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**DYNAMIC ANALYSIS AND FAULT DIAGNOSIS OF
A WATER HYDRAULIC MOTOR**

CHEN HANXIN

**SCHOOL OF MECHANICAL AND AEROSPACE ENGINEERING
NANYANG TECHNOLOGICAL UNIVERSITY**

2005

**Dynamic Analysis And Fault Diagnosis
Of A Water Hydraulic Motor**

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School of Mechanical and Aerospace Engineering

**A thesis submitted to the Nanyang Technological University
in fulfillment of the requirement for the degree of
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2005

Abstract

This research is concerned with condition monitoring and fault diagnosis of the piston of the water hydraulic motor by vibration signal analysis. Vibration signatures are obtained from the casing of the water hydraulic motor. The size and locations of straight-line cracks on the piston were introduced for the experiments. The lengths of the short piston cracks and long piston cracks are 5mm and 10mm, respectively. They are in the front and back sections of the piston, respectively. There are four kinds of piston cracks, i.e. back long crack (BLC), back short crack (BSC), front long crack (FLC) and front short crack (FSC).

For effective fault diagnosis of the water hydraulic motor, it is important to understand the vibration mechanism of the motor. A dynamic mathematical model of the water hydraulic motor was developed for studying the vibration mechanism. The model was verified by comparing the simulated vibration results with experimental results. The results showed that the vibration characteristics of the water hydraulic motor are affected by the supply pressure in the piston chamber and the structure of the water hydraulic motor. The pressure ripple in the piston chamber was the source of the vibration in the water hydraulic motor. The major frequencies of the casing vibration were determined by the angular speeds of the water hydraulic motor.

To study the mechanism and determine the relationships between the angular speed, pressure, flow rate and output torque, theoretical models of the pressure, flow rate and the shaft output torque were presented. It was verified that the output torque and angular speed can be kept at a constant value to obtain stable and repeatable vibration signals under the five piston conditions, which are normal condition (NC), BLC, BSC, FLC and FSC.

The water hydraulic motor generates nonstationary dynamic vibration signals. This is typical of the impulse vibration signals which contain technical information about the condition of the water hydraulic motor. A novel method for the feature extraction from the impulse vibration signals of the water hydraulic motor was proposed based on the second generation wavelet, which consists of the lifting scheme. It was verified that the wavelet multi-decomposition was capable of analyzing the signals in the localized wavelet

functions and represented the local characteristic energy distribution. The wavelet-based statistic parameters can quantify both the scale-and location-dependent behavior successfully. The results showed that the statistical feature values of the second wavelet multi-decomposition for the impulse vibration signals were effective for diagnosing the five piston conditions.

The adaptive wavelet analysis was more effective and useful to enhance the nonstationary features of machinery vibration signals than conventional signal analysis when the vibration characteristics of the machinery were known. The adaptive wavelet-based method as feature extractor was developed by making use of Genetic Algorithm (GA). The model of the vibration signals for the fault diagnosis of the piston crack was proposed. The model was capable of extracting the characteristic amplitudes and frequencies from the vibration signals, which can be used to detect the five piston conditions. The adaptive spectrogram algorithm optimized by GA was proposed for analyzing the vibration signals. The adaptive spectrogram can extract the characteristic impulse signals in finer resolution than that of conventional continuous wavelet transform (CWT).

The feature optimization and classification were the key aspects for the intelligent fault diagnosis of the water hydraulic motor. The multi-classification method for the fault diagnosis of the piston crack in the water hydraulic motor based on Support Vector Machines was proposed. The new optimization algorithm by bi-classification SVM to extract the optimal features was developed. The results showed that the optimal features can be extracted by reducing the fifty-nine features to three optimal features. The proposed two-level multi-classification method was suitable for the detection of the sizes and locations of the piston crack in the water hydraulic motor. The classification success rate can be up to 80.7%.

The vibration signals contained the important information of the piston condition. The feature values of the piston condition can be extracted from the vibration signals by the wavelet analysis. An intelligent fault diagnosis system of the different size and locations of the piston crack in the water hydraulic motor was established by vibration analysis.

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List of Symbols and Abbreviation

A_p	piston cross-section area
$A_n(t)$	intake area of the piston bore
C_{HZ}	damping coefficient of the interface between piston and cylinder port
C_{Sh}	damping coefficient of the interface between shaft and valve cover and outer shell
C_{Sw}	damping coefficient of the interface between piston and swash plate
C_{Va}	damping coefficient in the interface between valve cover (valve port plate) and cylinder block
C_i	inlet orifice-coefficient
f_p	fundamental frequency of the hydraulic pump
$f_m(=5f_0=1/T_m)$	fundamental frequency of the water hydraulic motor
F_{Cz}	exciting force on the cylinder block in Z axis
F_{Pz}	exciting force on the piston in Z axis
I_{Cx}	moment of inertia of the cylinder block around X_C axis
I_{Cy}	moment of inertia of the cylinder block around Y_C axis
I_{Fx}	moment of inertia of the outer shell and swash plate around X_F axis
I_{Fy}	moment of inertia of the outer shell and swash plate around Y_F axis
I_{Px}	moment of inertia of the piston and retaining ring around X_P axis
I_{Py}	moment of inertia of the piston and retaining ring around Y_P axis
K_{Sw}	stiffness of the interface between piston and swash plate
K_{Bo}	stiffness of the bolt between outer shell and valve cover (port flange)
K_{Sh}	stiffness of the motor shaft bearing

K_{HZ}	stiffness of the interface between piston and cylinder port
K_p	spring stiffness
K_{Va}	stiffness of the interface between valve port plate and cylinder block
l_x	equivalent center coordinates of the exerting force F_{Cz} in the direction of Y_C axis in the cylinder block cross-section
l_y	equivalent center coordinates of the exerting force F_{Cz} in the direction of X_C axis in the cylinder block cross-section
L_{PF}	distance between the point O_P and the point O_F , referred to Figure 3.18
L_{F1}, L_{F2}	lengths, refer to Figure 3.18
L_{C1}, L_{C2}	lengths, refer to Figure 3.18
L_b, L_{Sh}	lengths, refer to Figure 3.18
M_C	cylinder masses
M_P	piston and retaining ring masses
M_F	masses of the outer shell and the swash plate
M_n	water mass
n	number of piston
p	pressure outside the piston bore
p_p	pressure in the piston
P_i	high supply pressure
P_o	low return pressure.
P_s	pressure in the slipper pool
Q	volumetric flow rate into the piston bore
r	radius of the spring port circle.
r_p	radius of the piston
r_s	outer radius of the slipper
R_V	radius of force point circle between cylinder and valve cover (valve port plate), refer to Figure 3.18

R	radius of the cylinder port circle, refer to Figure 3.18
T_{Cx}	torque on the cylinder around X_C axis
T_{Cy}	torque on the cylinder around Y_C axis
δ_0	angle of swash plate
ω_0	hydraulic motor angular velocity.
ρ	fluid density
V_n	instantaneous volume in the piston bore
AWT	adaptive wavelet transform
BLC	Back long crack
BSC	Back short crack
FLC	Front long crack
FSC	Front short crack
NC	normal condition
CWD	Choi-William distribution
CWT	continuous wavelet transform
DOF	degree of freedom
DWT	discrete wavelet transform
FDD	feed-forward neural network
FT	Fourier Transform
GA	Genetic algorithm
GCV	generalized cross validation
LMS	The least mean square
NFPA	National Fluid Power Association
RBF	radial basis function nets
RFE	Recursive Feature Elimination
SVM	support vector machine
STFT	Short-Time Fourier Transform
TSA	time synchronous average
WVD	wigner-ville distribution

Chapter 1

Introduction

For the manufacturing industry, an important aspect of efficient production is the reliability of machinery. Knowledge of the production equipment's condition is useful in reducing maintenance costs and overall production costs, as well as in improving plant safety. "Condition monitoring" refers to the set of the engineering techniques which involve the measurement and interpretation of machinery parameters and conditions in order to provide efficient maintenance as its goal. It includes the evaluation of the temperatures, pressures, vibration, and other measurable features of equipment in order to predict potential losses of productivity due to the wear, inefficiencies, and breakdowns. It also includes the detection and diagnosis of the incipient faults or faults which have already occurred. Using condition monitoring techniques, the costly downtime of machinery can be reduced by replacing parts before breakdown occurs and by continuous regular maintenance.

1.1 Motivation

Water has been historically used as the working medium for fluid power systems, sometimes with additives to prevent freezing. Recently a new interest in environmentally friendly fluids has evolved. The advantages of using mineral oil instead of water as the working fluid were recognized by the mid-19th Century. The replacement of water by oil in hydraulic systems, and the use of higher pressures to achieve high power density, increased the risk of fire in some applications. The need to minimize the effect of leakage or spillage of hydraulic fluid is a major concern in farming, forestry, food, pharmaceuticals and paper industries. New health and safety legislation will enhance the attractiveness of water hydraulic systems in industrial plants as well as in applications where fire risk is high. An increasing emphasis is being placed on health and safety issues and environmental protection. One concern is that there will not be any significant requirement for environmentally acceptable fluids in normal industrial applications. That view may be negated by changes in legislation and /or customer requirements as concern for the environment grows and health and safety regulations become more stringent. Moreover, more widespread availability of biodegradable fluids will lead to more general acceptance of modern water hydraulic system.

In the past twenty years, there have been significant improvements in the use of improved materials for water hydraulic motors. Recent advancement in technology has produced material that can withstand highly corrosive environments and lubrication-free material for water hydraulic components. With precision machining becoming possible, very close tolerances can now be achieved to reduce internal leakage due to the low

viscosity of water. However, a simple and reliable technique for the fault diagnosis of water hydraulic motor was not found in the published literature. The use of water for the working fluid in hydraulic system has several inherent benefits: water is inexpensive, and it will not ignite. Water has low compressibility and viscosity, making it a better energy transmitter than oil hydraulics, and it also is more suitable for use in precision and accurate control programs. There is practically no difficulty in its availability, replacement, storage, cost and disposal. Properties of water are recorded under various pressure and temperature with other compositions such as additives. The main benefit of water hydraulics is its hygiene, environmentally friendliness and fire proofness.

Detection of these various failure modes during normal course of operation of water hydraulic motor is of vital importance, and this issue should attract considerable interest in the area of predictive or preventive maintenance technology. This is because failures resulting from any of the aforementioned abnormalities could cascade into more severe equipment failures, significant plant down time, lost revenue, as well as other serious economic and safety consequences during the operation of equipment in industrial plants and manufacturing processes.

Furthermore, having on-line monitoring, i.e. the continuous assessment of the performance and health/state of a motor throughout its useful life, can provide management with the flexibility to schedule maintenance approximately on an “as needed” basis rather than at a fixed interval of time. In addition, it could help management to understand the performance of the system, which could be very important in the design of future systems and applications.

Machinery vibration monitoring programs are effective in reducing overall operation costs in industrial plants. Vibration produced by industrial machinery is a vital indicator of machinery health and history. Monitoring vibration levels over a period of time allow the plant engineer to predict problems before serious damage occurs. Vibration analyses are then used as a tool to determine machine condition and the specific cause and location of machinery problems. On-line condition monitoring supercedes that of a monthly or weekly measurement, which might not be frequent or consistent enough to detect developing problems on many of the critical machines operating 24-hour a day, seven days per week.

Courtney [1] illustrated the cost effectiveness of condition monitoring on electrical motor and pump using vibration monitoring and spectrum analysis. The results show that the repair costs are reduced by 30% compared with previous situation where the strategy was a combination of routine and breakdown maintenance. The program of current spectrum monitoring, to detect rotor bar faults, has given a net benefit of 140% of the cost of monitoring. The water hydraulic motor used in this research is a very important component of a water hydraulic system. Failure of these motors, especially those designed for safety operations, could impair plant safety.

1.2 Objective

A hydraulic motor and pump are the important elements in a hydraulic system. The piston of the hydraulic pump and motor is an important component so that any faulty piston can cause the hydraulic motor, pump and system to behave abnormally. The pressure and flow signals have been used to diagnose the health condition of the hydraulic

pump and motor. However, the vibration signal is an important and convenient method to extract features for diagnosing the mechanical system, especially for the reciprocated and rotary machine. Until now there is no efficient method by vibration signal analysis for the fault diagnosis of oil and water hydraulic pump and motor.

The aim of this research project is to develop an intelligent fault diagnosis system for the size and locations of the piston crack of the water hydraulic motor. The main objectives are:

- (1) To develop an experimental measurement system for acquiring effective vibration signals for the water hydraulic motor of a modern water hydraulic system for the five piston conditions under certain pressure, flow rate, torque and rotational speed
- (2) To study the vibration characteristics of the casing of the water hydraulic motor, and identify and evaluate the factors/parameters related to the vibration characteristics.
- (3) To develop effective and specific methods to extract the features from the vibration signatures for the size and locations of the piston cracks in the water hydraulic motor.
- (4) To investigate intelligent methods for optimizing the feature values and automatically classify the different size and locations of the piston crack in the water hydraulic motor according to the optimized feature values.

1.3 Scope

In order to reach the objectives of this research project, the fault diagnosis approaches and methods were investigated. They include dynamic vibration analysis, data acquisition,

signal processing and analysis, feature extraction, parameter optimization and automatic classification. Figure 1.1 shows the water hydraulic motor fault detection and diagnosis system.

The scope of the research project encompasses the following areas:

- (1) To investigate the dynamic vibration mechanism of the water hydraulic motor for a sound understanding of the vibration mechanism in the water hydraulic motor.
- (2) To analyze the important factors including the pressure ripple, flow ripple and output torque which affect the vibration characteristics of the casing of the water hydraulic motor, and study the pressure, flow and torque mechanism of the motor.
- (3) To investigate the wavelet multi-decomposition based on the lifting scheme for the impulse vibration signal analysis to extract the feature values and to develop the algorithm based on the second generation wavelet and generalized cross validation for de-noising the vibration signal.
- (4) To study the adaptive filter on wavelet domain least mean square to denoise vibration signal and evaluate its applicability using simulated signals corrupted with white Gaussian noise and impulse noise.
- (5) To propose the vibration model method based on the adaptive wavelet for the fault diagnosis of the piston crack and develop the optimization algorithm of the vibration model by the genetic algorithm.
- (6) To propose and evaluate the adaptive wavelet spectrogram for the nonstationary vibration signals for the detection of the piston crack.
- (7) To investigate the feature extraction on the statistical wavelet coefficients to quantify the temporal and spectral distribution of the energy, to introduce the

Wavelet-based statistics such as wavelet variance, skewness, flatness and intermittence index to quantify the scale and location-dependent behavior of the vibration signal and study the novel optimization method of the support vector machine (SVM) for selecting the optimal features and reducing the number of the feature values.

- (8) To investigate the automatic classification based on the support vector machines and propose the multi-classification algorithm for the fault diagnosis of the piston crack in water hydraulic motor.

Figure 1.1 Overview of the water hydraulic motor fault detection and diagnosis system

1.4 Preview

This thesis consists of seven chapters. The motivation for this research was presented in Chapter 1 which includes the objective and scope. The water hydraulic motor fault detection and diagnosis system was proposed. Chapter 2 reviewed the development and trend of the water hydraulic system. It contains an overall view on the dynamic analysis of the axial piston pump and motor, vibration mechanism of the hydraulic pump and motor, the fault diagnosis of hydraulic system and application of advanced signal processing and artificial intelligence in fault diagnosis and condition monitoring.

In Chapter 3, the water hydraulic motor test system and experimental procedure were described. The dynamic characteristics of the piston pressure, flow ripple and shaft torque were studied. The model of the pressure mechanism was presented with considering on leakage due to the slipper. The idealized flow and actual flow model were derived. The numerical results of the flow ripple were obtained. The instantaneous and average output torques of the axial piston motor have been derived according to the geometry, piston accelerations and the piston pressure. A mathematical model for the vibration characteristics of the swash-plate water hydraulic motor in a water hydraulic system was developed. The dynamic equilibrium equations of motion were formulated to analyze the response with the pressure pulsation as the excitation force. The validity of the analysis was confirmed by comparing it with experimental results. The study included the investigation of the influence of torque on the vibration signals of the outer shell in the water hydraulic motor.

In Chapter 4, the novel method for the feature extraction from the vibration signals of the water hydraulic motor was proposed according to the second generation wavelet that consists of the lifting scheme. The algorithm and method of the multi-decomposition based on the lifting scheme were developed. The denoise method for the vibration signals was presented on the lifting scheme and the generalized cross validation.

Chapter 5 investigated the fault diagnosis of water hydraulic motor based on adaptive wavelet analysis. A novel method for modelling the vibration signals based on the adaptive wavelet transform (AWT) was proposed. The new adaptive joint time-frequency signal representation was studied to extract the feature value from the vibration signals. The adaptive spectrogram procedure based on the parameter optimization by genetic algorithm (GA) was developed.

In Chapter 6, the new optimization method by bi-classification SVM to extract the optimal features was proposed. The multi-classification method of SVM for the fault diagnosis of the piston crack was investigated. Chapter 7 presented the conclusion and future work.

Chapter 2

Literature Review

Water hydraulics was overtaken by oil hydraulics in the early part of the last century in terms of research effort and industrial applications. In recent years, due to the advancement in materials and machining technology, it has become possible to produce water hydraulic components that are made of lubricant-free and anticorrosive materials and to achieve very close tolerances to reduce internal leakage due the low viscosity of water. Growing interest about environmental issues has led to renewed interest in water hydraulics [2,3,4]. This chapter reviews the development and trends of modern water hydraulic systems. It contains an overview on the dynamic analysis of the axial piston pump and motor, the vibration mechanism of hydraulic pump and motor, the fault diagnosis of hydraulic system and applications of advanced signal processing and the artificial intelligence in condition monitoring and fault diagnosis.

2.1 Modern Water Hydraulic System

Water hydraulic system has been around for a long time. As early as 200 B.C, Ctesibus, invented the first pump for water [5]. In 1906, Janney coined in the idea of replacing water-based fluid by oil, thus avoiding corrosion, lubrication, freezing and leakage problems at

high temperature involving water. The following years saw a tremendous increase in the applications of oil hydraulics. The turning point came in early 90s, when Danfoss Hydraulics revived water hydraulics. This time round, with the advances in material and design, the ‘tap-water’ fluid hydraulic was made possible. Figure 2.1 shows the history and trend in oil and modern water hydraulics.

Figure 2.1 Earlier applications of water and oil hydraulics [5]

In recent years, prevalent water hydraulic research work has been going on in several European countries. Biennial conferences such as the Bath International Fluid Power Workshop [6,7,8] and the Scandinavian International Conference on Fluid Power [9,10] cover many fluid power applications, with certain sessions devoted to water hydraulics alone. The National Fluid Power Association (NFPA) in the United States of American regulates the standard used in hydraulics. Various articles have been published by NFPA addressing the emerging modern water hydraulics trend, sometimes collaborating with associating academics and industries [11].

Since water hydraulic production debuted in the 1990s, the academic arena has seen few publications on water hydraulics research, especially relating to condition monitoring and fault diagnosis of water hydraulic systems [12,13]. Zhou [14] carried out a number of pump experimental tests to show the effects of the cavitation and inner leakage based on low frequency pressure fluctuation. Given that water has poor lubricity, material selection is important in order to reduce friction and wear. This necessitates the use of non-metallic materials, special surface treatments or coatings on metal components [15,16,17]. With the perspective of using tap water as the fluid pressure medium, the Danfoss company, after several years of research and development effort, has recently initiated the marketing of a new range of products for water hydraulics called Nessie. This range of the Nessie products includes hydraulic motors, pumps, valves, power packs, and accessories that allow for the design and implementation of the complete water hydraulic control systems [18,19].

To overcome the challenges of the difference between the water and oil as the fluid pressure medium, many attempts have been made around the world to develop a rotary water hydraulic motor [20]. The water hydraulic motor developed by Danfoss company is a swash plate axial piston motor with fixed displacement and five pistons. The motor shaft and the cylinder barrel are made of stainless steel. All friction surfaces on cylinders, thrust plate and piston shoes are made of reinforced plastic or overmolded stainless steel. The motor housing and flanges are made of sand-casted aluminium, which is anodized for an optimally low corrosion on internal and external surfaces. All moving parts in the motor are lubricated by water itself. The specifications of the motor are listed in Table 2.1. The practical applications of water hydraulic systems can be found in references [2,3,4]. Thus the market is real and sizeable.

Table 2.1 Technical Data for Nessie Motor

MAH type		Model 12.5	
Geometric displacement (cm^3)	12.5	Max.pressure drop and inlet pressure (bar)	140
Max.speed (rev/min)	3000	Return line pressure pin=140bar,no shaft load (bar)	50
Min.speed (rev/min)	300	Return line pressure at pin=140bar, max.shaft load (bar)	10
Max.torque (Nm)	25	Max.system press at serial operation,no shaft load (bar)	105
Starting torque at Max.pressure drop (Nm)	17.5	Drain flow at 140 bar/1500 min ⁻¹	<1.5
Starting pressure at unloaded shaft (bar)	12	Max. waterflow (l/min)	40
Max.power at max.speed (kW)	7.8	Mass (kg)	6.3

2.2 Dynamic Analysis of Axial Piston Pump and Motor

The dynamic behaviour of the axial piston motor is usually non-linear in nature and the factors that influence the performance of the axial piston motor are complicated. In order to improve the performance and increase its ratings, it is important to understand the pumping dynamics of hydraulic pump and motor which relates to the pressure, flow rate and torque. The structural vibration of hydraulic motor and pump results from the interaction between the pressure and flow rate with the structure. Obtaining a better understanding of the factors affecting the vibration dynamics is important so as to achieve further improvement in piston pump and motor performance. With increasing number of applications of water hydraulics in industry, the fault diagnosis of power system is receiving more attention.

2.2.1 Theoretical Dynamic Analysis

Axial piston pump and motor are used extensively with high overall efficiency. There is a great demand for machines capable of operating at high rotational speeds and delivery pressures. The pumping mechanism becomes more important and receives great attention for improvement in the design of the port plate relief grooves to reduce the reverse flow. The pumping dynamics of the axial piston pump produces the pressure ripple and flow ripple, which are the major sources of the vibration and fluid-borne-noise. In order to reduce the vibration and noise in the hydraulic pump system, some research has been done on many factors of the pumping mechanism. Ivantysyn and Ivantysynova [21] investigated the control volume of the pressure in the cylinder, valve plate area opening to the cylinder, flow rate between cylinder block and valve plate as well as slipper and swash plate, and instantaneous cylinder pressure. Edge and Darling [22,23] studied the pumping dynamics of the swash plate piston pump. Harris et al [24] studied the pressure and suction flow ripple in the suction performance. The different air-release and cavitation models are also investigated. Their results showed that the reverse flow has a strong influence on the fluid-borne noise and cavitation.

The flow is produced in a periodic waveform as a result of the pumping piston. The flow ripple interacts with the system to create a complex pressure ripple which is superimposed on the mean system pressure. The pressure ripple can result in the failure of the components and is an important factor in determining the reliability of the hydraulic system. Manring [25] investigated the discharge flow ripple of an axial hydrostatic pump. The results showed that the harmonic frequencies of the flow ripple are equal to integer multiples of the piston pass frequency.

Mathematical models are useful in representing the equation of the motion of swash plate. The torque is an important factor in the model and is the result of complex dynamic phenomena. Zeiger and Akers [26] derived the mathematical equations of the swash plate torque. Manring [27] and Manring & Damtew [28] used the “power-in, power-out” approach to model the theoretical torque on the input shaft of a hydrostatic pump. The instantaneous torque was analyzed. The integral average of the instantaneous torque was performed and compared with the traditional method of computing this quantity. Furthermore, the non-traditional pump utilizing piston-bore springs was also investigated to analyze the control torque.

The understanding of the open loop dynamics of the swash plate is fundamental to the control system design with the axial piston pump. The open-loop dynamics is governed primarily by the pressure variations in the pistons, the geometrical features of the pump and the inertia effects of the reciprocating piston-slipper assemblies [29]. Zeiger & Akers [30] used the first-order equations describing the flow continuity into the pump discharge chamber. Kaliafetis & Costopoulos [31] modeled and simulated the axial piston variable displacement pump with pressure control. The static and dynamic characteristics of the axial piston variable displacement pump with pressure regulator were studied. The results showed that the control valve and the piston areas influenced the outlet pressure. Kim et al [32] used the parameter sensitivity analysis to reduce the nonlinear dynamic equation from a fourth-order model to a second-order model. The piston forces and moments are the most important factors that produce the structure borne noise. The piston forces for different valve plate timings and different swashplate angles have been investigated [33]. The influence of the suction port timing on both the structure borne and fluid borne noise

potential was discussed. Axial piston motors rely on the close fit of the piston to the cylinder bore to minimize the piston leakage. The imperfections in the cylinder bore and piston result in the leakage and change the torque and angular speed of the axial piston motor [34].

The flow is not constant and consists of a periodic flow ripple superimposed on the mean flow rate for axial piston motor and pump. The flow ripple interacts with the system to produce a pressure wave that is propagated along the pipe at the speed of sound in the fluid. The fluidborne vibration brings about structural vibration and an audible noise. Kojima [35] studied the fluidborne vibration (noise) generated by a close circuit hydrostatic power transmission consisting of a swash plate type axial piston motor, pump and a connecting piping. The mathematical models for flow ripple and pressure ripple were developed. These models predicted the pressure ripple up to harmonic frequencies of 2500 Hz with good accuracy. The results showed that the pressure ripple was affected predominantly by the fundamental component of the axial piston motor and pump. Ichibanagi et al [36] investigated the flow ripple of an axial piston motor using the second source method. The motor flow ripple is similar to that generated by axial piston pump. The flow ripple consists of the kinematic component and the compressibility flow spike that is dominant. The compressibility flow spike in the return port flow is larger than that in the supply port due to the larger volume of fluid in the cylinder at bottom dead center. Shu et al [37] presented the distributed parameter model of the pipeline transmission line. The affecting factors of the pressure and flow pulsation characteristics were discussed. The new method and theory were also developed to model the pressure ripple and flow ripple [38,39].

The swash plate designs of the axial piston motors and pumps operate with partially hydrostatic slipper pads. The hydrostatic pressure in the pocket at the center of the slipper supports the majority of the piston load. The fluid flow into this pocket comes from the above piston via a control orifice and flow out of the pocket by a narrow land around its perimeter. The dynamic characteristics of the slipper balance in axial piston motor and pump were studied [40,41]. Manring [42] investigated the dynamic characteristics of the slipper for the purpose of predicting the slipper tipping. The results showed that the slippers require a slightly convex surface on the running face. The slipper performance was dependent on adequate oil supply to the slipper plate. Many slipper failures and problems arise from this source. The lubrication between the pistons and cylinder greatly affects the total performance of the axial piston motor and pump. The sliding friction characteristics between a piston and a cylinder for low-speeds in the axial piston motor were studied [43]. The experimental and theoretical results clarified the sliding characteristics with different roughness of the sliding surface of pistons, cylinder materials, method of lubrication and coating [44,45].

2.2.2 Mathematical Model and Vibration Analysis of Oil Axial Piston Motor and Pump

For the purpose of the control, noise reduction and design, the researches were conducted on the oil hydraulic motor and pump. Dobchul et al [46] reviewed the publications in order to develop a complete and accurate mathematical model of the oil hydraulic motor and pump. The publications about the model of the axial piston motor and pump were classified into two groups. The first one is to describe a small group of the

components to study the specific phenomena. The second one is the model of the hydraulic motor system. The model analysis of the pistons belongs to the first one. Tsutomu et al [47] investigated the friction force characteristics between the piston and cylinder bore in the swash plate axial piston motor, considering the elastic deformation of the piston and cylinder. The results showed that there is stress concentration at the end of the piston and cylinder which is affected by the supply pressure, piston tube thickness and phase angle. When the thickness of the piston becomes smaller, the deformation of the piston becomes greater.

The tribological condition between the piston and cylinder wall is an important criterion to realize high efficiency and reliability in oil piston motor and pump. The solid contacting forces and power losses under medium and high-speed operations are analyzed [48]. Three calculating methods are discussed with regard to the cavitation of the fluid film. The power loss ratio due to the solid contact forces decreased with the hydrodynamic effects and the power loss ratio due to the leakage decreased with the hydrodynamic effects. Considering some models of the lubricants, a multibody dynamic model of the piston slipper in the axial piston pump was presented [49]. The basic equations of the motion of this piston-slipper system were formulated. A program has been developed using the Newmark- β method. The validity of the model was proved by the comparison between the experimental results and simulated results. Harris [50] studied the spin of the piston relative to the cylinder for the purpose of providing guidance on the nature of the friction forces acting on the piston.

The oil hydraulic pump and motor contain a finite number of pumping elements, which produce the flow ripple. The flow ripple interacts with the system to produce the pressure

ripple. The pressure ripple propagates in the pipeline and causes the system to vibrate. The pressure ripple and the structural vibration are the major factors resulting in the fatigue failure of the components. Nishimura et al [51] developed the 4-mass and 20 degrees of freedom model to study the vibration characteristics of every component in the variable displacement oil axial piston pump. The simulated signals were compared with the experimental results to evaluate the validation of the model. It was shown that the vibration characteristics of the casing from the axial piston pump were produced by the pressure pulsation of the deliver port, which is a predominant factor. The variable swash plate type axial piston pump is widely used for the simple control and easy adaptation to energy saving systems. The static characteristics of the operating moment affect the ease of operation and the dynamic characteristics affect the operating smoothness and noise level. Inoue et al [52] studied the operating moment of a swash plate type axial piston pump. The cylinder pressures and the operating moment were predicted by the newly-developed calculation method with reasonable accuracy.

The pressure ripple and the vibration of the casing due to the pressure transients in the cylinder are two sources of the piston pump noise. Qiu et al [53] studied the vibrational energy transmission from the cylinder pressure transients to swash plate vibration in an axial piston pump. The exciting force and torque acting on the swash plate were derived. The vibration mode of swash plate vibration was analyzed by the finite element method. The vibration of the constant power regulated swash plate axial piston pumps was analyzed with different operational and design conditions [54]. The results showed that the frequency of the first harmonic was at the pump rotational speed. The frequencies of the higher harmonics were integer multiples of the first frequency. The vibration and the transmission

paths of the piston pumps are very complicated. Qi and Lu [55] showed that the impact between the slipper and the swash plate is the main source of vibration. The impact force excites a resonant frequency of the pump housing. The method based on autoregressive (AR) model for the vibration analysis was proposed for fault diagnosis for the looseness of slipper from the piston. The piston design has been well described by Ivantysyn and Ivantysynova [21].

2.3. Fault Diagnosis of Hydraulic System

The maintenance of process equipment is the inescapable task associated with the operation of the process plants. Until recently, it was conducted on a routine basis or after the failure of equipment. It is necessary to adopt a method to identify the incipient faults before any impending failures. The on-line fault diagnosis of hydraulic motor and pump is an important method for increasing the reliability and performance of hydraulic system. Hunt [56] investigated the condition monitoring of British coal high pressure water pumps. The failure mode of the high water pump included the piston crack, cylinder block crack, valve spring break-up and piston packing seal failure. These faults may result in the loss in the output flow and pressure. The monitoring results showed that dynamic vibration monitoring can be considered to be the best method for the failure mode, which is produced because of the vibration and fatigue. Although the pressure signal is an important parameter to diagnose the faulty components in hydraulic pump, the conventional spectrum analysis is difficult to extract the features for diagnosis due to the high noise level. Gao et al [57] investigated the method based on wavelet analysis for the fault diagnosis of the oil hydraulic pump. Wavelet can improve the capability for the diagnosis of hydraulic pump.

Some researches on the fault diagnosis of the oil fluid power system were conducted. Higham & Perovic [58] studied the predictive maintenance of pumps based on the pressure and flow signal analysis. Neural network is the most important method in the fault diagnosis of mechanical system. The fault diagnosis of a oil hydraulic actuator circuit using neural network was investigated [59]. Le et al [60] applied multiplayer perception type neural network to detect the leakage in an electrohydraulic cylinder drive. Both single-leakage and multiple-leakage type faults were investigated.

Water hydraulic system has been applied in the farming, forestry, food, pharmaceutical and paper industries [61, 62,63]. Hydraulic motor and pump are the important components in the hydraulic system. It is therefore important to improve the reliability of hydraulic motor and pump. The vibration signal detection is an important parameter for the fault diagnosis of mechanical systems. In a hydraulic system, the pressure ripple interacts with the hydraulic system to produce the structural vibration and the flow ripple produced acoustic signal. The vibration signals and acoustic signals contain some useful information for predicting the hydraulic system condition.

Lim et al [64] used the acoustic signals for the fault diagnosis of the piston crack in the water hydraulic motor. Chen et al [65] developed the method to diagnose the piston crack in modern water hydraulic motor. Wavelet was applied to analyze the vibration signals. Hodkiewicz and Pan [66] identified the transient vibration signals on double-suction pumps during the partial flow operation by statistical, short-time Fourier and wavelet techniques. Cavitation erosion is a root cause of hydraulic pump and motor failures. The detection of cavitation is to prevent the pump and motor from the cavitation damage. Tan and Sepehri [67] studied the condition monitoring of the pump pressure in a hydraulic servo-drive

system. A novel model-based pump pressure condition monitoring scheme for nonlinear hydraulic systems was presented. Koo and Kim [68] introduced the Wigner distribution to analyze the vibration signals for monitoring abnormalities in the reactor coolant pumps such as the bearing rubbing, the shaft bending and the misalignment. The on-line diagnostic method using neural network was developed for hydraulic motor and pump [69,70].

