

**ENHANCEMENT OF BEARING DEFECT
DIAGNOSIS VIA GENETIC ALGORITHM
OPTIMIZED FEATURE SELECTION**

CHIA YEE SHIN



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20 April 2015

Chia Yee Shin
PK20118069



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CERTIFICATION

NAME : **CHIA YEE SHIN**

MATRIC NO. : **PK20118069**

TITLE : **ENHANCEMENT OF BEARING DEFECT DIAGNOSIS VIA
GENETIC ALGORITHM OPTIMIZED FEATURE SELECTION**

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(ELECTRICAL AND ELECTRONIC ENGINEERING)**

VIVA DATE : **06 MARCH 2015**

DECLARED BY

1. **SUPERVISOR**
Associate Professor Ir. Dr. Yang Soo Siang
Signature
2. **CO- SUPERVISOR**
Mr. Kenneth Teo Tze Kin

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Chia Yee Shin
20 April 2015



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ABSTRACT

The main objective of this research is to enhance the classification performance of the neural network-based bearing fault diagnostic module particularly when the input data has unpredictable variations compared to the training data under various working conditions. The most challenging problem in the fault diagnosis tasks is classifying testing data that has never been seen before by the classifier during training. Therefore genetic algorithm (GA) is employed to search for a minimum number of relevant features nonlinearly to increase the classification accuracy while reducing the computational effort of the training process. However this feature selection algorithm might be unstable due to the stochastic property of GA. In addition, GA has the limitation on generalization which causes the problem of over-fitting to the training data. Therefore a correlation-based filtering algorithm is embedded into GA feature selection to solve the over-fitting problem and increase the adaptability of the diagnostic scheme to unpredictable input data. The developed bearing fault diagnosis system has been evaluated and assessed for various working conditions such as rotating speeds, bearing types, fault types and fault sizes. Results show that the reinforced network classifier with GA feature selection algorithm has successfully increased the classification accuracy of training process and testing process by 13.87% and 14.21% respectively compared to the conventional neural network classifier. However the average classification accuracy of 84.74% on the unseen test data did not achieve the acceptable average success rate of 90% in this application. This is due to the features selected in this classifier is over-fitted to the training data and not generalized for variations in testing data. Subsequently, the integration of embedded correlation-based filtering algorithm has further increased the classification accuracy of training process and testing process by 4.93% and 14.73% respectively. The average classification accuracy of 99.47% on the test data achieved the acceptable average success rate. Thus, it can be concluded that the developed algorithm is capable to improve the classification efficiency by improving the generality of the classifier in classifying test data with unpredictable variations under various working conditions.

ABSTRAK

PENINGKATAN PRESTASI MODUL DIAGNOSIS GALAS MELALUI PEMILIHAN CIRI YANG DIOPTIMUMKAN OLEH ALGORITMA GENETIK

Objektif utama kajian ini adalah untuk meningkatkan prestasi pengkelasan untuk modul diagnosis gelas bebola berasaskan rangkaian neural, terutamanya untuk data yang mempunyai variasi yang tidak menentu berbanding dengan data latihan di pelbagai keadaan operasi. Masalah yang paling mencabar dalam tugas pengkelasan ialah mengklasifikasikan data yang tidak pernah wujud semasa latihan. Oleh itu, algoritma genetik (AG) dicadangkan untuk mencari ciri-ciri yang penting dalam bilangan minimum untuk meningkatkan peratusan ketepatan pengkelasan serta mengurangkan usaha pengiraan dalam proses latihan. Walau bagaimanapun, AG mungkin tidak stabil disebabkan perubahan AG yang tidak menentu. Maka, algoritma pemilihan ciri berasaskan korelasi dibenamkan ke dalam AG untuk meningkatkan pengitlakan terhadap data input yang tidak menentu. Sistem ini telah dianalisis dan dikaji untuk pelbagai keadaan seperti variasi kelajuan, jenis gelas bebola, jenis kerosakan dan saiz kerosakan. Keputusan menunjukkan bahawa pengkelasan berasaskan rangkaian neural yang diperkukuhkan dengan AG algoritma pemilihan ciri telah berjaya meningkatkan ketepatan klasifikasi untuk proses latihan dan proses ujian sebanyak 13.78% dan 14.21% masing-masing berbanding dengan pengkelasan berasaskan rangkaian neural konvensional. Walaubagaimanapun, peratus ketepatan klasifikasi sebanyak 84.74% untuk data ujian tidak mencapai purata ketepatan klasifikasi yang dapat diterima dalam kerja ini, iaitu sebanyak 90%. Ini adalah kerana ciri-ciri yang dipilih adalah lebih sesuai untuk data latihan dan tidak stabil untuk variasi data ujian. Justeru, algoritma pemilihan ciri berasaskan korelasi yang dibenamkan ke dalam AG dapat meningkatkan lagi ketepatan klasifikasi proses latihan dan proses ujian sebanyak 4.93% dan 14.73% masing-masing. Purata ketepatan klasifikasi sebanyak 99.47% untuk data ujian dapat mencapai purata ketepatan klasifikasi yang dapat diterima. Oleh itu, kesimpulan dapat dibuat bahawa sistem ini mampu meningkatkan ketepatan klasifikasi dengan meningkatkan pengitlakan dalam mengklasifikasikan data ujian dengan variasi yang tidak menentu di bawah pelbagai keadaan.

