Fault Diagnosis with Machine Learning Methods
MSc Preliminary Project Report

Jiachang (Ernest) Xu
jiachang.xu@kcl.ac.uk 1819235
supervised by Dr. Hak-Keung Lam

April 26, 2019

1 Introduction

This project aims to develop a new algorithm and/or train a new classifier to devise a new bearing fault detection strategy, which can assist machinery operators to notice the presence of defects in the early stage, and therefore allow maintenance crew to schedule repairing, reducing service downtime, and saving operating costs. This project work with bearing fault datasets. More specifically, the devised bearing fault detection model should be able to distinguish the signatures of the normal condition, and the fault condition. Three datasets have been acquired: (1) the bearing dataset from Case Western Reserve University (CWRU), (2) the bearing data set from Society for Machinery Failure Prevention Technology (MFPT), and (3) the bearing data set from National Aeronautics and Space Administration (NASA). The Data Acquisition Report iterates the details of these 3 bearing fault datasets. This project follows the methodology of iterative development to perform literature review and model replication to incrementally build the knowledge base around this subject matter, and seeks to invent new approaches to solve the above problem.

2 Background Material

2.1 Bearing envelope analysis (BEA)

Eric Bechhoefer introduces a powerful condition monitoring approach, bearing envelope analysis (BEA), to detect defective bearings [1]. The bearing envelope analysis is characterized by the envelope window frequency, and the envelope window bandwidth, both of which, if not properly selected, would severely reduce the effectiveness of this method. Bechhoefer suggests the use of spectral kurtosis (SK) technique to guide the window selection objective.

2.2 Morlet wavelet filter-based de-noising method

Hai Qiu, Jay Lee, Jing Lin, and Gang Yu acknowledge the fact that the real-word practice of de-noising and extraction of the weak signatures of bearing faults are usually challenged due to the masking of workplace noise [2]. In order to detect the fault at the early stage, alert the maintenance crew, and therefore prevent a complete breakdown of machinery, Qiu, Lee, Lin, and Yu develop a Morlet wavelet filter-based de-noising method to filter impulse-like, periodic signatures of bearing faults that are masked by noises.

The Morlet wavelet filter-based de-noising method produces a daughter Morlet wavelet characterized by a shape factor β and a scale factor α to filter the weak impulse-like defect signatures masked by noises. The optimal value of the shape factor β can be determined, by minimizing the Shannon entropy; the optimal value of the scale factor α can be obtained by a SVD(Singular

Value Decomposition)-based method to evaluate the results of wavelet transform, assuming the periodicity of the underlying defect features.

The Morlet wavelet filter-based de-noising method effectively address the task to unveil the weak signatures of bearing defects, while the traditional method of wavelet decomposition-based de-noising approach only performs well with fault signals that are not masked by noises. This leap of progress makes the Morlet wavelet filter-based de-noising approach the top contender in the field of fault prognostics.

2.3 Enhancement deep feature fusion method

Haidong Shao, Hongkai Jiang, Fuan Wang, and Huiwei Zhao proposed a fusion method to extract deep features of bearing to detect faults in rotary machines [3]. Their proposed model contains 3 functional components: (1) a revamped deep auto-encoder that is constituted by both denoising auto-encoders (DAE), and contractive auto-encoders (CAE) for the enhancement of its ability to learn features, (2) a locality preserving projection (LPP) mechanism that fuses the learnt features to enhance their quality, and (3) a *softmax* classifier that uses the fusion features to predict the category of machinery defects.

The authors compare their proposed model with standard deep DAE, standard deep CAE, artificial neural network, and support vector machine. The results prove that the proposed model outperforms other methods.

2.4 Continued Literature Review

Due to the time invested on courseworks and revision, the time available for literature review has been limited for the past month. Now that all the courseworks have been submitted, more time become available for iterative literature review. The next section will show the schedule for this project, including more literature review.