2.4 Techniques of Mechanical System Fault Diagnosis

Most industries use four types of measurement, monitoring, and analysis to determine maintenance schedules, and to anticipate and avoid breakdowns. They include the simple maintenances, scheduled maintenance and operator heuristics and advanced monitoring using on-line identification or estimation of machinery conditions by analysis of measured datum. Different types of signals are sensitive to different machinery faults. With the rapid advancement of transducer and measurement technology, various physical quantities, such as vibration, noise, acoustic emission, stress and strain, force, temperature, infrared ray, contaminants in lubricating oils, etc., have been successfully utilized [71,72,73,74] for the condition monitoring and fault diagnosis. In this thesis, the vibration signals were used for the fault diagnosis of a water hydraulic motor.

2.4.1 Modern Mechanical Fault Diagnosis System

With the development of complicated, integrated and automated mechanical systems, it is increasingly difficult to detect the mechanical system failures by conventional methods. Therefore newer techniques are applied to detect and diagnose the mechanical faults

[69,75]. Mechanical fault diagnosis has integrated more research areas including engineering mechanics, sensors and measurement, optimization theory, signal processing, pattern recognition and artificial intelligence, etc. The approach in a mechanical fault diagnosis system is shown in Figure 2.2.

Figure 2.2: The approach of a mechanical fault diagnosis system

The fault diagnosis approaches include performance modeling, signal processing, feature extraction, feature level fusion, automating classification and knowledge fusion. The performance modeling can provide a knowledge base of the acceptable parameter responses over the operational regime. Signal processing is the basis of feature extraction. Its purpose is to transform the signals from the original domain to the new one in order to make the feature values outstanding. Feature extraction is to extract the useful feature values from the processed signals. Feature level fusion is to optimize all kinds of features to acquire the optimal class of features. The automated classification resulted in the production of health estimates based on the fused features.

2.4.2 Signal Processing and Feature Extraction

The fault diagnosis of reciprocating and rotating machines from vibration analysis belongs to the most sophisticated methods of quality control or quality assurance. Vibration generated by reciprocated machines or by the parts strongly depends on the rotation speed of the main shaft of the tested reciprocating system. With regard to this fact, signals produced by reciprocating machines are non-stationary ones [76]. The vibration-based diagnosis has been the most popular monitoring technique because of the ease of measurement [77]. Vibration monitoring has been a useful tool for the early detection of incipient faults in rotating and reciprocating parts [78,79].

Time Synchronous Average (TSA) is an important method in time domain of mechanical signals. The other important time domain techniques include adaptive noise canceling [80], Hilbert transform [81] and demodulated resonance analysis [82]. Fourier transform (FT)-based spectral analysis is the mainstay of signal processing for noise and vibration analysis [83]. However, in practice, many actual sound and vibration signals analyzed with FFT do not sufficiently satisfy these conditions. During the 1990s, certain power spectrum has received growing attention and has gained acceptance in the field of condition monitoring [84].

In order to overcome the limitations of FT, which is not suitable for non-stationary signal, Wigner-Ville distribution (WVD) and the Choi-William (CWD) distribution are proposed and extensively used. The 1990s has shown an increasing interest in Wigner-Ville method in the fault diagnosis of rotary and reciprocating machines [85,86].

The wavelet transform is a new method of signal processing that has recently been applied to various sciences and engineering fields with great success. Its development was reported by a number of researchers in the late 1980s and early 1990s. Wavelet transform uses a changing width function so that not one but a series resolutions can be achieved in a single time-scale display. Unlike the Fourier transform, in which a signal is decomposed to be a sinusoid function basis, the wavelet transform uses a more general function as the basis. The property of the time-scale location of the wavelet is applied to the analysis of local phenomena in vibration signals, such as the short-time variations caused by faults. It may be possible to give the time and scale information for all of the possible sizes of features.

Compared with FT, the major advantages of the wavelet transform are that it possesses multi-resolutions for localizing short-time components. It was a new method of feature extraction and feature assessment. It was proposed as a method of detecting transient signals and early faults in mechanical systems [87,88,89,90]. The vibration signals of a machine always carry the dynamic information of the machines corrupted by noise. Some effective methods from noisy signals based on the wavelet were proposed [91,92,93,94].

Feature extraction can be viewed as signal compression, which will inevitably result in the loss of information from the original signals. For the monitoring of machining processes, the sensor signals typically contain information and noise. Therefore, it is desirable to extract the features that represent the characteristics of the process and to separate these features from various noise disturbances. The effectiveness of the extracted features is referred to as feature assessment [95,96].

Natural frequency signals reflect the inherent property of the system. The wavelet filter with very narrow frequency-band and autocorrelation enhancement was proposed as a means of monitoring the natural frequencies in real-time. With the efficient, reliable and flexible wavelet filters, any number of natural frequencies in either the time or the frequency domain can be observed at the same time [97].

2.4.3 Feature Optimization and Decision Making

Neural networks have demonstrated a great potential application in pattern recognition and classification. Artificial neural networks have been shown to be very useful for data handling and information processing. They are particularly useful for the problems of condition monitoring and diagnostics. The multilayer feed-forward network is one of the most widely used models and is usually trained by means of error backpropagation algorithm. Neural algorithms that use a multiplayer feed-forward neural network (FNN) have been employed in the condition monitoring and fault diagnosis for mechanical machines [98,99,100,101]. Self-organizing map (SOM) networks can perform clustering and feature extraction without requiring beforehand information about the actual classes of objects and hence are suitable for condition monitoring and diagnostics of machinery systems [102,103,104].

Support vector machines (SVMs) are a comparatively recent development. Support-vector learning is very useful in two respects. First, SVM learning provides a clear intuition of what the learning from examples is about. Second, it can lead to high performance in practical applications. SVM algorithm can be considered as the intersection of learning theory and practice: for certain types of algorithm, statistical learning theory can identify

rather precisely the factors, which need to be taken into account. Real-world applications, however, often mandate the use of more complex models and algorithms such as neural networks that are much harder to analyze theoretically. The SV algorithm achieves both. It constructs models that are complex enough to contain a large class of neural nets, radial basis function (RBF) nets, and polynomial classifiers as special cases. It can be shown to correspond to a *linear* method in a high-dimensional nonlinear feature space related to input space. Moreover, even though it can be thought of as a linear algorithm in a higher-dimensional space, in practice, it does not involve any computations in that higher-dimensional space. By use of kernels, all necessary computations are performed directly in input space. This is the characteristic of SV methods - complex algorithms for nonlinear pattern recognition, regression, or feature extraction are handled, but for the sake of analysis and algorithm, a simple linear algorithm is working [105].

Although the use of SVM methods in applications has only recently begun, the application developers have already reported state-of-the-art performances in a variety of applications in pattern recognition, regression estimation, object recognition, speaker identification, gene function prediction and time series prediction [106,107,108].

The origins of SVM can be traced back to the late 1960s [109]. SVMs have been gaining acceptance in machine learning, computer vision and pattern recognition communities for their high accuracy and good generalization. Haney and Precetti [110] studied the real-time machine vision system for color matching of wood. Jack and Nandi [111] presented the support vector machines for detection and characterization of the bearing faults. It is widely accepted that SVMs exceeds the performance of the artificial neural network (ANN).

Chapter 3

Dynamic Mechanism Analysis of Water Hydraulic Motor

3.1 Introduction

Axial piston motors are used as the generating torque member in a hydraulic system. The dynamics of the swash plate axial piston motor is fundamental to the understanding of the vibration mechanism in a water hydraulic motor. The dynamic mechanism is governed primarily by the pressure variations within the pistons, the geometrical features of the motor and the inertia effects of the reciprocating piston-slipper assemblies. The pressure ripple that is fluid-borne noise causes mechanical vibration and the airborne noise.

This chapter investigated the dynamic mechanism, the flow ripple characteristics and pressure ripple characteristics of the water hydraulic motor in a modern water hydraulic system. The dynamic vibration mechanism of a swash-plate water hydraulic motor was studied. A swash-plate mechanism was modeled as a system with three masses and fourteen degrees of freedom (DOF). The numerical simulation analysis of the dynamic response of the model due to pressure pulsation was presented and compared with experimental results.

The model simulated the vibration signals of the hydraulic motor casing. The waveforms and frequencies of the simulated signals were similar to the experimental signals. The simulated signals in other directions showed that the vibration signals in all the directions mainly consist of the hydraulic pump and hydraulic motor rotational frequencies.

Section 3.2 described the experimental method and rig. A brief description of the water hydraulic motor was provided in Section 3.3. Section 3.4 studied the pressure mechanism. The piston kinetics was analyzed. The models of the piston pressure were obtained with and without leakage. In Section 3.5, the mechanism of flow ripple was analyzed. The simulated results from the flow ripple model were presented. The equations of the shaft output torque were derived in Section 3.6. The experimental pressure ripple of the piston chamber in the water hydraulic system was obtained and analyzed in Section 3.7. In Section 3.8, a theoretical model of the vibration mechanism analysis was developed.

3.2 Water Hydraulic Test System

3.2.1 Experimental Set-up and Procedure

The water hydraulic motor test apparatus as shown in Figure 3.1 was established in Mechanics of Machines Lab in Nanyang Technological University in Singapore. It consists of a MAH12.5 Nessie water hydraulic motor, a brushless servo motor, a digital torque meter and a water hydraulic system. The water hydraulic system allows as axial piston motor to operate in the speed range of 300-3000 *rev/min* and provides a torque range of 0–6Nm.

The digital torque meter consists of a detector and display unit. The detector converts the shaft rotating angle, which is proportional to an applied axis torque of the motor, into a phase difference signal. In order to measure the rotational speed of the detector shaft, the detector is provided with a rotation detector and a gearbox on the torsion bar. The operational display that is a torque converter processes the signals and shows the results as the digital value of torques and rotational speeds. The accuracy of the torque detector is $\pm 0.2\%$ and the accuracy of the rotating speed detector is $\pm 0.02\%$.

The brushless servo motor is superior in providing the precise and stable torque in the range of $0-10.2\text{ Nm}$ for the motor. The servo digital control modules were used to control the brushless servo motor and caused it to generate the constant output torque. The arbitrary function generator can output DC voltage to the servo digital control modules for adjusting the output torque of the servo control motor. The servo digital control system can also be controlled and displayed by the interface control software installed in a personal computer.

A piezoelectric accelerometer ((*Brüel & Kjaer* type 4393) was mounted on the casing of the motor near the inlet of the water hydraulic motor. The output signals from this accelerometer were simultaneously fed to the amplifier and 5B41 filters for noise reduction and anti-aliasing. A data acquisition card (AT-MIO-16L-9 from National Instruments Inc.) used in conjunction with LabView was used to convert analog signals to digital signals. The sampling rate is under the Nyquist formula requirements and was chosen to be 20 kHz that was sufficient for the type of signals considered in this work. A time record of 2048 data points was taken in each experimental run. The rotational speed of the motor was 630 rev/min . The output axis torque of Nessie motor was 5 Nm . The data points of vibration signals covered one rotational period of the motor detected by the torque and speed detector.

The signal characteristics can be fully described within the rotational period.

Figure 3.1 Water hydraulic motor test system

Piston crack was simulated in the axial piston of the Nessie motor by using an electro-discharge machine to produce the crack. The introduced crack is 0.1 mm wide. There were five operating conditions in this test. These were a normal condition (NC) and four faulty conditions with four different kinds of piston cracks. In order to detect the different piston crack locations and piston crack lengths in Nessie motor as shown in Figure 3.2, four kinds of piston cracks were introduced as follows: (1) back long crack (BLC): the crack is 10 mm long and located in the back section of the piston. (2) back short crack (BSC): the crack is 5

mm long and located in back section of the piston. (3) front long crack (FLC): the crack is 10 mm long and located in the front section of the piston. (4) front short crack (FSC): the crack is 5 mm long and located in the front section of the piston. The length of 5 mm can represent the earlier fault condition and the length of 10 mm represents the serious fault condition.

Figure 3.2 Piston cracks in back section and front section.

3.2.2 Water Hydraulic System

Figure 3.3 shows the hydraulic test rig which used tap-water as its fluid medium. Appendix A shows the schematic diagram of the hydraulic circuit with its electrical circuit and its control program. Several instruments were used in this research. To monitor the system comprehensively, two pressure transducers were located along the inlet and outlet actuator line. Next to the pressure sensors, two flowmeters with the $\pm 1\%$ accuracy and $\pm 0.1\%$ repeatability were also located on the fluid lines. The inlet temperature was tapped to record the water temperature before it enters the actuator. Figure 3.3 shows the sequence of the sensors where the right hydraulic lines is the inlet flow and the left line is the outlet from the actuator

Figure 3.3 The Architecture of Water hydraulic system

3.3. Water hydraulic motor description

The actuator studied here was a five-piston axial piston motor used in a water hydraulic system. An accelerometer mounted on the casing of the MAH 12.5 water hydraulic motor was used to obtain the vibration signal from the motor. The complete water hydraulic system was provided by Danfoss [112].

Section A-A

Figure 3.4: General structural configuration of an axial piston motor [112]

Figure 3.4 shows the general structure of the water hydraulic motor test [112]. An axial piston motor consists mainly of a valve port plate with inlet and outlet ports, a swash-plate, an outer shell, a cylinder block, pistons with shoes, a bias spring, a port flange and a shaft. The piston fits within the bores of the cylinder barrel and is on the same axis as the output shaft. The swash-plate is positioned at an angle and acts as a surface on which the piston shoes travel. The shoes are held in contact with the swash-plate by the retaining rings and the bias spring. The port plate separates the incoming fluid from the discharging fluid. The output shaft is connected to the cylinder barrel.

The pistons are nested in a circular array in the cylinder at equal intervals about the z - axis. The cylinder block is held tightly against the valve cover using the compressed force of the springs. The valve cover is separated from the cylinder block by a thin film, which forms a hydrodynamic bearing between these two under normal operating conditions. A ball-and-socket joint connects the base of each piston to a slipper. The slippers themselves are kept in reasonable contact with the swash plate support by the retaining rings. The hydrostatic and hydrodynamic bearing surface separates the slippers from the swash plate support.

The pistons drive the cylinder block to rotate around the z axis at a constant angular speed ω by the reaction load torque creating the supply port pressure. Each piston periodically passes over the supply and return line ports on the valve plate. The slippers are held against the inclined plane of the swash plate. The pistons undergo an oscillatory displacement in and out of the cylinder block. When the piston passes over the supply port, the pressure causes the piston to withdraw from the cylinder block. The piston passes over

the return line port and the fluid is pushed out of the piston chamber. These motions of the piston and cylinder block repeat and the basic task of the output torque is then met.

As the water enters the inlet and exits at the outlet of the hydraulic motor, the pressure in the cylinder chamber alternates from the high pressure to the low pressure. This causes the pressure pulsation to occur. The total cylinder area inside a supply port is variable as a result of the cycle variations of the piston passing through the supply port. It generates the variations of the axial output moment. The variations of the forces are applied from the piston to the swash plate and the valve cover. The forces between the support for the swash plate and the valve cover are equal and opposite. The hydraulic motor body vibrates as a result of force fluctuations.

3.4 Pressure Mechanism Analysis

3.4.1 Piston Kinematics

Figure 3.5 shows the piston kinematics in the swash plate hydraulic motor [30]. The position of the n^{th} piston along the x axis is obtained from the geometrical relation of the hydraulic motor.

$$x_p = -R \tan(\delta_0) \sin(\alpha) \quad (3.1)$$

where δ_0 is the angle of swash plate, α is the rotational angle. The instantaneous volume of the n^{th} piston bore is determined by the area on the cross-section of a single piston A_p and the reference volume V_0 . This value is defined as follows:

$$V = V_0 - A_p R \tan(\delta_0) \sin(\alpha) \quad (3.2)$$

Figure 3.5 Piston kinematics in hydraulic motor

3.4.2 Control-volume Analysis in Cylinder Bore

As the cylinder of the hydraulic pump and motor rotates, the pistons are caused to move from one region of pressure to another by the force generated by the piston pressure. The pressure versus time in the piston is derived by the control-volume approach [24,30]. The schematic of the control volume in the cylinder is shown in Figure 3.6 [21]. The volume of the fluid within the bore is considered as the control volume. The instantaneous flow balance and volumetric rate of change in the piston chamber at the associated angular position are analyzed for this control volume. The pressure outside the piston bore $P(t)$ varies with time when the cylinder block rotates about the axis and repeatedly changes from the high supply pressure P_i to the low return pressure P_o . The intake area of the piston bore $A_n(t)$ also varies with time on the valve plate to model the variable opening in the transition regions in each port.

Figure 3.6 The cylinder-bore control volume [21]

The instantaneous mass in the piston bore is defined by $M_n = \rho V_n$, where ρ is the instantaneous fluid mass-density and V_n is the instantaneous volume in the piston bore. The relationship of the control volume in the cylinder relating to the volume in the piston bore V_n , fluid density ρ and the water mass M_n is shown as follows:

$$\frac{dM_n}{dt} = \frac{d\rho}{dt} V_n + \rho \frac{dV_n}{dt} \quad (3.3)$$

The continuity of fluid flow in the piston bore requires

$$\frac{dM_n}{dt} = \rho Q \quad (3.4)$$

where Q is the volumetric flow rate into the piston bore. The definition of the fluid bulk-modulus β is

$$\frac{d\rho}{dt} = \frac{\rho}{\beta} \frac{dP_p}{dt} \quad (3.5)$$

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Where P_p is the pressure in the piston. Assuming the flow goes into and out of the piston bore at very high velocity that result in a high Reynolds number, the flow rate Q into the piston bore through the inlet of the hydraulic motor is defined as follows, using the classic orifice equation [25]:

$$Q = \text{sign}(P - P_p) C_i A_n(t) \sqrt{\frac{2|P - P_p|}{\rho}} \quad (3.6)$$

where the function “sign” will be the value ± 1 , which is determined by the sign of the argument. The sign is $+1$ when the piston is in the supply port and the sign is -1 when the piston is in the delivery port. C_i is the inlet orifice-coefficient, and P is the boundary pressure outside the control volume that is the supply pressure P_i and return line pressure P_o .

Equations (3.4) and (3.5) are substituted into the equation (3.3) to obtain the following equation.

$$\frac{dP_p}{dt} = \frac{\beta}{V} (Q - \frac{dV}{dt}) \quad (3.7)$$

Combining the equations (3.2), (3.6) and (3.7), the pressure rise-rate within the n^{th} piston chamber can be obtained as [21]:

$$\frac{dP_p}{d\alpha} = \frac{-\beta(\text{sign}(P - P_p) C_i A_n(t) \sqrt{\frac{2}{\rho} |P - P_p|} + A_P R \tan(\delta_0) \cos(\alpha) \omega)}{\omega(V_0 - A_P R \tan(\delta_0) \sin(\alpha))} \quad (3.8)$$

The above equation is a first order differential equation. This nonlinear equation should be solved numerically without the analytical solution. Figure 3.7 shows the typical numerical pressure-profile. The port area $A_n(t)$ and pressure P_p are plotted. This figure demonstrates that the port area is a maximum when the piston bore passes over both the supply port and return line port. In these regions, the pressure in the piston bore is constant. The two ports are connected by transition regions where the port area $A_n(t)$ changes from the maximum value to the minimum value and then returns to the original maximum value. The actual pressure shows the same basic characteristics in hydraulic pump [35]. The pressure changes almost linearly from one port pressure to the other.

Figure 3.7 Piston pressure-profile

3.4.3 Piston Pressure with Leakage

Equation (3.8) is based on the assumption that the hydraulic motor does not leak. In fact, leakage exists in the design of the piston chamber. The leakage occurs through the piston duct into the slipper pad in order to provide the lubrication in the clearance spaces between the slipper pad and swash plate support, between the piston and the cylinder and between the moving surface of the barrel and valve plate. Wang and Yamaguchi [113] studied the

characteristics of hydrostatic bearing and seal parts for water hydraulic pumps and motors.

Figure 3.8 shows the basic characteristics of a special slipper [41,42]. The effects of the clamping ratio and the orifice size on the performance can be displayed. The central clearance can be adjusted when the total hydrodynamic and hydrostatic loads balance the clamping force the slipper exerts on the swash plate support. The pool pressure P_s is variable due to the effect of the orifice. When the balance point is obtained, the slipper couples can be calculated and compared with those acting on the slipper. The variations of the clearance, slipper altitude and leakage with tilting couple are obtained by the range of slipper tilt [113]. The load F_c clamping the slipper to the swash plate support without the friction between the piston and cylinder is obtained as follows:

$$F_c = P_p \pi r_p^2 / \cos \delta_0 \quad (3.9)$$

where P_p is the pressure in the piston, r_p is the radius of the piston. Equation (3.9) is modified with a correction factor when the friction is considered. The load F_c is supported by the hydrostatic and hydrodynamic forces from the slipper. The following equation can be obtained:

$$\bar{W}_s = W_c^* \bar{P}_p \bar{r}_p^2 \quad (3.10)$$

where

$$\bar{W}_s = W / P_s r_s^2 \quad W_c^* = W_c / P_p r_p^2 \quad \bar{P}_p = P_p / P_s, \quad \bar{r}_p^2 = r_p^2 / r_s^2 \quad (3.11)$$

where P_s is the pressure in the slipper pool, r_s is the outer radius of the slipper.

Figure 3.8 Slipper clearance, force, pressure and surface profile

The leakage $Q_{Leakage}$ from the pool across the slipper outer land must be balanced by the equal flow rate into the pool through the orifices. Under the most general condition, the following equation can be derived according to the viscosity-controlled flow through the orifices.

$$Q_{Leakage} = (P_p - P_s)C_0/\eta \quad (3.12)$$

where η is kinematic viscosity of the fluid, C_0 is a coefficient that depends on the geometry of the particular orifice and is defined by the length L , and diameter d , of the orifice, as follows:

$$C_0 = \pi d^4/128L \quad (3.13)$$

Equation (3.12) can be rewritten in non-dimensional form as:

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$$C_0^*(\bar{P}_p - 1)[G\bar{r}_p/\bar{P}_p]^{1.5} - \bar{Q} = 0 \quad (3.14)$$

and

$$C_0^* = C_0/h_{ref}^3, \quad h_{ref} = [\eta u r_p / P_p]^{0.5} \quad (3.15)$$

$$\text{and the hydrodynamic parameter } G = \eta \mu r_s / P_s h_c^2 \quad (3.16)$$

where η is kinematic viscosity of the fluid, u is the sliding velocity of the slipper. The parameter G relates to the hydrodynamic and hydrostatic pressures. Using equations (3.14), (3.15) and (3.16), the net flow into the slipper pool can be obtained. The above analysis shows the leakage from the slipper. In practice, there are circumferal leakages between the cylinder, valve cover and piston. It is difficult to estimate the leakages. Generally, the leakage is given as follows [22]:

$$Q_{Leakage} = C_L \times P_p \quad (3.17)$$

Considering all the leakages, equations (3.4) should be modified as follows:

$$\frac{dM_n}{dt} = \rho(Q - Q_{Leakage}) \quad (3.18)$$

Equations (3.5) and (3.18) is substituted into equation (3.3) and equation (3.7) is modified to obtain the following equation.

$$\frac{dP_p}{dt} = \frac{\beta}{V} (Q - Q_{Leakage} - \frac{dV}{dt}) \quad (3.19)$$

Derived from equations (3.2), (3.6) and (3.19), equation (3.8) is modified as follows [21]:

$$\frac{dP_p}{d\alpha} = \frac{\beta(\text{sign}(P - P_p)C_i A_n(t) \sqrt{\frac{2}{\rho}} |P - P_p| - C_L P_p + A_P R \tan(\delta_0) \cos(\alpha) \omega)}{\omega(V_0 - A_P R \tan(\delta_0) \sin(\alpha))} \quad (3.20)$$

Equation (3.20) is difficult to solve. In practice, the pressure in the piston is expressed by a simpler equation. The equation assumes that the pressure remains constant as the piston passes the supply and return line port. The pressure over the transition region changes linearly in the range of the pressure carry-over angle γ [24].

$$P_p = \begin{cases} P_i & 3\pi/2 + \gamma < \alpha < \pi/2 \\ P_i - m(\alpha - \pi/2) & \pi/2 < \alpha < \pi/2 + \gamma \\ P_o & \pi/2 + \gamma < \alpha < 3\pi/2 \\ P_i + v(\alpha - 3\pi/2) & 3\pi/2 < \alpha < 3\pi/2 + \gamma \end{cases} \quad (3.21)$$

where $v = (P_i - P_o)/\gamma$, the pressure carry-over angle $\gamma = \left(\sqrt{\frac{4V}{\beta K_\alpha}} \right) \sqrt{\omega} (P_i - P_o)^{0.25}$.

3.4.4 The Pressure with Overshoot and Undershoot

Figure 3.9 shows the piston pressure with overshoot and undershoot in axial piston pump. This phenomenon is strictly the result of the volumetric compression and expansion with the cylinder chamber. At the end of inlet phase, the reduction in port plate flow area, associated with the port plate silencing groove, results in the flow from the inlet port being throttled. During high-speed conditions this throttling action may cause undershoot in cylinder pressure. If the magnitude of undershoot is sufficient, the cavitation in the cylinder block is compressed by the reverse flow passing from the delivery port through the port plate orifice into the cylinder. The motion of the piston also provides some compression during this phase. The boundary pressure in the cylinder bore is not sufficiently large

compared with the delivery pressure. The volumetric compression of the fluid will cause the pressure in the piston bore to overshoot (Figure 3.9) the approaching boundary condition. The silencing groove flow area continues to increase with cylinder barrel rotation. The reduction in port differential pressure leads to a reduction in the magnitude of the reverse flow. So the fluid in the silencing groove is initially accelerated into the cylinder and then decelerates as the level of reverse flow reduces. The cylinder pressure continues to rise and eventually reaches the level of the delivery port pressure.

At the end of the delivery phase, the reduction of the delivery port flow area results in a throttling of the piston flow. During the high speed conditions, it will lead to overshoot in the cylinder pressure. At the start of the inlet phase, a rapid reverse flow occurs. The initial direction of flow at the start of inlet stroke is from the cylinder into the low-pressure inlet port. When the pressure in the cylinder falls, the level of reverse flow will reduce and the fluid entering the cylinder block will be decelerated. Due to the motion of the piston out of the cylinder bore, the flow from the cylinder results in undershoot (Figure 3.9) in the cylinder pressure. Some papers [22,23,24,25] have studied the pressure overshoot and undershoot.

Figure 3.9 Numerical piston pressure with overshoot and undershoot in the transition regions

The operating principle of the axial piston motor is opposite to that of the axial piston pump. The direction of the motion in the axial piston motor is reverse to that of the hydraulic pump. The flow ripple of hydraulic motor is similar to that of the hydraulic pump [33]. At the start of the supply port in the hydraulic motor, the flow ripple behaves as a compressible flow, which occurs once per pumping cycle. The fluid flows rapidly into the cylinder due to the pressure imbalance between that inside the cylinder and supply line. The magnitude of the compressible flow spike increases proportionally with motor differential pressure. This flow ripple spike results in the overshoot of the pressure in the cylinder. At the start of return line, the compressible flow spike is in the opposite direction to that of the supply line. The fluid flows rapidly from the cylinder to the return line. The amplitude of the compressibility flow spike in the supply line is bigger due to the much larger volume of fluid in the cylinder at bottom dead center than at top dead center. This compressible flow spike results in the undershoot of the pressure curve in the cylinder of hydraulic motor.

3.5 The Flow Ripple of a Swash Plate Motor

Axial piston motor outputs the torque by the hydraulic power and consists of a discrete number of pistons that reciprocate and rotate in a sinusoidal fashion. The input flow of an axial piston motor is not perfectly smooth and tends to maintain some of the sinusoidal characteristics of the fluid displaced. These sinusoidal characteristics are usually referred to as the flow ripple of the hydraulic motor.

3.5.1 Mechanism of Flow Ripple

The generating mechanism of flow ripple in the axial piston motor is similar to the axial piston pump. There are two important factors in generating the flow ripple of the axial piston motor. Firstly, the motion of the pistons results in the kinematic waveform of the flow ripple. The other more dominant factor affecting the flow ripple is the sharp compressible flow spike, which occurs each time when a piston is exposed to the high pressure supply port. During the discharge phase, the piston is exposed to the return line pressure. The flow in the return line is returned to the tank whose pressure is close to atmospheric pressure. Therefore the piston pressure is lower than the supply pressure. When the cylinder block rotates past top dead center, the cylinder port starts to communicate with the supply port. At the beginning of the stroke, the piston pressure is approximately the return line pressure. Because of the pressure imbalance between that inside the cylinder and the return line, the fluid flows rapidly into the cylinder block. The flow ripple, which is produced by the sharp compressible flow once per pumping cycle, is superimposed on the kinematic ripple. The magnitude of the compressible flow spike increases proportionally with motor differential pressure. This is due to the area of each spike corresponding to the volume of the fluid in each cylinder being compressed. This compressed volume is proportional to the difference between the supply pressure and the cylinder pressure at the point of the port opening. The duration of the spike remains independent of the pressure. The magnitude of the spike increases in direct proportion to the different pressure.

A similar process occurs as the cylinder passes bottom dead center and opens to the return port. The pressure differential is reversed and the sharp flow spike takes place into

the return line. The amplitude of the compressibility flow spike is bigger due to the larger volume of fluid in the cylinder at bottom dead center than at top dead center.

3.5.2 Idealized Hydraulic Motor Flow

For the idealized inlet flow, it is assumed that a perfect hydraulic motor is studied in which leakage is assumed to be zero and the fluid is considered to be incompressible. So the closed-form expression is used to describe the characteristics of the idealized flow ripple. The flow rate generated by a piston is equal to the time rate-of-change of the instantaneous volume of the piston chamber. It is shown by the following equation:

$$Q = \frac{dV}{dt} \quad (3.22)$$

where the flow into the piston bore is considered to be positive. The instantaneous volume of the piston bore is given in equation (3.2). So the idealized instantaneous flow in the piston is generated by substituting equation (3.2) to equation (3.22) as follows:

$$Q = A_p R \omega \tan(\delta_0) \cos(\alpha) \quad (3.23)$$

where ω is the rotational speed of the hydraulic motor. The total discharge flow of the hydraulic motor is equal to the net flow from each piston chamber that is instantaneously positioned in the inlet port. The total inlet flow can be obtained as:

$$Q = A_p R \tan(\delta_0) \omega \sum_{n=1}^{n'} \cos(\alpha) \quad (3.24)$$

where ω is the angular speed. n' is the total number of the pistons that are instantaneously positioned over the supply port of the hydraulic motor. For the hydraulic motor with odd

pistons, this quantity is expressed as:

$$n' = \frac{N_0 \pm 1}{2} \quad (3.25)$$

where N_0 is the total number of odd pistons in the hydraulic motor and the ± 1 indicates that the number of pistons positioned over the inlet port is repeatedly fluctuating and depends on the rotational position of the hydraulic motor or amount of overlap. Using the integral average of equation (3.24), the nominal inlet flow of the hydraulic motor can be expressed as [25]:

$$\bar{Q} = \frac{N A_p R \tan(\delta_0) \omega}{2\pi} \int_{-\pi/2}^{\pi/2} \cos(\alpha) d\alpha = \frac{N A_p R \tan(\delta_0) \omega}{\pi} \quad (3.26)$$

Equation (3.26) shows that the relation between the flow rate and the shaft speed is linear when the piston chamber volume is constant. By dividing equation (3.24) by equation (3.26), the normalized discharge flow from the hydraulic motor is obtained as:

$$\hat{Q} = \frac{\pi}{N} \sum_{n=1}^{n'} \cos(\alpha) \quad (3.27)$$

The piston pass frequency is given by following equation:

$$f_{pass} = \frac{N_0 \omega}{2\pi} \quad (3.28)$$

The simulation results of equation (3.24) are shown in Figure 3.10 for a 5-piston water hydraulic motor. Figure 3.11 shows the FFT of equation (3.24) for the 5-piston motor. The frequencies in Figure 3.11 are normalized by the piston pass frequency of hydraulic motor. The idealized flow in the inlet port is fluctuating repeatedly. The principle frequency is the

piston pass frequency.

Figure 3.10 Idealized flow for 5-piston axial piston motor

Figure 3.11 FFT of the idealized flow for 5-piston axial piston motor

3.5.3 Actual Hydraulic Flow

The idealized hydraulic motor flow is based on the idealized assumption that the motor does not leak and the fluid is incompressible. Because this assumption is not true in practice, it is necessary to consider the complicated condition in which leakage occurs and the fluid

compresses due to the pressure that is instantaneously applied to the piston. Dividing equation (3.6) by equation (3.26), the normalized inlet flow of the hydraulic motor is obtained as follows [21]:

$$\hat{Q} = \left(\frac{\pi}{NA_p R \tan(\delta_0) \omega} \right) \sum_{n=1}^{n'} \text{sign}(P - P_p) C_i A_n(t) \sqrt{\frac{2}{\rho} |P - P_p|} \quad (3.29)$$

Figure 3.12 shows numerical normalized amplitude of the simulated actual flow for 5-piston axial piston motor. Figure 3.13 shows the FFT of equation (3.6) for 5-piston motor. The supply line pressure P_i was $1.94 \times 10^6 \text{ Pa}$ and the return line pressure was $0.1 \times 10^6 \text{ Pa}$. The frequency in Figure 3.13 was normalized by the piston pass frequency of hydraulic motor. The results showed the actual flow change with the piston pass frequency and its harmonic frequencies.