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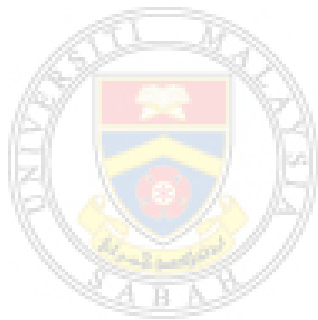
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LIST OF ABBREVIATIONS

AI	-	Artificial intelligence
ANN	-	Artificial Neural Network
AR	-	Autoregressive
BFF	-	Ball fault frequency
BMU	-	Best matching unit
BPFI	-	Ball passing frequency inner race
BPFO	-	Ball passing frequency outer race
BSF	-	Ball spin frequency
EMD	-	Empirical mode decomposition
FEA	-	Finite element analysis
FFT	-	Fast Fourier transform
FTF	-	Fundamental train frequency
GA	-	Genetic algorithm
HMM	-	Hidden Markov model
J-M	-	Jeffries-Matusita
k-NN	-	k-nearest neighbour
LDR	-	Levinson-Durbon recursion
MED	-	Minimum entropy deconvolution
MLP	-	Multilayer perceptron
MQE	-	Minimum quantization error
MRA	-	Multiresolution analysis
MSE	-	Mean square error
RL	-	Reinforcement learning
RMS	-	Root-mean-square

RNN	-	Reinforced neural network
SK	-	Spectral Kurtosis
SNR	-	Signal-to-noise ratio
SOM	-	Self-organizing map
STFT	-	Short Time Fourier Transform
SVM	-	Support Vector Machine
WT	-	Wavelet Transform
WVD	-	Wigner-Ville distribution



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LIST OF SYMBOLS

x	-	Time signal
wf	-	Time window
T	-	Time interval
f	-	Frequency
g	-	Mother wavelet
b	-	Translation factor
a	-	Dilation factor
a_i	-	Autoregression coefficient terms
p	-	Order of autoregression model
ε_n	-	Residual error of the autoregression filter
σ	-	Standard deviation
δ	-	Kronecker delta function
h	-	Transmission path
fi	-	Fault impulses
d	-	Deterministic part of signal
n_o	-	Noise signal
v	-	Filter coefficient vector
A	-	Toeplitz autocorrelation matrix
E	-	Expected value
\emptyset	-	Bearing contact angle
Pd	-	Pitch diameter
Bd	-	Ball diameter
S	-	Shaft rotation rate
μ	-	Average of vibration signal

$\rho(f)$	-	Noise-to-signal ratio
$S_N(f)$	-	Power spectral densities of noise
$S_X(f)$	-	Power spectral densities of fault
O	-	Network output
T	-	Actual target output
w	-	Network weight vector
i	-	Sample index number
n	-	Number of samples
γ	-	Discounting factor
α	-	Learning rate
d	-	Euclidean distance
Q	-	Q-value
r	-	Reward
P	-	Probability
IC	-	Incorrect classification
E	-	Root mean square error
D	-	Number of selected features in chromosome

CHAPTER 1

INTRODUCTION

1.1 Project Background

Rotating machinery is widely used in industries including machining tools, milling machines, and aircraft gas turbine engines, due to their relatively low cost. The most frequent failure that causes an unexpected machine breakdown is due to bearing defects, so bearings are classified as critical mechanical components. A reliable condition monitoring system is important for predictive maintenance actions to reduce the need of periodic shutdowns for routine inspections. Consequently, there is a high demand for researches to be conducted on the development of bearing condition monitoring system. The condition monitoring system consists of incipient fault detection, fault isolation and severity monitoring. Due to the shortage of experienced personnel, an automated on-site diagnosis system that does not require human interpretations to analyze the data is desirable.

