Fault Diagnosis with Machine Learning Methods
Second MSc Project Progress Report

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1 Introduction

This report summarises my progress by 26$^{\text{th}}$ July, 2019. Section 2 specifies how this project uses different data sets; Section 3 discusses the features extraction methods on trial, and the most discriminative features; Section 4 summarises the architecture of the classification model, and how the proposed method generalise to other data sets.

2 Usage of Data Set

This project focuses on 2 bearing fault data sets:(1) the bearing data set from Case Western Reserve University (CWRU), and (2) the bearing data set from Society for Machinery Failure Prevention Technology (MFPT). The CWRU data set is processed to produce 3 subsets, based on different load factors, 1-3 HPs: the CWRU subset A is used to identify discriminative features using visualisation, and test the performance of the proposed method; the CWRU subset C and D are used to see how the proposed method generalises to different load factors. The MFPT data set is used to check if the proposed method generalises to completely different data sets.

3 Feature Extraction

The features on trial include 19 statistical features (6 time-domain features + 13 frequency-domain features) [5], energy entropy using empirical mode decomposition [4], and derived features from ensemble empirical mode decomposition [1]. Based on visualisation, the most discriminative features are the EEMD features #1 #5 #6, and the statistical features #14 #19.

4 Classification and Generalisation

Because the extracted features are visually discriminative enough, a 3-layer ANN with 10 hidden neurons are adopted to test how different combinations of features performs. A shallow architecture is chosen specifically to prevent overfitting. The preliminary conclusion is that the proposed method can achieves 100% test accuracy on the CWRU data subsets, and 100% test accuracy on the MFPT data set, by stacking the top 3 features: the EEMD features #5 #6, and the statistical feature #14.

References

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