Figure 3.12 Actual flow for 5-piston axial piston motor

Figure 3.13 FFT of the actual flow for 5-piston axial piston motor

3.6 Shaft Output Torque Analysis

Figure 3.14 shows the geometrical relation between the piston and swash plate [21]. The friction force between the piston and swash plate is small and can be neglected. The force produced by the pressure pulse is F_{Cz} . The torque arm l_y is $R \cos(\alpha)$, where R is the radius of cylinder block port circle. Therefore, the piston torque is expressed by

$$T_p = F_{Pz} \sin(\delta_0) l_y = F_{Pz} \sin(\delta_0) R \cos(\alpha) \quad (3.30)$$

Where F_{Pz} is the force on the piston along the z axis. Considering the inertia force of the moving piston, the longitudinal displacement of the piston is given in equation (3.1). The acceleration under steady state is shown as follows:

$$\ddot{x}_p = \omega^2 R \tan \delta_0 \sin \alpha = \omega^2 R \tan \delta_0 \sin(\omega t) \quad (3.31)$$

Equation 3.13 showed that the acceleration has relation with the rotating speed of the hydraulic motor under steady states. The rotating speed of hydraulic motor is determined by

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the flow rate of the water hydraulic system as shown in equation 3.26.

The inertia-related force is obtained as:

$$F_{inertia} = M_p \omega^2 R \tan \delta_0 \sin \alpha \quad (3.32)$$

The reaction force from the piston against the swash plate support is derived as follows:

$$F_{pz} = \frac{M_p \ddot{x}_p + P_p A_p}{\cos \delta_0} \quad (3.33)$$

Using equations (3.30), (3.32) and (3.33), the instantaneous torque of n^{th} piston is expressed as

$$T_n = (M_p \ddot{x}_p + P_p A_p) \tan \delta_0 R \cos(\alpha) \quad (3.34)$$

The net instantaneous output torque can be expressed as:

$$T = \sum_{n=1}^N T_n \quad (3.35)$$

where N is the number of the piston in the hydraulic motor. The average torque is obtained by the integration of equation (3.35)

$$\bar{T} = \frac{N}{2\pi} \int_0^{2\pi} (M_p \ddot{x}_p + P_p A_p) \tan(\delta_0) R \cos(\alpha) d\alpha \quad (3.36)$$

where $\alpha_n = \alpha_0 + \left(\frac{n-1}{N}\right) \times 2\pi$. Equation (3.36) shows that the average torque is related to

the inlet pressure of hydraulic motor and angular velocity of hydraulic motor. When the inlet pressure and angular velocity of hydraulic motor increases, the torque increases.

Figure 3.14: Geometrical relation of the load force and torque in the piston coordinate system and cylinder coordinate system [21]

Figure 3.15 shows the numerical result of equation (3.36). The output torque is 2 Nm . The normalized amplitude of the shaft output torque changes periodically in a small range. Figure 3.16 shows the frequency analysis of the equation (3.36). The principle frequencies are two times the piston pass frequency or the even harmonic frequencies.

Figure 3.15: Shaft output torque pulse shape under normal condition

Figure 3.16: Frequency analysis (FFT) of the shaft output torque pulse shape

The defects in the piston pump and motor can be reflected in some frequency bands of the pulsation pressure. The relation between the rational discharge flow, pump discharge pressure and hydraulic damping is defined as $q_s = q_0 + (P_0/Z_s)$, where q_s is the rational discharge pressure, P_0 is pump discharge pressure and Z_s is the pump hydraulic damping [54]. The defects in piston such as a loose or damage piston shoe and a crack in the piston would increase the overall leakage and result in a drop in the actual discharge flow. The reduction in the supplying flow would result in a decreased discharge pressure in the above equation. Similar to the piston pump, the piston crack in the piston motor would decrease the piston pressure and affect the output torque according to equations (3.20) and (3.36). Figure 3.17 shows the shaft output torque waveform. There is variation in the amplitude of the torque. Figure 3.18 shows the frequency of the output torque. The first frequency shows the one crack piston pass frequency in the hydraulic motor which is different from Figure 3.16.

Figure 3.17: Shaft output torque pulse shape under piston crack condition

Figure 3.18: Frequency analysis of the shaft output torque pulse shape under piston crack condition

3.7. Characteristics of Pressure Ripple in Water Hydraulic System

A hydraulic system generates more complicated vibration (noise) because of the interaction between the two pressure pulsations produced by the motor and pump. The fluidborne vibration causes structureborne vibration that has negative effect on the

hydraulic motor and pump. Kojima and Shinada [35] and Edge et al. [39] investigated the fluidborne vibration in a combination circuit consisting of a pump, a motor and a connecting pipe. The pressure ripple is characteristic of a fundamental component at piston frequency obtained in a general hydraulic system. The characteristic frequencies of fluidborne vibration in hydraulic system have two flow and pressure pulsating sources that the pump and motor generate respectively.

Figure 3.19 shows the typical experimental supply pressure ripples of water hydraulic motor in water hydraulic system that consists of axial piston pump, swash-plate type water hydraulic motor and connection. The output torque and flow rate of the water hydraulic motor were $2Nm$ and $0.12l/s$. The angular speeds of hydraulic motor and pump were $630rev/min$ and $1450rev/min$. The supply pressure ripple of hydraulic motor is affected predominantly by the fundamental component of the pump's harmonic frequency (f_p) and the motor's harmonic frequency (f_m and f_0), where $f_m = 5f_0$, where f_m is the motor's frequency and f_0 is one piston's frequency, here the water hydraulic motor has five pistons.

Figure 3.20 shows the spectrum of the supply pressure ripple of the water hydraulic motor. One revolution of the motor occurs in $T_0 (1/f_0)$. During this period, there are five pulses to be generated as direct result of the unsteady flow produced by the water hydraulic motor. Each pulse produced by each piston of water hydraulic motor occurs in $T_m (1/f_m)$. The inter-cylinder pulse variation is function of leakage and piston circumferential pressure. The waveform is periodic over each revolution and the period of the waveform cover one cycle of motor. The delivery pulse associated with axial piston pump occurs in $T_p (1/f_p)$. There is the small-amplitude and high-frequency decaying oscillation in the

pressure ripple as a result of the flow pulse.

Figure 3.19: Water hydraulic motor supply pressures waveform

Figure 3.20. The spectrum of the supply pressure ripple of hydraulic motor

3.8. Theoretical Model of Water Hydraulic Motor

Figure 3.21 shows the dynamic model of a swash plate type water hydraulic motor. The model has three masses and fourteen DOF including outer shell and swash plate, cylinder block, piston and retaining ring as well as valve cover (valve port plate and port flange). The overall coordinate system $O - XYZ$ is set on the valve cover. The original O is set at the intersection of the centerline of the motor shaft and the internal plane of the valve cover. The axis Z is along the centerline of the motor shaft. The axis X is on the perpendicular plane. The axis Y is on the horizontal plane. The coordination systems of each mass are defined with the subscripts F , P and C . These subscripts are added to the symbols X , Y and Z that represent the translational motion along the x , y and z axial directions. This subscripts are also added to the symbols ϕ and θ which represent the circular motion around axes X and Y . These symbols represent the freedom of movement for each mass.

Figure 3.21. Dynamic model of a water hydraulic motor

3.8.1 Exciting force on cylinder block, piston and swash plate

The supply pressure pulsation of hydraulic motor produces the exciting force that causes the hydraulic motor to vibrate. The exciting force from the pressure pulsations act on the piston and the inlet port of the cylinder. It creates the force on the contact surface between the piston and cylinder inside the hydraulic motor in opposing manner. The geometrical relation of the piston and cylinder coordinate system is shown in Figure 3.14. The exerting

force F_{Cz} on the cylinder along the Z axis, the torque T_{Cx} on the cylinder about X_C axis and the torque T_{Cy} on the cylinder about Y_C axis in the coordinate system $O_C - X_C Y_C Z_C$ can be expressed by

$$F_{Cz} = pA, \quad T_{Cx} = l_y F_{Cz} \quad T_{Cy} = -l_x F_{Cz} \quad (3.37)$$

where p is the pulsation pressure in the piston, A is the cross-sectional area of the piston inside the inlet port of hydraulic motor, l_x and l_y are the equivalent center coordinates in the cylinder block cross-section of the exerting force F_{Cz} . The counterforce of F_{Cz} on the piston is expressed by $F_{Cz} = -F'_{Cz}$.

The exerting force F_{Pz} on the piston and retaining ring along the axis Z , the torque T_{Px} on the piston and retaining ring around axis X_P and the torque T_{Py} on the cylinder block around axis Y_P can be expressed in the coordinate system $O_P - X_P Y_P Z_P$ by

$$F_{Pz} = -F_{Cz} / \cos \delta_0 \quad T_{Px} = -T_{Cx} / \cos \delta_0 \quad T_{Py} = -T_{Cy} \quad (3.38)$$

where δ_0 is the angle of the swash plate.

3.8.2 Dynamic model of swash plate and outer shell

The coordinate system of the outer shell and swash plate is defined as $O_F - X_F Y_F Z_F$. The original point O_F is set on the gravity center of the outer shell and swash plate. The Z_F axis of the coordinate system $O_F - X_F Y_F Z_F$ is along the centerline of the motor shaft.

(X_F, Y_F) axes are parallel to the (X, Y) coordinates. The dynamic equilibrium equation of the motion of the outer shell and swash plate along the direction of the X_F can be expressed as follows:

$$\begin{aligned}
 & M_F \ddot{X}_F + C_{Sw} \sin \delta_0 \times \\
 & \left\{ \left(\dot{X}_F \sin \delta_0 + \dot{Z}_F \cos \delta_0 - \dot{Z}_P \right) - RB_1 (\dot{\phi}_F \cos \delta_0 - \dot{\phi}_P) - \right. \\
 & \left. \left[\left(L_{PF} \sin \delta_0 + \frac{RB_2}{\cos \delta_0} \right) \dot{\theta}_F - \frac{RB_2}{\cos \delta_0} \dot{\theta}_P \right] \right\} \\
 & + K_{Sw} \sin \delta_0 \\
 & \times \left\{ \left(X_F \sin \delta + Z_F \cos \delta_0 - Z_P \right) - RB_1 (\phi_F \cos \delta_0 - \phi_P) - \right. \\
 & \left. \left[\left(L_{PF} \sin \delta_0 + \frac{RB_2}{\cos \delta_0} \right) \theta_F - \frac{RB_2}{\cos \delta_0} \theta_P \right] \right\} \\
 & + 4K_{Box} (X_F + L_{F2} \theta_F) + K_{Shx} \{ (X_F - L_{F1} \theta_F) - (X_C - L_{C1} \theta_C) \} \\
 & + C_{Shx} \{ (X_F - L_{F1} \theta_F) - (X_C - L_{C1} \theta_C) \} = 0
 \end{aligned} \tag{3.39}$$

where $B_1 = \sum_{i=0}^{n-1} \cos(\omega_0 t + i\eta)$, $B_2 = \sum_{i=0}^{n-1} \sin(\omega_0 t + i\eta)$, $\eta = 2\pi/n$. K_{Sw} is the stiffness of the piston. C_{Sw} is the damping coefficient of the interface between the piston and the swash plate. K_{Box} is the stiffness of the bolt between the outer shell and the valve cover in the direction of the X_F axis. K_{Shx} is the stiffness of the motor shaft in direction of the X_F axis. C_{Shx} is the damping coefficient of the interface between the shaft, valve cover and outer shell in the direction of X_F axis and n is the number of pistons.

The dynamic equation of the motion in the direction of Y_F is expressed as:

$$\begin{aligned} & M_F \ddot{Y}_F + 4K_{Boy} (Y_F - L_{F2} \phi_F) \\ & + K_{Shy} \{ (Y_F + L_{F1} \phi_F) - (Y_C + L_{C1} \phi_C) \} + \\ & C_{Shy} \{ (\dot{Y}_F + L_{F1} \dot{\phi}_F) - (\dot{Y}_C + L_{C1} \dot{\phi}_C) \} = 0 \end{aligned} \quad (3.40)$$

where K_{Boy} is the stiffness of the bolt between the outer shell and the valve cover in direction of axis Y_F . K_{Shy} is the stiffness of the motor shaft in the direction of the Y_F axis. C_{Shy} is the damping coefficient of the interface between the shaft and valve cover and outer shell in the direction of the Y_F axis.

In the direction of the Z_F , the equation of motion is derived as:

$$\begin{aligned} & M_F \ddot{Z}_F + C_{Sw} \cos \delta_0 \times \left\{ \left(\dot{X}_F \sin \delta_0 + \dot{Z}_F \cos \delta_0 - \dot{Z}_P \right) - RB_1 (\dot{\phi}_F \cos \delta_0 - \dot{\phi}_P) - \right. \\ & \left. \left[\left(L_{PF} \sin \delta_0 + \frac{RB_2}{\cos \delta_0} \right) \dot{\theta}_F - \frac{RB_2}{\cos \delta_0} \dot{\theta}_P \right] \right\} \\ & + K_{Sw} \cos \delta_0 \times \left\{ \left(X_F \sin \delta_0 + Z_F \cos \delta_0 - Z_P \right) - RB_1 (\phi_F \cos \delta_0 - \phi_P) - \right. \\ & \left. \left[\left(L_{PF} \sin \delta_0 + \frac{RB_2}{\cos \delta_0} \right) \theta_F - \frac{RB_2}{\cos \delta_0} \theta_P \right] \right\} + 4K_{Boz} Z_F = 0 \end{aligned} \quad (3.41)$$

where K_{Boz} is the stiffness of the bolt between the outer shell and the valve cover in direction of Z_F axis.

The dynamic equations of rotation around X_F and Y_F can be respectively expressed as follows:

$$\begin{aligned}
 & I_{Fx} \ddot{\phi}_F \\
 & - C_{Sw} \cos \delta_0 R \left\{ B_1 \left(\dot{X}_F \sin \delta_0 + \dot{Z}_F \cos \delta_0 - \dot{Z}_P \right) + RB_3 \left(-\dot{\phi}_F \cos \delta_0 + \dot{\phi}_P \right) + \right. \\
 & \left. - \left[L_{PF} B_1 \sin \delta_0 + \frac{RB_5}{\cos \delta_0} \right] \dot{\theta}_F + \frac{RB_5}{\cos \delta_0} \dot{\theta}_P \right\} \\
 & - K_{Sw} \cos \delta_0 R \left\{ B_1 \left(X_F \sin \delta_0 + Z_F \cos \delta_0 - Z_P \right) + RB_3 \left(-\phi_F \cos \delta_0 + \phi_P \right) + \right. \\
 & \left. - \left[L_{PF} B_1 \sin \delta_0 + \frac{RB_5}{\cos \delta_0} \right] \theta_F + \frac{RB_5}{\cos \delta_0} \theta_P \right\} - \quad (3.42)
 \end{aligned}$$

$$\begin{aligned}
 & 4K_{Boy} L_{F2} (Y_F - L_{F2} \phi_F) + 4K_{Boz} L_b^2 \phi_F \\
 & + K_{Shy} \times L_{F1} \{ (Y_F + L_{F1} \phi_F) - (Y_C - L_{C1} \phi_C) \} + \\
 & C_{Shy} L_{F1} \{ (\dot{Y}_F + L_{F1} \dot{\phi}_F) - (\dot{Y}_C - L_{C1} \dot{\phi}_C) \} = 0
 \end{aligned}$$

where $B_3 = \sum_{i=0}^{n-1} \cos^2(\omega_0 t + i\eta)$, $B_5 = \sum_{i=0}^{n-1} \sin(\omega_0 t + i\eta) \cos(\omega_0 t + i\eta)$. I_{Fx} is the inertia of mass

of the outer shell and swash plate about the X_F axis.

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$$\begin{aligned}
 & I_{Fy} \ddot{\theta}_F + 4K_{B0x} L_{F2} (X_F + L_{F2} \theta_F) + 4K_{B0z} L_b^2 \theta_F - \\
 & C_{Sw} \left\{ \left(\dot{X}_F \sin \delta_0 + \dot{Z}_F \cos \delta_0 - \dot{Z}_P \right) \left(L_{PF} \sin \delta_0 + \frac{RB_2}{\cos \delta_0} \right) - \right. \\
 & \quad \left. R(\dot{\phi}_F \cos \delta_0 - \dot{\phi}_P) \left(L_{PF} \sin \delta_0 B_1 + \frac{RB_5}{\cos \delta_0} \right) \right\} + \\
 & C_{Sw} \left\{ \left(L_{PF}^2 \sin^2 \delta_0 + 2L_{PF} RB_2 \tan \delta_0 + \frac{R^2 B_4}{\cos^2 \delta_0} \right) \dot{\theta}_F - \right. \\
 & \quad \left. \left(RB_2 \tan \delta_0 L_{PF} + \frac{R^2 B_4}{\cos^2 \delta_0} \right) \dot{\theta}_P \right\} - \\
 & K_{Sw} \left\{ \left(X_F \sin \delta_0 + Z_F \cos \delta_0 - Z_P \right) \left(L_{PF} \sin \delta_0 + \frac{RB_2}{\cos \delta_0} \right) - \right. \\
 & \quad \left. R(\phi_F \cos \delta_0 - \phi_P) \left(L_{PF} \sin \delta_0 B_1 + \frac{RB_5}{\cos \delta_0} \right) \right\} + \\
 & K_{Sw} \left\{ \left(L_{PF}^2 \sin^2 \delta_0 + 2L_{PF} RB_2 \tan \delta_0 + \frac{R^2 B_4}{\cos^2 \delta_0} \right) \theta_F \right. \\
 & \quad \left. - \left(RB_2 \tan \delta_0 L_{PF} + \frac{R^2 B_4}{\cos^2 \delta_0} \right) \theta_P \right\} - \\
 & K_{Shx} L_{F1} \{ (X_F - L_{F1} \theta_F) - (X_C - L_{C1} \theta_C) \} - \\
 & C_{Shx} L_{F1} \{ (\dot{X}_F - L_{F1} \dot{\theta}_F) - (\dot{X}_C - L_{C1} \dot{\theta}_C) \} = 0
 \end{aligned} \tag{3.43}$$

where $B_4 = \sum_{i=0}^{n-1} \sin^2(\omega_0 t + i\eta)$. I_{Fy} is the inertia of mass of the outer shell and swash plate

about the Y_F axis.

3.8.3 Dynamic model of piston and retaining ring

$O_p - X_p Y_p Z_p$ is the coordinate system of the piston and retaining ring. The original point O_p is set on the gravity center of the piston and retaining ring. The Z_p axis of the coordinate system $O_p - X_p Y_p Z_p$ is along the centerline of the motor shaft. (X, Y) coordinates are on (X_p, Y_p) axis. As shown in figure 3.4, the swash plate supports the pistons by the shoes. The interface between the swash plate and piston shoe is very smooth. The friction of the interface along the Y axis is very small. The swash plate interface is symmetrical about the X axis. The damping and stiffness coefficient of the interface between the swash plate and piston shoe is zero along the Y axis. The damping, stiffness and friction coefficients of the interface between the swash plate and piston along the Y axis are zero. Two kinds of forces are effective in the axial piston motor, which are pressure dependent and pressure independent forces. The pressure forces are dominant, which are produced by the piston pressure. To simplify calculation, all the other forces are neglected [21]. Therefore the motion and force in the direction of Y_p are zero. The dynamic equilibrium equation of motion of the piston and retaining ring along the direction of X_p and Z_p can be respectively expressed by

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$$\begin{aligned}
 & M_p \ddot{X}_p - \\
 & C_{HZ} \sin \delta_0 \left\{ n(\dot{Z}_p \cos \delta_0 - \dot{X}_p \sin \delta_0 - \dot{Z}_c) \right. \\
 & \quad \left. + RB_1(-\dot{\phi}_p \cos \delta_0 + \dot{\phi}_c) - RB_2(\dot{\theta}_p - \dot{\theta}_c) \right\} - \\
 & K_{HZ} \sin \delta_0 \left\{ n(Z_p \cos \delta_0 - X_p \sin \delta_0 - Z_c) \right. \\
 & \quad \left. + RB_1(-\phi_p \cos \delta_0 + \phi_c) - RB_2(\theta_p - \theta_c) \right\} - \\
 & K_p \sin \delta_0 \left\{ n(Z_p \cos \delta_0 - X_p \sin \delta_0 - Z_c) \right. \\
 & \quad \left. + RA_1(-\phi_p \cos \delta_0 + \phi_c) - RA_2(\theta_p - \theta_c) \right\} \\
 & = 0
 \end{aligned} \tag{3.44}$$

where $A_1 = \sum_{i=0}^n \cos(\omega_0 t + 1.5i\eta)$, $A_2 = \sum_{i=0}^{n-i} \sin(\omega_0 t + 1.5i\eta)$. C_{HZ} is the damping coefficient of the interface between the piston and the cylinder port. K_{HZ} is the stiffness in the interface between the piston and the cylinder port and K_p is the stiffness of the spring.

$$\begin{aligned}
 & M_p \ddot{Z}_p - \\
 & C_{Sw} \left\{ n(\dot{X}_F \sin \delta_0 + \dot{Z}_F \cos \delta_0 - \dot{Z}_p) - RB_1(\dot{\phi}_F \cos \delta_0 - \dot{\phi}_p) - \right. \\
 & \quad \left. \left[\left(L_{PF} \sin \delta_0 + \frac{RB_2}{\cos \delta_0} \right) \dot{\theta}_F - \frac{RB_2}{\cos \delta_0} \dot{\theta}_p \right] \right\} - \\
 & K_{Sw} \left\{ n(X_F \sin \delta_0 + Z_F \cos \delta_0 - Z_p) - RB_1(\phi_F \cos \delta_0 - \phi_p) - \right. \\
 & \quad \left. \left[\left(L_{PF} \sin \delta_0 + \frac{RB_2}{\cos \delta_0} \right) \theta_F - \frac{RB_2}{\cos \delta_0} \theta_p \right] \right\} + \\
 & C_{HZ} \cos \delta_0 \left\{ n(\dot{Z}_p \cos \delta_0 - \dot{X}_p \sin \delta_0 - \dot{Z}_c) \right. \\
 & \quad \left. + RB_1(-\dot{\phi}_p \cos \delta_0 + \dot{\phi}_c) - RB_2(\dot{\theta}_p - \dot{\theta}_c) \right\} + \\
 & K_{HZ} \cos \delta_0 \left\{ n(Z_p \cos \delta_0 - X_p \sin \delta_0 - Z_c) \right. \\
 & \quad \left. + RB_1(-\phi_p \cos \delta_0 + \phi_c) - RB_2(\theta_p - \theta_c) \right\} + \\
 & K_p \cos \delta_0 \left\{ n(Z_p \cos \delta_0 - X_p \sin \delta_0 - Z_c) \right. \\
 & \quad \left. + RB_1(-\phi_p \cos \delta_0 + \phi_c) - RB_2(\theta_p - \theta_c) \right\} = F_{PZ}
 \end{aligned} \tag{3.45}$$

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The rotation around X_p and Y_p can be respectively expressed as below:

$$\begin{aligned}
 & I_{Px} \ddot{\phi}_p - \\
 & C_{HZ} R \cos \delta_0 \left\{ B_1 (\dot{Z}_p \cos \delta_0 - \dot{X}_p \sin \delta_0 - \dot{Z}_c) \right. \\
 & \quad \left. + RB_3 (-\dot{\phi}_p \cos \delta_0 + \dot{\phi}_c) - RB_5 (\dot{\theta}_p - \dot{\theta}_c) \right\} - \\
 & K_{HZ} R \cos \delta_0 \left\{ B_1 (Z_p \cos \delta_0 - X_p \sin \delta_0 - Z_c) \right. \\
 & \quad \left. + RB_3 (-\phi_p \cos \delta_0 + \phi_c) - RB_5 (\theta_p - \theta_c) \right\} + \\
 & C_{Sw} R \left\{ nB_1 (\dot{X}_F \sin \delta_0 + \dot{Z}_F \cos \delta_0 - \dot{Z}_p) + B_3 R (-\dot{\phi}_F + \dot{\phi}_p) + \right. \\
 & \quad \left. - \left(L_{PF} B_1 \sin \delta_0 + \frac{RB_5}{\cos \delta_0} \right) \dot{\theta}_F + \frac{RB_5}{\cos \delta_0} \dot{\theta}_p \right\} + \\
 & K_{Sw} R \left\{ nB_1 (X_F \sin \delta_0 + Z_F \cos \delta_0 - Z_p) + B_3 R (-\phi_F + \phi_p) + \right. \\
 & \quad \left. - \left(L_{PF} B_1 \sin \delta_0 + \frac{RB_5}{\cos \delta_0} \right) \theta_F + \frac{RB_5}{\cos \delta_0} \theta_p \right\} - \\
 & K_P r \cos \delta_0 \left\{ A_1 (Z_p \cos \delta_0 - X_p \sin \delta_0 - Z_c) \right. \\
 & \quad \left. + A_3 (-\phi_p \cos \delta_0 + \phi_c) - rA_5 (\theta_p - \theta_c) \right\} = T_{Px}
 \end{aligned} \tag{3.46}$$

where $A_3 = \sum_{i=0}^{n-1} \cos^2(\omega_0 t + 1.5i\eta)$, $A_5 = \sum_{i=0}^{n-1} \sin(\omega_0 t + 1.5i\eta) \cos(\omega_0 t + 1.5i\eta)$. I_{Px} is the inertia

of mass of the piston and swash plate about X_p axis.

$$\begin{aligned}
 & I_{Py} \ddot{\theta}_P - \\
 & C_{HZ} R \cos \delta_0 \left\{ B_2 (\dot{Z}_P \cos \delta_0 - \dot{X}_P \sin \delta_0 - \dot{Z}_C) + \right. \\
 & \left. RB_5 (-\dot{\phi}_P \cos \delta_0 + \dot{\phi}_C) - RB_4 (\dot{\theta}_P - \dot{\theta}_C) \right\} - \\
 & K_{HZ} R \cos \delta_0 \left\{ B_2 (Z_P \cos \delta_0 - X_P \sin \delta_0 - Z_C) + \right. \\
 & \left. RB_5 (-\phi_P \cos \delta_0 + \phi_C) - RB_4 (\theta_P - \theta_C) \right\} + \\
 & C_{Sw} (R / \cos \delta_0) \left\{ B_2 (\dot{X}_F \sin \delta_0 + \dot{Z}_F \cos \delta_0 - \dot{Z}_P) + B_5 R (-\dot{\phi}_F \cos \delta_0 + \dot{\phi}_P) + \right. \\
 & \left. \left[- \left(L_{PF} B_2 \sin \delta_0 + \frac{RB_4}{\cos \delta_0} \right) \dot{\theta}_F + \frac{RB_4}{\cos \delta_0} \dot{\theta}_P \right] \right\} + \\
 & K_{Sw} (R / \cos \delta_0) \left\{ B_2 (X_F \sin \delta_0 + Z_F \cos \delta_0 - Z_P) + B_5 R (-\phi_F \cos \delta_0 + \phi_P) + \right. \\
 & \left. \left[- \left(L_{PF} B_2 \sin \delta_0 + \frac{RB_4}{\cos \delta_0} \right) \theta_F + \frac{RB_4}{\cos \delta_0} \theta_P \right] \right\} - \\
 & K_P r \cos \delta_0 \left\{ A_2 (Z_P \cos \delta_0 - X_P \sin \delta_0 - Z_C) + \right. \\
 & \left. r A_5 (-\phi_P \cos \delta_0 + \phi_C) - r A_4 (\theta_P - \theta_C) \right\} = T_{Py}
 \end{aligned} \tag{3.47}$$

where $A_4 = \sum_{i=0}^{n-1} \sin^2(\omega_0 t + 1.5i\eta)$. I_{Py} is the inertia of mass of the piston and swash plate

about the Y_P axis.

3.8.4 Dynamic model of cylinder block

The coordinate system of the cylinder block is $O_C - X_C Y_C Z_C$. The original point O_C is at the gravity center of the cylinder block. The Z_C axis is on the centerline of the motor shaft. (X_C, Y_C) axes are parallel to the (X, Y) coordinates. The dynamic equilibrium equation of the motion of the cylinder block in the direction of the X_C , Y_C and Z_C can be respectively expressed as follow:

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$$\begin{aligned} M_C \ddot{X}_C - K_{Shx} \{ (X_F - L_{F1} \theta_F) - (X_C - L_{C1} \theta_C) \} - \\ C_{Shx} \{ (\dot{X}_F - L_{F1} \dot{\theta}_F) - (\dot{X}_C - L_{C1} \dot{\theta}_C) \} = 0 \end{aligned} \quad (3.48)$$

$$\begin{aligned} M_C \ddot{Y}_C - K_{Shy} \{ (Y_F + L_{F1} \phi_F) - (Y_C + L_{C1} \phi_C) \} + K_{Shy} (Y_C - L_{C2} \phi_C) \\ - C_{Shy} \{ (\dot{Y}_F + L_{F1} \dot{\phi}_F) - (\dot{Y}_C + L_{C1} \dot{\phi}_C) \} + C_{Shy} (\dot{Y}_C - L_{C2} \dot{\phi}_C) = 0 \end{aligned} \quad (3.49)$$

$$\begin{aligned} M_C \ddot{Z}_C - \\ C_{HZ} \{ n(\dot{Z}_P \cos \delta_0 - \dot{X}_P \sin \delta_0 - \dot{Z}_C) + RB_1(-\dot{\phi}_P \cos \delta_0 + \dot{\phi}_C) - RB_2(\dot{\theta}_P - \dot{\theta}_C) \} - \\ K_{HZ} \{ n(Z_P \cos \delta_0 - X_P \sin \delta_0 - Z_C) + RB_1(-\phi_P \cos \delta_0 + \phi_C) - RB_2(\theta_P - \theta_C) \} - \\ K_P \{ n(Z_P \cos \delta_0 - X_P \sin \delta_0 - Z_C) + RA_1(-\phi_P \cos \delta_0 + \phi_C) - RA_2(\theta_P - \theta_C) \} + \\ C_{Vaz} \dot{Z}_C + K_{Vaz} Z_C = F_{Cz} \end{aligned} \quad (3.50)$$

where K_{Va} and C_{Va} is the stiffness and damping coefficient in the interface between the valve cover and the cylinder block respectively.

The equation of rotation about x_C and y_C can be respectively expressed by

$$\begin{aligned} I_{Cx} \ddot{\phi}_c + \\ C_{HZ} R \{ B_1(\dot{Z}_P \cos \delta_0 - \dot{X}_P \sin \delta_0 - \dot{Z}_C) + RB_3(-\dot{\phi}_P \cos \delta_0 + \dot{\phi}_C) - RB_5(\dot{\theta}_P - \dot{\theta}_C) \} + \\ K_{HZ} R \{ B_1(Z_P \cos \delta_0 - X_P \sin \delta_0 - Z_C) + RB_3(-\phi_P \cos \delta_0 + \phi_C) - RB_5(\theta_P - \theta_C) \} + \\ K_P r \{ A_1(Z_P \cos \delta_0 - X_P \sin \delta_0 - Z_C) + rA_3(-\phi_P \cos \delta_0 + \phi_C) - rA_5(\theta_P - \theta_C) \} + \\ \frac{C_{Vaz}}{2} R_V^2 \dot{\phi}_C + \frac{K_{Vaz}}{2} R_V^2 \phi_C - K_{Shy} L_{C1} \{ (Y_F + L_{F1} \phi_F) - (Y_C + L_{C1} \phi_C) \} \\ - C_{Shy} L_{C1} \{ (\dot{Y}_F + L_{F1} \dot{\phi}_F) - (\dot{Y}_C + L_{C1} \dot{\phi}_C) \} = T_{Cx} \end{aligned} \quad (3.51)$$

$$\begin{aligned}
 & I_{Cy} \ddot{\theta}_C + C_{HZ} R \{ B_2 (Z_P \cos \delta_0 - X_P \sin \delta_0 - Z_C) + B_5 (-\phi_P \cos \delta_0 + \phi_C) + B_4 (-\theta_P + \theta_C) \} + \\
 & K_{HZ} \{ B_2 (Z_P \cos \delta_0 - X_P \sin \delta_0 - Z_C) + B_5 (-\phi_P \cos \delta_0 + \phi_C) + B_4 (-\theta_P + \theta_C) \} + \\
 & K_{Shx} L_{C1} \{ (X_F - L_{F1} \theta_F) - (X_C - L_{C1} \theta_C) \} + C_{Shx} L_{C1} \{ (\dot{X}_F - L_{F1} \dot{\theta}_F) - (\dot{X}_C - L_{C1} \dot{\theta}_C) \} \\
 & = T_{Cy}
 \end{aligned} \tag{3.52}$$

where I_{Cx} is the inertia of mass of the cylinder block about the X_C axis. I_{Cy} is the inertia of mass of the cylinder block about Y_C axis.