The main components of rolling element bearings consist of an outer race, an inner race, rolling elements in between the two races, and a cage around the rolling elements. The rolling elements can be needles, balls, cylindrical rollers, tapered rollers or barrel rollers. The outer race is typically mounted to the stationary housing, and the inner race is mounted on the rotating shaft. The function of cage is to separate the rolling elements to avoid contact between them (Kiral and Karagülle, 2003). The load carrying capability of roller bearing is usually higher than ball bearing because the balls can only transfer the load applied to a ball bearing via point contact with the races, whereas the rollers can transfer the load to races through line contact. Radial ball bearings are most commonly used due to its simple design and suitability for high speed operation with little maintenance requirement (Braun and Datner, 1979).

The analysis of defective bearing signals depends on the type of defects in the bearing. The two main types of defects are initial small localized defects and extended spalls if the spalls are smoothed by wear. The former is described as the visible faults that appear at the races, cage or rolling elements. This type of defect refers to spalls, cracks, pits and brinelling on the rolling surfaces, which are caused by shock loading or overloading during the operation and installation process. The distributed defect is defined as the damages on an unhealthy bearing that is not apparent, including roughness on surface, off-size rolling elements and misaligned races which caused by manufacturing error and abrasive wear (Amarnath *et al.*, 2004). The adhesive wearing process might be accelerated by lubricant deficiency due to the increase of bearing component temperature, and this speed up of the deterioration process. In general, localized defect diagnostics are more important than distributed defect diagnostics because the spalls on the races and rolling elements are the most common failures in real-world applications. Distributed defects usually originate from localized spalls so it is more important to diagnose the initial stage of the faults (McFadden and Smith, 1984). Therefore the research in this thesis is focused on the condition monitoring of bearings with localized bearing defects.

The influence of external noise from the other machinery components such as pumps, gears, and turbines leads to the need of more advanced bearing fault detection and diagnosis approaches. Some existing algorithms for bearing characteristic-fault-frequencies detection and diagnosis are artificial neural network, statistical methods, wavelet, spectral model, model-based techniques, and high-frequency resonance methods. Among these methods, Artificial Intelligence (AI) technologies such as neural network and fuzzy logic could predict the dynamic performance of the system accurately where bearings are parts of the system (Piyush and Prajapati, 2011). In fact, intelligent bearing condition monitoring is one of the challenging scientific industrial researches in recent years.

1.2 Motivation

Fault diagnosis is vital for advanced supervision and fault management of a system. They have to be capable of detecting incipient faults and diagnose faults. Generally fault diagnostics focuses on detection, isolation and identification of faults. Early fault detection and diagnosis is crucial for counteraction to be planned, such as reconfiguration, maintenance or repair. The traditional approaches of fault diagnosis relies on skilled personnel to identify faults based on the extracted features, which are time-consuming and can be inaccurate when the amount of data for monitoring the machinery condition is vast and the data is degraded by noise. Therefore an automated system which does not require human interpretations to analyze the data is required as an alternative solution. This can be achieved by automatic pattern recognition and classification based on the features extracted from the vibration signals.

Furthermore, feature selection is an important technique to make the diagnosis process faster and more accurate using the minimum number of relevant features. The discovery of feature set with predictive ability is essential for non-linear analysis and modeling process. Neural network-based classifier is one of the non-linear pattern recognition or classification techniques, which can implement non-linear feature mapping with sigmoidal basis function. In this research, neural network is used to design an accurate model for the automated bearing defect classifier. In order to keep the model simple and accurate, suitable feature selection technique is employed to extract the important discriminating attributes of the data and ignore the irrelevant characteristics, such as noise.

