], Linear Regression (LR) [3], and Support Vector Machine (SVN) [4].

II. FAULT DIAGNOSIS METHODS

A. Gearbox data

The Gearbox data is collect from Spectra Quest's Gearbox Prognostics Simulator (GPS) and uploaded to OpenEI home page [5]. The GPS gearbox consists of a two-stage parallel shaft test gearbox with rolling or sleeve bearings, which can be configured with a gear ratio from 1 to 6. The gearbox can be submitted to a torque large enough to induce wear and damage in the gears. All elements of the GPS have been designed to maximize the number of gearbox configurations to investigate gearbox dynamics and acoustic behavior, health monitoring, and vibration-based diagnostic and prognostics techniques. It is robust enough to handle heavy loads and spacious enough for easy gear placement, setup, and installation of monitoring devices. In the Simulation, 4 vibration sensors are used to collect data in 4 different directions, include g_x, g_y, g_z, g_T. Data set has been recorded under 50 percent of load, and recorded in two different scenarios: 1) Healthy condition and 2) Broken Tooth Condition (Figure 1).



(b)

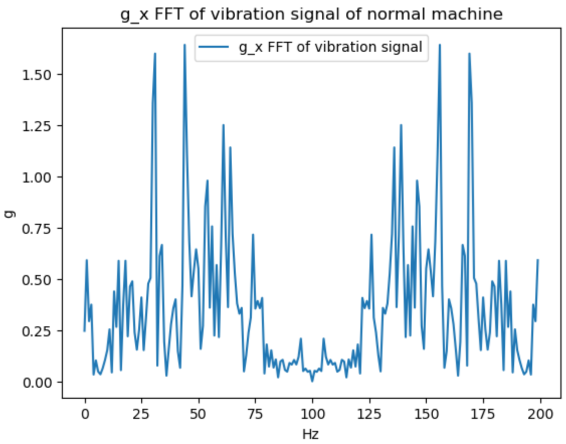
Figure 1: G_x vibration signal of: (a) normal machine and (b) broken machine

B. Data processing

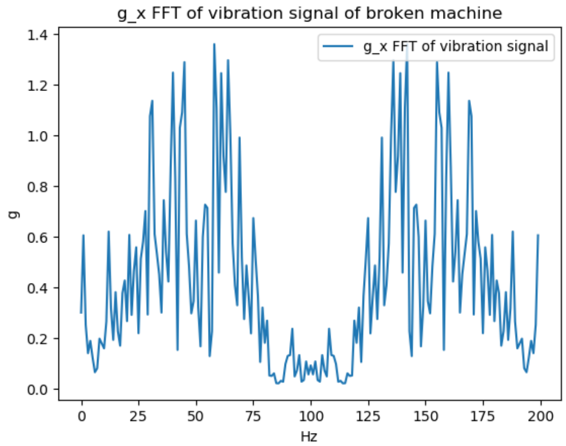
Feature extraction in machine learning is a process of extracting significant characteristics of the input signal. These characteristics vary from signal to signal, that can be statistical, domain-specific features or both. The collected vibration data was in time series, and this signal is transformed into the frequency domain using fast Fourier transforms as shown in Figure 2. The main purpose of this paper is to classify the broken machine signal and the normal one, which is essential in fault diagnosis experiments and evaluate its effect to final results.

The Fourier transform of a function of time is a complex-valued function of frequency, whose magnitude (absolute value) represents the amount of that frequency present in the original function, and whose argument is the phase offset of the basic sinusoid in that frequency. The Fourier transform is not limited to functions of time, but the domain of the original function is commonly referred to as the time domain (Figure 2). The signal in the frequency domain contains more unique features that can be used to distinguish the normal and broken machine signals. For the fault diagnosis methods, the FFT is the best way to extract the input pattern for further analysis, so we keep it as the primary preprocessing process. Based on the

FFT input signal, we apply different AI models that can affect to Fault Diagnosis results.



(**a**)



(**b**)

Figure 2: FFT of V_x vibration signal of (a) normal machine and (b) broken machine

C. *Machine Learning Algorithm*

In our study, the FFT signal will be feed directly into the AI model to classify if the machine has errors or not. The AI models applied in this study are ANN, LR, and SVN, which are robust for classification applications. ANN, LR, and SVN are selected due to the flexibility that can adapt to a variety of data types.

The proposed ANN model for full FFT signal has 200 input neural, 100 hidden units, and 2 output neural with softmax activation function for classification. The input of ANN has the shape of 200x4, which contains 4 FFT signal of g_x, g_y, g_z, g_T. The weights of all LSTM cells are initialized as per Xavier and are applied DROP with 0.7 keeping probability. The activation function for the input and hidden layer is Leaky ReLU, and the loss function is sparse categorical cross-entropy. We adaptive momentum (ADAM) as the iterative optimization algorithm. The proposed ANN model for fully FFT signal was trained over 1000 epochs. The LR and SVN are configuration as in our previous research, applied in [6].

AI algorithms	Accuracy
ANN	100%
LR	100%
SVN	100%

III. Conclusions

The role of fault detection in industrial manufacturing is more and more important and requires more effort to improve its accuracy as well as efficiency. With vibration signal combine with machine learning techniques, fault detection becomes easy to implementation with low cost and high accuracy, satisfy the requirement of the commercial applications.

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