3.8.5. Generalized system equations of motion

The equation of motion for the hydraulic motor can be written in matrix form as:

$$[M] \{\ddot{q}\} + [C] \{\dot{q}\} + [K] \{q\} = \{Q(t)\} \tag{3.53}$$

where $\{q\} = \{X_F, Y_F, Z_F, \phi_F, \theta_F, X_P, Z_P, \phi_P, \theta_P, X_C, Y_C, Z_C, \phi_C, \theta_C\}^T$

$$\{Q(t)\} = \{0, 0, 0, 0, 0, 0, F_{Pz}, T_{Px}, T_{Py}, 0, 0, F_{Cz}, T_{Cx}, T_{Cy}\}$$

By incorporating the equivalent viscous modal damping, the equation in the form of modal components is expressed as $\{q\} = [\tilde{u}] \{\eta(t)\}$, where $[\tilde{u}]$ is the orthonormal modal matrix.

The generalized force is given by $\{N(t)\} = [\tilde{u}]^T \{Q(t)\}$. By applying the orthogonal condition to simplify the above couple equations and transpose of the orthonormal modal matrix, the following modal forced vibration equations can be obtained.

$$\ddot{\eta}_r + 2\xi_r p_r \dot{\eta}_r + p_r^2 \eta_r = N_r(t) \tag{3.54}$$

where ξ_r is the equivalent modal damping ratio. The applicable Matlab simulation program has been developed based on the above approaches [114].

3.8.6. Results and Discussion

The numerical simulation result of this dynamic model can be obtained using the parameter value in Table 3.1 [115], which was shown in Appendix B.

Table 3.1: Parameters used in the model.

Parameter		Parameter	
A	$2 \times 10^{-4} \text{ (m}^2\text{)}$	L_{F2}	$5.5 \times 10^{-2} \text{ (m)}$
C_{HZ}	$3.4 \times 10^4 \text{ (N.s/m)}$	L_{C1}	$7.7 \times 10^{-2} \text{ (m)}$
C_{Shx}	$1.0 \times 10^5 \text{ (N.s/m)}$	L_{C2}	$4 \times 10^{-2} \text{ (m)}$
C_{Shy}	$1.0 \times 10^5 \text{ (N.s/m)}$	L_b	$3.6 \times 10^{-2} \text{ (m)}$
C_{Sw}	$1.8 \times 10^6 \text{ (N.s/m)}$	L_{Sh}	$11.7 \times 10^{-2} \text{ (m)}$
C_{Va}	$3.6 \times 10^6 \text{ (N.s/m)}$	M_C	1.515 kg
K_{Sw}	$4.3 \times 10^7 \text{ (N/m)}$	M_F	1.012 kg
K_{Box}	$6.5 \times 10^8 \text{ (N/m)}$	M_P	0.353 kg
K_{Boy}	$6.5 \times 10^8 \text{ (N/m)}$	n	5
K_{Boz}	$2.3 \times 10^9 \text{ (N/m)}$	r	$12 \times 10^{-3} \text{ (m)}$
K_{Shx}	$1.04 \times 10^7 \text{ (N/m)}$	R_V	$30 \times 10^{-3} \text{ (m)}$
K_{Shy}	$1.04 \times 10^7 \text{ (N/m)}$	R	$22 \times 10^{-3} \text{ (m)}$
K_{Hz}	$1.2 \times 10^7 \text{ (N/m)}$	I_{Cx}	$9.4 \times 10^{-4} \text{ kg} \cdot \text{m}^2$
K_P	4444 (N/m)	I_{Cy}	$9.4 \times 10^{-4} \text{ kg} \cdot \text{m}^2$
K_{Va}	$9.8 \times 10^8 \text{ (N/m)}$	I_{Fx}	$2.26 \times 10^{-3} \text{ kg} \cdot \text{m}^2$
l_x	0.021 (m)	I_{Fy}	$2.26 \times 10^{-3} \text{ kg} \cdot \text{m}^2$
l_y	$4 \times 10^{-5} \text{ (m)}$	I_{Px}	$1.291 \times 10^{-4} \text{ kg} \cdot \text{m}^2$
L_{F1}	$5 \times 10^{-2} \text{ (m)}$	I_{Py}	$1.291 \times 10^{-4} \text{ kg} \cdot \text{m}^2$
		δ_0	17

In order to confirm the validity of the dynamic model, the numerical simulations of the vibration waveforms were compared with the experimental vibration waveforms. The radial vibration of the outer shell that is sensitive to the fluidborne and structural vibration was the dominant factor affecting the vibration of water hydraulic motor system. It is suitable to test

the model by comparison with the simulated signal. The experimental vibration signals in the other axes as obtained by the experimental procedure in the section 3.2 are less sensitive to the fluiborne and structural vibration due to the structural solidity, especially along the Y_F axis and Z_F axis.

The experimental procedure was described in section 3.2. The rotational speed of Nessie motor was 630 rev/min so the 1024 samples of the vibration signal can just cover one rotational cycle of the water hydraulic motor. The vibration signals can contain the characteristic vibration information in one rotational cycle of the water hydraulic motor for the repeatability and stability of vibration signals. The rotational speed of the water hydraulic pump was 1450 rev/min . The output torque of the Nessie hydraulic motor was 2 Nm . The flow rate of the water hydraulic system was 0.12 l/s . The digitization of the time series by the computer program was carried out at a sampling rate that obeys the Nyquist formula, given by $f_s \geq 2f_h$ where f_s is the sampling frequency, and f_h is the highest frequency in the Fourier spectrum of the analyzed signal. The highest frequency f_h of the motor vibration signal was about 3 kHz . So the sampling frequency f_s was chosen to be 12.8 kHz . This sampling rate was found to be satisfactory for the type of signals considered in this work. A time record of 1024 data points was taken in each experimental run. The frequencies of the vibration from the shell of the hydraulic motor consisted of the hydraulic motor's fundamental frequency, hydraulic pump fundamental frequency and its harmonics.

Figure 3.22 shows the comparison of the radial acceleration waveform between the simulated and experimental signals. It can be seen that there is a high degree of correlation between the numerical analysis results and experimental results for both the cycle period

and amplitude of the vibration. Figure 3.23 shows the spectrum comparison of the simulated acceleration signals and the experimental signals. The fundamental frequencies are approximately the same, which are the hydraulic motor rotational speed (f_0 and f_m) and hydraulic pump speed (f_p). The integer multiples of the fundamental frequency are also approximately the same. The results of the above comparison confirm the validity of the dynamic analysis presented.

Figure 3.22: The vibration waveform comparison between simulation and experimental results

Figure 3.23. Comparison of vibration spectrum between the simulation results and experimental results

In order to clarify the vibration response characteristics for the total water hydraulic motor, the vibration responses from each mass of the hydraulic motor were obtained from the simulated dynamic mode.

Figure 3.24 shows the result of the acceleration of the outer shell in the direction of X_F , Y_F and Z_F axes. The amplitudes of the acceleration in X_F axis are the largest among the three axes. The amplitudes of the acceleration in Y_F are smallest. This was as a result of the external force produced by the pressure pulse in the Z_F axis. The external force tends to warp the swash plate support and the outer shell in a downward direction in the X_F axis and pushes the outer shell in the opposite direction in the Z_F axis. Because the stiffness of the outer shell in the Z_F axis is larger than the stiffness in the X_F axis, the magnitudes of the vibration acceleration in the Z_F axis are smaller than that in the X_F axis.

Figure 3.24. Simulated acceleration of the outer shell in the direction of X_F , Y_F and Z_F axes

Figure 3.25 shows the angular acceleration around the X_F axis and the Y_F axis. The vibration characteristics around the X_F and Y_F axes are similar.

Figure 3.25 Simulated angular acceleration of the outer shell X_F and Y_F axes.

Figure 3.26 shows the acceleration of the piston and swash plate in the direction of the X_p axis and the Z_p axis. The vibration characteristics in the X_p axis are different from that in the Z_p axis. The vibration characteristics in the X_p axis are as a result of the piston frequency and the vibration characteristics in the Z_p axis are as a result of the external load force including the hydraulic motor frequency and pump frequency. Compared with the vibration characteristics of outer shell and swash plate, the amplitudes of the vibration in the pistons are large. This was due to the direct external force on the pistons from the pressure pulse and the small stiffness of the piston coordinate system.

Figure 3.26: Simulated acceleration of the piston and swash plate in the directions of X_p and Z_p axes.

Figure 3.27 shows the results of the acceleration of the cylinder in the direction of the X_C axis, the Y_C axis and the Z_C axis. The vibration in the Z_C axis was generated by the direct supply pressure pulse of hydraulic motor. The amplitudes of the vibration in the Z_C axis are higher than those in the X_C axis and the Y_C axis. Because the stiffness in the X_C axis is larger than that in the Y_C axis, the influence of the pressure pulse on the vibration of the cylinder X_C axis is smaller than that in the Y_C axis. The amplitudes of the vibration of the cylinder in the X_C axis are lowest.

Figure 3.27: Simulated acceleration of the cylinder in the direction of X_c , Y_c and Z_c axes.

Figure 3.28 shows the simulated acceleration of the radial vibration of the outer shell under the different output torque of hydraulic motor. When the output torque of hydraulic motor increased from 2 Nm to 5 Nm, the amplitude of vibration clearly increased. The vibration characteristics are the same.

Figure 3.28: Simulated acceleration of the radial vibration of the outer shell. (a) torque = 2 Nm. (b) torque = 5 Nm.

3.9 Conclusion

In this chapter, the dynamic analyses of the piston pressure, flow ripple and shaft torque are studied. The theoretical analysis of the pressure mechanism is introduced. The leakage due to the slipper is considered for the pressure profile. The idealized flow and actual flow are studied. The numerical results of the flow ripple show the harmonic frequencies are equal to the integer multiples of the piston pass frequency. The instantaneous and average output torques of the axial piston motor have been derived according to the geometry, piston accelerations and the piston pressure profile in the cylinder. The numerical results show that the average output torque is nearly constant and stable. The frequencies of the torque are even integer of the piston pass frequency.

Chapter 3

Dynamic Mechanism Analysis of Water Hydraulic Motor

A mathematical model is developed to investigate the vibration characteristics of the swash-plate water hydraulic motor in a water hydraulic system. The three mass and fourteen DOF model is applied to represent the complete hydraulic motor, which consisted of components, such as a outer shell and a swash plate, piston and retaining ring and cylinder block. The dynamic equilibrium equations of motion are formulated to analyze the response with the pressure pulsation as the excitation force. The simulation results reveal the vibration characteristics of each component in the water hydraulic motor. The validity of the analysis is confirmed by comparing it with experimental results. The results show that the frequency of the harmonic is at the hydraulic motor rotational speed and hydraulic pump rotational speed. The frequencies of the higher harmonics are integer multiples of the hydraulic motor and pump rotational speed. The influence of the torque on the vibration of the outer shell in the water hydraulic motor is also investigated. The simulation results show that the amplitudes of the vibration increased with the increase of output torque of the water hydraulic motor and the frequencies is not variable.

Chapter 4

Second Generation Wavelet for Feature Extraction

The dynamic vibration mechanism of the water hydraulic motor was investigated in Chapter 3. The pumping mechanism about the pressure ripple and flow ripple, especially the overshoot and undershoot in the pressure and ripple, was studied. The water hydraulic motor is driven by the supply pressure in the water hydraulic system. The vibration in the hydraulic motor is produced by the interaction of the pressure pulse, which is generated by the pumping mechanism. The pressure ripple generated the characteristic impulse vibration that matches the pumping behaviour in the hydraulic motor.

The impulse vibration signals from the different mechanical condition demonstrate the different local distribution of the vibration energy. The wavelet multi-decomposition can analyze the signals in the localized wavelet functions and represent the local characteristic energy distribution. The statistical feature values of the wavelet coefficients can extract the local signal components, which reflect the mechanical condition, when there was no prior information about the vibration characteristics of the machinery. The wavelet-based statistics enable both the scale- and location-dependent behaviour to be quantified. Second

generation wavelet was based on the lifting scheme that is a particularly powerful implementation method. It can yield integer-to-integer transforms allowing for the lossless compression. Computationally it allows a parallel, in-place implementation which is faster by a factor of 2 for large datasets. In this Chapter, the method for extracting local features in the wavelet domain from the impulse vibration signals of the hydraulic motor was presented. The multi-decomposition based on the second generation wavelet analysis was proposed for the vibration analysis. In spline theory, the generalized cross validation (GCV) technique was an effective statistical way for the optimal estimation. A noise reduction algorithm of using GCV for wavelet thresholding was proposed. The wavelet domain statistical features were used for the classification of the mechanical condition.

The repeatability and stability of the vibration signal was proven in Section 4.1. In Section 4.2, the wavelet theory was introduced. The second generation wavelet was introduced in Section 4.3. The method for the vibration analysis based on the second generation wavelet was proposed. GCV was used for the vibration de-noise algorithm. A thorough discussion of the results was presented, followed by conclusion.

4.1 The Repeatability and Stability of the Vibration Signal

In Chapter 3, the relations among the pressure, the flow rate, the torque, angular speed and vibration were analyzed. The shaft torque and flow rate are determined by the pressure and the angular speed. The shaft torque and flow rate are constant and stable with constant pressure and angular speed. So the pressure and flow rate are constant under the constant angular speed and shaft torque. The casing vibration signals in the water hydraulic motor

are excited by the piston pressure in the cylinder bore. The vibration characteristics of the water hydraulic motor casing are deterministic under the certain pressure and flow rate of the water hydraulic system, which can determined the certain output torque and angular speed of the water hydraulic motor.

The means of the random vibration signals are the important parameter to define the characteristics of the random vibration signals. The vibration signals are repeatable and stable if the means of the random vibration signals are statistically stationary. Section 3.2 describes the experimental method in detail. There are 49 vibration signals under NC and 50 vibration signals for BLC, BSC, FLC and FSC operating condition respectively and the number of the raw vibration signals $(f_1, f_2, \dots, f_i, \dots, f_{249})$ is 249. The means $(m_1, m_2, \dots, m_i, \dots, m_{249})$ of all the raw vibration signals are calculated. The real mean (m_{real}) of all of the raw vibration signals is obtained by calculating the mean of the means $(m_1, m_2, \dots, m_i, \dots, m_{249})$.

Figure 4.1 shows the distribution of the normalized means of the experimental vibration signals. The results show that the means of the random vibration signals are concentrated in the real mean (m_{real}) .

In order to test that the means of the random vibration signals are statistically stationary, the hypothesis testing is applied to prove the every mean of the raw random vibration signals equals to the real mean (m_{real}) . Statistical hypothesis testing is the fundamental method used at the data analysis stage of a comparative experiment.

Figure 4.1 the distribution of the mean

For the mean m_i in every vibration signal, the hypothesis testing is defined as $H_0 : m_i = m_{real}$ and $H_1 : m_i \neq m_{real}$. The statement $H_0 : m_i = m_{real}$ is called the null hypothesis and the statement $H_1 : m_i \neq m_{real}$ is called the alternative hypothesis. This hypothesis is called a two-sided alternative hypothesis. The hypothesis-testing procedures rely on the information in a random sample. If the information is consistent with the hypothesis, it can be concluded that the hypothesis is true. It should be emphasized that the truth or falsity of a particular hypothesis can never be known with the certainty. The null hypothesis is the hypothesis to be tested. Rejection of the null hypothesis always leads to accepting the alternative hypothesis. Testing the hypothesis involves taking a random sample, computing a test statistic from the sample data and then using the test statistic to make a decision about the null hypothesis.

The decision procedure can lead to either of two wrong conclusions. The **type I error** is that the null hypothesis H_0 is rejected when it is true. The **type II error** is that the hypothesis H_0 is not rejected when it is wrong. The probability of making a type I error is denoted by the Greek letter α . That is $\alpha = P(\text{type I error}) = P(\text{reject } H_0 \text{ when } H_0 \text{ is true})$.

The type I error probability is called the **significance level**. In evaluating a hypothesis-testing procedure, it is important to examine the probability of a **type II error** that is defined as $\beta = P(\text{type II error}) = P(\text{fail to reject } H_0 \text{ when } H_0 \text{ is false})$. The power is computed as $1 - \beta$ and the power can be interpreted as the **probability of correctly rejecting a false null hypothesis**. The power is a very descriptive and concise measure of the sensitivity of a statistical test that is the ability of the test to detect the differences.

The hypothesis on the means of the random signals with unknown variances is considered. It is assumed that the vibration signal distribution is normal distribution. If $X_1, X_2, \dots, X_n$ is a random sample from the signals with mean m_{real} , the random variable $T = (\bar{X} - m_{real}) / (S / \sqrt{n})$ has a t distribution with $n - 1$ degrees of freedom. When the null hypothesis is true, T has a t distribution with $n - 1$ degrees of freedom. The distribution of the test statistic is obtained when H_0 is true. The critical region is located to control the type I error probability at the desired level. The points $-t_{\alpha/2, n-1}$ and $t_{\alpha/2, n-1}$ are used as the boundaries of the critical region so that $H_0 : m_i = m_{real}$ is rejected if $t > t_{\alpha/2, n-1}$ or if $t < -t_{\alpha/2, n-1}$, where t is the observed value of the test statistic T and $m_{real} = 8.05 \times 10^{-5}$.

The procedure for the hypothesis testing is as follows:

- (1) The parameter of interest is the mean coefficient m_i of the every vibration signal f_i .
- (2) The null hypothesis $H_0 : m_i = m_{real}$, the alternative hypothesis $H_1 : m_i \neq m_{real}$.
- (3) The significant level $\alpha = 0.05$.
- (4) The test statistic is $t_i = ((\bar{X})_i - m_{real}) / (S / \sqrt{n})$, where $(\bar{X})_i$ is the sample mean of i^{th}

vibration signal.

(5) Reject H_0 if $t > t_{0.025,248}$ or $t < -t_{0.025,248}$. Where $t_{0.025,248} = 1.96$.

This procedure is programmed in Matlab. The results show that the test statistic t_i of the i^{th} vibration signal is between -1.96 and 1.96 , where $i = 1, \dots, 249$. So H_0 is accepted and the mean coefficient of every vibration signal equal to m_{real} .

The P -value for a t -test is just the smallest level of significance at which the null hypothesis would be rejected. Considering the t -test based on the 249 degrees of freedom, the relevant critical values is as follows:

Table 4.1 The critical value of the t -test

Critical Value	0.253	0.674	1.282	1.645	1.960	2.326	2.576	2.807	3.09	3.291
Tail Area	0.40	0.25	0.10	0.05	0.025	0.01	0.005	0.0025	0.001	0.0005

It is shown that the tail value is less with the larger critical value. The maximum test statistic of 249 vibration signals is considered and $t_{\max} = 0.6703$. It is between two tabulated values, 0.253 and 0.674 corresponding to 0.25 and 0.4. So the lower and upper bounds on the P -value would be $0.5 < P < 0.8$. The results show that the mean coefficient is much more concentrated than that for significance level of 0.05 and 0.01 which is generally used in hypothesis testing.

The hypothesis testing is used to prove that every mean of every raw random signal equals to the real mean (m_{real}) of the vibration signals of the water hydraulic motor. Hence it is proved that the vibration signals are repeatable and stable. The random vibration

signals have the same mean with each other. So 100 percent of the random vibration signals are repeatable and stable.

4.2 Introduction to Wavelet Analysis

4.2.1 Time-Frequency Analysis

A signal $f(t)$ satisfies the finite energy condition

$$\int_{-\infty}^{\infty} f(t)^2 dt < \infty \quad (4.1)$$

and its Fourier transform (FT) is defined by

$$\hat{f}(\omega) = \langle f(t), e^{i\omega t} \rangle = \int_{-\infty}^{+\infty} f(t) e^{-i\omega t} dt \quad (4.2)$$

where t and ω represent time and angular frequency respectively. Fourier transform (FT) thus has perfect resolution in frequency domain. However, FT provides only the average information of time domain. This makes FT unsuitable for dealing with nonstationary signals.

Short-Time Fourier Transform (STFT) [116] is an important linear approach of time-frequency analysis. Given a signal $f(t)$, its STFT is defined as the Fourier transform of the windowed signal, $f(t)g^*(t - \tau)$, i.e.,

$$STFT(\tau, \omega) = \int_{-\infty}^{+\infty} f(t)g^*(t - \tau)e^{-i\omega t} dt \quad (4.3)$$

where $g^*(t)$ denotes the complex conjugate of the window function $g(t)$. The squared

modulus of STFT is usually referred to as the spectrogram of the signal. Since the window suppresses the signal outside a neighborhood around the analysis time τ , the STFT at τ therefore provides a ‘local spectrum’ of the signal. The shortcoming of *STFT* is that the resolution in time and frequency can not be arbitrarily small simultaneously. This results in *STFT* being unable to characterize some nonstationary signals well, such as a signal composed of high frequency components of short duration plus low frequency components of long duration.

The Wigner-Ville distribution (WVD) of a signal $f(t)$ is defined by

$$WVD(\tau, \omega) = \int_{-\infty}^{+\infty} f\left(\tau + \frac{t}{2}\right) f^*\left(\tau - \frac{t}{2}\right) e^{-i\omega t} dt \quad (4.4)$$

WVD has desirable properties for time-frequency analysis. It is shift-invariant in both time and frequency.

The main drawback of WVD is the so-called cross-term interference. It often obscures the useful pattern over the time-frequency plane. To overcome this problem, one of the most successful approaches is using Choi-Williams distribution (CWD). For a signal $f(t)$, its CWD is defined by

$$CWD(\tau, \omega) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \frac{1}{\sqrt{4\pi\alpha t^2}} \exp\left\{-\frac{(\tau-u)^2}{4\alpha t^2}\right\} f\left(u + \frac{t}{2}\right) f^*\left(u - \frac{t}{2}\right) e^{-i\omega t} du dt \quad (4.5)$$

where α is an adjustable parameter. CWD is able to effectively reduce cross-term interface. However, because of some theoretical difficulties, there still exist some limitations in time-frequency distribution.

4.2.2 Wavelet function

Wavelets [117] are the elementary function of WT. Wavelets are generated by dilating and translating a function $\psi(t)$ called mother wavelet, i.e.,

$$\psi_{\tau,\mu}(t) = |a|^{-1/2} \psi\left(\frac{t-\mu}{\tau}\right) \quad \tau, \mu \in R, \tau \neq 0 \quad (4.6)$$

where τ and μ are called dilation parameter and translation parameter respectively, and $|a|^{-1/2}$ is introduced to maintain the norm of the wavelet.

The mother wavelet is generally required to satisfy

$$C_\psi = \int_{-\infty}^{+\infty} \frac{|\hat{\psi}(\omega)|^2}{|\omega|} d\omega < +\infty \quad (4.7)$$

which is referred to as the admissibility condition. Admissibility condition implies that $\hat{\psi}(0) = 0$. This means that the mother wavelet should be an oscillatory function with zero mean. It is evident that the dilated and translated wavelet $\psi_{\tau,\mu}(t)$ is also localized both in time and in frequency. In time domain, its duration and location are determined by the scale parameter, τ , and the translation parameter, μ , respectively. Both the frequency and the frequency bandwidth of the wavelet are inversely proportional to the scale parameter τ [116].

4.2.3 Wavelet Transform

The WT method is a well developed mathematical tool for digital signal processing. Given a family of basis functions, the dilated and translated wavelets can be used to formulate the signal process in a localized time and frequency. These functions can be modelled by the linear combination of the shifted and scaled functions in the space spanned by the wavelet family. If the scale and transform parameters τ and μ are allowed to change continuously, the continuous wavelet transform (CWT) $W_f(\tau, \mu)$ of a signal $f \in L^2(\mathbb{R})$ at time τ and scale μ is defined as:

$$\begin{aligned} W_f(\tau, \mu) &= \int_{-\infty}^{\infty} f(t) \overline{\psi_{\tau, \mu}}(t) dt = \int_{-\infty}^{\infty} f(t) \frac{1}{\sqrt{\mu}} \overline{\psi}\left(\frac{t - \tau}{\mu}\right) dt \\ &= \frac{1}{2\pi} \int_{-\infty}^{\infty} F(\omega) \overline{\Psi_{\tau, \mu}}(\omega) d\omega \end{aligned} \quad (4.8)$$

where the wavelet atoms, $\psi_{\tau, \mu} = \frac{1}{\sqrt{\mu}} \psi\left(\frac{t - \tau}{\mu}\right)$, are constructed by translation and dilation of a mother wavelet function $\psi(t)$. $F(\omega)$ is the Fourier transform of the function $f(t)$. The FT of wavelet atoms are given by

$$\Psi_{\tau, \mu}(\omega) = \int_{-\infty}^{\infty} \psi_{\tau, \mu}(t) \exp(-i\omega t) dt = \sqrt{\mu} \Psi(\mu\omega) \exp(-i\omega\tau) \quad (4.9)$$

The discrete wavelet transform (DWT) is defined by discretizing the scale and translation parameter as $\tau = \tau_0^j$ and $\mu = k\mu_0\tau_0^j$ respectively. Particularly, if $\tau_0 = 2$ and $\mu_0 = 1$, a family of wavelets is obtained as:

$$\psi_{j,k}(t) = 2^{-j/2} \psi(2^{-j}t - k) \quad j, k \in \mathbb{Z} \quad (4.10)$$

The discrete wavelet transform (DWT) of a signal $f(t)$ is then given by

$$DWT(j, k) = \langle f(t), \psi_{j,k} \rangle = 2^{-j/2} \int_{-\infty}^{+\infty} f(t) \psi(2^{-j}t - k) dt \quad j, k \in \mathbb{Z} \quad (4.11)$$

Unlike CWT, DWT cannot guarantee perfect reconstruction of the original signal unless the frame condition is satisfied [116].

If the mother wavelet $\psi(t)$ satisfies the orthonormal condition, then the family of wavelets defined in Equation (4.10) forms an orthonormal basis for the square-integrable space $L^2(\mathbb{R})$, and Equation (4.11) gives the orthonormal WT of the signal. Such a mother wavelet is referred to as an orthogonal wavelet. Typical examples of orthogonal wavelets are Haar wavelet, Daubechies wavelets, Meyer wavelet, etc. For orthogonal wavelets, the original signal can be reconstructed by

$$f(t) = \sum_{j,k \in \mathbb{Z}} \langle f(t), \psi_{j,k} \rangle \psi_{j,k}(t) \quad (4.12)$$

WT using orthonormal basis is of particular importance in wavelet analysis. Differing from STFT, WT performs as bandpass filters with constant relative-bandwidth. This makes it suitable to deal with signals which are composed of high frequency components of short duration plus low frequency components of long duration.

4.2.4 Multi-resolution Analysis of Wavelet

Multiresolution analysis allows us to approximate a signal $f \in L^2(\mathbb{R})$ at different resolution or scales. For each $j \in \mathbb{Z}$, the function $\phi_{j,k}(t) = 2^{-j/2} \phi(2^{-j}t - k)$ ($k \in \mathbb{Z}$) forms an

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orthonormal basis for subspace V_j . As such, once the scaling function $\phi(t)$ is determined, the signal f can be approximated by f_j , which is the orthogonal projection of the signal on V_j . Note that f_j is a linear combination of the basis function in V_j , i.e., $f = \lim_{j \rightarrow \infty} f_j$.

The sequence of closed subspace $\{V_j : j \in \mathbb{Z}\}$ of $L^2(\mathbb{R})$ with the following properties defined a multiresolution analysis of $L^2(\mathbb{R})$ [116]:

$$(1) V_j \subset V_{j-1}$$

$$(2) f(t) \in V_j \Leftrightarrow f(2t) \in V_{j-1}, j \in \mathbb{Z}$$

$$(3) f(t) \in V_0 \Rightarrow f(t-k) \in V_0, k \in \mathbb{Z}$$

$$(4) \bigcap_{j \in \mathbb{Z}} V_j = \{0\}, \text{ and } \overline{\bigcup_{j \in \mathbb{Z}} V_j} = L^2(\mathbb{R})$$

$$(5) \phi(t) \in V_0 \text{ such that } \{\phi(t-k) : k \in \mathbb{Z}\} \text{ forms an orthonormal basis for } V_0^1.$$

The function $\phi(t)$ is called the scaling function of the multiresolution analysis. Since $\phi(t) \in V_0 \subset V_{-1}$, it follows that

$$\phi(t) = \sqrt{2} \sum_n h_n \phi(2t-n) \quad n \in \mathbb{Z} \quad (4.13)$$

where h_n are scaling function coefficients, which constitute a low-pass filter. The factor $\sqrt{2}$ is introduced to maintain the norm of the scaling function.

This lost information when it goes from the approximation at the higher resolution

$j-1$ to that at the lower resolution j can be described by a set of functions, which span the difference between V_{j-1} and V_j . Denoted by W_j , the subspace spanned by these functions W_j is then the orthogonal complement of V_j in V_{j-1} , i.e.,

$$V_{j-1} = V_j + W_j \quad \text{and} \quad W_j \perp V_j \quad (4.14)$$

$$L^2(R) = \bigoplus_{j \in Z} W_j \quad \text{and} \quad W_j \perp W_{j'} \quad \text{if} \quad j \neq j' \quad (4.15)$$

Define

$$\psi(t) = \sqrt{2} \sum_n g_n \phi(2t - n) \quad n \in Z \quad (4.16)$$

where $g_n = (-1)^n h_{n-1}$, which constitutes a high-pass filter. It can be shown that for each $j \in Z$, the functions $\psi_{j,k} = 2^{-j/2} \psi(2^{-j}t - k)$ ($k \in Z$) form an orthonormal basis for the subspace W_j , and the family of functions $\{\psi_{j,k}(t) : j, k \in Z\}$ forms an orthonormal basis for $L^2(R)$.

4.3 Second Generation Wavelet for Vibration Signal Analysis

4.3.1 Wavelet Subband Transform

The wavelet analysis produces a family of hierarchically organized decompositions. The level is chosen based on a desired low-pass cutoff frequency. The one-dimensional wavelet decomposition represents a real-value discrete-time signal in terms of shifts and dilations of a lowpass scaling function and a bandpass wavelet function. The wavelet decomposition

consist of a set of scaling coefficients (A) that represent the coarse signal information and wavelet coefficients (D) that represent wavelet coefficients.

Figure 4.2 shows the general block scheme of wavelet sub-band transform. The low pass filter $\tilde{h}$ and band pass filter $\tilde{g}$ is used for the forward transform followed by subsampling. The low pass synthesis filter h and high pass synthesis filter g are used for the inverse transform after the upsamples. The four filters h , g , $\tilde{h}$, and $\tilde{g}$, of WT are finite impulse response (FIR) filters. The condition for the perfect reconstruction are given as:

$$\tilde{h}(z^{-1})h(z) + \tilde{g}(z^{-1})g(z) = 2 \quad (4.17)$$

$$\tilde{h}(-z^{-1})h(z) + \tilde{g}(-z^{-1})g(z) = 0 \quad (4.18)$$

Figure 4.2 The block scheme of subband transform

The above shows that half of the filtered samples are thrown away which is not efficient. In order to solve this problem, the signal would be subsampled before the filtering. The input signal is divided as the even samples (x_e) and odd samples (x_o). The scale coefficients and wavelet coefficients can be obtained in the polyphase representation:

$$\begin{pmatrix} D(z) \\ A(z) \end{pmatrix} = \begin{pmatrix} \tilde{h}_e(z) & \tilde{h}_o(z) \\ \tilde{g}_e(z) & \tilde{g}_o(z) \end{pmatrix} \begin{pmatrix} x_e(z) \\ z^{-1}x_o(z) \end{pmatrix} \quad (4.19)$$

The polyphase matrix is defined as:

$$\tilde{P}(z) = \begin{pmatrix} \tilde{h}_e(z) & \tilde{h}_o(z) \\ \tilde{g}_e(z) & \tilde{g}_o(z) \end{pmatrix} \quad (4.20)$$

The even output sample (y_e) and odd output sample (y_o) from the inverse wavelet transform in Figure 4.2 is given in the polyphase matrix:

$$\begin{pmatrix} y_e(z) \\ z \cdot y_o(z) \end{pmatrix} = \begin{pmatrix} h_e(z) & g_e(z) \\ h_o(z) & g_o(z) \end{pmatrix} \begin{pmatrix} D_e(z) \\ A_e(z) \end{pmatrix} \quad (4.21)$$

The second polyphase matrix is defined as:

$$P(z) = \begin{pmatrix} h_e(z) & g_e(z) \\ h_o(z) & g_o(z) \end{pmatrix} \quad (4.22)$$

Figure 4.3 shows the one stage filter for signal decomposition and reconstruction using polyphase matrices. Equations (4.19) and (4.21) are incorporated in split and merge boxes. For the perfect reconstruction, the following equation can be obtained:

$$\tilde{P}(z^{-1})P(z) = 1 \quad (4.23)$$

Figure 4.3 The polyphase representation for signal analysis and reconstruction

The following equation can be derived from equation (4.23) and Cramer's rule.

$$\begin{aligned}\tilde{h}_e(z) &= g_o(z^{-1}) & \tilde{h}_o(z) &= -g_e(z^{-1}) \\ \tilde{g}_e(z) &= -h_o(z^{-1}) & \tilde{g}_o(z) &= h_e(z^{-1})\end{aligned}\tag{4.24}$$

Equation (4.24) implies the following equation as:

$$\tilde{h}(z) = -z^{-1}g(-z^{-1}) \qquad \tilde{g}(z) = z^{-1}h(-z^{-1})\tag{4.25}$$

4.3.2 Lifting Scheme

Lifting scheme is a new approach to study the construction of the wavelet and developed by Sweldens [118]. The lifting scheme is a spatial or time domain construction of biorthogonal wavelets. The basic idea behind lifting is that it provides a simple relationship between all multi-resolution analyses that share the same low-pass filter or high pass filter. The low pass filter gives the coefficients of the refinement relation, which entirely determines the scaling functions where the coefficients are given by the high-pass filter.