1.3 Aim and Objectives

The aim of this research is to improve the efficiency of the neural network-based bearing fault diagnostic module by implementing the feature optimization algorithm under various working conditions. The genetic algorithm (GA)-based approach is used to search for optimal features nonlinearly by creating the feature combinations randomly while correlation-based filtering algorithm is adapted into GA to increase the feature selection stability and reduces the over-fitting problem to the training data.

The research aim can be achieved through the development of an automated bearing fault diagnostic scheme based on reinforced neural network, enhancement of the diagnostic scheme with feature optimization algorithm and the assessment of the developed diagnostic algorithm. The developed bearing fault diagnosis system is evaluated and assessed for ball bearings with seeded faults and double roller bearings with real defect propagation process under various working conditions and fault types. The classification performances of the diagnostic schemes with and without feature optimization algorithm are compared. In addition, the feature subsets selected by the GA feature optimization algorithm and filter embedded GA feature optimization algorithm are evaluated and compared. The measures of association between features are investigated for the task of quantifying feature-feature correlations. The correlation between the selected features has to be sufficiently small to minimize redundancy.

1.4 Thesis Outline

This thesis is organized as the following:

Chapter One describes the overview on the bearing condition monitoring system and elaborates on optimization of the bearing fault diagnostic algorithm. The research aims and scope of work are presented and the organization of the thesis is explained in the thesis outline.

Chapter Two presents the literature review concerning optimization approaches in bearing condition monitoring systems. The chapter is initiated with an introduction to existing vibration-based condition monitoring techniques. The techniques discussed are classified into time-domain based, frequency-domain based and time-frequency based. A review on existing bearing fault detection and diagnostic algorithms follows. In addition, the past researches of the artificial intelligent methods in optimizing the bearing condition monitoring system are also reviewed. Lastly, the enhancement of the diagnosis process with the feature selection algorithms is studied.

Chapter Three presents the enhancement of the bearing signals through the time-domain and frequency-domain analysis. The chapter begins with the development of autoregressive linear prediction and minimum entropy deconvolution techniques to isolate the bearing signals from noise. In addition, the integration of the Fast Kurtogram into envelope analysis is introduced to enhance the signal-to-noise ratio (SNR) and helps in identification of the peaks associated with bearing fault impulses.

Chapter Four discusses the implementation of neural network-based classifier in bearing fault diagnosis process. Reinforcement learning is theoretically explained and practically integrated into the neural network training process. In addition, the development of a bearing degradation indicator based on quantization error is also included in this chapter.

Chapter Five illustrates the implementation of feature extraction and feature optimization techniques. The procedures to implement the developed GA-based feature selection algorithm to extract the feature set with important discriminating attributes are proposed. The performance of the developed algorithm is then further enhanced by embedding the correlation-based filtering algorithm into it.

Chapter Six shows the evaluation and assessment of the proposed enhanced bearing diagnostic scheme for ball bearings with seeded faults and roller bearings which developing natural defect propagation processes. The performances of the diagnostic scheme are evaluated on case studies with and without feature optimization algorithms. The efficiency of these diagnostic algorithms is investigated and compared under different working conditions. Furthermore, the damage levels of the bearings are trended with the degradation indicator based on minimum quantization error.

Finally, the summary of this thesis is concluded in Chapter Seven. Achievement and future works are presented in this chapter.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

A bearing condition monitoring system is crucial to prevent malfunction and catastrophic failure of the machine caused by bearing faults. The techniques used for bearing condition monitoring are commonly achieved via vibration analysis, acoustic signal analysis, thermal analysis, oil debris analysis, and electrical current analysis.

The most widely employed approach in monitoring the bearing defects is vibration-based. It has been employed for a long time and has become more economical and reliable in recent years. The faults in bearing will typically produce salient signature in the vibration signal. The fault signature produced by the interaction between the bearing fault and its rotating component is the first indication of the defect (Yan and Gao, 2005). Therefore vibration analysis is suitable for diagnosis of both localized and distributed defects in their incipient stage.

Acoustic-based analysis is another effective bearing condition monitoring technique. Acoustic emission refers to the emission of a certain level of seismic signals when the materials are subjected to deformation or stress. The generation of high-frequency stress waves are caused by the rapid release of strain energy if there is a structural modification in material under stress. The measurement of these waves is analyzed to detect the bearing defect (Elmaleeh *et al.*, 2007). This method can provide higher SNR compared to the vibration analysis. However, it has a drawback of incurring high cost and specialized expertise is required to measure acoustic emission.