3 Project Schedule

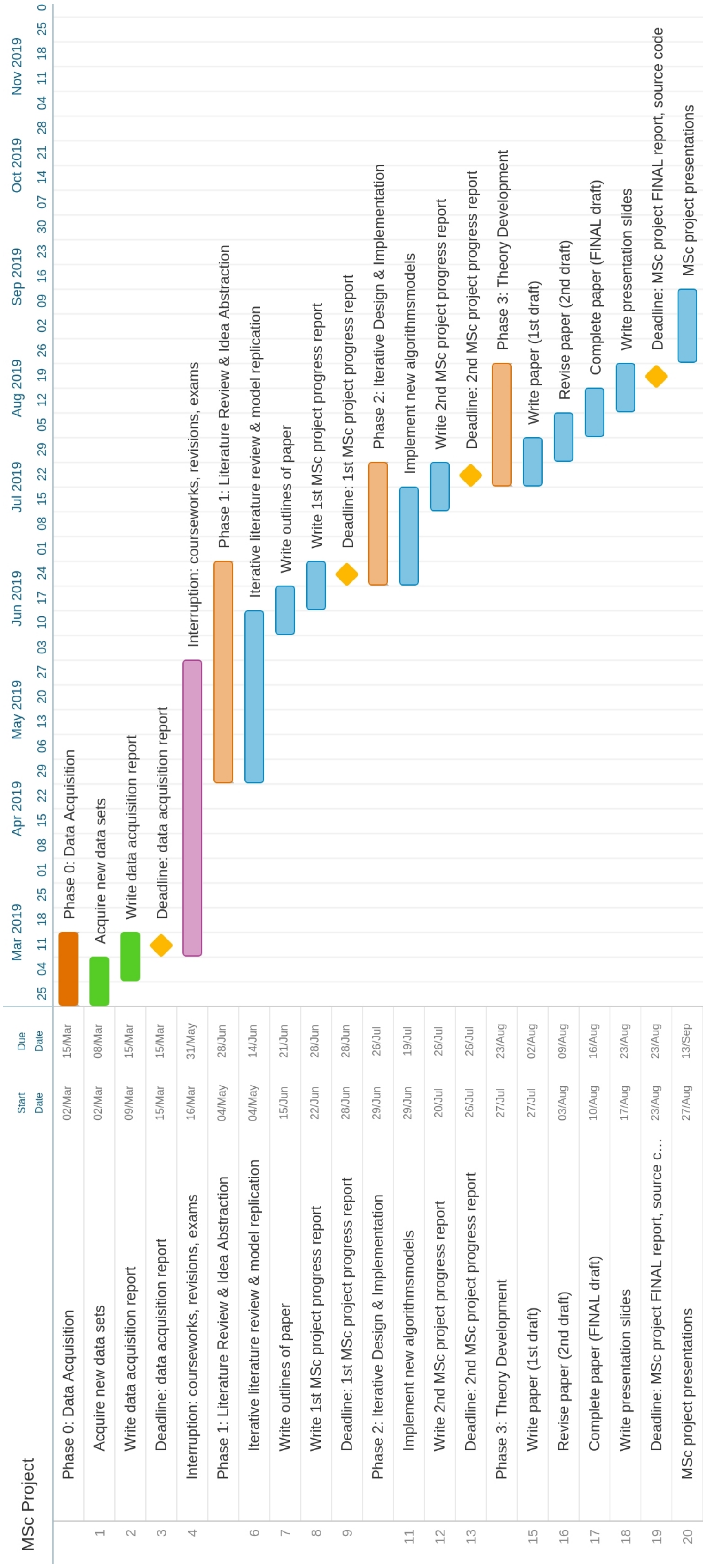

Figure 1: Project schedule

References

[1] Eric Bechhoefer. *A Quick Introduction to Bearing Envelope Analysis.*

[2] H. Qiu et al. Wavelet filter-based weak signature detection method and its application on rolling element bearing prognostics. *Journal of Sound and Vibration* 289 (2006) 10661090.

[3] Shao H, Jiang H, Wang F, et al. An enhancement deep feature fusion method for rotating machinery fault diagnosis[J]. *Knowledge-Based Systems* 119 (2017) 200-220.