Lifting scheme consists of iterations of the following three basic operations as shown in Figure 4.4 [119]. Firstly, the split divides the original data into two disjoint subsets. The original signal is split to the even indexed points and the odd indexed points, that is $x_e[n] = x[2n]$ and $x_o[n] = x[2n+1]$. The predict generates the wavelet coefficients $d[n]$ as the error by the predicting operator P:

$$d[n] = x_o[n] - P(x_e[n])\tag{4.26}$$

The process of computing a prediction and recording it is called a lifting step. The original signal is transformed from (x_o, x_e) to (d, x_e) . There is aliasing in the even samples due to the subsample. Because x_e was obtained from the even-numbered coefficients by removing the odd-numbered coefficients from the signal x and can not represent the scale coefficients. The second lifting step is introduced to solve the problem. The update combines $x_e[n]$ and $d[n]$ to obtain the scaling coefficients $c[n]$ that represents the coarse approximation in the original signal. The update operator U is used to the wavelet coefficients for $x_e[n]$.

$$c[n] = x_e[n] + U(d[n]) \quad (4.27)$$

Figure 4.4 Lifting step and inverse lifting step [119]

These three steps form the lifting stage. The iterations of the lifting stage on the output samples create the complete set of discrete wavelet transform scaling and wavelet coefficients $c^j[n]$ and $d^j[n]$ at each scale j .

Figure 4.5 shows the low-pass sub-band is lifted with the help of the high-pass sub-band (predict) and the high-pass sub-band is lifted with the help of the low-pass sub-band (update) [119]. The lifting steps are easily inverted. The following equations for invertible

lifting is derived:

$$x_e[n] = c[n] - U(d[n]) \quad x_o[n] = d[n] + P(x_e[n]) \quad (4.28)$$

Figure 4.5 The low-pass subband was lifted with the help of the high-pass subband (predict) and the high-pass subband was lifted with the help of the low-pass subband (update) [119]

The lifting theory shows that any other new finite filter g^l complementary to h is of the form that is called the update step.

$$g^l(z) = g(z) + h(z)s(z^2) \quad (4.29)$$

where $s(z^2)$ is a Laurent polynomial. The new polyphase matrix is shown as:

$$P^l(z) = \begin{pmatrix} h_e(z) & h_e(z)s(z) + g_e(z) \\ h_o(z) & h_o(z)s(z) + g_o(z) \end{pmatrix} = P(z) \begin{pmatrix} 1 & s(z) \\ 0 & 1 \end{pmatrix} \quad (4.30)$$

The new filter $\tilde{h}^{new}(z)$ complementary to $\tilde{g}(z)$ is indicated as:

$$\tilde{h}^l(z) = \tilde{h}(z) + \tilde{g}(z)\tilde{s}(z^2) \quad (4.31)$$

The new dual polyphase matrix is given by

$$\tilde{P}^l(z) = \begin{pmatrix} \tilde{h}_e(z) + \tilde{g}_e(z)\tilde{s}(z) & \tilde{h}_o(z) + \tilde{g}_o(z)\tilde{s}(z) \\ \tilde{g}_e(z) & \tilde{g}_o(z) \end{pmatrix} = \begin{pmatrix} 1 & \tilde{s}(z) \\ 0 & 1 \end{pmatrix} \quad (4.32)$$

Similarly, the high-pass subband is lifted with the help of the low-pass subband. The dual lifting equations (the predict step) are given as

$$h^l(z) = h(z) + g(z)t(z^2) \quad (4.33)$$

$$P^l(z) = \begin{pmatrix} h_e(z) + g_e(z)t(z) & g_e(z) \\ h_o(z) + g_o(z)t(z) & g_o(z) \end{pmatrix} = P(z) \begin{pmatrix} 1 & 0 \\ t(z) & 1 \end{pmatrix} \quad (4.34)$$

$$\tilde{g}^l(z) = \tilde{g}(z) + \tilde{h}(z)\tilde{t}(z^2) \quad (4.35)$$

$$\tilde{P}^l(z) = \begin{pmatrix} \tilde{h}_e(z) & \tilde{h}_o(z) \\ \tilde{g}_e(z) + \tilde{h}_e(z)\tilde{t}(z) & \tilde{g}_o(z) + \tilde{h}_o(z)\tilde{t}(z) \end{pmatrix} \quad (4.36)$$

4.3.3 The Factoring Algorithm

Any pair of complementary filters (g, h) can be factored into the lifting steps. The polyphase matrix can be represented by the Laurent polynomials $s_i(z)$, $t_i(z)$ and a non-zero constant k . The following equation is given:

$$P(z) = \prod_{i=1}^m \begin{bmatrix} 1 & s_i(z) \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ t_i(z) & 1 \end{bmatrix} \begin{bmatrix} k & 0 \\ 0 & 1/k \end{bmatrix} \quad (4.37)$$

The dual polyphase matrix is given as:

$$\tilde{P}(z) = \prod_{i=1}^m \begin{bmatrix} 1 & 0 \\ -s_i(z^{-1}) & 1 \end{bmatrix} \begin{bmatrix} 1 & -t_i(z^{-1}) \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1/k & 0 \\ 0 & k \end{bmatrix} \quad (4.38)$$

Some wavelet filters such as Haar, Daubechies, 9-7 and Cubic B-splines wavelet function can be used to build the second-generation wavelet transform into lifting steps

[119]. Haar wavelet is used in this research to generate the lifting step. Haar wavelet has the following filters:

$$\begin{aligned} h(z) &= 1 + z^{-1} & g(z) &= -1/2 + 1/2 z^{-1} \\ \tilde{h}(z) &= 1/2 + 1/2 z^{-1} & \tilde{g}(z) &= -1 + 1z^{-1} \end{aligned} \quad (4.39)$$

The multi-decomposition consists of the following implementation:

$$\begin{aligned} s_l^{(0)} &= x_{2l} & d_l^{(0)} &= x_{2l+1} \\ d_l &= d_l^{(0)} - s_l^{(0)} & s_l &= s_l^{(0)} + 1/2 d_l \end{aligned} \quad (4.40)$$

4.3.4 Generalized Cross Validation for noise reduction

4.3.4.1 Generalized Cross Validation

The following model of a discrete noisy signal is considered:

$$y = f + \varepsilon \quad (4.41)$$

The vector y represents the input signal and f is an unknown and deterministic signal. The noise ε is stochastic signal. The wavelet representation is used to reconstruct the original data. The following transform is considered:

$$v = Wf \quad \zeta = W\varepsilon \quad w = Wy = v + \zeta \quad (4.42)$$

This transform localizes the most important spatial and frequency characteristics of a regular signal in a limited number of wavelet coefficients. The Donoho's 'soft-thresholding' or 'shrinking' function is proposed to reduce the small coefficients.

The shrinking (soft-thresholding) operations can be represented as:

$$w_{\delta} = D_{\delta} w \quad (4.43)$$

$$\text{where } D_{\delta} = \text{diag}[d_{ii}] \text{ with } d_{ii} = \begin{cases} 0 & \text{if } |w_i| < \delta \\ 1 - \delta/|w_i| & \text{otherwise} \end{cases}$$

The elements of the matrix D_{δ} depend on the signal w . In the same way, the inverse transform can be obtained:

$$y_{\delta} = A_{\delta} y \quad (4.44)$$

where A_{δ} is the influence matrix $A_{\delta} = W^{-1} D_{\delta} W$

The optimal parameter δ is applied to the wavelet coefficients to improve the maximum signal-to-noise ratio. It means to minimize the mean square error

$$R(\delta) = \frac{1}{N} \|\omega_{\delta}\|^2 = \frac{1}{N} \|w_{\delta} - v\|^2 = \frac{1}{N} \|W\varepsilon_{\delta}\|^2. \text{ However the signal } f \text{ is unknown. The}$$

optimal threshold cannot be found. Donoho and Johnstone [120] propose to use the ‘universal threshold’ estimation:

$$\delta = \sqrt{2 \log(N)} \sigma \quad (4.45)$$

This equation needs the knowledge of the noise variance σ of the noise signal, which is not readily available in practice.

In order to find the optimal threshold directly by using the input data, Weyrich and Warhola [121] applied the idea of cross validation to obtain the excellent results. This cross validation [122] is a function of the threshold value only based on the input data. Its

minimum is a good approximation for the optimal threshold.

In order to minimize the function $R(\delta)$, a new matrix is introduced as:

$$D'_{ij} = \frac{\partial w_{\delta_i}}{\partial w_j} \quad (4.46)$$

Here if $i \neq j$, then $D'_{ij} = 0$. For $i = j$, the following equation can be defined:

$$D'_{ii} = \begin{cases} 0 & \text{if } |w_i| < \delta \\ 1 & \text{otherwise} \end{cases} \quad (4.47)$$

The trace of the matrix D' is calculated as:

$$Tr(D') = \#\{i \mid w_{\delta_i} \neq 0\} \quad (4.48)$$

The derivative influence matrix is introduced and defined as:

$$A' = W^{-1}D'W \text{ and } Tr(A') = Tr(D') \quad (4.49)$$

The cross validation in an informal way is introduced to minimize the error function based on an unknown exact signal. The generalized cross validation is defined as:

$$GCV(\delta) = V(\delta) = \frac{(1/N) \|y - y_{\delta}\|^2}{[Tr(I - A')/N]^2} \quad (4.50)$$

The paramter GCV is the estimation of the optimal threshold δ .

4.3.4.2 Results and Discussion

Wavelet denoising is a noise reduction method by transforming the corrupted signals into the wavelet domain by applying thresholding in the wavelet domain and inversely transforming the denoised wavelet coefficients. The wavelet coefficients can be obtained by the decomposition of Haar wavelet filter into the lifting step. The discrete wavelet transform based on the lifting step is used for the multi-level wavelet decomposition. At each scale, GCV is used as the threshold to process and discriminate the original signals and noise.

The procedure to be executed can be described as follows:

- (1) Obtain the wavelet coefficient by computer $w = Wy$, using the multi-level decomposition based on the second generation wavelet, that is lifting scheme.
- (2) Determine a start threshold value.
- (3) Minimize the value of the parameter $GCV(\delta)$.
- (4) Computer $w_\delta = D_\delta w$
- (5) Inverse wavelet transform: $y_\delta = W^{-1}w_\delta$ to obtain the denoised signal.

This algorithm was developed and programmed in Matlab software by the author. The simulated signal was generated by the following functions to test this proposed algorithm. This used signal is similar in frequencies and amplitudes to the vibration signals obtained from the water hydraulic motor casing. This simulated signal is randomly chosen to test the applicability to denoise the corrupted vibration signal for fault diagnosis of water hydraulic motor. Figures 4.6 (a) and (b) show the original signals and the corrupted signals with SNR of 1dB. Figures 4.6 (c), (d) and (e) show the de-noise signals by the multi-decomposition at

first scale, second scale and third scale respectively. The SNR is improved at second scale and third scale compared with at first scale.

$$y_1 = 0.01\sin(120\pi t) + 0.003\sin(240\pi t) + 0.02\cos(400\pi t) \quad (4.51)$$

Figure 4.6 Original signal, corrupted signal and the denoised signal by different scale decomposition with GCV. (a) original signal. (b) corrupted signal with SNR of 1dB. (c) clean signal by first scale (d) clean signal by second scale. (e) clean signal by third scale.

Figure 4.7 shows the relation between the SNR and GVC at the different scales. In Figure 4.7 (a), the corrupted signal is denoised at the first scale. The corrupted signal is

decomposed by one level as shown in Figure 4.6 (b) and (c), which will be denoised by the prior proposed algorithm. The SNR increases with the decrease of the GCV. The SNR is improved up to about 9 dB . The range of GCV is between 6×10^{-4} and 4×10^{-4} . The value of GCV is lower and the denoised signal is better. Figure 4.7 (b) shows the results at second scale of the multi-decomposition, where the corrupted signal is decomposed by two levels as shown in Figure 4.6 (d) and (e). The decomposed signals at second level are denoised by the prior proposed algorithm. The SNR increases from 9.7 dB to 14.7 dB . The GVC value decreases from the 1.6×10^{-3} to 0.8×10^{-3} . The SNR value increases with the decrease of the GCV value. Figure 4.7 (c) shows the similar results at third scale as that at first and second scale. The SNR is up to 19.5 dB

Figure 4.7 The relation between the SNR and GCV at the different scale. (a) first scale. (b) second scale. (c) third scale

4.3.5 Statistical Feature Extraction of the Localized Impulse Vibration Signal

The wavelet transform can be used to represent efficiently the localized features of the signals. It is an ideal tool for the extraction of features. Especially, the vibration is induced by the fluid, which is characteristic of the impulse signal. The impulse component in the vibration signals is an important feature to diagnose the mechanical condition. As shown in Figure 4.5, the original signal is decomposed into the scaling coefficients $c_1[n]$ and wavelet coefficients $d_1[n]$. The multi-decomposition based on the lifting scheme splits the scaling coefficients into two parts using the same scheme, producing $c_2[n]$ and $d_2[n]$ in the next step. Hence the wavelet decomposition of the signal at scale j has the structure $[c_j[n], d_j[n], \dots, d_j[n]]$. The terminal nodes of wavelet decomposition tree are shown in Figure 4.8.

Figure 4.8 Wavelet decomposition tree based on lifting scheme [118]

Figure 4.9 shows the typical wavelet multi-decomposition of the experimental vibration signals. Figure 4.9(a) shows the original signal (s). Figure 4.9(b) shows the scaling

coefficient at first scale ($c_1[n]$). Figure 4.9(c) shows the wavelet coefficient $d_1[n]$ that is characteristic of the impulse signal. The impulse pressure signal is produced by the pumping mechanism when the piston rotates from the return line to supply line, which results in the overshoot of the piston pressure. Figures 4.9 (d) and (e) show the scaling coefficients $c_2[n]$ and wavelet coefficients $d_2[n]$ at second scale.

Figure 4.9 The multi-decomposition based on the lifting scheme of the experimental housing vibration signal of motor

The scaling coefficients in the multi-decomposition of the vibration signal are the important information in the impulse vibration signals. In order to diagnose the different condition, the wavelet scaling coefficients at first scale are used to extract the features.

The intermittency index is used to determine the wavelet scaling coefficients at first scale. The intermittency at each scale can be viewed directly using the intermittency index defined as:

$$I_{m,n} = \frac{(T_{m,n})^2}{\langle T_{m,n}^2 \rangle_m} \quad (4.52)$$

Here $T_{m,n}$ are the wavelet coefficients at scale index m . $\langle T_{m,n}^2 \rangle_m$ is the second order statistical moment of the wavelet coefficients at scale index m . For example, a constant value of $I_{m,n} = 1$ for all m and n means that there is no flow variation. A value of 10 at a specific set of indices m and n means that there is ten times more energy contained within the coefficients at that location than for the temporal mean for the scale at that location in the signal. Figure 4.10 showed the intermittency indices at the first wavelet scale for the vibration signals under the five conditions. There are different amplitudes and number of the intermittency indices.

Figure 4.10 Intermittency indices at the first wavelet scale for the vibration signal under five conditions (a) BLC. (b) BSC. (c) FLC.(d) FSC. (e) NC

Figure 4.11 shows the statistical probability distribution of the means of the highest intermittency indices at the first wavelet scale. The results show the different probability distribution under five different conditions. Similarly, Figure 4.12 shows the statistical probability distribution of the variances of the highest intermittency indices at the first wavelet scale. The results under different conditions were also different. These statistical indexes can be used as feature values to diagnose the different conditions of the water hydraulic motor. As shown in Figure 4.11 (a), there is two higher points in the statistical probability distribution and the statistics distribution of the data is not uniform. The results showed the vibration condition is not stable because the back long crack produced the worse unstable vibration signal of the water hydraulic motor.

Figure 4.11 The statistical probability distribution of the mean of the highest intermittency indices (a) BLC. (b) BSC. (c) FLC.(d) FSC. (e) NC

Figure 4.12 The statistical probability distribution of the variance of the highest intermittency indices (a) BLC. (b) BSC. (c) FLC.(d) FSC. (e) NC

The scaling coefficients in the multi-decomposition based on the lifting scheme include the low frequency of the vibration signals, which is the response of the mechanical structure condition. Figure 4.13 shows the statistical probability distribution of the second order statistical moment of the scaling coefficients at first, second and third scale. As shown in Figure 4.13 (a) and (b), the mean at first scale under BLC is larger than under BSC. The means at second and third scale under BLC are about 1.3 and 3.0. The means at second and third scale under BSC are about 0.9 and 2.2. The ranges at the three scales between BLC and BSC are different. The ranges and means of the statistical probability distribution of the scaling coefficients are different under different conditions.

Figure 4.13 The statistical probability distribution of the second order statistical moment of the scaling coefficients at first, second and third scale. (a) BLC. (b) BSC. (c) FLC. (d) FSC. (e) NC

4.4 Conclusion

Wavelet analysis provides a new tool for dealing with nonstationary signals. Wavelet transform represents a signal with a family of elementary functions which are localized at different levels in both time and frequency domains. The concepts of wavelet and wavelet transform were introduced in this chapter. The important characteristics and method of wavelet analysis including continuous wavelet transform, discrete wavelet transform and multiresolution analysis were discussed. Wavelet analysis overcomes the shortcoming of short-time Fourier transform in the analysis of signals composed of small bursts associated with low frequency quasi-stationary components. The water hydraulic motor test rig was established and introduced. The novel method for the feature extraction from the vibration signals of the water hydraulic motor was proposed according to the second generation wavelet, which consists of the lifting scheme. The algorithm and method of multi-decomposition based on the lifting scheme was developed. The denoise method for the vibration signals was presented on the lifting scheme and the generalized cross validation. The relation between the SNR and GCV was investigated. The corrupted simulated signal was used to test the proposed denoise algorithm. The method for extracting the feature values from the impulse vibration signals based on the statistical method was studied. The results showed the applicability of this method.

Chapter 5

Vibration Analysis Using Adaptive Wavelet

In the condition monitoring and fault diagnosis, it is essential to find appropriate methods to process signals in order to best reveal the information about the condition of a machine. Traditional techniques represent a signal either in time domain or frequency domain but not usually simultaneously. Wavelet analysis provides an effective way to analyze signals. It represents a signal with a joint function of time and frequency and can well characterize the spectrum of a nonstationary signal.

In practice, the vibration signals were contaminated by noise. The signal-to-noise ratio (SNR) is very low about vibration information, which is typically less than 1 dB. It needs to reduce the noise to improve the SNR for the feature extraction from the vibration signal. The least-mean-square algorithm is most popular adaptation method. It tracks non-stationarities well and is robust against error propagation in limited precision implementations. The noise reduction method based on the wavelet domain LMS was proposed. The Shannon wavelet was used to improve the least mean square (LMS) performance. The simulated signals corrupted by Gaussian white noise and impulse noise were used to test the proposed algorithm.

In this Chapter, the fault diagnosis of the water hydraulic motor in the water hydraulic system was investigated based on the adaptive wavelet analysis. A novel method for modelling the vibration signals based on the adaptive wavelet transform (AWT) was proposed. A linear combination of wavelets was introduced as the wavelet itself and adapts the wavelet to the particular vibration signals, which go beyond adapting parameters of a fix-shape wavelet. The AWT procedure based on the parameter optimization by genetic algorithm (GA) was developed. The model-based method by AWT was applied to extract the features in the fault diagnosis of the water hydraulic motor. The results of the experimental signals demonstrated the characteristic vibration signal details in fine resolution. The magnitude plots of the continuous wavelet transform (CWT) showed the characteristic signal's energy in time and frequency domain, which can be used as feature values for the fault diagnosis of the water hydraulic motor.

The new adaptive joint time-frequency signal representation was studied to extract the feature values from the vibration signals. The Gaussian basis functions were used to adaptively parameterize the vibration signals, which go beyond the parameters of a fix-shape wavelet. The characteristic frequencies of the vibration signals can be separated. The adaptive spectrogram procedure based on the parameter optimization by genetic algorithm (GA) was developed. The experimental vibration signal analysis by the adaptive joint time-frequency representation demonstrated the characteristic vibration signal details in fine resolution.

Section 5.1 investigated the noise reduction method based on the wavelet domain LMS. The Shannon wavelet domain LMS algorithm was developed. In Section 5.2, the adaptive wavelet for the vibration signal model was studied. The fault diagnosis of the piston crack

in hydraulic motor based on the vibration model was investigated. In Section 5.3, GA was introduced and the algorithm for the adaptive wavelet was developed. Finally the adaptive spectrogram based on the adaptive Gaussian wavelet was studied and applied for the detection of the piston crack.

5.1 Wavelet Domain LMS Adaptive Filter for Vibration Signal Denoise

The least mean square (LMS) first introduced by Widrow and Hoff [123]. It is one of the most widely used algorithms for adaptive filtering. The shortcoming is that the convergence rate is highly dependent on the conditioning of the autocorrelation matrix of the inputs. The small eigenvalue creates slow convergence models in the mean square error (MSE) function. The transform domain LMS was introduced to solve this problem [124]. The transform domain filtering is used to improve the convergence performance of the standard LMS algorithm by exploiting the orthogonality property of the WT. The power normalization makes the eigenvalues of the LMS filter inputs to cluster and speeds up the convergence of the adaptive weights. Each adaptive weight in the filter was responsible for a given frequency band and update independently from the other weights.

5.1.1 Wavelet Transform Domain LMS

The time-domain LMS algorithm was based on the calculation of the output y_n of the filter

$$y_n = \sum_{i=0}^p h_i x_{n-i} \quad (5.1)$$

where h_i is the filter impulse response and x_n was the input signal. The filter coefficients are updated by the gradient method. The output error e_n is defined as:

$$e_n = d_n - y_n \quad (5.2)$$

where d_n was the desired output of the filter. The filter coefficients were updated by the gradient method defined as follows:

$$h_i = h_i - g \frac{\partial e_n^2}{\partial h_i} \quad (5.3)$$

where g was the gain factor. Equations (5.1) and (5.2) were substituted in equation (5.3), the following equation can be obtained:

$$h_i = h_i + 2g\Delta_n x_{n-1} \quad (5.4)$$

The WT domain LMS was composed of three steps as shown in Figure 5.1. Firstly, the tap-delay input signals $x_k, x_{k-1}, \dots, x_{k-n+1}$ were processed by Shannon CWT, that is

$$X_k(\mu) = \sum_{t=0}^{n-1} \bar{\psi}(\mu, t) x_{k-t} \quad (5.5)$$

where $\mu = 0, \dots, n-1$. $\psi_{\tau, \mu}(t)$ is the Shannon wavelet function.

Figure 5.1: Shannon WT LMS block diagram

The elements of the transformed tap input vector $X_k(\mu)$ constitute a set of random processes with approximately exclusive spectral bands. This result implies that the elements of $X_k(\mu)$ are approximately uncorrelated with each other. The correlation matrix of transformed input is $B_n(k) = E\{X_k X_k^T\} = E\{TX_k X_k^T T^T\} = TR_n(k)T^T$, where $R_n(k)$ is original input signal correlation matrix. The eigenvalues are same for $B_n(k)$ and $R_n(k)$ due to their similarity. The normalization matrix converts $R_n(k)$ to a normalized matrix whose eigenvalue spread is much smaller and improves the convergence of the LMS algorithm in the transform domain.

The normalized WT output signals are inputted to an adaptive linear combiner whose weights $w_k(0), w_k(1), \dots, w_k(n-1)$ are adjusted using the LMS algorithm. The filter tap-weights are updated according to the following recursion:

$$w_{k+1} = w_k + 2g\hat{D}^{-1}e(n)X_k \quad (5.6)$$

where $\hat{D}$ is the power matrix of transform outputs. It is defined as follows:

$$D = \begin{bmatrix} E[X_k(1)] & 0 & \dots & 0 \\ 0 & E[X_k(2)] & \dots & 0 \\ \vdots & \vdots & E[X_k(3)] & \vdots \\ 0 & 0 & 0 & E[X_k(4)] \end{bmatrix} \quad (5.7)$$

Equation (5.7) is used to different step-size parameters in various tap. Each tap weight adaptation is dependent on the inverse of the input power.

The WT LMS algorithm step is described as follows:

- (1) The original signal is transformed by Shannon wavelet function to obtain the wavelet coefficients. The WT equation is $X_k = Tx_k$.
- (2) The resulting wavelet coefficients are filtered by the LMS filter weights to obtain the output $y_k = w^T X$.
- (3) Calculate the error between the desired signal and output signal by the equation $e_k = d_k - y_k$.
- (4) The tap-input power estimates are updated as $\hat{\sigma}_k(i) = \ell \hat{\sigma}_{k-1}(i) + (1 - \ell)X_k(i)$.

- (5) The tap-weight vector is updated by $w_{k+1} = w_k + 2g\hat{D}^{-1}e(n)X_k$.
- (6) The inverse WT is used to calculate the denoise signal by the weights w_{k+1} . Steps (1) to (6) are repeated by n time until all the signals are computed.

5.1.2 Results and Discussion

Shannon wavelet is an important class of wavelets whose Fourier transforms are derived from the general orthogonal wavelet formula introduced by Mallat and Meyer [125]. The Shannon wavelet is constructed from the Shannon multi-resolution approximation, which approximates functions by the restriction to low frequency intervals. Shannon wavelet is derived as:

$$\hat{\psi}(\omega) = \begin{cases} \exp(-i\omega/2) & \text{if } \omega \in [-2\pi, -\pi] \cup [\pi, 2\pi] \\ 0 & \text{otherwise} \end{cases} \quad \text{and} \quad (5.8)$$

$$\psi(t) = \frac{\sin 2\pi(t-1/2)}{2\pi(t-1/2)} - \frac{\sin \pi(t-1/2)}{\pi(t-1/2)} \quad (5.9)$$

Shannon wavelet has a slow asymptotic time decay. The function ψ has an infinite number of vanishing moments. Figure 5.2 shows the corresponding waveform of the Shannon wavelet function, where the typical scale is 2^8 and proved to be optimal parameter for denoise of the corrupted signal in the following Figure 5.7 and the sample frequency is 12.8 kHz under the Nyquist formula requirement for Shannon wavelet.

Figure 5.2: The Shannon wavelet waveform

Two simulated signals are denoised by the proposed method based on the WT domain LMS algorithm. The first simulated signal is generated from the function $f(t) = 0.01(\sin(120\pi t) + \sin(260\pi t) + \cos(400\pi t))$. This signal is corrupted by Gaussian white noise with signal-to-noise ratio of 2 dB . Figure 5.3 shows the waveform of the corrupted signal. Figure 5.4 shows the comparison of the original signal and denoised signal in time domain and frequency domain. The noise of the corrupted signal is reduced up to SNR of 20.4 dB . The waveform and frequencies are the same.

Figure 5.3: The contaminated signal by Gaussian noise with 2 dB SNR

Figure 5.4: Comparison of the waveform (Upper) and frequency (Low) between the original signal and denoise signal (20.4dB)

The vibration in fluid power system is often contaminated by impulse noise. Figure 5.5 shows the simulated signal corrupted by impulse noise with SNR of 2 dB . This corrupted simulated signal was de-noised by the proposed noise reduction algorithm. Figure 5.6 shows the comparison of the original signal and denoised signal in time domain and frequency domain. The SNR of the de-noised simulated signal was improved up to 22.4 dB .

Figure 5.5: The contaminated signal by impulsive noise with 2dB SNR

Figure 5.6: Comparison of the waveform (Upper) and frequency (Low) between the original signal and denoise signal (22.4dB)

When the Shannon wavelet is used to transform the original input signal, the scale is important to the de-noise of the signal. The Shannon wavelet is a band-pass filter for signal process. The different scale results in the different center frequency of the Shannon wavelet.

Figure 5.7 shows the relation between the SNR and the scales. When the scale equal to 8, the SNR is maximum. The center frequency of the Shannon is 196 Hz which matches the principle frequencies of the simulate signals. Figure 5.8 shows the relation between the SNR and the number of the tap-weight. The optimal number of the tap-weight is 24 for the maximum SNR.

Figure 5.7: The relation between the SNR and the scale

Figure 5.8: The relation between the SNR and the number of the tap-weight

5.2 Adaptive Wavelet Transform for the Model of Vibration Signal

5.2.1 The Wavelet Time-Frequency Window

The CWT of a signal is localized in a time-frequency window, and τ^* and $\Delta\tau^*$ represent the center and the radius of $\psi(t)$. These parameters are defined as follows:

$$\tau^* = \frac{1}{\|\psi\|_2^2} \int_{-\infty}^{\infty} t |\psi(t)|^2 dt \quad (5.10)$$

$$\Delta\tau^* = \frac{1}{\|\psi\|_2} \left\{ \int_{-\infty}^{\infty} (t - \tau^*)^2 |\psi(t)|^2 dt \right\}^{\frac{1}{2}} \quad (5.11)$$

The time window t_w is calculated as follows:

$$t_w = [\tau + \mu\tau^* - \mu\Delta\tau^*, \tau + \mu\tau^* + \mu\Delta\tau^*] \quad (5.12)$$

The wavelet transform can also be derived from the frequency domain and calculated as:

$$W_f(\tau, \mu) = \frac{\mu|\mu|^{-1/2}}{2\pi} \int_{-\infty}^{\infty} F(\omega) e^{j\tau\omega} \overline{\Psi(\mu\omega)} d\omega \quad (5.13)$$

ω^* and $\Delta\omega^*$ are assumed to be the center and radius of the function $\overline{\Psi(\omega)}$ respectively and can be deduced from the equations (4.9), (5.10) and (5.11). The center and radius of the ω^* function $\overline{\Psi(\mu\omega)}$ will be ω^*/μ and $(1/\mu)\Delta\omega^*$. The frequency window f_w is formed as:

$$f_w = \left[\frac{\omega^*}{\mu} - \frac{1}{\mu} \Delta \omega^*, \frac{\omega^*}{\mu} + \frac{1}{\mu} \Delta \omega^* \right] \quad (5.14)$$

So the time-frequency window was obtained as $t_w \times f_w$. The time-frequency localization characteristics can be achieved. It reveals that a higher center frequency was mapped to a time axis with a higher resolution and vice versa.

5.2.2 Adaptive Morlet Wavelet Function

Several types of functions have been proposed as wavelet basis in the wavelet theory and application. There are two kinds of wavelets, which are real analytic wavelet and complex analytic wavelet. The complex analytic wavelets can separate the amplitude and phase component and be used to measure the time evolution of the frequency transitions. The real analytic wavelets can be used to detect the transient signals. The Morlet wavelet is most popular non-orthogonal complex wavelets. The Morlet wavelet is defined as:

$$\psi(t, \lambda) = e^{-t^2/2} e^{i\lambda_0 t} \quad (5.15)$$

where λ_0 is the frequency of the mother wavelet that corresponds to the radian frequency of the Gaussian windowed complex sinusoid. The son wavelet is obtained by dilation with μ and translation with τ as follows:

$$\psi_{\mu, \tau} = e^{-\frac{(t-\tau)^2}{2\mu^2}} e^{i\lambda_0 \frac{t-\tau}{\mu}} \quad (5.16)$$

It is shown that the function decays exponentially on both sides. Equations (5.15) and (5.16) can be transformed from time domain to frequency domain. These functions in time domain can be mapped to the frequency domain as follows:

$$\Psi(\omega) = \sqrt{2\pi} e^{-\frac{(\omega - \lambda_0)^2}{2}} \quad (5.17)$$

$$\Psi_{\tau, \mu}(\omega) = \sqrt{2\pi} \mu e^{-\frac{(\mu\omega - \lambda_0)^2}{2}} e^{-i\omega\tau} \quad (5.18)$$

With equations (5.10) and (5.11), the center and radius of the wavelet basis functions shown in equations (5.15) and (5.17) can be obtained as follows:

$$\tau^* = 0, \quad \Delta\tau^* = \sqrt{2}/2, \quad \omega^* = \lambda_0, \quad \Delta\omega^* = \sqrt{2}/2 \quad (5.19)$$

The time-frequency windows can be obtained as follows:

$$\left[\tau - \frac{\mu}{\sqrt{2}}, \tau + \frac{\mu}{\sqrt{2}} \right] \times \left[\frac{\lambda_0}{\mu} - \frac{1}{\mu\sqrt{2}}, \frac{\lambda_0}{\mu} + \frac{1}{\mu\sqrt{2}} \right] \quad (5.20)$$

Equation (5.20) shows that the parameter τ determines the center of the time window and the parameter μ determines the center of frequency window. The result of the ratio of the frequency bandwidth to the center frequency is $\sqrt{2}/\lambda_0$ which is variable. So the adaptive Morlet wavelet function can adjust its parameter to represent the signal in adequate resolution.

Given the function is finite in time and frequency, it can be considered suitable for the basis function formulation. A wavelet function $\psi(t)$ has the following properties:

- (1) The average of the function is zero, that is: $\int_{-\infty}^{\infty} \psi(t) dt = 0$
- (2) The amplitude $|\psi(t)|$ must decay rapidly to zero when $|t|$ approaches infinity.
- (3) It satisfies the following admissibility condition, that is: $\int_0^{\infty} \frac{|\Psi(\omega)|}{\omega} d\omega < +\infty$

As shown in equation (5.17), $\Psi(\omega) = \Psi^*(\omega)$, the wavelet function in frequency domain is a real function. This wavelet function is not an admissible wavelet, that is:

$$\int_{-\infty}^{\infty} \psi(t) dt \neq 0 \text{ and } 2\omega_s \mu = \lambda_0 + \sqrt{\lambda_0^2 + 2} \quad (5.21)$$

Although it did not satisfy the admissible condition, the value of its integral is much smaller. In practice, when the parameter λ_0 ($\lambda_0 > 5$) is large enough, it can render $\int_{-\infty}^{\infty} \psi(t) dt \approx 0$. This is small enough for Morlet wavelet to be applied for wavelet analysis.

The relation between Morlet wavelet frequency ω_m and dilation scale μ can be obtained when the absolute value of the Fourier transform of the Morlet wavelet atoms $\Psi_{\tau,\mu}(t)$ is a maximum. The result is obtained from equation (5.18) as:

$$\frac{\partial |\Psi_{\tau,\mu}(\omega)|}{\partial \omega} = 0, \quad \text{So } \mu \omega_m = \mu 2\pi f_m = \lambda_0 \quad (5.22)$$

The above result is the same as that in adaptive time-frequency window as shown in equation (5.20). The center frequency and the frequency bandwidth at certain scale are variable. Equation (5.22) shows that the relationship between the scale μ and Morlet wavelet frequency f_m varies according to the frequency of mother wavelet λ_0 . Compared

with adaptive wavelet function, the relation among them in the fixed wavelet function is constant. This shows the advantage of adaptive wavelet function over the fixed wavelet function. The frequency of adaptive wavelet atoms f_m , can be adjusted more automatically than the fixed wavelet atoms at the same scale. Hence the adaptive wavelet can be applied to analyze the signals in acceptable small value resolution.

An analytical wavelet transform of a signal $x(t)$ with known frequency is calculated with an analytic wavelet function $\psi_{\tau,\mu}(t)$. The scalogram can reach a maximum at certain scale to obtain the relation between the scale and its equivalent Fourier frequency. The scalogram is the wavelet energy function that is defined as:

$$P_W(\tau, \mu) = |W_f(\tau, \mu)|^2 \quad (5.23)$$

For sinusoidal function with unit amplitude and angular frequency ω_s , that is $x(t) = \sin(\omega_s t)$, the result of its Morlet wavelet transform is obtained as:

$$W_{\omega_s}(\tau, \mu) = \left(\sqrt{2\pi\mu}/2i\right) e^{-(s\omega_s - \lambda_0)/2} e^{(i\omega_s \tau)} \quad (5.24)$$

The scalogram of $W_{\omega_s}(\tau, \mu)$ is as follows:

$$|W_f(\tau, \mu)|^2 = (\pi\mu/2) \exp\left[-(\mu\omega_s - \lambda_0)^2\right] \quad (5.25)$$

By maximizing the scalogram, that is,

$$\frac{\partial |W_f(\tau, \mu)|^2}{\partial \mu} = 0 \quad (5.26)$$

The relation between the scale and the angular frequency of the sinusoidal function is obtained:

$$2\omega_s \mu = \lambda_0 + \sqrt{\lambda_0^2 + 2} \quad (5.27)$$

From equations (5.22) and (5.27), the relation between the Morlet wavelet frequency f_m and the Fourier frequency of the sinusoidal function f_s is derived as:

$$f_m = \frac{2\lambda_0}{\lambda_0 + \sqrt{\lambda_0^2 + 2}} f_s \quad (5.28)$$

It can be derived that the Morlet wavelet frequency is almost equal to the sinusoidal angular frequency, that is $f_m = f_s$, when the frequency λ_0 is large enough. Generally, it is enough for $\lambda_0 > 5$ [125].

5.2.3 Model of signal with adaptive Morlet wavelet

The model of signals can be regarded as feature extraction problems. The goal was to find a set of son wavelets that best represent the signals in the resulting feature space. The adaptive wavelet can be adaptively computed to adjust the wavelet parameter and shape in order to minimize the energy function. It was different from the fixed wavelets that test a large fixed set of wavelets and discard the one with the least contribution. The adaptive wavelet can change its shape to be adapted to the particular signal rather than the adaptation of parameter of a fix-shape wavelet.

A signal $f(t)$ can be approximated by sons of a mother wavelet $\psi(t)$ shown as follows:

$$\hat{f}(t) = \sum_{k=1}^K W_k \psi_k \left(\frac{t - \tau_k}{\mu_k} \right) \quad (5.29)$$

where the W_k , τ_k and μ_k are the weight coefficients, shifts and dilations for each son wavelet. The parameter W_k , τ_k and μ_k can be optimized by minimizing an energy function. The least-mean-square (LMS) energy for the signal model is applied as follows:

$$E = \frac{1}{2} \sum_{t=1}^T [f(t) - \hat{f}(t)]^2 \quad (5.30)$$

The model of the signal is to assess the parameter measured in the wavelet domain. Considering the signal $f(t) = \cos(\omega_c t)$, its CWT by complex Morlet wavelet, defined in equation (5.16) is:

$$W_f(\mu, \tau) = \frac{\sqrt{2\pi\mu}}{2} \exp \left[-\frac{1}{2} (\mu\omega_c - \lambda_0)^2 + i\omega_c \tau \right] \quad \text{when } \mu\omega_c \lambda_0 > 6 \quad (5.31)$$

To maximize the scalogram defined in equations (5.25) and (5.26), the maximum magnitude of $W_f(\mu, \tau)$ can be derived. The frequency of mother wavelet λ_0 can be obtained as $\lambda_0 = \mu\omega_c$. The frequency of the sinusoidal signal can be measured by the changing rate of the phase in the complex wavelet transform with respect to τ . The phase of $W_f(\mu, \tau)$ is $\omega_c \tau$.

The CWT by complex Morlet wavelet, $f(t) = \cos(\omega_c t) \exp(-0.5(t/\sigma)^2)$, is defined in equation (5.16) as follows:

$$W_f(\mu, \tau) = \frac{\sigma}{2} \sqrt{\frac{\mu}{\mu^2 + \sigma^2}} \exp \left[\frac{\tau^2}{2(\mu^2 + \sigma^2)} + \frac{\sigma^2(\lambda_0 - \mu\omega_c)}{2(\mu^2 + \sigma^2)} \right] \exp \left[i\tau \frac{(\mu\lambda_0 + \sigma^2\omega_c)}{(\mu^2 + \sigma^2)} \right] \quad (5.32)$$

where $\frac{\mu\sigma^2\lambda_0\omega_c}{\mu^2 + \sigma^2} > 1.16$.

The magnitude of $W_f(\mu, \tau)$ is obtained as:

$$W_f(\mu, \tau) = \frac{\sigma}{2} \sqrt{\frac{\mu}{\mu^2 + \sigma^2}} \exp \left[\frac{\tau^2}{2(\mu^2 + \sigma^2)} + \frac{\sigma^2(\lambda_0 - \mu\omega_c)}{2(\mu^2 + \sigma^2)} \right] \quad (5.33)$$

The magnitude is represented as a Gaussian curve with the variance $\mu^2 + \sigma^2$. The phase of $W_f(\mu, \tau)$ is shown to be $(\mu\lambda_0 + \sigma^2\omega_c)/(\mu^2 + \sigma^2)$. So the necessary parameters in the characteristic signals can be extracted. For the characteristic signals which consist of Gaussian pulses, the magnitudes of $W_f(\mu, \tau)$ consist of many distinct peaks. The frequency and phase of the cosine, as well as the center location and standard deviation of the Gaussian window can be estimated with each peak.

Given that a signal can be regarded as the sum of Gaussian modulated cosines, Morlet wavelet function is applied for its CWT. The model of signal can be established by the information of the peaks of the magnitude plot of Morlet wavelet transform from the following parameters. That is the relative amplitude W , frequency ω , phase θ , standard deviation of the Gaussian envelope σ and location of the center of the Gaussian envelope τ . As shown in equation (5.29), the model of the signal can be established as:

$$\hat{f}(t) = \sum_i W_i \cos(\omega_i t - \theta_i) \exp \left[-\frac{1}{2} \left(\frac{t - \tau_i}{\sigma_i} \right)^2 \right] \quad (5.34)$$

Figure 5.9: Procedure of the adaptive wavelet model algorithm with GA and LMS

The software of this algorithm is developed and programmed by author.

Figure 5.9 shows the adaptive wavelet model algorithm for the vibration signals optimized by GA for the detection of the size and location of the piston crack. The step is as follows:

- (1) $i = 1$ and $f_i(t) = f(t)$.
- (2) GA is applied to optimize the parameters in the signal model with LMS as shown in equation (5.30). GA is described in the following section 5.3. This step can obtain the first set of optimal parameters from $f_i(t)$.
- (3) The remaining signal will be obtained by minus the optimal signal from the original signal.
- (4) If the LMS of the remaining signal is not less than the threshold value, then repeat steps (1) to (3) until stop. In this work, the repeated times is six to extract the most important frequencies of the vibration signal, which can represent the vibration characteristics of the water hydraulic motor. The CPU running time of the software at Pentium III is thirty minutes for this procedure.
- (5) By applying the obtained several sets of optimal parameters to produce the simulated signal as shown in equation (5.34)
- (6) The CWT is applied to the simulated signal to extract the features.

5.2.4 Simulated Signal

Two experimental signals were presented to test the proposed algorithm of the signal model based on the adaptive Morlet wavelet. The two experimental signals were generated by the functions as shown in equations (5.35) and (5.36).

$$\begin{aligned}
y_1(x) = & 0.02\cos(120\pi x - 1)\exp\left[-0.5(x - 0.02/0.02)^2\right] \\
& + 0.01\cos(260\pi x - 2)\exp\left[-0.5(x - 0.04/0.2)^2\right] \\
& + 0.015\cos(400\pi x - 5)\exp\left[-0.5(x - 0.04/0.4)^2\right]
\end{aligned} \tag{5.35}$$

$$\begin{aligned}
y_2(x) = & 0.02\sin(120\pi x) + 0.015\sin(260\pi x - 2) \\
& + 0.02\cos(400\pi x - 5)\exp\left[-0.5(x - 0.04/0.4)^2\right]
\end{aligned} \tag{5.36}$$

Gaussian noise is the most popular noise in the vibration signals of a mechanical system. In order to test the proposed model algorithm based on adaptive Morlet wavelet analysis, the original signal generated by the functions in equation (5.35) was added with Gaussian noise to a SNR of 1 dB to obtain the corrupted experimental signal. The corrupted experimental signal is presented in Figure 5.10(b). The simulated signal in Figure 5.10(a) is obtained by applying the proposed model based on the adaptive wavelet analysis to analyze the corrupted experimental signal in Figure 5.10(b). Figure 5.10(a) shows the comparison results between the original signal and the simulated signal. The results in Figure 5.10(a) show that the waveform of the simulated signal is the same as the original signal in the characteristic frequencies and amplitudes. The corrupted signal in Figure 5.10(b) is de-noised and modeled by the proposed model algorithm. The SNR of the simulated signal in Figure 5.10(a) is 39.8 dB.

The original signal generated by equation (5.36) was added with Gaussian noise to obtain the corrupted signal as shown in Figure 5.11(b). The SNR of the corrupted signal in Figure 5.11(b) was 1 dB. The proposed model is applied to analyze the corrupted signal to obtain the simulated signal. Figure 5.11(a) shows the comparison between the original signal and the simulated signal. The simulated signal is about the same as the original waveform signal. The SNR of the simulated signal is 40.7 dB.

Figure 5.10: (a) Original experimental signal and simulated signal from the adaptive wavelet model, (b) Original experimental signal added with Gaussian noise.

Figure 5.11: (a) Original experimental signal and simulated signal from the adaptive wavelet model, (b) Original experimental signal added with Gaussian noise.

The above results from the two simulated signals show that the proposed model algorithm was applicable to simulate the signals even though the signals are corrupted by noise with 1 dB SNR. The proposed method can be used to denoise the corrupted signals and extract the characteristic frequencies and amplitudes. The simulated signal was the same as the original signal.

The proposed model algorithm was applied to analyze the experimental vibration signals acquired from the shell of the motor using the test rig, shown in Figure 4.2. The original accelerometer signal in Figure 5.12 is a typical vibration signal from the shell of the water hydraulic motor. Its fundamental frequencies consist of the hydraulic motor fundamental frequency (55 Hz) and the hydraulic pump fundamental frequency (120 Hz) as explained in Chapter 3. Figure 5.12 displays the waveform comparison in time domain between the original experimental signal and the simulated signal. The original signal includes noise.

The comparison result showed that the waveform of the simulated signal is the same as the original signal. In order to show the similarity between the two signals, the frequency comparison of the two signals is presented in Figure 5.13. The results show that the simulated signal is the same as the original experimental signal in frequency domain. The harmonic frequencies of the simulated signal are similar to the original signal, especially the fundamental frequencies below 300 Hz.

Figure 5.12: Waveform comparison between actual original motor signal and simulated signal

Figure 5.13: Frequency comparison in between actual original motor signal and simulated signal

The results from the above signal analysis show that the proposed model algorithm based on the adaptive wavelet was effective and applicable for the model of vibration signals. This method can extract the characteristic fundamental parameters such as the

relative amplitude w , frequency ω , phase θ , standard deviation of the Gaussian envelope σ and location of the center of the Gaussian envelope τ as described in equation (5.34) in the vibration signals. The signal simulated by the model fits the real vibration signal very well. The model can be applied to de-noise the vibration signals with low SNR and to improve SNR of the vibration signals dramatically.

5.2.5 Fault Diagnosis of Piston Crack

The proposed model algorithm based on adaptive Morlet wavelet was applied to diagnose the piston crack in Nessie water hydraulic motor. Firstly, the proposed model as shown in equation (5.34) was applied to simulate the real vibration signals to obtain the simulated signals. The parameters such as relative amplitude W and frequency ω in equation (5.34) are the important factors to determine the waveform of the vibration signals. Figure 5.14 shows the relation between the frequency ω and relative amplitude W . The horizontal axis represents the parameter-frequency ω and vertical axis represents the parameter - relative amplitude W . The major frequency of BLC is 80 Hz that is the common harmonics of the Nessie hydraulic motor and hydraulic pump. Under BLC and BSC condition, the frequency of the highest relative amplitude is 80 Hz. The relative amplitude of the harmonics of **BLC** is larger than that of **BSC**. Between 150 Hz and 200 Hz, the relative amplitudes of the **BLC** and **BSC** were larger than that of **FLC**, **FSC** and **NC**. This result showed the location of the piston crack. Under FLC condition, the highest relative amplitude is at 160 Hz. The highest relative amplitude under NC condition is at 330 Hz and the highest relative amplitude under FSC condition is at 370 Hz. There were no frequency for **FSC** below 140 Hz.

Figure 5.14: Relation between frequency and relative amplitude obtained by the proposed model from the vibration signal under five operational conditions.

Below the frequency of 200 Hz , the major frequencies and its corresponding amplitudes are different for **FLC**, **FSC** and **NC**. The frequency between 200 Hz and 300 Hz is similar. Between the frequency of 300 Hz and 400 Hz is also different for **FLC**, **FSC** and **NC**. Hence the characteristic frequencies and its corresponding amplitudes can be regarded as feature values for the different piston conditions. Figure 5.14 shows the major frequencies and corresponding amplitudes obtained by the model based on adaptive wavelet. The results are repeatable.

The obtained simulated signal by modeling the experimental vibration signal (see Figure 5.9) was analyzed by complex Morlet **CWT** in order to show the characteristics in time-frequency plane. The low characteristic frequency of the vibration signals was the most important factor to evaluate the condition of mechanical system. The low frequency of the

vibration signal was changed because the variation of the machine structure produced the different vibration characteristics. In this work, **CWT** of the simulated signal was applied to extract the feature values from the low frequencies that can be used to evaluate the five different piston conditions.

Figure 5.15 shows the time-frequency planes of the simulated signals obtained by modeling real vibration signals on five piston conditions. The **CWT** time-frequency plane of the vibration signals can display the change of the waveform and the impulse signals much clearly at every frequency and every time. The amplitudes of the impulse signals increase from (a) to (c). In Figure 5.15(a), the **CWT** amplitudes of **NC** vibration signal are smallest among the five piston conditions. There are five impulse signals in the time-frequency plane of the vibration signals of **NC**. The five impulse signals are generated by the pumping behavior of the five pistons in the hydraulic motor.

When there is a crack in the front section of the piston, the amplitudes and number of the impulse signals change. Figures 5.15(b) and (c) show the **CWT** time-frequency plane of the simulated signals by modeling the **FSC** and **FLC** experimental vibration signals. The **CWT** amplitudes of the simulated signals in Figures 5.15(b) and (c) are higher than that in Figure 5.15 (a). In Figure 5.15 (b), there is one impulse signal at 0.06 s in the **FSC** condition. Figure 5.15 (c) also shows one impulse signal at 0.08 s in the **FLC** condition and its amplitudes are higher than that in **FSC** condition.

(a) Time-frequency plane under NC condition

(b) Time-frequency plane under FSC condition

(c) Time-frequency plane under FLC condition

Figure 5.15: Complex Morlet CWT time-frequency planes of the simulated signal obtained by modeling real vibration signal under five piston conditions: (a) **NC**; (b) **FSC**; (c) **FLC**;

As shown in Figures 5.16 (a) and (b), the amplitudes and numbers of the impulse signals increase when there is a crack in the back section of the piston. Compared with the energy in Figures 5.15 (a)-(c) that is extended to 400 Hz, the energy of the vibration signals is concentrated below 200 Hz. The time-frequency plane of the **BSC** vibration signals is different from that of **BLC** vibration signals. In Figure 5.16 (a), one impulse signal was near 0.08 s when the frequency is 80 Hz. The number of the **BSC** impulse signal was less than the three **BLC** impulse signals. The amplitudes of the **BSC** impulse signal are also smaller than that of **BLC**. Figure 5.16 (b) showed the time-frequency plane of the **BLC** vibration signal. There were three impulse signals at 0.02 s, 0.03 s and 0.09 s respectively when the frequency is 80 Hz, which is the Nessie hydraulic motor rotational frequency.

(a) Time-frequency plane under BSC condition

(b) Time-frequency plane under BLC condition

Figure 5.16: Complex Morlet **CWT** time-frequency planes of the simulated signal obtained by modeling real vibration signal under five piston conditions: (a) **BSC**; (b) **BLC**;

From above results, it was shown that the amplitudes and number of the impulse signals are higher when the crack is located in the back section of the piston (**BLC** and **BSC**) than that when the crack was located in the front section of the piston. The amplitudes and number of the impulse signals increase when the crack became bigger. Although the motor leakage is negligible under normal condition, the contact surface between the piston and cylinder was important factor for the leakage in the hydraulic motor when there is crack in the piston as discussed in introduction and hydraulic motor vibration mechanism. Because the leakage from the piston crack is larger enough to change the torque, flow rate and pressure, which can produce the different vibration characteristics. The leakages with the different sizes and locations of the piston crack resulted in the change of the vibration impulse signals.

5.3 Genetic Algorithm for Parameter Optimization

As shown in Figure 5.9, the parameters in the equation (5.34) need to be optimized to obtain the simulated vibration signal. GA is the most important optimization method and applied to obtain the optimal simulated vibration signal in this work.

GAs are applied in a wide variety of areas with increasing interest [126]. GA is used to search the optimal solution space through simulated evolution of ‘survival of the fittest’ that is analogous with natural behavior of a species. The GA considers six basic issues: chromosome representation, selection function, genetic operator such as crossover and mutation for reproduction function, creation of initial population, termination criteria and the evaluation function.

In the reproduction phase, it produces the chromosomes randomly. Every chromosome represents a solution to the problem. The fitness of each chromosome can be calculated and determined by the objective function. The reproduction operator is implemented by using a roulette wheel with slots sized according to fitness. The chromosomes with higher fitness are given opportunities to reproduce by mating with other individuals in the population. The chromosomes with smaller fitness are less likely to get selected for reproduction and gradually die out. In the cross phase, strings are chosen by pairs. For each random pair, two random numbers are generated to decide which pieces of the strings are to be interchanged. The crossover operator is applied by probability p_c . In the mutation phase, the bits in the string in the population will be chosen with probability p_m .

(1) Chromosome representation

The binary encoding is applied in traditional genome representation. It is no longer appropriate for real number encoding. The real number encoding is applied in the present work because of the closeness of the representation to the problem space, better average performance and more efficient numerical implementation. The chromosome (c) contains the real number of the features. The features represent the five parameters of the model as shown in equation (5.34). The numbers ($c_i, i = 1, 5$) in the genome string are constrained to be in the range $c_{\min} < c_i < c_{\max}$. The parameter $c_{\min}$ and $c_{\max}$ represent respectively the lower and the upper bounds on the parameters of the model. The example is shown as $C = \{c_1, c_2, c_3, c_4, c_5\} = \{0.005, 50, 100, 0.08, 0.005\}$. The numbers in the chromosome represent respectively the relative amplitude, angular frequency, phase, location of the center of the Gaussian envelope and standard deviation of the Gaussian envelope as

described in equation (5.34).

(2) Population initialization

A population of N strings is randomly generated. In our experiments, N is equal to 60. The length of each string is m , which is the number of parameters in model. The number encode in each chromosome represents value of the parameter in the model.

(3) Fitness computation

The real number in each initial chromosome can be substituted respectively into the function as shown in the model in equation (5.34). The estimated signal from each chromosome can be obtained from:

$$\hat{f}(t) = \sum_i c_1 \cos(c_2 t - c_3) \exp \left[-\frac{1}{2} \left(\frac{t - c_4}{c_5} \right)^2 \right] \quad (5.37)$$

In order to approximate the real signal with the estimated signal, the least-mean-square energy for signal model is applied. The function in equation (5.30) is regarded as the objective function E . The objective function value E of each chromosome can be obtained from the objective function.

The estimated signal is a better model for the real signal when the objective function value E is smaller. The corresponding chromosome will be good candidate for the following reproduction. It is shown that this parameter optimization is for minimization problems. GA requires the fitness value to be positive in order to be able to perform the roulette wheel select and reproduction. Hence the fitness can be defined as follows:

$$G(x) = E_{\max} - E(x) \quad (5.38)$$

where $E_{\max}$ is the maximum value of the objective function in the current population. GA will have an undesirable behavior that highly fit individuals will dominate the selection. This will lead to a premature convergence. The fitness scaling is applied to deal with this problem. The scaled function is defined as:

$$T(x) = aG(x) + b \quad (5.39)$$

The average fitness value should be the same after and before scaling. That is $T_{avg} = G_{avg}$. In order to map the minimal fitness to be zero, the parameters a and b are defined as follows:

$$a = \frac{T_{avg}}{T_{avg} - T_{\min}}, \quad b = T_{avg}(1 - a) \quad (5.40)$$

(4) Selection

The selection process selects the chromosome which forms the mating pool directed by the survival of the fittest concept of the natural genetic systems. Roulette wheel selection is one common technique that implements the proportional selection strategy. The roulette wheel selection will not produce the expected numbers if the population is small. The fitter individuals may dominant at much higher proportion. The stochastic universal selection (SUS) is applied in this work. In SUS, the wheel is rotated once with n markers on the wheel. These n markers will give n strings.

Generally, the entire generation is replaced by the offspring. This is referred to as non-overlapping generation, i.e. no overlapping between the parents and the children. The

disadvantage is that some good building blocks in the parents may be lost and would not contribute to the evolution process. The offspring will be worse than the parents sometimes. The elitist strategy solves the problem. The elitist strategy copy the best or best few parents into the next generation to replace the worst children or some children randomly.

(5) Crossover

Crossover is a probabilistic process that exchanges information between two parent chromosomes for generating two child chromosomes. The single-point crossover with a fixed crossover probability of p_c is used. For the chromosome of length l , a random integer, called the crossover point, is generated in the range $[1, l-1]$. The portions of the chromosomes lying to the right of the crossover point are exchanged to produce two offsprings.

(6) Mutation

Mutation introduces a degree of diversity to the populations, prevents a premature convergence and samples the unexplored regions of the search space. Each chromosome undergoes mutation with a fixed probability p_m . For binary representation of chromosomes, a bit position is mutated by flipping its value. In this work, the dynamic or non-uniform mutation is used for real value representation. It is designed for the fine tuning aimed at achieving a high degree of precision. Given a parent C , if the gene C_k is selected for mutation, the resulting offspring is $C' = [c_1 \cdots c_k' \cdots c_m]$ where c_k' is mutated from the following equation:

$$c'_k = c_k + r(c_{\max} - c_k) \left(1 - \frac{t}{T}\right)^b \quad \text{or} \quad c'_k = c_k + r(c_k - c_{\min}) \left(1 - \frac{t}{T}\right)^b \quad (5.41)$$

where r is a random number chosen uniformly from $[0,1]$, t is the current generation number, T is the maximum number of generation and b is a parameter determining the degree of non-uniformity. It is shown that the amount of mutation decreases as the number of generation increases. The equation will be standard non-dynamic mutation of replacing a number with one chosen randomly from the interval $(c_{\min}, c_{\max})$.

(7) Termination criterion

The process of fitness computation, selection, crossover and mutation are executed for a maximum number of iterations. The best chromosome in the last generation provides the best solution to the parameter in the model in equation (5.34). When the optimal parameter is chosen, the remained signal can be obtained by subtracting the optimal estimated signal as shown in equation (5.37) from the original signal $f(t)$. The GA procedure is repeated for this different signal to obtain the next optimal parameters. So the result of the simulated model is the optimal simulated signal of the experimental signal.

5.4 Optimal Adaptive Spectrogram and Signal Representation

5.4.1 Adaptive Gaussian wavelet function

The Gaussian wavelet is most popular non-orthogonal complex wavelets. The normalized adaptive Gaussian wavelet function is defined as:

$$\psi_p(t) = (\pi\sigma_p^2)^{-0.25} \exp\left[-(t - t_p)^2 / 2\sigma_p^2\right] \exp(j2\pi f_p t) \quad (5.42)$$

where $\sigma_p, t_p, f_p \in R^+$, σ_p is the adjustable standard deviation and determines a tradeoff between the time and frequency resolution. (t_p, f_p) is the time-frequency center. The adaptive wavelet function $\psi_p(t)$ can be optimally concentrated in the joint time-frequency domain. Equation (5.42) can be transformed from time domain to frequency domain. This function in frequency domain can be shown to be as below:

$$\Psi_p(\omega) = [\pi(1/2\pi\sigma_p)^2]^{0.25} \exp\left[-(f - f_p)^2 / (\sqrt{2}/2\pi\sigma_p)^2\right] \exp[-j2\pi(f - f_p)t_p] \quad (5.43)$$

With the equations (5.10) and (5.11), the center and radius of the wavelet basis functions shown in equations (5.42) and (5.43) can be obtained respectively:

$$\tau^* = t_p, \quad \Delta\tau^* = \sqrt{2}\sigma_p/2, \quad \omega^* = f_p, \quad \Delta\omega^* = \sqrt{2}/4\pi\sigma_p \quad (5.44)$$

The time-frequency windows can be obtained as follows:

$$\left[\tau + \mu t_p - \frac{\mu\sigma_p}{\sqrt{2}}, \tau + \mu t_p + \frac{\mu\sigma_p}{\sqrt{2}} \right] \times \left[\frac{f_p}{\mu} - \frac{\sqrt{2}}{4\mu\pi\sigma_p}, \frac{f_p}{\mu} + \frac{\sqrt{2}}{4\mu\pi\sigma_p} \right] \quad (5.45)$$

Equation (5.45) shows that the parameter t_p determines the center of the time window and the parameter f_p determines the center of frequency window. The basis functions have a time-frequency extent as shown in Figure 5.17.

Figure 5.17: Joint time-frequency of the adaptive Gaussian function with center (t_p, f_p) and standard deviation σ_p .

The ratio of the center frequency to the frequency bandwidth is $\sqrt{2\pi}\sigma_p f_p$, which is variable. Adaptive Gaussian wavelet function can adjust its parameter to represent the signal in fine resolution. Although the Gaussian function is not compact in time and frequency domain, it possesses the best joint time-frequency resolution due to the minimum time-bandwidth product obtained from equation (5.44) as follows:

$$\Delta\tau^* \Delta\omega^* = \frac{1}{4\pi} \quad (5.46)$$

5.4.2 Signal representation with adaptive Gaussian wavelet

The signals in the real world are non-stationary and it is important to explore their local behavior simultaneously in time and frequency. The Gabor expansion and wavelet decomposition [116] are the most popular methods. But their bandwidths of the analysis and synthesis functions are fixed in the Gabor expansion. The time and frequency

resolutions of the elementary functions in the wavelet decomposition are regulated in a uniform manner. Both the Gabor expansion and the wavelet decomposition are defined on a regular sampling grid. The frequency resolution is obtained at the cost of lower range resolution. It is difficult for the Gabor expansion to automatically distinguish the frequency-dependent events from the frequency-independent ones. Thus it is desirable to have flexible elementary functions to represent the different components of the analyzed signals.

When the wavelet function is orthogonal basis, the signal can be perfectly constructed from the decomposed signal. The signal representation is to retain the major characteristic components in the signals to efficiently reconstruct the signal with a limited amount of the distortion such as in signal compression and noise reduction.

A novel joint time-frequency algorithm based on adaptive Gaussian wavelet is adopted for adaptive signal representation [127]. This method is to use the adaptive normalized Gaussian functions to expand the signal $\phi(t)$ defined as follow:

$$\phi(t) = \sum_{p=1}^{\infty} B_p (\pi\sigma_p^2)^{-0.25} \exp\left[-(t-t_p)^2 / 2\sigma_p^2\right] \exp(j2\pi f_p t) \quad (5.47)$$

The adaptive Gaussian basis representation can match a signal by adjusting the time and frequency resolution and its time-frequency centers that are different from the Gabor expansion and the wavelet decomposition. The time and frequency - shifted Gaussian functions do not constitute an orthogonal basis, the selection of the coefficient B_p is generally not unique. To characterize the time-varying nature of the signal, the elementary function $\psi_p(t)$ is localized in the joint time-frequency domain and the coefficient

B_p reflects the signal local behavior. The coefficient B_p is defined as inner products of the signal $\phi(t)$ and Gaussian elementary functions $\psi_p(t)$ that reflect the signal behavior at the time-frequency instant. $t_w \times f_w$, directly associated with the localized elementary functions $\psi_p(t)$. The definition of the coefficient B_p is as follows:

$$|B_p|^2 = \max_{t_p, f_p, \sigma_p} \left| \int \phi(t) \psi_p^*(t) \right|^2 \quad (5.48)$$

Here the parameters σ_p, t_p and f_p are chosen such that $\psi_p(t)$ is most similar to $\phi(t)$. The parameter σ_p can be used to adjust the bandwidth of $\psi_p(t)$ to best match a variety of signals. It avoids the disadvantage in the Gabor expansion and wavelet decomposition where there is difficulty to select the window bandwidth.

For $p \geq 1$, $\phi_p(t)$ is expressed as follows:

$$\phi_p(t) = \phi_{p-1}(t) - B_{p-1} \psi_{p-1}(t) \quad (5.49)$$

The following equation can be obtained by the normalization of $\psi_p(t)$.

$$\|\phi_p(t)\|^2 = \|\phi_{p-1}(t)\|^2 - |B_{p-1}|^2 \quad (5.50)$$

where $\|\cdot\|$ denotes the Euclidean norm. According to equations (5.49) and (5.50), the signal $\phi(t)$ can be performed with multistage decomposition. At each stage, the coefficient B_p is determined according to equation (5.48). The signal with Q stages of decomposition results in the following relationships:

$$\phi(t) = \sum_{p=0}^Q B_p \psi_p(t) + \phi_{Q+1}(t) \quad (5.51)$$

$$\|\phi(t)\|^2 = \sum_{p=0}^Q |B_p|^2 + \|\phi_{Q+1}(t)\|^2 \quad (5.52)$$

Equation (5.52) shows that the norm of residual $\phi_{Q+1}(t)$ monotonically decreases and converges to zero. This advantage makes it easy to keep balance between the error tolerance and the computation complexity. In order to obtain the optimal parameters $(B_p, t_p, f_p, \sigma_p)$, the genetic algorithm is introduced in the section 5.3.

5.4.3 Adaptive spectrogram of adaptive Gaussian wavelet

Wigner-Ville distribution (WVD) is very useful time-localization method for linear transformations of the signal $\phi(t)$ except the Gabor expansion, the wavelet decomposition and the adaptive Gaussian representation. The WVD is defined as follows:

$$WVD_s(t, f) = \int \phi(t + \tau/2) \phi^*(t - \tau/2) e^{-j2\pi f\tau} d\tau \quad (5.53)$$

WVD has its disadvantage in the cross-term interference and the problem with negativity that greatly impede its useful application. However, the WVD of the Gaussian function is non-negative and well localized in the joint time-frequency domain. The WVD of a complete set of Gaussian functions can be decomposed. The signal $\phi(t)$ can be decomposed into a linear combination of time and frequency shift Gaussian functions $g_p(t)$ defined as:

$$g_p(t) = (\pi\sigma_p)^{-0.25} \exp[-t^2/2\sigma_p] \quad (5.54)$$

$$\phi(t) = \sum_{p=0}^{\infty} B_p g_p(t - t_p) e^{j2\pi f_p t} \quad (5.55)$$

The WVD of equation (5.55) is as follows:

$$\begin{aligned} WVD_s(t, f) = & \sum_{p=0}^{\infty} |B_p|^2 WVD_{g_p}(t - t_p, f - f_p) \\ & + 2 \sum_{p=0}^{\infty} \sum_{q>p} \operatorname{Re} \left\{ |B_p B_q^*| \times WVD_{g_p g_q} \left(t - \frac{t_p + t_q}{2}, f - \frac{f_p + f_q}{2} \right) \right\} \end{aligned} \quad (5.56)$$

Equation (5.56) contains two parts. The first part is a linear sum of the time-frequency shifted Gaussian functions WVD, which are non-negative and concentrated at (t_p, f_p) . The second part consists of the sum of the cross-Gaussian functions WVD that are oscillating at $(0.5(t_p + t_q), 0.5(f_p + f_q))$. When the second part with cross-terms is negative, the first part can be used to represent a signal spectrogram. This is called the cross-term deleted representation (CDR) that is non-negative and cross-term free.

The signal $\phi(t)$ can be decomposed by the Gabor expansion. The Gabor expansion is defined as follows:

$$\phi(t) = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} C_{m,n} g(t - m\Delta T) \exp[j2\pi n\Delta F t] \quad (5.57)$$

where $C_{m,n} = \int \phi(t) \gamma^*(t - m\Delta T) \exp[-j2\pi n\Delta F t] dt$, $\gamma(t) \approx \beta g(t)$, the analysis function $\gamma(t)$ is chosen to be similar to the synthesis function $g(t)$, β is a real constant.

The CDR can be described as follow based on the Gabor expansion [116]:

$$\begin{aligned} CDR(t, f) &= \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} |C_{m,n}|^2 \times WVD_g(t - m\Delta T, f - n\Delta F) \\ &= 2 \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} |C_{m,n}|^2 \times \exp \left\{ -\frac{(t - m\Delta T)^2}{\sigma^2} - (2\pi\sigma)^2 (f - n\Delta F)^2 \right\} \end{aligned} \quad (5.58)$$

The CDR based on the Gabor expansion is cross-term interference free and has good time-frequency resolution. Similar to the CDR, equation (5.47) is transformed by WVD and removes the cross-term part. The adaptive spectrogram (ADS) is obtained as follows:

$$ADS(t, f) = 2 \sum_{p=0}^{\infty} |B_p|^2 \exp \left\{ -\frac{(t - t_p)^2}{\sigma_p^2} - (2\pi)^2 \sigma_p^2 (f - f_p)^2 \right\} \quad (5.59)$$

where $\sigma_p \in R^+$, $t_p \in R^+$, $f_p \in [0, +\infty]$. It is shown that the exponential term in equation (5.59) is the WVD for a normalized Gaussian function. The adaptive spectrogram in following equation can be obtained as:

$$\|ADS(t, f)\|^2 = \sum_{p=0}^{\infty} |B_p|^2 = \|\phi(t)\|^2 \quad (5.60)$$

Equation (5.60) shows that the energy contained in $ADS(t, f)$ is identical to the energy contained in the signal $\phi(t)$. The ADS can be considered as a signal energy distribution in the joint time-frequency domain. This adaptive spectrogram is non-negative, cross-term interference free and has high resolution. GA is used to optimize the parameter as described in the following section.

5.4.4 Algorithm

The procedure that is applied to obtain the adaptive spectrogram is as follows:

- (1) Set $p = 1$, where n is the index of iteration to extract the optimal parameters in equation (5.47) from the p^{th} signal $\phi_p(t)$.
- (2) Obtaining the optimal parameters $(B_p, f_p, t_p, \sigma_p)$ by applying the GA optimization in the following section and Least-Mean-Square (LMS) as shown in the following equation:

$$E_p = \sum_{i=1}^K \left| \phi_p(t_i) - B_p \psi_p(t_i) \right|^2 \quad (5.61)$$

- (3) As shown in equation (5.49), obtain the remained signal ϕ_{p+1} after subtracting the signal obtained in step 2.
- (4) Let $p = p+1$. Return to step 2 unless the reconstructed error is sufficiently small.
- (5) The optimal parameters are then applied to equation (5.59) to obtain the adaptive spectrogram.

The software of the algorithm is developed and programmed by author. The GA is described in Section 5.3. GA is also used to optimize the parameters in equation (5.47). The chromosome (C) contains the five real numbers of the features. The features represent the four parameters of the model as shown in equation (5.47). The example is shown as:

$$\begin{aligned} C = \{c_1, c_2, c_3, c_4, c_5\} &= \{real(B_p), imag(B_p), f_p, t_p, \sigma_p\} \\ &= \{0.003, -0.002, 55, 0.04, 0.003\} \end{aligned} \quad (5.62)$$

The numbers in the chromosome represent respectively the real part and imaginary part of the amplitude, center of the frequency & time and standard deviation. The objective function is obtained by the LMS function, which is defined as:

$$E_p = \sum_{k=1}^K \left| \phi_{p-1}(t) - B_{p-1} \psi_{p-1}(t) \right|^2 \quad (5.63)$$

The GA procedure is applied to obtain the next optimal parameters again. So the result of all the optimal parameters applied in equation (5.47) is the optimal signal representation of the original signal $\phi(t)$. The optimal parameters are also used in equation (5.59) to obtain the adaptive spectrum.

5.4.5 Results and Discussion

5.4.5.1 Simulated Signal

Two simulated signals were presented to test the proposed algorithm of the signal representation based on the normalized adaptive Gaussian wavelet. The simulated signals were generated by the functions as shown in the following equations.

$$\begin{aligned} \phi_1(x) = & 0.015 \cos(180\pi t - 1) \exp \left[-0.5(x - 0.02/0.002)^2 \right] \\ & + 0.012 \cos(600x - 2) \exp \left[-0.5(x - 0.05/0.002)^2 \right] \\ & + 0.01 \cos(340\pi x - 5) \exp \left[-0.5(x - 0.08/0.004)^2 \right] \end{aligned} \quad (5.64)$$

$$\begin{aligned} \phi_2(x) = & 0.004 \cos(180\pi t - 1) \exp \left[-0.5(x - 0.02/0.8)^2 \right] \\ & + 0.012 \cos(600x - 2) \exp \left[-0.5(x - 0.05/0.02)^2 \right] \\ & + 0.007 \cos(340\pi x - 5) \exp \left[-0.5(x - 0.08/0.6)^2 \right] \end{aligned} \quad (5.65)$$

Gaussian noise is the most popular noise in the vibration signals of mechanical system. The original signals generated by the functions in equation (5.64) and (5.65) were added with Gaussian noise to signal-to-noise (SNR) 4dB to obtain the corrupted experimental signals. Figures 5.18 (a) and 5.19 (a) show the simulated signals ϕ_1 and ϕ_2 . Figures 5.18 (b) and 5.19(b) show the corrupted simulated signals.

Figure 5.18 (a) Simulated signal ϕ_1 , (b) Simulated signal ϕ_1 with added noise (4 dB)

Figure 5.19 (a) Simulated signal ϕ_2 , (b) Simulated signal ϕ_2 with added noise (4 dB)

In order to test the proposed adaptive spectrogram algorithm, the adaptive spectrogram ADS was applied to analyze the two simulated signals ϕ_1 & ϕ_2 and the results of ADS were

compared with the results of CWT. Figures 5.20 showed the comparison between the adaptive joint time-frequency plane and CWT plane of the simulated signal ϕ_1 . Compared with CWT, the adaptive spectrogram *ADS* can extract the impulse signals in the finer resolution and a much smaller subspace. Figure 5.21 showed the comparison between the adaptive joint time-frequency plane and CWT plane of the corrupted simulated signal ϕ_1 . The results of *ADS* are also better than that of CWT. It is due to that the adaptive normalized Gaussian wavelet as shown in equation (5.47) can approximate the signal $\phi(t)$ in a very small subspace. The subspace representation can effectively improve the SNR. The adaptive Gaussian wavelet representation is more efficient to de-noise signals than other conventional methods due to the highly concentrated signal energy.

Figure 5.20 Time-frequency plane of the simulated signal ϕ_1 , (a) adaptive spectrogram *ADS*. (b) Continuous wavelet transform.

Figure 5.21 Time-frequency plane of the simulated signal ϕ_1 with added noise, (a) adaptive spectrogram *ADS*. (b) Continuous wavelet transform.

Figures 5.22 and 5.23 show the time-frequency plane between the *ADS* adaptive spectrogram and CWT of the simulated signal ϕ_2 and its corrupted signal. The *ADS* adaptive spectrogram can extract the three characteristic frequencies effectively in fine resolution. The *ADS* also de-noise the corrupted signal. However time-frequency plane of CWT cannot extract and separate the characteristic frequencies.

Figure 5.22 Time-frequency plane of the simulated signal ϕ_2 , (a) adaptive spectrogram *ADS*. (b) Continuous wavelet transform.

Figure 5.23 Time-frequency plane of the simulated signal ϕ_2 with added noise, (a) adaptive spectrogram *ADS*. (b) Continuous wavelet transform.

The above results from the two simulated signals show that the proposed adaptive spectrogram algorithm is applicable to represent the signal in a finer resolution even though signals are corrupted by noise with low signal-noise-ratio. The results show the advantage of the adaptive spectrogram than CWT. The adaptive Gaussian representation can distinguish the frequency-dependent events from the frequency-independent ones by the extent of the basis functions. The basis functions with very small σ_p are used to represent the signal with very narrow length time. The basis functions with very large σ_p result in the highly localized frequencies.

5.4.5.2 Detection of size and location of piston crack

As shown in equation (5.48), the coefficient B_p is the maximum inner product between the signal $\phi(t)$ and normalized Gaussian function $\psi_p(t)$ in optimizing the parameters σ_p, t_p and f_p . It is the indication of the signal at the joint time-frequency plane, which is

characterized by the signal $\phi(t)$. Hence the parameter B_p can be regarded as showing the different conditions of the piston in water hydraulic motor. The amplitudes of the adaptive spectrogram at certain frequencies are mainly determined by the parameter B_p as shown in equation (5.59).

In Figures 5.24-5.26, the adaptive spectrogram of the vibration signal is shown. Figure 5.24 (a) show the spectrogram of the vibration signal under NC condition. There is the highest amplitude of the adaptive spectrogram at 325 Hz that is $1.5 \times 10^{-6} \text{ m/s}^2$. Under FSC condition as shown in Figure 5.24 (b), the highest amplitude of the adaptive spectrogram is $2.5 \times 10^{-6} \text{ m/s}^2$ and the frequency is 370 Hz. Under FLC condition shown in Figure 5.25 (a), the highest amplitude of the adaptive spectrogram is $1.5 \times 10^{-6} \text{ m/s}^2$ and the frequency is also 370 Hz. So when there is a crack in the piston, the frequency of the highest amplitude in the adaptive spectrogram is changed compared with that of the NC condition. The highest amplitude in FLC is lower than that in FSC and their frequencies of the highest amplitude is same. When the crack is in the front section, the frequency and its amplitude is different from that in the rear. Figure 5.25 (b) show the adaptive spectrogram under BSC condition. The highest amplitude is $1.5 \times 10^{-5} \text{ m/s}^2$ and its frequency is about 80 Hz. Figure 5.26 shows the adaptive spectrogram under BLC condition. The highest amplitude is $2.5 \times 10^{-5} \text{ m/s}^2$ and its frequency is about 80 Hz.

Figure 5.24. The adaptive spectrogram of real vibration signal under two piston conditions: (a) NC; (b) FSC

Figure 5.25. The adaptive spectrogram of real vibration signal under two piston conditions: (a) **FLC**; (b) **BSC**

Figure 5.26. The adaptive spectrogram of real vibration signal under **BLC** piston conditions.

From above results, the adaptive spectrogram indicates the different characteristic frequencies under the different piston conditions. The location of the crack in the piston can be indicated by the frequencies of the highest amplitude. The severity of the piston crack can be diagnosed by the highest amplitude in the adaptive spectrogram. The results show that adaptive spectrogram can be an effective method in diagnosing the location and severity of the crack in the piston.

5.5. Conclusion

A noise reduction method based on the adaptive wavelet domain LMS filter was proposed. The wavelet domain LMS algorithm was developed. The orthogonal Shannon wavelet

function was used to reduce the complexity of LMS filter and improve the convergence performance of the LMS algorithm. The results of the simulated signals showed its applicability.

The model-based fault diagnosis of piston crack was proposed. A new model algorithm of the vibration signals based on the adaptive Morlet wavelet was presented. The shape of the adaptive wavelet functions can be altered by adjusting the parameters of the wavelet functions. The genetic algorithm was applied to optimize the parameters of wavelets in the model. The least mean square of the signal was regarded as the criteria for the model of signals. The proposed model algorithm was successful in modeling the signals and can improve the SNR dramatically. The model can extract the characteristic amplitudes and frequencies in signals. The model was applied to diagnose the piston crack in a water hydraulic motor. The CWT of the simulated signal by the adaptive model of the vibration signals can show the time-frequency plane of the vibration signals in fine resolution. The amplitudes and frequency component of the impulse vibration signals can be extracted and are displayed in the time-frequency plane effectively. These feature values can be used to diagnose the different sizes and locations of the piston crack in the water hydraulic motor.

The adaptive spectrogram algorithm for the detection of the piston crack was proposed to analyze the vibration signals. The GA-based optimization algorithm for the adaptive spectrogram was developed to optimize the parameters of the adaptive wavelet representation. In order to test the applicability of the adaptive spectrogram, two popular simulated signals were generated and added with Gaussian noise; and the adaptive spectrogram and conventional CWT were applied to analyze the two simulated signals. The

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results show that adaptive spectrogram can extract the characteristic impulse signals in finer resolution than that of conventional CWT. The adaptive spectrogram is used to diagnose the piston crack in Nessie water hydraulic motor. The defect amplitudes and frequency component of the vibration signals can be extracted and displayed in the time-frequency plane effectively. These feature values can be used to diagnose different sizes and locations of piston crack in a water hydraulic motor.

Chapter 6

Feature Optimization and Automatic Classification

There are two basic approaches in the development of machinery fault diagnosis. Firstly, the machinery fault diagnosis is based on the dynamic vibration characteristics for the feature extraction. Secondly, there is no known vibration characteristics or no any prior information about the machinery. The statistical pattern recognition is an important method to extract the feature values for the machinery fault diagnosis and to extract the features for the fault diagnosis of the water hydraulic motor in this chapter. Due to the large number of feature values, a novel statistical pattern recognition method was proposed to optimize the feature selection process for the fault diagnosis of the piston conditions in the water hydraulic motor. Support vector machines (SVMs) are a comparatively recent development, which is characteristic of the high accuracy and good generalization. The optimized feature set feed the SVMs classifier to reduce the burden of the classifier and improved the learning speed and classification accuracy for fault diagnosis of the piston condition in the water hydraulic motor.

The outline of this chapter is as follows. The statistical feature was described in Section 6.1. Section 6.2 described the SVMs' theory, algorithm and classifiers. Section 6.3 proposed the novel method for the optimization of the features. Section 6.4 investigated the

SVMs' multi-classification. The classification results for the fault diagnosis of the piston condition in the water hydraulic motor were presented.

6.1 Statistical Measures

The wavelet method can quantify the temporal and spectral distribution of the energy. Wavelet-based statistics can quantify the scale and location dependent behaviour. In order to extract the feature value for condition classification, a number of the different statistical features were taken on the basis of the moments of the wavelet coefficients and scale coefficients of the vibration wavelet decomposition. The discrete wavelet transform coefficients $T_{m,n}$ generated from the full decomposition using the second generation wavelet as shown in Chapter 4 were considered. The wavelet statistics such as the variance, skewness and flatness was applied as the feature values in this research.

The p^{th} order statistical moment of the wavelet coefficients $T_{m,n}$ at the scale index m is defined as:

$$\langle T_{m,n}^p \rangle_m = \frac{\sum_{n=1}^{2^{M-n}-1} (T_{m,n})^p}{2^{M-m}} \quad (6.1)$$

where the coefficients at scale m are used in the summation. The brackets denote the average on the number of the coefficients at scale m . The 2^{th} order to 7^{th} order statistical moments of the detail coefficients and approximation coefficients at each level are used as the feature values for the classification. There are twelve feature values at each level. As shown in Chapter 4, the multi-decomposition by the second generation wavelet has three

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levels. These thirty-six feature values are included in the input feature set. That is

$\langle T_{1,n}^2 \rangle_{1,A} \cdots \langle T_{1,n}^7 \rangle_{1,A}$ for the approximation coefficients $C_1[n]$ of the first level, $\langle T_{1,n}^2 \rangle_{1,D} \cdots \langle T_{1,n}^7 \rangle_{1,D}$ for the detail coefficients $D_1[n]$ of the first level, $\langle T_{1,n}^2 \rangle_{2,A} \cdots \langle T_{1,n}^7 \rangle_{2,A}$ for the approximation coefficients $C_2[n]$ of the second level, $\langle T_{1,n}^2 \rangle_{2,D} \cdots \langle T_{1,n}^7 \rangle_{2,D}$ for the detail coefficients $D_2[n]$ of the second level, $\langle T_{1,n}^2 \rangle_{3,A} \cdots \langle T_{1,n}^7 \rangle_{3,A}$ for the approximation coefficients $C_3[n]$ of the third level, and $\langle T_{1,n}^2 \rangle_{3,D} \cdots \langle T_{1,n}^7 \rangle_{3,D}$ for $D_3[n]$,

The general dimensionless moment function is defined as:

$$F_m^p = \langle T_{m,n}^p \rangle_m / \left(\langle T_{m,n}^2 \rangle_m \right)^{p/2} \quad (6.2)$$

where the p^{th} order moment was normalized by the rescaled variance. The scale-dependent coefficient skewness factor was defined as the 3^{th} order moment F_m^3 . The scale-dependent coefficient flatness factor was defined as the 4^{th} order moment F_m^4 . The 3^{th} order to 6^{th} order statistical moments of the detail coefficients and approximation coefficients at the first and second level were used as the feature values for the classification. They are $F_{1,D}^3 \cdots F_{1,D}^6$ for the detail coefficients of the first level, $F_{1,A}^3 \cdots F_{1,A}^6$ for the approximation coefficients of the first level, $F_{2,D}^3 \cdots F_{2,D}^6$ for the detail coefficients of the second level, and $F_{2,A}^3 \cdots F_{2,A}^6$ for the approximation coefficients of the second level. At the third level, the 3^{th} order to 6^{th} order statistical moments of the approximation coefficients were used. They are the $F_{3,A}^3 \cdots F_{3,A}^6$ for the approximation coefficients of the third level. Here there were

twenty features chosen in the input feature set.

In Chapter 4, the intermittency and correlation index was used to analyze the vibration signals. The results about the mean M_I , variance V_I and sum S_I were shown in Figure 6.1. These three moments are also used as the feature values in the input feature set for the classification. There are fifty- nine feature values to be input for the classification in section 6.4.

Figure 6.1 The statistical moments of the intermittency index

6.2 Support Vector Machine

6.2.1 Linear margin classifier

In the late 1960s, SVMs are introduced by Vapnik [128] based on the foundation of statistical learning theory. The algorithm for the numerous practical applications by SVMs emerged following greater availability of computing power from the middle of 1990s [129,130,131,132]. SVM for separating two classes was used to create a line or hyperplane, which was defined by support vectors. The margin between both planes was maximized. The SVMs orient the boundary such that the distance between the boundary and the nearest data point in the class was maximal. The line or boundary was in the middle of the margin between two kinds of data. The nearest data points are known as support vectors.

There are two finite subsets of vectors from a training set,

$$(x_1, y_1), (x_2, y_2), \dots, (x_l, y_l), \quad (6.3)$$

where $x_i \in R^n$ and $y_i \in \{-1, 1\}$, for $i = 1, 2, \dots, N$.

One subset I for which $y = 1$, and another subset Π for which $y = -1$ are separable by the hyperplane $(x * \varphi) = c$, where φ is one vector. A unit vector φ ($|\varphi| = 1$) and a constant c will exist. So the following inequalities will hold true.

$$(x_i * \varphi) > c \quad \text{if } x_i \in I \quad (6.4)$$

$$(x_j * \varphi) < c \quad \text{if } x_j \in \Pi \quad (6.5)$$

where $x * \varphi$ is the inner product between vectors x and φ .

The vector φ_0 and the constant c_0 will exist and determine the hyperplane. This hyperplane was called the maximal margin hyperplane or the optimal hyperplane, as shown in Figure 6.2.

Figure 6.2: The optimal separating hyperplane separates the data with the maximal margin

The parameter $\|\zeta\|$ is the modulus. In order to construct the optimal hyperplane, the vectors ζ_0 and b_0 satisfy the following constraints:

$$(x_i * \zeta_0) + b_0 \geq 1, \quad \text{if } y_i = 1 \quad (6.6)$$

$$(x_j * \zeta_0) + b_0 \leq -1, \quad \text{if } y_j = -1 \quad (6.7)$$

The optimal hyperplane is orthogonal to the shortest line connecting the convex hulls of the two classes (dotted), and intersects it half way. There is a weight vector ζ and a threshold b such that $y_i \cdot ((\zeta \cdot x_i) + b) > 0$. The point(s) closest to the hyperplane satisfy $|(\zeta \cdot x_i) + b| = 1$, it can also obtain the hyperplane with $y_i((\zeta \cdot x_i) + b) \geq 1$. The measured margin perpendicular to the hyperplane equals to $\frac{2}{\|\zeta\|}$. In order to maximize the margin, $\|\zeta\|$ is minimized subject to $y_i((\zeta \cdot x_i) + b) \geq 1$. It can be uniquely constructed by solving a constrained quadratic optimization problem whose solution ζ has an expansion $\zeta = \sum_i v_i x_i$ in terms of a subset of training patterns that lie on the margin where $k_i \geq 0$ are the Lagrange multipliers. These training patterns called support vectors carry all relevant information about the classification problem. Both the quadratic programming problem and the final decision function only depend on dot products between patterns. This is generalized to the nonlinear case.

The above presents the linearly separable data that is for training data sets without overlapping. For the overlapping data points, some data points cannot be correctly classified. In order to find a classifier with a maximal margin, equations 6.6 and 6.7 should be changed to allow some data to be unclassified or on the wrong side of a decision boundary. A soft margin and all data in this margin are neglected. The width of a soft margin can be controlled by a corresponding penalty parameter that determines the trade-off between the training error and the VC dimension of the model [128].

The non-negative slack variables $\xi_i (i = 1, l)$ in the statement of the optimization problem are introduced to generalize the optimal margin for the nonseparable problems. The separating hyperplane must satisfy $y_i((\zeta \cdot x_i) + b) \geq 1 - \xi_i, \quad i = 1, l, \quad \xi_i \geq 0$. This function is to be minimized by an extra term accounting the cost of the overlapping errors. The final quadratic optimization is practically the same as the separable case.

6.2.2 Algorithm

To find the optimal linear hyperplane, which have a maximal margin, is a classic nonlinear optimization problem with inequality constraints. This optimization problem was solved by the following equation:

$$L(\zeta, b, \alpha) = \frac{1}{2} \zeta^T \zeta - \sum_{i=1}^l \alpha_i \{y_i [\zeta^T x_i + b] - 1\} \quad (6.8)$$

where the α_i are Lagrange multipliers. The Lagrange L must be minimized with respect to ζ and b , and maximized with respect to non-negative, α_i , to search for the optimal saddle point (ζ_0, b_0, α_0) . At the saddle point, the derivatives of Lagrange L with respect to primal variables vanish. The complementarity conditions must be satisfied:

$$\alpha_i \{y_i [\zeta^T x_i + b] - 1\} = 0, \quad i = 1, l \quad (6.9)$$

The following equations can be obtained from equation (6.8) and (6.9).

Maximizing

$$L_d(\alpha) = -0.5 \alpha^T H \alpha + f^T \alpha \quad (6.10)$$

subject to

$$\begin{aligned} y^T \alpha &= 0 \\ \alpha &\geq 0 \end{aligned} \quad (6.11)$$

where $(\alpha)_i = \alpha_i$, H denotes the Hessian matrix $(H_{ij} = y_i y_j (x_i x_j) = y_i y_j x_i^T x_j)$, and f is a unit vector ($f = [1 \ 1 \ 1 \ 1]$).

The parameters ζ_0 and b_0 of the optimal hyperplane are obtained as:

$$\zeta_0 = \sum_{i=1}^l \alpha_{0i} y_i x_i, \quad i = 1..l \quad (6.12)$$

$$b_0 = \frac{1}{N_{sv}} \left(\sum_{s=1}^{N_{sv}} \left(\frac{1}{y_s} - x_s^T \zeta_0 \right) \right), \quad s = 1, N_{sv} \quad (6.13)$$

where N_{sv} is the number of the support vectors and l is the number of the training data. The optimal weights vector ζ_0 and the bias term b_0 are calculated by support vectors.

The decision hyperplane $D(x)$ and the indicator function i_F are defined as:

$$\begin{aligned} D(x) &= \sum_{i=1}^l y_i \alpha_i x_i^T x + b_0 \\ i_F &= \text{sign}(D(x)) \end{aligned} \quad (6.14)$$

For the nonlinear classifiers, the procedure is the same as the construction of the above linear margin classifier. The following equation is obtained from equation (6.10) by using kernel function.

$$L_d(\alpha) = \sum_{i=1}^l \alpha_i - \frac{1}{2} \sum_{i,j=1}^l y_i y_j \alpha_i \alpha_j K(x_i, x_j) = f^T \alpha - 0.5 \alpha^T H_k \alpha \quad (6.15)$$

where the symmetric Hessian matrix H_k is given as:

$$H_k = \sum_{i,j=1}^l y_i y_j K(x_i, x_j) \quad (6.16)$$

The bias b_k is not a direct procedure as it is for a linear hyperplane in equation (6.13).

Depending on the applied kernel, the bias is implicitly part of the kernel function. It can be derived from equation (6.13) as:

$$b_k = \frac{1}{l} \left(\sum_{s=1}^l \left(\frac{1}{y_s} - \sum_{i=1}^l \alpha_{0i} y_i K(x_s, x_i) \right) \right) \quad (6.17)$$

The decision function hyperplane $d(x)$ is determined by

$$i_F(x) = \text{sign}(d(x)) = \text{sign} \left(\sum_{s=1}^l y_i \alpha_i K(x, x_s) + b_k \right) \quad (6.18)$$

6.2.3 Feature Space and Kernels

Kernel function maps the training data nonlinearly into a higher-dimensional feature space via Φ , and constructs a separating hyperplane with a maximum margin. It yields a nonlinear decision boundary in input space. It is possible to compute the separating hyperplane without explicitly carrying out the map into the feature space. Figure 6.3 shows the basic idea of SV machines, which is to map the data into some other dot product space (called the feature space) F via a nonlinear map given by

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$$\Phi : \Re^N \rightarrow F \quad (6.19)$$

and perform the above linear algorithm in F . It requires the evaluation of dot products.

$$k(x, y) := (\Phi(x) \cdot \Phi(y)) \quad (6.20)$$

if F is high-dimensional, the right-hand side of Equation (6.20) will be very difficult to compute. In some cases, however, there is a simple *kernel* k that can be evaluated efficiently. For instance, the polynomial kernel can be shown to correspond to a map Φ into the space spanned by all products of exactly d dimensions of $\Re^N$.

$$k(x, y) = (x \cdot y)^d \quad (6.21)$$

For $d = 2$ and $x, y \in \Re^2$, the following equation is derived as:

$$(x \cdot y)^2 = \left(\begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \cdot \begin{pmatrix} y_1 \\ y_2 \end{pmatrix} \right)^2 = \left(\begin{pmatrix} x_1^2 \\ \sqrt{2}x_1x_2 \\ x_2^2 \end{pmatrix} \cdot \begin{pmatrix} y_1^2 \\ \sqrt{2}y_1y_2 \\ y_2^2 \end{pmatrix} \right) = (\Phi(x) \cdot \Phi(y)) \quad (6.22)$$

defining $\Phi(x) = (x_1^2, \sqrt{2}x_1x_2, x_2^2)$. It can be proved that every kernel gives rise to a positive matrix $(k(x_i, x_j))_{ij}$ and construct a map Φ . The radial basis function (RBF) kernel is defined as:

$$k(x, y) = \exp(-\rho d_{a,b}(x, y))$$

$$d_{a,b}(x, y) = \sum_i |x_i^a - y_i^a|^b \quad (6.23)$$

The decay rate around zero is given by $d_{a,b}(x, 0) = \sum_i |x_i|^{ab}$. In the case of Gaussian RBF

kernels ($b = 2$), $ab = 2$ decreasing the value of ab would provide for a slower decay. A data-generating interpretation of *RBF*'s is that they correspond to a mixture of local densities that is generally Gaussian. The heavy tailed distributions is used by lowering the value of b . When the parameter b equals to 1 and 0.5, the RBF is non-Gaussian RBF kernel and they are the Laplacian RBF and sublinear RBF. The improved performances of these distributions can be improved from Gaussian to Laplacian and sublinear RBF [133].

Figure 6.3 Basic idea of SV machines

6.2.4 Architecture of SV

Figure 6.4 shows the architecture of SV methods. In order to substitute $\Phi(x_i)$ for each training example x_i and perform the optimal hyperplane, kernels are applied to form nonlinear decision function

$$f(x) = \text{sign} \left(\sum_{i=1}^i v_i \cdot k(x, x_i) + b \right) \quad (6.24)$$

Figure 6.4 Architecture of SV methods

The parameters v_i are computed as the solution of a quadratic programming problem. In input space, the hyperplane corresponds to a nonlinear decision function whose form is determined by the kernel. The input x and the support vectors x_i are nonlinearly mapped by Φ into a feature space F , where dot products are computed. By the use of the kernel k , these two layers are in practice computed in one single step. The results are linearly combined by weights v_i found by solving a quadratic program. The linear combination is fed into the function

$$\sigma(x) = \text{sign}(x + b) \quad (6.25)$$

The algorithm described thus far has a number of astonishing properties: It is based on statistical learning theory. This is practical as it reduces to a quadratic programming problem with a unique solution. It contains a number of more or less heuristic algorithms as

special cases: by the choice of different kernel functions, the different architectures can be obtained such as linear classifiers, polynomial classifiers and RBF classifiers .

6.3 SVM-RFE for Feature Optimization

6.3.1 Recursive Feature Elimination

A known challenge in the classification and machine learning in general is to find ways to reduce the dimensionality of the feature space to overcome the risk of “overfitting”. Data overfitting arises when the number of features is large and the number of training patterns is comparatively small. A decision function can be easily found to separate the training data but will perform poorly on the test data. The training techniques that use the regularization in SVMs avoids the overfitting of the data to some extent without requiring space dimensionality reduction. Projecting on the first new principle directions of the data is a method commonly used to reduce the feature space dimensionality. The new features are obtained that are linear combination of the original features. One disadvantage of the projection methods is that none of the original input features can be discarded. In this research, the new pruning method was investigated to eliminate some of the original input features and retain a minimum subset of the features that yield best classification performance.

The feature selection is well known in machine vision learning [134]. It was conceivable to select the best subset of the features satisfying a given model selection criterion by the exhaustive enumeration of all subsets of the features. However, exhaustive enumeration is

impractical for large numbers of the features due to the combinational explosion of the number of subsets. The feature-ranking techniques are particularly attractive. A fix number of the top ranked features can be selected for further analysis or to design a classifier. The Structural Risk Minimization is possible for use in the ranking to define nested subsets of the features and select an optimum subset of the features with a model selection criterion by varying a single parameter.

Evaluating the contribution of an individual feature to the classification can produce a simple feature ranking. Various correlation coefficients are used as the ranking criteria. The feature ranking with the correlation method is the implicit orthogonality assumption. Each coefficient is computed with the information about a single feature and does not take into account mutual information between the features.

The use of the feature ranking is the design of a class predictor based on a pre-selected subset of the features. Each feature that is correlated with the separation of the interesting features is by itself a class predictor. It is established that the feature ranking coefficients can be used as the classifier weights. Reciprocally the weights multiplying the inputs of a given classifiers can be used as the feature ranking coefficients. The inputs with the largest weights correspond to the most informative features. The linear discriminant functions provide a better feature ranking than the correlation coefficients. These two methods are known in statistics as multivariate classifiers, which means that they are optimized during training to handle multiple variables simultaneously.

In this research, the method using the ranking features with the magnitude of the weights in a linear discriminant classifier are principle to optimize the features. However a good

feature ranking criterion is not necessarily a good ranking criterion for subsets. The criteria overcome the effect of removing one feature at a time on the objective function. They become the sub-optimal set when it removes several features at a time. The problem can be solved by using the following iterative procedure that is Recursive Feature Elimination (RFE).

- (a) Train the classifier.
- (b) Compute the ranking criterion for all features.
- (c) Remove the feature with smallest ranking criterion.

This method produces a feature subset ranking. The feature subsets are nested. Precetti [135] developed the structure of a Binary Linear Classifier. The structure is built by a recursive dichotomy of the color space, isolating color classes from each other using linear discriminant functions. This classification algorithm fits the specialized hardware and only depends on the number of color classes. The Binary Linear Classifier has more advantage in real-time color classification than the conventional neural network classification of the trial and error.

6.3.2 SVMs-RFE algorithm

SVMs can handle the linear or non-linear decision boundaries of the arbitrary complexity. The linear SVMs are particular linear discriminant classifiers. It can extend to non-linear discriminant classifiers. The training data set is linearly separable and the linear SVMs is a maximum margin classifier. The decision boundary is positioned to leave the largest possible margin on either side. The SVMs and SVMs-RFE algorithm is developed

programmed in Matlab by the author. The SVMs algorithm procedure in Figure 6.5 is described as follow:

Figure 6.5 SVMs algorithm procedure

- (a) Input the training examples $\{X_1, X_2, \dots, X_k, \dots, X_l\}$ and class labels $\{Y_1, Y_2, \dots, Y_k, \dots, Y_l\}$.
- (b) Maximize equation (6.10) subject to equation (6.11) and output the optimal coefficients α_k .
- (d) The optimization of SVMs is typical of a quadratic program. GA is applied to optimize the SVMs to obtain the optimal parameters. GA algorithm is developed in Chapter 5.
- (e) Calculate the parameters ζ_0 and b_0 of the optimal hyperplane according to equations (6.12) and (6.13), output the decision function by equation (6.14).

The new ranking criterion is proposed in SVM-RFE according to the data characteristics.

The SVMs-RFE algorithm procedure is Figure 6.6 is shown as:

Figure 6.6 SVM-RFE algorithm procedure

- (a) Input the training data $\{X_1, X_2, \dots, X_k, \dots, X_l\}$ and class labels $\{Y_1, Y_2, \dots, Y_k, \dots, Y_l\}$.
Initialize the subset of the surviving features and feature ranked list.
- (b) Training the classifier $\alpha = SVM - train(X, Y)$. The optimization of the classification is shown in Figure 6.3. Computer the weight vector ζ according to equation (6.12)
- (c) Computer the ranking criteria $c_i = 1/(\zeta_i)^2$ for all i .

- (d) Find the feature with the smallest ranking criteria. Update the feature ranked list and eliminate the feature with the smallest ranking criterion.
- (e) Output the ranked list and repeat steps (b) to (e) until the rate of the classification is constant.

In section 5.3, genetic algorithm has been introduced and its algorithm is described. The real number encoding, fitness scaling, stochastic universal selection, single-point crossover and non-uniform mutation are employed for the optimization of parameter in SVM. The size of the population is 60. GA is used to optimize the parameter α in SVM. So the length of each string equals to the number of the training data. The number of the string in a population equals to the number of testing data, which is 119. The generations are 2000. The crossover rate is set to the typical values of 0.6 [136]. It is typical to use the relatively higher mutation value such as 0.14 when the real number encoding is used. The population can converge more rapidly by increasing the crossover and mutation rate to introduce more variation into the population [137]. The mutation and crossover rates are set to be 0.2633 and 0.6, respectively, to obtain better classification success rate and increase the speed of convergence for this experiment as shown in Figure 6.7. Figure 6.7 shows the relation between the generation and the average fitness and optimal fitness. Here GA is used to optimize the parameters in SVM, which is simple linear optimization to classify two classes of data. The classification results also deeply depend on the clusters of feature values in two classes. When the clusters of feature values are better, the convergence speed of classification is shorter. Therefore, based on the good feature values and linear SVM with good parameters in GA, the speed of GA convergence and SVM classification are faster, which is especially suitable for on-line machinery fault diagnosis.

Figure 6.7 The relation between the fitness and generation
(a) Average fitness, (b) Optimal fitness

6.4 Method for Multiclass Support Vector Machines

SVMs were originally developed for the binary classification. The extension from the binary two-class to multi-class is an important question for the support vector machine approach. Some research proposed multiclass classifier that considers all classes at once. The major problem of this method is that the much larger optimization problem is required so up to now experiments are limited to small data sets. The work introduced two multiclassifier methods based on binary classifications. That is one-against-all and one-against-one. The one-against-all method is probably the earliest used implementation for SVM multiclass classification. It constructs k SVM models where k is the number of classes. The i th SVM is trained with all of the examples in the i th class with the positive labels and all other examples with negative labels. Given training data $(x_1, y_1), \dots, (x_l, y_l)$,

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where $x_i \in R^n$, $i = 1, \dots, l$ and $y_i \in \{1, \dots, k\}$ is the class of x_i , the i th SVM solves the following equation:

$$\min \quad \frac{1}{2}(\zeta_i)^T \zeta_i + C \sum_{j=1}^l \xi_i^j (\zeta_i)^T \quad (6.26)$$

subject to

$$\begin{aligned} (\zeta_i)^T * x_j + b_i &\geq 1 - \xi_i^j & \text{if } y_j = i \\ (\zeta_i)^T * x_j + b_i &\leq -1 + \xi_i^j & \text{if } y_j \neq i \\ \xi_i^j &\geq 0, & j = 1, \dots, l \end{aligned} \quad (6.27)$$

where the training data x_i can be mapped to a higher dimensional space by the kernel function and C is the penalty parameter.

The margin between the data of two classes $2/\|\zeta_i\|$ is maximized by minimizing $(1/2)(\zeta_i)^T \zeta_i$. The penalty term $C \sum_{j=1}^l \xi_i^j$ can reduce the number of the training error when the data are not linear separable. The basic concept of SVM is to search for the balance between the regularization term $(1/2)(\zeta_i)^T \zeta_i$ and the training errors.

The k decision functions are as follows:

$$\begin{aligned} &(\zeta_1)^T * x + b_1 \\ &\vdots \\ &\vdots \\ &(\zeta_k)^T * x + b_k \end{aligned} \quad (6.28)$$

The class is defined by the following decision functions with largest value.

$$D(x) \equiv \arg \max_{i=1 \dots k} ((\zeta_i)^T * x + b_i) \quad (6.29)$$

One-against-one method is another major method of the SVM multiclassification. It constructs $k(k-1)/2$ classifiers and each one is train on the data between the two classes. The following equations can be used to solve the binary classification between random i th class and j th class.

$$\begin{aligned} \text{Min} \quad & \frac{1}{2}(\zeta_{ij})^T \zeta_{ij} + C \sum_t \xi_{ij}^t (\zeta_{ij})^T \\ & (\zeta_{ij})^T * x_i + b_{ij} \geq 1 - \xi_{ij}^t \quad \text{if} \quad y_t = i \\ & (\zeta_{ij})^T * x_i + b_{ij} \leq -1 + \xi_{ij}^t \quad \text{if} \quad y_t = j \quad \xi_{ij}^t \geq 0 \end{aligned} \quad (6.30)$$

The method constructs $k(k-1)/2$ classifiers. The decision function is as follows:

$$D(x) = ((\zeta_{ij})^T * x + b_{ij}) \quad (6.31)$$

The voting strategy is that the vote of the i th class is added by one when x belongs to the i th class. Otherwise the vote of the j th class is increased by one. The value x belongs to the maximal vote.

The work applied the “one-against-all” method for the SVM multiclassification. The winner-takes-all scheme of the “one-against-all” method is proposed for multi-class classification. The two-class decision function is extended to multi-class by constructing binary decision functions for all classes as follows:

$$f_k : R^N \rightarrow \{\pm 1\} \quad \begin{cases} +1 & \text{For all samples in class K} \\ -1 & \text{else} \end{cases} \quad (6.32)$$

Figure 6.8 shows the winner-takes-all scheme for the three classes. The three lines can separate one class from the both others correctly. However in the middle of the picture all the decision functions hint that this region belongs to none of the three classes. The similar question arises for the three outer triangles with the shade region that in each case where two decision functions are +1 simultaneously.

Figure 6.8 Winner-takes-all for three classes

To solve the problem, the tie situation is broken to neglect the signum operation in the decision functions and to use the real input values. The classification results can be viewed as the discriminant vector where the largest component is chosen as the class decision. The tie breaking is shown in Figure 6.9.

Figure 6.9 Tie breaking by “winner-takes-all” for three classes

6.5 Results and Discussion

In order to classify the five piston conditions, the two-level classification structure by the multi-classification (one-against-all) is proposed. Figure 6.10 shows the structure of the two-level classification. In the first level, the multi-classification is applied to classify the BLC, BSC and other condition. In the second level, the FLC, FSC and NC are classified.

Figure 6.10 The structure of the two-level classification

There are 47 experimental vibration signals of the water hydraulic motor under BSC and 192 vibration signals for BLC, FLC, FSC and NC operating conditions. The training data consists of 23 vibration signals under BSC and 96 vibration signals under BLC, FLC, FSC

and NC operating conditions. The testing data consists of another 24 vibration signals under BSC and another 96 vibration signals under BLC, FLC, FSC and NC operating conditions.

There are 47 experimental vibration signals of the water hydraulic motor under BSC and 48 vibration signals for BLC, FLC, FSC and NC operating conditions. The training data consists of 23 vibration signals under BSC and 24 vibration signals under BLC, FLC, FSC and NC operating conditions. The testing data consists of another 24 vibration signals under BSC and another 96 vibration signals under BLC, FLC, FSC and NC operating conditions.

As shown in section 6.1, there are 59 feature values to be used for classification which are $\langle T_{1,n}^2 \rangle_{1,A} \cdots \langle T_{1,n}^7 \rangle_{1,A}$, $\langle T_{1,n}^2 \rangle_{1,D} \cdots \langle T_{1,n}^7 \rangle_{1,D}$, $\langle T_{1,n}^2 \rangle_{2,A} \cdots \langle T_{1,n}^7 \rangle_{2,A}$, $\langle T_{1,n}^2 \rangle_{2,D} \cdots \langle T_{1,n}^7 \rangle_{2,D}$, $\langle T_{1,n}^2 \rangle_{3,A} \cdots \langle T_{1,n}^7 \rangle_{3,A}$, $\langle T_{1,n}^2 \rangle_{3,D} \cdots \langle T_{1,n}^7 \rangle_{3,D}$, $F_{1,D}^3 \cdots F_{1,D}^6$, $F_{1,A}^3 \cdots F_{1,A}^6$, $F_{2,D}^3 \cdots F_{2,D}^6$, $F_{2,A}^3 \cdots F_{2,A}^6$, $F_{3,A}^3 \cdots F_{3,A}^6$, M_I , V_I , and S_I . The corresponding input item number of the classifier is from 1 to 59. These feature values are optimized by the SVMs-RFE algorithm as shown in Figure 6.6 and one-against-all multiclassification in Figure 6.10.

Figure 6.11 shows the results of the feature value optimization at first level of Figure 6.10. The x axis represents the number of the features with the optimization algorithm. The y axis represents the classification success rate. With the process of the SVMs-RFE, the number of the feature values decrease and the success rate of the optimal feature values increase. The first thirty-six feature values are selected as the optimal features and its

success rate is optimal. Table 6.1 shows the thirty-six optimal features at first level of Figure 6.10.

Table 6.1 The thirty-six optimal features at first level

Piston condition (One-Against-All)	The corresponding item number of the thirty-six optimal features																																			
BLC	1	2	3	7	8	13	14	15	19	20	25	26	31	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59
BSC	1	2	3	7	8	9	13	14	16	19	20	25	26	31	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58
Second level (FLC, FSC and NC)	1	2	3	7	8	9	13	14	15	16	19	25	26	31	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58

Figure 6.11 The feature value optimization at first

Figure 6.12 shows the results of the feature values optimization by SVMs-RFE at second level of Figure 6.10. The first thirty-six feature values are selected as the optimal feature values. The success rate is optimal and constant. Table 6.2 shows the thirty-six optimal features at first level of Figure 6.10.

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Table 6.2 The thirty-six optimal features at second level

Piston condition (One-Against-All)	The corresponding item number of the thirty-six optimal features																																			
FLC	1 48	2 49	3 50	7 51	8 52	9 53	13 54	14 55	15 56	19 57	20 58	25 59	31	37	38	39	40	41	42	43	44	45	46	47												
FSC	1 45	2 46	3 47	7 48	8 49	9 50	13 51	14 52	15 53	16 54	19 55	20 56	25	26	31	32	37	38	39	40	41	42	43	44												
NC	1 47	2 48	3 49	7 50	8 51	9 52	13 53	14 54	15 55	19 56	20 57	25 58	31 59	37	38	39	40	41	42	43	44	45	46

Figure 6.12 The feature value optimization at second level

Table 6.3 show the classification success rate by the multi-classification success rate by two level multi-classification structure in Figure 6.10. The linear and nonlinear classifiers as described in section 6.2.3 are used to detect the piston conditions. The “winner-takes-all” method by tie breaking is also used for the nonlinear classifier to improve the classification success rate.

At first level, the classification success rates of the training data by the linear and nonlinear kernel of the multi-classification under BLC, BSC and Other (FLC, BSC, NC) piston conditions were 80.7%, 79.8%, 60.5% and 80.67%, 79.8%, 60.5%. The classification

success rates of the training data by the nonlinear kernel of Winner-takes-all (Tie-breaking) under BLC, BSC and Other (FLC, BSC, NC) were 80.7%, 79.8%, 60.5%. Compared with the classification success rate of the training data, the classification success rates of the testing data by the linear and nonlinear kernel of the multi-classification under BLC, BSC and Other (FLC, BSC, NC) piston conditions were 80%, 80%, 60% and 80%, 80%, 60%. The classification success rates of the training data by the nonlinear kernel of Winner-takes-all (Tie-breaking) under BLC, BSC and Other (FLC, BSC, NC) were 80%, 80%, 60%.

At second level, the classification success rates of the training data by the linear and nonlinear kernel of the multi-classification under FLC, FSC and NC piston conditions were 66.7%, 66.7%, 66.7% and 66.7%, 66.7%, 66.7%. The classification success rates of the training data by the nonlinear kernel of Winner-takes-all (Tie-breaking) under BLC, BSC and NC were 72.2%, 69.4%, 72.2%. The classification success rates of the testing data by the linear and nonlinear kernel of the multi-classification under BLC, BSC and NC piston conditions were 66.7%, 66.7%, 66.7% and 66.7%, 66.7%, 66.7%. The classification success rates of the training data by the nonlinear kernel of Winner-takes-all (Tie-breaking) under BLC, BSC and Other (FLC, BSC, NC) were 66.7%, 33.3%, 66.7%.

The classification success rate showed that the classification of the five piston conditions was successful. The classification success rate of the testing date was as good as the training data under the all the piston conditions and different classifiers. The classification success rate of tie-breaking was better than the multi-classification without tie-breaking expect the testing data under FSC piston condition. Because the classification success rate of the piston conditions has the close relation to the input feature values.

Table 6.3: The results of the two-level classification success rate

		Piston condition	Multi-classification (%)		Winner-takes-all (Tie breaking) (%)
			Linear	No-linear	No-linear
First level	Training data	BLC	80.7	80.67	80.7
		BSC	79.8	79.8	79.8
		Others (FLC, FSC, NC)	60.5	60.5	60.5
	Testing data	BLC	80	80	80
		BSC	80	80	80
		Others (FLC, FSC, NC)	60	60	60
Second level	Training data	FLC	66.7	66.7	72.2
		FSC	66.7	66.7	69.4
		NC	66.7	66.7	72.2
	Testing data	FLC	66.7	66.7	66.7
		FSC	66.7	66.7	33.3
		NC	66.7	66.7	66.7

6.6 Mechanical Fault Diagnosis Procedure

For users to apply the techniques and models developed in this work, the following procedure for performing condition monitoring and fault diagnosis should be followed:

Step 1: Mechanical condition monitoring and fault diagnosis test system needs to be established. The system includes the monitored mechanical system, vibration sensor, signal

conditioner and data acquisition card with software in a computer that is interfaced with the equipment. The vibration sensor is to be mounted on the mechanical system as near as possible to the internal target of interest. The vibration sensor is interfaced to the monitoring computer via the charge amplifier and signal conditioner. The data acquisition card should be installed in the computer and is used to acquire the vibration signals from the sensor for storage in the computer.

Step 2: The vibration signal is then acquired from the sensor under different machinery operating conditions to obtain the corresponding dynamic vibration signals. The different parts of the machinery have different vibration characteristics under the different fault conditions and normal condition, which are useful for analysis and extraction as feature values. The vibration signals corrupted with high noise need to be de-noised by the signal conditioner.

Step 3: The fault diagnosis system extracts the feature values from the vibration signals under different machinery operating conditions. The vibration signal is then de-noised and analyzed by the developed algorithm based on the second generation wavelet and adaptive wavelet. The wavelet-based statistics of the analyzed vibration signals under different machinery conditions is introduced and used as feature values for the classification of the different machinery conditions. The corresponding relation between the different classes of the feature values of the machinery vibration characteristics and the different fault part conditions was established.

Step 4: The feature values under the different machinery conditions are optimized and classified to detect the different fault machinery conditions and normal condition. The proposed algorithm is then used to reduce the feature values to obtain the optimal feature values. The developed two-level multi-classification method can be used to classify the machinery conditions successfully.

6.7 Conclusion

This chapter investigated the novel method for the machinery fault diagnosis without the prior information about the machinery. The statistical parameters of the multi-decomposition by the second generation wavelet were applied to extract the features. The novel statistical pattern recognition method based SVMs-RFE was applied to optimize the feature selection process and applied for the fault diagnosis of the piston condition in the water hydraulic motor. The optimization algorithm by bi-classification SVM and RFE to extract the optimal features was developed. The optimal feature values were selected successfully. In order to classify the five piston conditions, the two-level structure based on the multi-classification was developed with the linear and nonlinear classifiers. The multi-classification method of SVM by the one-against-all for the fault diagnosis of the piston crack was investigated. The results of the classification were successful. The machinery fault diagnosis procedure was described.

Chapter 7

CONCLUSIONS AND RECOMMENDATIONS

7.1 Conclusions

Detection of various failure models during normal operation of water hydraulic motor is of vital importance, and this issue has attracted considerable interest in the area of predictive or preventive maintenance technology. The on-line fault diagnosis of hydraulic motor and pump is an important method to increase the reliability and performance of hydraulic systems. The dynamic vibration monitoring can be considered to be the best method for machinery fault diagnosis. This research was to study the fault diagnosis of the different sizes and locations of the piston crack of the water hydraulic motor by vibration signal analysis with vibration signals obtained from the casing of the water hydraulic motor. In the following, the main contributions were summarized and future works are outlined.

The experimental measurement system of the water hydraulic motor was designed and developed for testing the five different operating conditions of the water hydraulic motor and acquiring the stable and repeatable vibration signals. The dynamic vibration analysis of the water hydraulic motor was investigated by identifying the relations among the pressure, flow ripple torque and vibration signals. The developed adaptive wavelet analysis methods

can be used to extract the feature values from the vibration signatures for the detection of the piston crack in the water hydraulic motor. The proposed intelligent optimization and automatic classification methods were used to extract the optimal feature values and classify the different sizes and locations of the piston crack in water hydraulic motor.

(1) Investigating the Dynamic Mechanism of the Water Hydraulic Motor

The dynamics of the swash plate axial piston motor is fundamental to the understanding of the vibration mechanism in water hydraulic motor. It was found that the characteristics of the vibration from the casing of the water hydraulic motor was closely related to the exerted force, which is produced by the supply pressure in the piston chamber. The results from the developed mathematical model with the three masses and fourteen DOF showed that the supply pressure ripple in the piston chamber is the source to cause the water hydraulic motor to vibrate. It was verified that the principle frequencies of the casing vibration are the hydraulic motor angular speed and hydraulic pump angular speed. This is because the characteristic frequencies of the pressure ripple are determined by the angular speeds of the hydraulic motor and pump in the hydraulic system. The frequencies of the higher harmonics are integer multiples of the angular frequencies of the water hydraulic motor and pump in the modern water hydraulic system. The amplitudes of the vibration signals increased with the increasing output torque of the water hydraulic motor and their frequencies were almost similar when the angular speed was constant.

The relations among the piston pressure, the flow rate and the output torque were determined. The introduced theoretical analysis of the pressure mechanism with and without the leakage due to the slipper shows that the pressure in the piston chamber varies

from the supply pressure to outlet pressure periodically. The piston pressure is only affected by the structure of the water hydraulic motor system and the rotational speed of the hydraulic motor. The flow rate is determined by the supply pressure, outlet pressure and the rotational speed. The simulated results of the idealized flow and actual flow showed that their harmonic frequencies equal to the integer multiples of the piston pass frequency. The output torque of the axial piston motor is determined by the piston pressure and the angular speed. The simulated waveform of the output torque is constant and stable. The frequencies of the instantaneous torque are even integer of the piston pass frequency. The simulated results of the shaft torque due to the piston crack showed the variation of the shaft torque and frequency characteristics. Theoretically, it was verified that the vibration characteristics are deterministic with the constant pressure, which can be determined by the constant output torque and angular speed. In order to obtain the repeatable and stable vibration signals, it was required that the output torque and angular speed were kept at the constant value to obtain the vibration signals under the five piston conditions.

(2) Developing Feature Extraction Method Based on Adaptive Wavelet analysis

Water hydraulic motor test system can be used to obtain the stable and repeatable vibration signals. The introduced hypothesis test proved that each mean of every raw random vibration signals is equal to the real mean (m_{real}). The random vibration signals have the same mean with each other. The 100 % of the random vibration signals is repeatable and stable.

The pressure ripple generated the impulse vibration of the casing of the water hydraulic motor, which matches the pumping behavior in the water hydraulic motor. These types of

signals are characteristic of the non-stationary events of machinery signals such as spikes, transients, modulation and others with the time-varying spectrum. The impulse vibration signals from the different mechanical conditions demonstrated the different local distributions of the vibration energy. It is verified that the wavelet multi-decomposition can analyze the signals in the localized wavelet functions and represent the local characteristic energy distribution. The wavelet-based statistic parameters can quantify both the scale- and location-dependent behavior successfully. The results showed that the statistical feature values of the second wavelet multi-decomposition for the impulse vibration signals were effective to detect the piston crack under the five piston conditions. The proposed noise reduction method combining the Generalized Cross Validation and second wavelet multi-decomposition can improve the vibration signals, which were corrupted by the Gaussian noise and impulse noise, from the SNR of 1 dB to 19.5 dB.

The adaptive wavelet analysis was found to be more effective and useful to enhance the nonstationary features of machinery signals than conventional signal analysis. This research focused on the adaptive feature extraction based on the adaptive wavelets. This method is to find a set of adaptive wavelets to model the signals, which contain the meaningful information about machinery conditions to serve as the feature extractor. The results from the proposed model algorithm for the simulated corrupted signals showed that it can simulate the corrupted vibration signals very successfully and improve the SNR from the SNR of 1dB to 39.8dB. It was precise to extract the principle characteristic amplitudes and frequencies of the simulated signals. It was found that the extracted frequencies and its amplitudes of the experimental vibration signals under the five piston conditions were very different and can be used as feature values to detect the piston crack under the five piston

conditions successfully. The adaptive spectrogram is to search for a global adaptive optimal solution to the feature extraction of signals with the small dimensionality. The results from the experimental vibration signals by the proposed adaptive spectrogram algorithm showed that it can be used for the detection of the different sizes and locations of the piston crack in the water hydraulic motor. The GA-based optimization algorithm can optimize the adaptive spectrogram by obtaining the optimal parameters of the adaptive spectrogram. It is found that the adaptive spectrogram can extract the characteristic frequencies of the vibration signals in finer resolution than that of conventional CWT even though the vibration signals are corrupted by noise with low SNR. A presented noise reduction method based on the adaptive wavelet domain LMS filter can improve the corrupted signals from the SNR of 2dB to 22.4dB.

(3) Feature Extraction and Automatic Classification

SVM is regarded as a good method for intelligent automatic classification due to the high generalization performance without the need to add a priori knowledge. The new automatic classification for the fault detection and diagnosis of the water hydraulic motor is proposed based on SVM. The new optimization method by bi-classification SVM to extract the optimal features from the fifty-nine statistical features is proposed. The results showed that the optimal features can be extracted by reducing the fifty-nine features to three optimal features and the classification success rate increased from 30% to 80%. It was found that the proposed two-level multi-classification method based on the linear and non-linear kernel function was suitable for the detection of the sizes and locations of the piston crack in the water hydraulic motor. The classification success rate can be up to 80.7%.

This research has established the intelligent fault diagnosis of piston conditions in water hydraulic system successfully. It studied the characteristics of vibration signals. The model algorithm of vibration signal was developed based on adaptive wavelet. The algorithm of the multi-decomposition with novel second generation wavelet was proposed to analyze the impulse vibration signal. The intelligent algorithm of classifications and optimization was studied. The developed methods and algorithm have significant applications in machinery fault diagnosis. The common failure modes in rotating equipment is misalignment, imbalance, rub, wearout, cavities, crack and oil whirl in critical components such as rotor and shaft, bearings, gears, seals and blades. The probability for each fault source can be established according to the vibration signal, which is analyzed by the develop algorithms in this research. The developed algorithm with wavelet analysis can be applied for fault diagnosis of gearboxes in transmission, roller bearings, rotary systems, and in-core flux detectors in nuclear reactors. This research has the interesting and significant applications in the reliability and maintenance of machinery and mechanical systems.

7.2 Recommendations

In order to improve the system and to further understand the dynamic vibration response and characteristics, the following recommendations are proposed.

(1) Studying the dynamic motion of the piston and characteristics of the impulse vibration

This research has investigated dynamic mechanism of the water hydraulic motor. It is necessary to investigate the vibration mechanism of the water hydraulic motor based on the

preliminary work on these aspects, considering the piston motion and the tribological contact force between the piston and cylinder block. The damping and stiffness coefficient need to be studied to improve the dynamic model.

This model need to be improved. The main source of the vibration is the flow ripple, which interacts with the hydraulic system to produce the pressure ripple. The vibration mechanism of the water hydraulic motor should be improved by considering the structure stiffness and the modal characteristic. The pressure ripple causes the mechanical vibration of the water hydraulic motor. The other source of the vibration is the piston motion that produces the force on the swash plate causing the impulse vibration. The motion mechanism of the piston require studying in order to understand the mechanism of the impulse vibration. Understanding the tribological force between the piston and the cylinder block is important in order to achieve the high efficiency and reliability in the piston motor. The relations between the contact force, piston motion and the vibration should be also studied in the future. The piston crack results in piston leakage and, therefore, change the pressure ripple and the vibration mechanism. So the vibration characteristics due to the piston crack should be studied.

(2) Construct Adaptive Wavelet for Feature Extraction

Feature extraction is an important approach for the fault detection and diagnosis of the water hydraulic system. The adaptive method based on the second generation method and adaptive wavelet have been investigated to diagnose the piston crack in the water hydraulic motor. These general wavelet concerns mainly the mathematical properties required for the

general applications. In order to improve the feature extraction, the specific wavelet should be constructed to characteristic signals. According to the characteristic impulse vibration signals, the specific adaptive second generation wavelet should be studied. The construction of the adaptive update-lifting schemes are worth investigating to extract the features more effectively, so that the adaptive update-lifting scheme can adapt themselves to the characteristics of the impulse signals. For the perfect reconstruction of the signals, the adaptive framework with the adaptive reconstruction filter bank should be investigated. The result scheme provides the possibility to extract the singularities from the noise.

(3) Improve the Optimization of Feature Value and Automatic Classification

In this study, the statistical feature values from the second generation wavelet were optimized for the classification of the mechanical conditions. The adaptive wavelet and spectrogram were also developed for analyzing the vibration signals effectively. The extracted feature values from the adaptive spectrogram should be studied to classify the piston condition. Support vector machines (SVMs) were designed for binary classification. How to extend the binary classification to the multiclass classification is still an ongoing research topic. In this research, the method for the decomposition implementations for the binary classification were proposed. In order to achieve the good results from the multiclassification, the classification method for all the classes should be proposed. Because of its large computation, there is a need to develop the optimization method to solve the equations. The kernel function is also important for the classification of the results. Every function has its own different characteristics and is suitable for specific classifications. It is necessary to analyze the optimal kernel function and to study the

method to optimize the mutation and crossover rate to increase the classification rate in SVM.

List of Publications

1. Chen, H.X., Chua, P.S.K., Lim, G.H., 2005, The adaptive wavelet analysis optimized by genetic algorithm for fault diagnosis of water hydraulic motor, *International Journal of Applied Mathematics and Mechanics* (published).
2. Chen, H.X., Chua, P.S.K., Lim, G.H., 2005, Adaptive wavelet transform for model of vibration signal and application in fault diagnosis of water hydraulic motor, *Mechanical Systems and Signal Processing* (in press).
3. Chen, H.X., Chua, P.S.K., Lim, G.H., 2005, Dynamic vibration analysis of a swash-plate type water hydraulic motor, *Mechanism and Machine Theory*, (in press).
4. Chen, H.X., Chua, P.S.K., Lim, G.H., 2005, Fault Detection in a Water Hydraulic Motor Using Wavelet Transform, *Journal of Testing and Evaluation*, (in press)
5. Chen, H.X., Chua, P.S.K. and Lim, G.H., 2003, Application of Wavelet for Feature Extraction of a Modern Water Hydraulic Motor in Vibration and Acoustic Analysis, *Proceedings of the 10th Asia-Pacific Vibration Conference*, 12-14 November, Gold Coast, Australia, Ed. Joseph Mathew, Vol.1.
6. Chen, H.X., Lim, G. H., Chua, P.S.K., 2005, Fault Diagnosis of a Water Hydraulic Motor by Second Generation Wavelet, 4th Asia Conference on Industrial Automation and Robotics, May, 11-13, 2005, Bangkok, Thailand.
7. Chen, H.X., Chua, P.S.K., Lim, G.H., 2005, Feature Extraction Optimization and Classification for Crack Detection, 4th Asia Conference on Industrial Automation and Robotics, May, 11-13, 2005, Bangkok, Thailand.
8. Lim, G.H., Chen, H.X., Chua, P.S.K., 2003, Fault Diagnosis of Piston Crack in a Water Hydraulic Motor, *Proceedings of the International Conference and Exhibition on Instrumentation and Control*, PICS-ICEIC 2003, ISBN: 1656-2364, November 2003, Manila, Philippines.

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Appendix A

18	PRESSURE SENSOR OUTLET	P1	1
17	PRESSURE SENSOR INLET	P2	1
16	FLOW SENSOR OUTLET	F1	1
15	FLOW SENSOR INLET	F2	1
14	TEMPERATURE SENSOR INLET	T1	1
13	AIR COOLED HEAT EXCHANGER		1
12	HYDRAULIC HOSES		2
11	QUICK CONNECT COUPLERS		6
10	SHAFT SPEED ENCODER	E1	1
09	MAIN CONTROL PANEL		1
08	TORQUEMETER	TQ1	1
07	MAH 12.5 PISTON MOTOR	180F0003	1
06	VOH30EPE PROPORTIONAL FCV	180H0254	1
05	VDH30E4/3 DCV – 24VDC	180L0053	1
04	VDH30E2/2 DCV – 24VDC	180U4100	1
03	PRESSURE GAUGE		1
02	[PRESSURE RELIEF VALVE		
01	PPH 12.5 PISTON PUMP	180B0291	1
No	DESCRIPTION	MODEL NO	QTY

Appendix A

Appendix B

The parameters in Table 3.1 were obtained as follows:

1. The stiffness of the spring is define as:

$$K = \frac{Gd^4}{8ND^3} = 4444$$

where mean diameter of coil $D = 4.9\text{mm}$, modulus of elasticity of spring material $G = 190\text{E}+9$, number of active coils $N = 25$, diameter of wire $d = 0.576\text{mm}$

2. The contact surfaces between the cylinder block and outer shell, and between the cylinder block and valve cover can be consider as the fluid film bearings [115], which were modeled by the damping and stiffness coefficients as shown in Ref [51]. The Figure 3.3-5 in Lee's book [115] shows the stiffness coefficients and damping coefficients for the rotational speed dependent bearing properties. The rotational speed of the water hydraulic motor in this work is 630rpm . So the stiffness coefficient is $1.04 \times 10^7 \text{ N/m}$ and the damping coefficient is $1.04 \times 10^7 \text{ N}\cdot\text{sec/m}$.

3. Nishimura and Tsuta [51] defined and provide the other stiffness and damping coefficients in the model of the swash-plate type hydraulic piston pump such as swash plate support stiffness K_{swz} , K_{swx} and K_{swy} , bolt stiffness K_{Box} , K_{Boy} and K_{Boz} , interface stiffness between piston and cylinder port K_{Hz} , interface damping coefficient between piston and cylinder port C_{Hz} , and interface damping coefficient between valve plate and cylinder block C_{Vaz} . The following table showed the value of stiffness and damping coefficients.

K_{swz}	$4.7 \times 10^9 \text{ (N/m)}$	C_{Hz}	3.4×10^4
K_{swx}	1.5×10^9		
K_{swy}	6.3×10^9		
K_{Box}	6.5×10^7	C_{Vaz}	3.6×10^5
K_{Boy}	6.5×10^7		
K_{Boz}	2.3×10^7		
K_{Hz}	1.2×10^7		

Appendix B